Nonlinearity in Market Efficiency: Comparison study of Malaysia, London and Singapore

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Abstract

It is argued that the efficiency in futures market depends on the nature of trading activity in futures and on its relation to the underlying security. Much of the studies in this are only focus on the linear relationship between this instruments and little has been done using the nonlinearity test. To explore this matter we use BDS test and Treshold autoregressive model (TAR) to model our data to investigate the efficiency of stock index futures in Malaysia, Singapore and London in a nonlinear way. If forecasting can be made by using the nonlinear model, market efficiency theory is challenging again and arbitrage opportunity will exists. The conclusion to be drawn from the threshold model is that, although the basis changes can be predicted by using a nonlinear model, arbitrageurs cannot make profits from nonlinear prediction because the basis only produce profits when profit making from the transaction exceed its transaction costs.

1. Introduction

Testing for nonlinear dependence has become an important area of research in financial econometrics because of its profound implications for model adequacy, market efficiency and predictability (Brooks, 1996). For example, Hinich and Patterson (1989) claim that if nonlinearity exists in financial time series, at least in the short term, forecasts may be improved by switching from a linear to a nonlinear modeling strategy, if only because a linear model can no longer be viewed as an accurate representation of the data. More generally, there is now substantial literature, which broadly agrees that there is nonlinear behaviour in financial time series such as stock market indices (Hsieh, 1991 and 1995), exchanges rates (Kodres and Papell, 1995, Krager and Krugler 1992) and for gold and silver prices (Frank and Stengos, 1989).

The purpose of this paper is to examine whether basis (basis=log (futures) – log (spot) prices) for FTSE-100, Nikkei 225 and KLCI series exhibits nonlinear dependence and its implications on the efficiency of these markets. Nonlinear dependence will be examined using the BDS test and the generalised autoregressive conditional heteroscedasticity (GARCH) family model to explain this behaviour, if any. Failing that a more complicated model such as threshold autoregressive (TAR), in particular the smooth transition autoregressive (STAR) family will be used. This investigation is undertaken to assess if nonlinear predictability is feasible (and hence inconsistent with efficiency) outside the bounds of transactions costs.

2. Reasons for the existence of nonlinearity in the time series.

Fat tailed return distribution

Nonlinearity in times series exists for several reasons. First, there is the possibility that a fat tailed returns distribution may be responsible for the rejection of linearity. Researchers have only focused on futures price return distributions because of the efficiency implications of skewed distributions (if skewed, the risk of margin calls differs between long and short positions (Sutcliffe, 1993)). There is fairly widespread evidence of skewness in analysing this futures price returns. Twite (1990) has analysed four years of daily closing price data on futures for the Australian Stock Exchange All Ordinaries Share Price Index and found that the distribution of returns is non-normal, with

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leptokurtosis[2] and positive skewness. Chan, Chan and Karolyi (1991) and Stulz, Wasserfallen and Stucki (1990) also found that the distributions of the future price returns are leptokurtic.

Table 1 shows the descriptive statistics of the filtered basis series (series that already adjusted with AR (p) process to extract any linear dependence) for the exchanges examined. The kurtosis[3] of the series are all well over 3[4], indicating that the basis distribution is leptokurtic. This fat-tailed distribution may exhibit nonlinear dependence in the basis series. However, this is only an indication, because, according to Sutcliffe (1993), the existence of leptokurtic time series may be related to the arrival rate of new information or the imposition of a minimum price movement. As information arrives at an uneven rate, the distribution will be a mixture of a number of normal distributions, which may produce serial correlation in the series.

Table 1: Descriptive statistics for filtered basis using AR(p) process

Exchanges	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**
FTSE-100	-1.38E-06	4.45E-03	0.062	19.395
Nikkei-225	-1.54E-05	5.24E-03	-0.879	17.715
KLCI	-5.17E-06	3.69E-03	0.058	3.601

3. Data

The data set used in this chapter are basis for London, Singapore and Malaysia. Daily closing prices for the futures and spot markets are used and the basis is calculated as the log difference between the futures and spot prices. The time period covered for the London market is from 1984 to 1997, Singapore from 1986 to 1997 and the Malaysian market from December 1995 to March 1997.

4 Test for nonlinearity

4.1 BDS Tests

The BDS test statistic (Brock, Dechert and Scheinkman (1987)) is a general test for nonlinearity, and is based on the correlation integral[5]. This test is more powerful than simple nonlinear deterministic systems as well as nonlinear stochastic processes. The BDS statistic is used to test the null hypothesis that a time series is independent and identically distributed (IID) against an unspecified alternative using a nonparametric technique (see Brock et al. 1991) and, as such, represents a general test of nonlinear behaviour from which specific models can be developed. The method has been used by Brock, Hsieh and Le Baron (1991) and Lee, White and Granger (1993).

The steps in the BDS tests are as follows:
First, the m-histories of the series is $x_t^m = (x_t, x_{t+k}, ..., _{t+m-1})$ are computed for times t =1,2,3..... $t+m-1$, where m is the embedding dimension. The correlation integral is defined as

$$C_m(\varepsilon) = \frac{1}{(T-m+1)(T-m)} \sum_{t,s} L_\varepsilon \left(x_t^m x_s^m \right) \qquad [1]$$

[2] A distribution with kurtosis much greater than 3 is said to be leptokurtic. For certain symmetric distributions this is associated with a sharp peak at the mean and fat tails.

[3] A measure of the 'pointed ness' of a probability distribution.

[4] The normal distribution or IID has a kurtosis measure of 3.

[5] Correlation integral is used to measure the proportion of embedded vectors of dimension (m) lying within the neighbourhood of an initial embedding (ε) (Abhyankar, et al. (1991)).

where L_ε is the indicator function that equals one if $||x_t^m - x_t^s|| \langle \varepsilon$ and zero otherwise. ||.|| denotes the sup-and max.-norm, which is used for measurement of distance. The correlation integral measures the fraction of pairs of m-dimensional points whose distance is no greater than a small number ε. The BDS statistic is

$$C_{m,t}(\varepsilon) = T^{1/2}(C_m(\varepsilon,T) - C_1(\varepsilon,T)^m) / \sigma_m(\varepsilon,T) \qquad [2]$$

where $\sigma_m(\varepsilon,T)$ is an estimate of the standard deviation under the null hypothesis of IID for selected m and ε, and where the BDS statistic is asymptotically normally distributed with zero mean and a known variance.

When conducting the BDS test, the data are usually pre-filtered through linear filters such as AR(p) model. The filter process is needed to extract any linearity effect in the data, thus leaving the nonlinearity effect, if any for further test. The residual from AR(p) models are used for the BDS test to detect any nonlinear behaviour in the basis. According to Granger (1991), BDS tests can be applied to filtered series, where the filter chosen gives an output with white noise properties: if the series being tested does not have white noise properties, the null hypothesis can be immediately rejected and there is no need for the test. The following table (2) displays the result of BDS tests for all the three exchanges we tested.

4.1.2 BDS test results and discussion

Table (2): BDS test statistics for London, Singapore and Malaysia

		Exchanges	
Dimension	**FTSE-100**	**Nikkei-225**	**KLCI**
AR (p) model Residuals			
2	1.47	2.14*	3.75 *
3	1.98*	1.88	2.45*
4	1.21	2.24*	2.88*
5	2.89*	3.21*	4.91*
6	3.32*	3.19*	4.04*
7	2.76*	4.17*	4.15*
8	3.68*	2.19*	4.75*
9	2.63*	3.25*	3.95*
10	3.06*	3.27*	3.91*

This table provides the results for BDS statistic at dimension 2 through 10 with the ε/σ equal to 1.0. BDS statistics are distributed N(0,1) under the H_0 of IID. Rejecting the H0 when BDS statistics more than 1.96 (at 5% significant level). The observations contain absolute basis changes and two non IID models: AR(p) residuals (pure autoregressive model) and GARCH(1,1) residuals (the generalised autoregressive heterocedasticity model. * significantly more than 1.96 (reject IID) (The test statistic is from Peters, Edgar E (1991)

BDS test results in table (2) indicate substantial nonlinear dependence in the basis series. The filtered AR(p) model does not remove any nonlinear dependence because the asymptotic distribution of the

BDS test is not altered by using the residuals from the filtered series instead of the raw data (Brock, 1987). This suggests that the filter process in the AR(p) model does not remove non-linear effects in the basis. The results reject the null hypothesis that the basis is identical and independently distributed (IID) at the 5% significance level. These findings indicate that the basis contains some nonlinear behaviour, which may contradict the market efficiency hypothesis, in a way that a basis can be forecasted, because it is possible for the basis to be linearly uncorrelated, but nonlinearly dependent. The reason for the existence of nonlinear effect in basis may be because of the distribution of the basis. As shown in the descriptive statistic for basis in table (1), basis exhibits fat/heavy-tailed distribution.

An alternative explanation for the existence of nonlinear dependence in the basis series relates to the feedback effect in price movements where price deviations from theoretical values encourage self-regulating forces to drive prices back to their no-arbitrage values. The nonlinearity arises because the extent of the correction in the market may not be proportional to the amount by which the price deviates from its true value. In such circumstances there might be some deviation of the price that relates to nonlinear feedback, if there are many participants in the exchanges with many attitudes and motives, which make their feedback to any news potentially different.

Our results are consistent with previous studies, which show that BDS has successfully detected nonlinear behaviour in time series when using an AR(p) model (Hsieh (1991), Abhyankar, Copeland and Wong (1995), Hsieh (1995)). This suggests that our results are valid for all three markets tested are not efficient in a nonlinear way.

4.2 Fitting a GARCH (1,1) model

This section will try to model basis series using GARCH (1,1) model to eliminate the effect of nonlinearity in the series. This GARCH (1,1) model is considered a general model. If the model does not fit the data, we will proceed with a more complex model such as the threshold model. The ARCH model was first suggested by Engle (1982) and further developed by Bolleslev (1986) in his generalised autoregressive conditional heteroscedasticity (GARCH) model. In the ARCH model, the process is modelled as being dependent on lags past squared residuals while in GARCH, the variance of the process is modelled as being dependent on lags squared residuals as well as lags variance. Within the class of GARCH process, GARCH (1,1) estimation is considered preferable for the purpose of filtering (Bolleslev, 1986; and Akgiray, 1989). The GARCH (1,1) models estimated in this study take the form of:

$$B_t = \phi_0 + \phi_1 B_{t-1} + \varepsilon_t \qquad [3]$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \qquad [4]$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad [5]$$

where B_t is the basis conditional on past information which is proxied by $\beta_{t-1}, \alpha_0, \alpha_1, \beta_1$ are parameter to be estimated. ψ_{t-1} is the information set at time t-1, ε_t is the stochastic error conditional on ψ_{t-1}, and is assumed to be normally distributed with zero mean and conditional (time varying) variance, h_t. As such, in GARCH models conditional variance of the error term as a linear function of the lagged squared residuals and the lagged residual conditional variance. The advantage of a GARCH model is that it captures the tendency in financial data for volatility clustering.

The basis series is fitted with the GARCH(1,1) model and the residual is evaluated by investigating its standardised residuals. If the GARCH(1,1) models for all the exchanges are correctly specified and fit the sample data, the standardised residuals and the squared standardised residuals should be IID. The Ljung-Box Portmanteau test is then used to test whether the GARCH (1,1) model removes serial correlation in the original data (Bolleslev, 1986). Under the condition that the GARCH(1,1) filtered residual fails to remove volatility clustering (first and second order serial dependence), a more complex model such as the threshold model is suggested to overcome the nonlinear dependence in the basis series.

4.2.1 GARCH (1,1) model results and discussions

Table (3): GARCH (1,1) model for all the three exchanges

London

$$B_t = 0.00 + 0.80 B_{t-1} + \varepsilon_{t1}$$
(11.81) (78.35)

$$h_t = 1.41E-06 + 0.24\varepsilon_{t-1}^2 + 0.73 h_{t-1}$$
(17.384) (24.01) (89.95)

Ljung Q-statistics

		1st order	2nd order
lag	5	98.38 (0.00)	4.70 (0.40)
	30	214.88 (0.00)	37.93 (0.15)
	90	353.48 (0.00)	119.50 (0.02)

Singapore

$$B_t = 0.00 + 0.82 B_{t-1} + \varepsilon_t$$
a. (84.82)

$$h_t = 2.41E-06 + 0.45\varepsilon_{t-1}^2 + 0.58 h_{t-1}$$
(12.54) (61.85) (67.81)

Ljung Q-statistics

		1st order	2nd order
lag	5	107.48 (0.00)	28.20 (0.00)
	31	265.88 (0.00)	34.15 (0.28)
	90	654.48 (0.00)	101.95 (0.18)

Malaysia

$$B_t = 0.00 + 0.76 B_{t-1} + \varepsilon_t \ \varepsilon$$
(8.56) (19.60)

$$h_t = 1.08E-05 + 0.34\varepsilon_{t-1}^2 + 0.55 h_{t-1}$$
(6.41) (3.41) (6.95)

Ljung Q-statistics

		1st order	2nd order
lag	5	19.66 (0.00)	4.38 (0.49)
	30	1.27 (0.00)	24.49 (0.74)
	90	100.91 (0.00)	62.26 (0.98)

Note: B_t is the basis, B_{t-1} is previous lag of the basis and h_{t-1} is the conditional variance and ε_{t-1}^2 is the squared residuals in the GARCH (1,1) estimation. Ljung first order and 2nd order are to look at the dependency of the residual of the GARCH (1,1) estimation. The number in the bracket in the equation is the T-statistics and in the L-Jung Q-statistics the number in the bracket represents the P-value of the statistic.

Table (3) tabulates the results of GARCH (1,1) model for the basis series. As we can see the L-Jung Box Q test statistics for lags 5,30 and 90 are statistically significant at 5% significance level, indicating first order serial correlation in the GARCH(1,1) basis series. However, the second order – test statistics of standardised residual squared due to McLeod-Li are not statistically significant at 5% level, suggesting that second order serial correlation dependence do not exist. This suggest that the GARCH(1,1)[6] model for all the three exchanges does not remove the nonlinear dependence in the series although the second order serial correlation is not significant for all the lags tested. This result suggests that basis needs to be modelled with a higher order GARCH model or with a more complicated model such as threshold autoregressive.

4.3 Threshold Autoregressive model for basis

One of the most important parametric nonlinear time series models is the threshold autoregressive model (TAR). There are some extensions to this class of model, namely the smooth transition threshold autoregressive (STAR) model. The STAR model is a combination of the Exponential Autoregressive model (EAR) originally proposed by Haggan and Ozaki (1981) and the TAR model, which was introduced by Tong and Lim (1980) and further investigated by Tong (1983). The TAR model is based on the observation that many empirical systems have some natural threshold value which results in a very distinctive behaviour of the system. This is accounted for, by the TAR model through modelling different autoregressive processes depending on the value of some lagged variable.

The STAR model is appropriate when there is a threshold level of the absolute deviation from the equilibrium beyond which the spread becomes mean reverting. In our case the spread is referred to as the basis. In this model the regime changes gradually (smoothly) rather that abruptly, as they do in the TAR model. A smooth rather than a discrete regime change is likely to be more realistic and appropriate when dealing with an aggregated process (Granger and Terasvirta (1993)).

The other characteristic of the STAR model is that the nonlinear adjustment process takes place in every period when the variable deviates from equilibrium, but the speed of adjustment varies with the extent of the deviation from equilibrium. The STAR model is considered to be more reliable than the TAR model because the statistical modelling procedures are more developed. In the TAR model the discontinuity at each of the thresholds makes the testing of linearity complicated and it is unclear how inference about the estimated thresholds should be conducted (Michael, Nobay and Peel ,1996).

The STAR model can be expressed as:

$$y_t = \beta_0 + \sum_{j=1}^{p} \beta_j y_{t-j} + \left(\beta_0^* + \sum_{j=1}^{p} \beta_j^* y_{t-j} \right) \left[F\left(y_{t-d} \right) \right] + \varepsilon_t \qquad [6]$$

where y_t is stationary and ε_t is an IID process with zero mean and finite variance. $F(y_{t-d})$ is a transition function bounded by zero and one. The STAR model can be divided into two popular classes namely the Logistic function (LSTAR) and the Exponential function (ESTAR).

(a) The LSTAR model can be expressed as :

$$F\left(y_{t-d}\right) = \left(1 + \exp\left(-\gamma\left(y_{t-d} - c\right)\right)\right)^{-1} \qquad \gamma > 0 \qquad [7]$$

where γ determines the speed of the transition process between two extreme regimes and c is the transition parameter. Note that when $\gamma \to \infty$ and $y_{t-d} > c$ then $F(y_{t-d})=1$, but when $c \geq y_{t-d}$, $F(y_{t-d}) = 0$, so that equation (6) collapses into a threshold AR(p). When $\gamma \to 0$, equation (7) becomes a linear AR(p) process.

The LSTAR model differs from the ESTAR model in that the parameters in the LSTAR model change monotonically with the transition function, while the ESTAR model changes in a non-monotonic way. This model can describe one type of dynamics for booming phases of the economy and another for slower phases. The logistic function provides asymmetric adjustment towards equilibrium according to the sign of (y_{t-d} -c).

[6] We have also tried higher order of GARCH model and, the results are the same.

(b) The exponential function –(ESTAR)

$$F\left(y_{t-d}\right) = 1 - \exp\left(-\gamma\left(y_{t-d} - c^2\right)\right) \qquad \gamma > 0 \qquad [8]$$

The ESTAR model becomes linear both when $\gamma \to 0$ and $\gamma \to \infty$. The model implies that contraction and expansion have similar dynamics (Terasvirta and Andersen, 1992). The transition function is U-shaped and the parameter γ determines the speed of the transition process between two regimes. This model may be viewed as a generalisation of a particular form of two threshold models whereas, the LSTAR model is a single-threshold TAR with asymmetric adjustment to positive/negative deviations (Michael et. al (1996).

4.3.1 ESTAR process with application to the arbitrage behaviour

The ESTAR application is based on modelling the evolution of differences in asset prices of equivalent assets (basis) traded in markets linked by arbitrage. Price differences could arise if the same asset is traded in two geographical locations or if one asset can be created synthetically from combinations of other assets, for example the futures price and the futures-equivalent cash price of a stock index. Equivalent assets should share the same stochastic trend and their prices should not diverge in the long run, if arbitrage-related forces link the markets in which they are traded. If both prices are traded in a perfect market, the two prices must be identical at all the times. However, prices could drift apart in the short term if trading in one of the two assets involves lower transaction costs than the other, which is due to inadequate incentive for arbitrage. Arbitrageurs will initiate the arbitrage trade only when the basis exceeds the transaction costs in the arbitrage strategy. Consequently, there exists a window of possible price differences within which arbitrageurs are not likely to make any effort to bring prices into lines with each other. This window is called the no-arbitrage window and futures and spot prices can easily move apart without triggering arbitrage-related market forces that would bring them back together. In the other window, called the outside no-arbitrage window, arbitrageurs will start to act if the profit from the price differences (basis) exceed the transaction costs.

In applying the ESTAR model, the no-arbitrage window refers to regime 1 and the outside window refers to regime 2. Every time the net profit (basis –transaction cost) of any transaction exceeds the basis, the basis will move outside the no-arbitrage window. In this boundary, that is regime 2, the basis will be mean reverting and arbitrage activities will push the basis back to its equilibrium level in the no-arbitrage window in regime 1.

4.3.2 ESTAR model testing strategy

The purpose of this section is to fit a suitable nonlinear model for basis. The strategy involves three basic steps.

1. The first step is to carry out the complete specification of linear AR(p) model. Over specification of the linear AR(p) model is preferable to under specification since autocorrelated errors may affect the linearity test.

2. After the appropriate linear AR(P) model has been determined, we proceed with testing for linearity, and if rejected, detect the delay parameter, d. This delay parameter is a positive integer representing the number of time periods necessary for the arbitrageurs to have a price impact. If linearity is rejected at more than one value of d, we select the one for which the p-value of the test is the lowest. Note that when testing equation (4.10) the value of γ implies F= 0 when $\gamma = 0$, and thus the linearity hypothesis may be expressed as $H_0: \gamma = 0$ and the alternative $H_1: \gamma > 0$. If the null cannot be rejected then the model is a linear AR(p) model.

Terasvirta (1994) derives an LM-test type of linearity against LSTAR or ESTAR models by estimating the following artificial regression:

$$y_t = \beta_{00} + \sum_{j=1}^{p}\left(\beta_{0j} y_{t-j} + \beta_{1j} y_{t-j} y_{t-d} + \beta_{2j} y_{t-j} y_{t-d}^2 + \beta_{3j} y_{t-j} y_{t-d}^3\right) + \varepsilon_t \quad [9]$$

and testing the null of

$$H_0 = \beta_{1j} = \beta_{2j} = \beta_{3j} = 0 \qquad j = 1,2,......p \qquad [10]$$

In practice the Lagrange Multiplier (LM) test of linearity is replaced by an ordinary F-test in order to improve the size and power of the test[7]. Once the value of the delay parameter, d has been determined, MNP(1996) suggest that a more powerful and specific test against the ESTAR model can be obtained by the following regression:

$$y_t = \beta_{00} + \sum_{j=1}^{p}\left(\beta_{0j}y_{t-j} + \beta_{1j}y_{t-j}y_{t-d} + \beta_{2j}y_{t-j}y_{t-d}^2\right) + \varepsilon_t \qquad [11]$$

and testing the null of

$$H_{0L}^{*}: \beta_{1j} = \beta_{2j} = 0 \qquad (j=1,2,.....p) \qquad [12(a)]$$

by using the ordinary F-test

The most powerful test of linearity is based on the test of the null

$$H_{0L}^{**}: \beta_{2j} = 0 / \beta_{1j} = 0 \qquad (j=1,2.....p) \qquad [12(b)]$$

The test for (12b) is the optimal test of the null of linearity against the specific alternative of an ESTAR model. After linearity is rejected for all the above hypotheses, the next step is to select the appropriate ESTAR model for London, Singapore and Malaysia.

In the estimation of the ESTAR, the estimation of the transition function γ and c may pose a problem (Terasvirta, 1994). This is because when γ is large, the slope of the transition function is steep and even relatively large changes in γ, only have a minor effect on the shape of $F_{(t-d)}$. The situation is even more intricate since we also do not know the parameter c. Terasvirta(1994) suggests standardising the exponent of $F_{(t-d)}$ by dividing it with the variance of the basis, such that γ=1 is an appropriate starting value. We carry out the tests with γ fixed at different values to get the best fitting ESTAR models for all the three exchanges tested.

4.3.3 Empirical Results and Discussions

Table (4) displays the results of the LM linearity test. The LM linearity test is significant for the hypothesis we tested (equation 12 (a) and (b)). The P-values reject the null hypothesis of linear series for all the exchanges at 5% significance level. This shows the basis series exhibit nonlinear behaviour.

Table (4): P-Values of linearity test (ESTAR model)

Market	London	Singapore	Malaysia
Lags AR (p)	4	5	2

[7] The LM-test is an asymptotic one, which has better performance when the sample size is large. In reality it is essential when the order p of the linear AR model is large while the number of observations is small (Harvey, 1990).

d(delay parameter)	1	1	1
Test			
H^{*}_{0L}	0.000	0.006	0.010
	(11.31)	(3.31)	(2.96)
H^{**}_{0L}	0.004	0.013	0.002
	(3.29)	(2.90)	(5.32)

The P-value is used to test the hypothesis in equation 12(a) and (b). The p-value is tested against the chi-square at 5% significance level. All of the above hypotheses reject the null hypothesis of linearity. Numbers in brackets are F-statistics of the respective hypothesis and markets

If linearity is rejected in favour of nonlinearity the next step is the estimation of the delay parameter. The delay parameter is determined by testing the hypothesis in equation (12) and confirms that the time periods necessary for arbitrageurs to have a price impact is one day. The results show that the p-value for day one is the lowest when compared to day 2 or day 3, as displayed in table (4).

Table (5): P-value of the delay parameter

Exchange	**Delay parameter** 1	2	3
London	0.000	0.001	0.001
Singapore	0.001	0.001	0.002
Malaysia	0.000	0.002	0.000

This table testing equation 4.16 to determine the delay parameter of the ESTAR model. The above p-value is significant at 5% significance level.

Once the delay parameter has been estimated, the final step is to model the basis series using the ESTAR model . Table (6) shows the ESTAR models for all the respective exchanges tested. DW is the Durbin Watson statistic, which is used to test for serial correlation in the model. None of the model exhibits serial correlation in their residuals and the Ljung-Box Q-statistic supports this result. The ARCH LM and White heteroscedasticity tests, test for the existence of ARCH effect and heteroscedasticity, which might otherwise suggest misspecification. According to Eirtheim and Terasvirta (1996), nonlinear models can be mispecified if any remaining nonlinearity is not modelled. The diagnostic of ARCH effects confirms that all three ESTAR models are clean of ARCH and heteroscedasticity effects.

Table 6: ESTAR model estimation for London, Singapore and Malaysia

London (ESTAR model)

$$b_t = \mathbf{0.25}b_{t-2} + \mathbf{0.28}b_{t-3} - \mathbf{0.19}b_{t-4} + (\mathbf{0.24}b_{t-1} - \mathbf{0.34}b_{t-2} + \mathbf{0.18}b_{t-3} + \mathbf{0.25}b_{t-4} -$$

(2.19) (2.16) (2.36) (5.78) (6.34) (4.02) (5.58)

$$* F_{(t-d)} + \varepsilon_t$$

$$F_{(t-d)} = (1-\exp(-2\mathbf{0.28}b_{t-1})^2)$$

(4.31)

R^2 = 0.5608	Q(5) = 7.922(0.161)	Arch(1) = 0.188 (0.664)
DW = 2.007	Q(30) = 35.55(0.125)	
SD = 0.0049	$Q^{\wedge 2}(5)$ = 3.105(0.684)	
	$Q^{\wedge}{}_2(30)$=43.60(0.052)	

Singapore (ESTAR model)

$$b_t = \mathbf{0.17}b_{t-1} - \mathbf{0.14}b_{t-2} + \mathbf{0.29}b_{t-3} + \mathbf{0.12}b_{t-4} + (-\mathbf{0.43}b_{t-1} - \mathbf{0.35}b_{t-2}$$
(2.34) (2.47) (2.94) (2.75) (5.78) (6.93)

$$+ \mathbf{0.17}b_{t-3} - \mathbf{0.23}b_{t-4)} * F_{(t-d)} + \varepsilon_t$$
(4.35) (3.29)

$$F_{(t-d)} = (1-\exp(-\mathbf{26.30}b_{t-1})^2)$$
(3.81)

R^2 = 0.543	Q(5) = 7.115 (0.212)	Arch(1) = 0.034(0.852)
SD = 0.0094	Q(30) = 7.527 (0.163)	
DW = 2.12	$Q^{\wedge 2}(5)$ = 2.842(0.724)	
	$Q^{\wedge}{}_2(30)$=17.28(0.991)	

Malaysia (ESTAR model)

$$b_t = \mathbf{0.21}b_{t-1} + \mathbf{0.24}b_{t-2} + (-\mathbf{0.29}b_{t-1} - \mathbf{0.19}b_{t-2}) * F_{(t-d)} + \varepsilon_t$$
(2.38) (2.29) (4.68) (3.55)

$$F_{(t-d)} = (1-\exp(-1\mathbf{0.14}b_{t-1})^2)$$
(3.59)

R^2 = 0.558	Q(5) = 0.704 (0.98)	Arch(1) = 0.094(0.758)
SD = 0.0054	Q(30)= 519.57(0.92)	
DW = 2.32	$Q^{\wedge 2}(5)$ = 2.912(0.550)	
	$Q^{\wedge}{}_2(30)$=15.30(0.210)	

*SD is standard deviation of the dependent variable
*Q(p)and $Q^{\wedge 2}(p)$ is the L-Jung Box statistic for the test of serial correlation
*ARCH (p) is used to detect the ARCH effect.
*Number in the bracket is the respective T-statistic of the coefficient

Table (6) is the ESTAR models for all the three exchanges and it indicates that the transition rate (γ) in $F_{(t-d)}$ is higher for London and Singapore when compared to the Malaysian market. The transition rates for London and Singapore are 20.28 and 26.30 respectively compared to 10.14 for Malaysia. This indicates that in the London and Singapore markets any deviation from the non-arbitrage window will be quickly corrected and prices will be pushed back to the no-arbitrage window. This quick transition from one regime to another regime prevents arbitrage to take place for a longer period and create abnormal profits. The reason behind this quick transition is that in well-developed and efficient markets, such as London and Singapore, transaction costs are low, compared to a relatively new market, like Malaysia, and therefore the no-arbitrage bounds for these markets are narrow. On the other hand, for less efficient or new markets, the higher transaction costs make the no-arbitrage bounds wider. As a result the time needed for the basis to move between the arbitrage bounds whenever mispricing occurs and restores the price at the equilibrium level is faster in London and Singapore compared to Malaysia. The wider no-arbitrage bounds in Malaysia will make the trading activity slow as arbitrageurs do not actively participate.

5 ESTAR model and BDS statistic

To support the results from the ESTAR model, a further BDS test is used against the residual from the linear AR(p) model. If the true model describing basis is an ESTAR, then the residuals obtained after fitting the estimated ESTAR model should arguably be independent and identically distributed. Thus, the test is employed as a diagnostic tool for the adequacy of the nonlinear fitted model obtained with

ESTAR. Additionally, if the market response to basis is efficient within the inner regime, the distribution of the basis must be IID.

Table (7) reports the results for the BDS test statistic for all the three exchanges examined by using the residuals of the fitted ESTAR model. The embedding dimension m, is chosen to be from 2-10 and the distance measure, $\varepsilon/\sigma = 1$. From table (7), the BDS test statistic for the residual from the ESTAR model reveals that we cannot reject the hypothesis that basis changes are IID compared to a 5% level of significance. This suggests that the ESTAR model is a good and adequate model in modelling the price differences between stock index futures and their respective spot market.

Table 7: BDS test for the ESTAR model residuals

Markets	London	Singapore	Malaysia
Dimension			
2	0.13	0.18	1.09
3	0.16	0.13	1.12
4	0.19	0.15	1.16
5	0.23	0.16	1.18
6	0.24	0.19	1.20
7	0.27	0.21	1.59
8	0.30	0.23	1.75
9	0.97	0.24	1.98*
10	1.26	0.26	2.00*

This tables provides the results for the BDS statistic at dimension 2 through 10 with the ε/σ=1.0. BDS statistics are distributed N(0,1) under null hypothesis of IID. We reject the IID null hypothesis when BDS statistic is more than 1.96% (at 5% significance level). The residuals are from the fitted ESTAR model for each of the respective markets to test the distribution of the basis changes.
* reject the null hypothesis

The conclusion to be drawn from the threshold model is that, although the basis changes can be predicted by using a nonlinear model, arbitrageurs cannot make profits from nonlinear prediction because the basis only produce profits when profit making from the transaction exceeds its transaction costs. It also clearly shows that, although the model is nonlinear, the basis remains in the inner window of no arbitrage possibilities, which exhibits an IID distribution, which is a characteristic of an efficient market. This means the basis can still be efficient, despite the existence of the nonlinear structure in the time series. It is suggested that nonlinear behaviour is not always inconsistent with the efficient market hypothesis. In other words, arbitrageurs can predict a market because of the existence of nonlinearity effects in the model, but they cannot make any money from this prediction.

To determine the proportion of observation that lie outside the transaction costs band by using daily data is impossible because other studies that look at this matter using a more shorter time period data such as Swintnerton, Curnio and Bennet (1988), Farbush (1981) and Yadav and Pope(1990) found that the primary reaction of arbitrageurs to an arbitrage opportunity occurs within five minutes to the first hour. Unfortunately our data is a daily data, which the effect of the reaction outside no-arbitrage bounds has disappeared by the end of the data. This is considered the limitation of this chapter.

6 Conclusions

This paper covers two different areas of nonlinear effects in the basis changes of stock index futures and its underlying cash market. The first area employed general nonlinear tests such as the BDS test. We tested the absolute value of basis AR(p) model for London, Singapore and Malaysia. The BDS test statistic results conclude the basis for all the exchanges exhibit nonlinear dependence in the time series. This nonlinear behaviour in the basis indicates that basis can be predicted and contradicted with market efficiency.

The second area covers a general nonlinear model such as the GARCH model. If the GARCH model failed to model the basis, will use a more specific model namely the STAR model is used. The GARCH (1,1) model for all the three exchanges failed to model the basis because the first order serial correlation coefficients of the basis exhibit serial correlation. The second order serial dependence as measured by the square of the Q-statistic in some lags failed to reject the null hypothesis of nondependence among the basis.

Further areas covered are nonlinear tests such as the STAR model, especially the ESTAR model. We modelled our data with the ESTAR model because this model has two thresholds and the deviations from equilibrium have the same adjustment whether positive or negative. All three exchanges reject the LM linearity test and successfully model as an ESTAR model. The next step is to test the residual from the fitted ESTAR model against the BDS test to detect the distribution of this residual. The result reveals that the residual is IID and is consistent with inner-regime behaviour. The conclusion drawn from this is that, although the basis can be modelled in a nonlinear way and may be used for forecasting, the profits from this prediction is not in excess of transaction costs. The results also show that nonlinear behaviour is not inconsistent with an efficient market because the ESTAR model residual of the basis changes remains within the no arbitrage window.

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