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Modelling Exchange Rates Using Regime Switching Models

(Pemodelan Kadar Tukaran Wang Asing Menggunakan Model Perubahan Rejim)

MOHD TAHIR ISMAIL & ZAIDI ISA

ABSTRAK

Gelagat siri masa kewangan pada dasarnya tidak boleh dimodelkan hanya dengan menggunakan model siri masa linear sahaja. Fenomena seperti min berbalik, kemeruapan pasaran saham dan perubahan struktur siri masa tidak boleh dimodelkan secara tersirat di dalam model linear mudah. Untuk itu, model siri masa tidak linear dibangunkan untuk mengatasi masalah ketidaklinearan yang ditunjukkan oleh data tersebut. Kertas kajian ini telah mengaplikasikan beberapa ujian "portmanteau" dan perubahan struktur untuk mengenalpasti tabiat ketidaklinearan di dalam kadar tukaran wang asing untuk tiga negara di ASEAN iaitu Malaysia, Singapura dan Thailand. Didapati bahawa hipotesis nol tentang kelinearan mampu ditolak dan wujudnya bukti bahawa perubahan struktur berlaku untuk ketiga-tiga siri yang dikaji. Untuk itu, penggunaan model perubahan rejim amatlah sesuai untuk kajian ini. Berdasarkan kriteria pemilihan model iaitu AIC, SBC dan HQC, pengkaji membandingkan kesuaian untuk dua bentuk model perubahan rejim iaitu model SETAR (Self-Exciting Threshold Autoregressive) dan model perubahan Markov (MS-AR). Berdasarkan kepada nilai AIC, SBC dan HQC, didapati bahawa model MS-AR memberikan darjah kesuaian yang lebih baik untuk kesemua siri masa yang dikaji. Sebagai tambahan, mdoel perubahan rejim juga memberikan darjah kesuaian yang lebih baik berbanding dengan model autoregresi mudah. Keputusan ini menunjukkan bahawa model tidak linear memberikan kesuaian dalam sampel yang lebih baik berbanding dengan model linear.

Kata kunci: kadar tukaran wang asing; model perubahan rejim; ketidaklinearan; kriteria pemilihan model

ABSTRACT

The behaviour of many financial time series cannot be modeled solely by linear time series model. Phenomena such as mean reversion, volatility of stock markets and structural breaks cannot be modelled implicitly using simple linear time series model. Thus, to overcome this problem, nonlinear time series models are typically designed to accommodate these nonlinear features in the data. In this paper, we use portmanteau test and structural change test to detect nonlinear feature in three ASEAN countries exchange rates (Malaysia, Singapore and Thailand). It is found that the null hypothesis of linearity is rejected and there is evidence of structural breaks in the exchange rates series. Therefore, the decision of using regime switching model in this study is justified. Using model selection criteria (AIC, SBC, HQC), we compare the in-sample fitting between two types of regime switching model. The two regime switching models we considered were the Self-Exciting Threshold Autoregressive (SETAR) model and the Markov switching Autoregressive (MS-AR) model where these models can explain the abrupt changes in a time series but differ as how they model the movement between regimes. From the AIC, SBC and HQC values, it is found that the MS -AR model is the best fitted model for all the return series. In addition, the regime switching model also found to perform better than simple autoregressive model in in-sample fitting. This result justified that nonlinear model give better in-sample fitting than linear model.

Keywords: exchange rates; regime switching model; nonlinearity; model selection criteria

INTRODUCTION

In the last decade we have seen an increasing interest in modelling financial time series as nonlinear time series models as opposed to linear time series models. This is due to the realization that a number of studies have uncovered significant non-linear behaviour in stock market (Poterba and Summers, 1988, Scheinkman and Lebaron, 1989) and in exchange rates (Hsieh, 1989, Brooks, 1996). A variety of nonlinear models have been considered as alternatives to the widely used linear model. Some of the models are the bilinear model of Granger and Anderson (1978), the autoregressive conditional heteroscedastic (ARCH) of Engle (1982) and the generalized ARCH (GARCH) of Bollerslev (1986). However, according to Franses and Dijk (2000), a recent nonlinear model that is getting a lot of attention is the regime switching model.

Regime switching models are designed to capture discrete changes in the series that generate the data. Two main classes of such models are considered in this paper, namely the Markov switching autoregressive model (MS-AR) and the self-exciting threshold autoregressive (SETAR). These two parametric models allow the transition between regimes to be abrupt but differ as how they model the movement between regimes. While in the MS-AR model the movement between regimes are unrelated to the past observations of the process. Whereas, the SETAR model movement between regimes depended on the past observations of the process. The former type assumed that the regime is an unobservable stochastic process but the latter type assumed regime is an observable variable.

The MS-AR model assigns probabilities to the occurrence of different regimes and the probabilities have to be inferred from the data. Previous studies that employed this model are Engel (1994), Kirikos (2000), Caporale and Spagnolo (2004) and Bergman and Hansson (2005). All these authors modelled regime shifts in exchange rates and found that regime switching models provide better in-sample and out-of-sample forecast than random walk specifications. An alternative to the MS-AR approach is to use the SETAR model where the regimes switching that occur in the past and the present are known certainly using statistical method. The motivation for using this model is provided by the work of Krager and Kugler (1993), Chappell et al. (1996) and Hendry et al. (2001). All of them studied the time series behaviour of exchange rates.

The assumption that the financial time series can be in two or more regimes has motivated the used of regime switching models. The SETAR model assumed that the changes between regimes are discrete and occur endogenously. In contrast with the SETAR model, the changes between regimes happen exogenously in MS-AR model using probabilistic interpretation. In this paper, we test for nonlinearity in the data to justify the decision to use regime switching models. Then, we use model selection criteria to compare the in-sample fitting performance of autoregressive, Markov switching autoregressive and self-exciting threshold autoregressive processes.

This paper has two objectives. The first is to compare the efficiency of regime switching model and the linear model using several ASEAN countries exchange rates. The second is to investigate whether the regime switching models is a useful tool for describing the nonlinearity features of exchange rates. The organisation of the paper is as follow. Section II introduces linear model and regime switching model specifications. Section III presents the empirical results and discussion on the results. Section IV contains summary and conclusion.

II. METHODOLOGY

In this section we discuss the competing models used in the fitting exercise. We begin by introducing the univariate linear time series model that serves as a benchmark for the fitting comparison. Then we consider regime-switching models namely self-exciting threshold autoregressive (SETAR) and Markov switching autoregressive (MS-AR) model.

UNIVARIATE LINEAR MODELS

A commonly used linear time series model in modelling financial returns is Yule (1927) autoregressive process or AR (p) where p is the lagged parameter. If y_t is a time series that follow an AR process, the model can be written as

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \varepsilon_t . \tag{1}$$

where α_i is the parameter and $\{\varepsilon_t\}$ is a sequence of independent and identically distributed random variables with mean 0 and variance σ_ε^2

The AR lag order p is selected to minimize the Bayesian Information Criterion (BIC) (Akaike 1979) using the following formula:

$$\text{BIC} = T\ \ln(\text{sum of squared residuals}) + n + n\ln(T). \tag{2}$$

where n is the numbers of parameter estimated and T is the number of usable observation.

Although the AR model is widely used by past researchers, empirical findings (Franses & Dijk 2000, Taylor 1986) showed that returns on financial data tend to exhibit erratic behaviour, in the sense that large returns are often negative, it occurs more often than expected and it tend to occur in cluster. Therefore, test for nonlinearity must be done to discriminate nonlinear series from linear series in financial returns modelling. If linearity is rejected, a nonlinear time series model is used. Below, we describe the two regime switching models that are used in this study.

SELF-EXCITING THRESHOLD AUTOREGRESSIVEMODELS

The threshold autoregressive model (TAR) was proposed by Tong (1978) in time series modelling. It was further discussed by Tong and Lim (1980) and Tong (1983). TAR model is a piecewise linear autoregressive model. The piecewise is in the space of threshold variable but not piecewise linear in time. It is also called the Self-Exciting Threshold Autoregressive (SETAR) when the threshold variable is taken to be a lagged value of the time series itself. The statistical properties of SETAR models have been extensively examined by Tong (1993) and Hansen (1996, 1997, 2000). Two regimes versions of SETAR are specified in the following wa y where α_i and β_i are coefficients to be estimated τ is the value of the threshold, p is the order of the S ETAR model, y_{t-d} is the threshold variable, d is the delay parameter $\underline{d \leq p}$ and $\{\varepsilon_t\}$ is a sequence of independent

$$y_t = \begin{cases} \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \varepsilon_t & if\ y_{t-d} \le \tau \\ \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t & if\ y_{t-d} > \tau \end{cases} \tag{3}$$

and identically distributed random variables with mean 0 and variance σ_ε^2

If τ is known, the observations can be separated according to whether y_{t-d} is above or below the threshold. Then we estimate the AR model for each segment using ordinary least squares method (OLS). In most cases the threshold is unknown and must be estimated along with other parameter of the SETAR model. Chan (1993) explain how to obtain a super-consistent estimate of the threshold parameter, τ by using least squares estimation. A grid search is done to find the smallest residual sum of squares and the value is the consistent estimate of the threshold. Enders (2004) explains the logic of Chan (1993) procedure in the last chapter of his book. After the threshold parameter is calculated, the SETAR model can be estimated using nonlinear least squares estimation (NLS) or the maximum likelihood estimation (MLE). Systematic procedures for modelling SETAR models have been proposed by Tsay (1989) and it is widely used in empirical studies.

MARKOV SWITCHING AUTOREGRESSIVE MODELS

The SETAR models consider regime switching as deterministic events but in real world the changes in regime happen quite suddenly. Therefore, to model this dramatic change a more practical and realistic model is the Markov switching autoregressive model. MS-AR model assume that the regime switching are exogenous and there are fixed probability for each regime changes. The model was originally developed by Hamilton (1989) to define changes between fast and slow growth regimes in the US economy.

Hamilton (1993, 1994) assumed that in the Markov switching autoregressive model the time series y_t is normally distributed with μ_i and variance σ_i^2 in each of k possible state where $i = 1,2,........ k$ The state is assumed to follow the Markov process with discrete, ergodic and irreducible states. This means, the state at time t is determined randomly and depends only on the state at time *t-1*. A Markov switching autoregressive model of two states with an AR process of order p is given as follow:

$$y_t = \mu(s_t) + \left[\sum_{i=1}^{p} \alpha_i (y_{t-i} - \mu(s_{t-i}) \right] + u_t \tag{4}$$
$$u_t \sim i.i.d(0, \sigma^2(s_t))$$
$$s_t = j, s_{t-i} = i \quad i, j = 1,$$

wheres S_t is the unobserved state variable that takes the values of 1 (expansion period) or 2 (contraction period) and the transition between states is governed by a first order Markov process as follows:

$$P(S_t = 1 \mid S_{t-1} = 1) = p_{11}$$
$$P(S_t = 1 \mid S_{t-1} = 2) = p_{12}$$
$$P(S_t = 2 \mid S_{t-1} = 1) = p_{21}$$
$$P(S_t = 2 \mid S_{t-1} = 2) = p_{22}.$$

with $p_{11} + p_{12} = p_{21} + p_{22} = 1$

The advantage of the transition probabilities of Eq. (5) is that they specified a probability which state occurs at each point in time rather than imposing particular dates at priori. These allow the data to tell the nature and incidence of significant changes.

As the state variable is unobserved, the parameters vector is estimated by the maximum likelihood using EM algorithm described by Hamilton (1990, 1994) i.e. The density of the data has two components and the log-likelihood function is built as a probability weighted sum of these two components.

III. APPLICATION TO ASEAN EXCHANGE RATES

This section starts by giving a description of the data and modelling the data as an AR process to test for nonlinearity. Then we model the data using the two regime switching models. We calculate the model selection criteria (AIC, HQC, SBC and likelihood ratio test) and compare the values to identify which model fits the data well.

DATA

The data under investigation are the monthly exchange rates of three ASEAN countries (Malaysia, Singapore and Thailand) over the period from February 1990 to June 2005 for a total of 185 observations. The exchange rates are the local currencies against the British pound. All the data are sourced from www.x-rates.com. The variables under investigation are exchange rate returns in percentage $y_t = 100 \times [(\ln P_t) - (\ln P_{t-1})]$ where P_t is the monthly exchange rates. We use monthly series because we assume that structural breaks can be observed more clearly across time if low period frequency data is used. We proved this by inspecting the plot of monthly returns for all the series. In Figure 1 we manage to detect significant structural breaks at 1992 for the Singapore dollar and 1997 for the Malaysia ringgit and the Thailand Bath.

NONLINEARITY TESTING

We begin by calculating the BIC using Eq. 2 to find the number of lags to be used in the AR process for the three exchange rates return series. We found that the number of lags to be used is one for the return series of the Malaysia ringgit and the Thailand bath and two for the return series

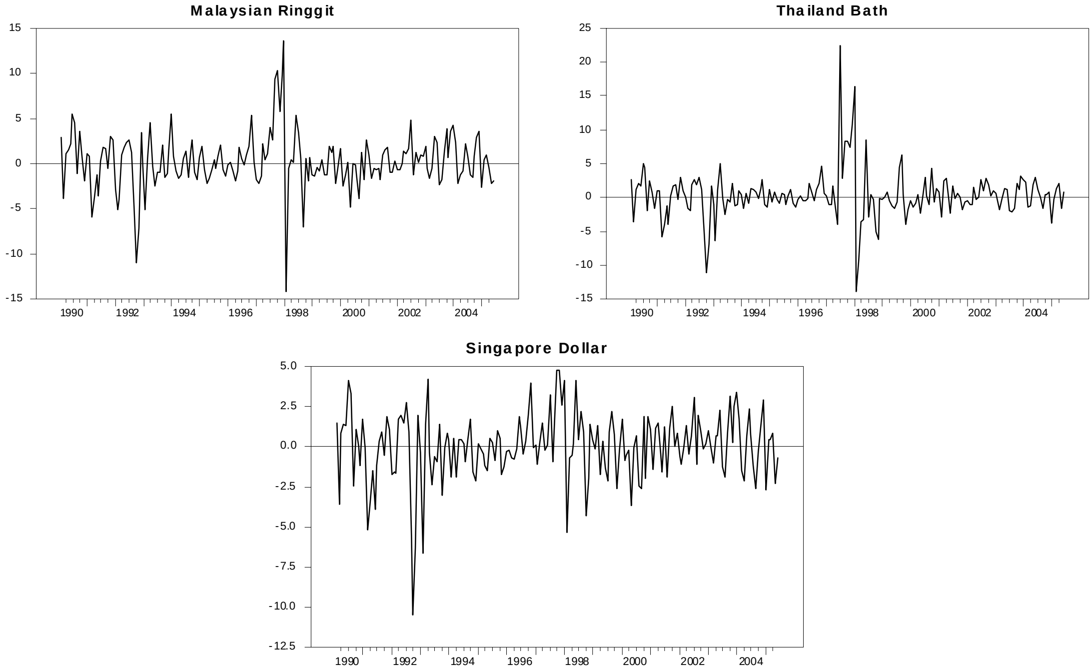

FIGURE 1. Monthly return of exchange rates, 1990:2-2005:6

of the Singapore dollar. Based on this information, we estimate the parameter for the AR models and test for departures from linearity using three portmanteau tests and three structural breaks tests. The three portmanteau tests are the McLeod-Li test, the RESET test and the BDS test. The McLeod-Li test was proposed by McLeod and Li (1983) based on suggestion by Granger and Andersen (1978) to test for ARCH effects. The objective of this test is to determine if there is a significant autocorrelation in the squared residuals from a linear equation. The Regression Error Specification Test or RESET test suggested by Ramsey (1969) is a specification test for linear least squares regression analysis. The BDS test is derived and discussed by Brock et al. (1996) to test the null hypothesis of independently and identically distributed (iid) in the data. In a small sample series it is found that the distribution of the BDS statistic departs from asymptotic normal distribution and as a result, a bootstrapped p-value is calculated.

While the three structural breaks tests are the CUSUM of squares test, the Andrew-Ploberger test and the Bai-Perron test. The CUSUM of squares test was developed by Brown et al. (1975) based on a plot of cumulative sum of the squared one-step-ahead forecast error resulting from recursive estimation between two critical lines. The movement outside the critical line is suggestive of parameter or variance instability. The Andrew-Ploberger test and the Bai-Perron test were introduced by Andrew and Ploberger (1994) and Bai and Perron (2003). The former test was used to find evidence of single structural break in the data and the latter test was used to search for multiple structural breaks in the data. These two tests will estimate the timing of the structural break or the breakdate using least squares method. We test for multiple breaks because if we discover one structural break, we want to know whether there is another break in the data.

The estimated AR models for monthly returns for the three exchange rates are given in Table 1. Based on more than one nonlinearity tests, it is proved statistically that the nonlinear behaviour exists in all the series. These suggest that in testing for nonlinearity, it is unwise to rely solely on a single test. In Figure 2, the CUSUM of squares test reveal instability variances in all the returns series. The Andrew-Ploberger test also found a single breakdate in all the returns series. While, another breakdate for the Malaysia Ringgit and the Singapore dollar and another two breakdate for the Thailand bath were obtained using the Bai-Perron test. From the results we can conclude that statistically, there is evidence of departures from linear behaviour and structural change in all the returns series. Next, we are going to model the returns series as a regime switching models.

REGIME SWITCHING MODELS

The estimated parameters for the MS-AR model and the SETAR model using maximum likelihood estimation are presented in Table 2 and Table 3.

For the SETAR model, we assume equal number of lag for every regime and the delay parameter, d has the same value as the order or the AR process ($d = p$). Estimations are carried out using MSVAR module for Ox (Krolzig 1998).

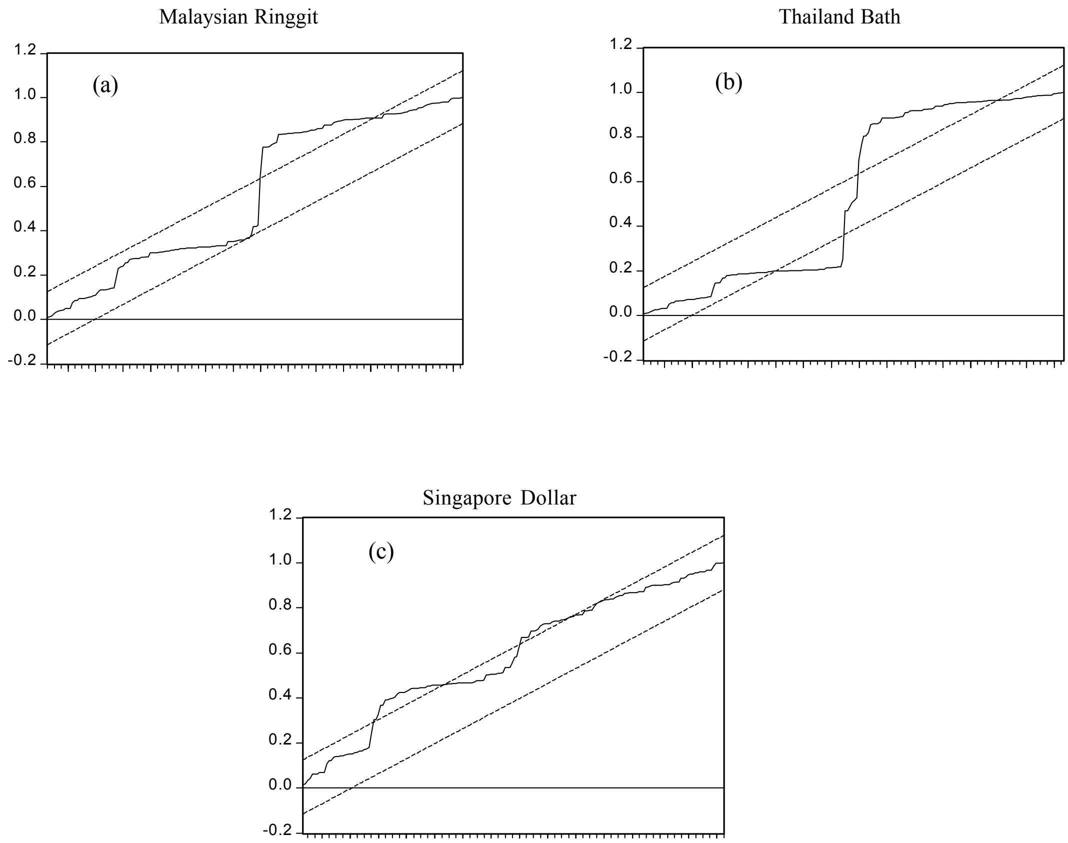

FIGURE 2. CUSUM of squares test

TABLE 1. Estimated of AR model with nonlinearity test and structural break test

Currency Parameters	Malaysia Ringgit	Singapore Dollar	Thailand Bath
α_0	0.213	0.004	0.287
	(0.704)	(0.025)	(0.853)
α_1	0.274	0.294	0.233
	(3.851)	(4.051)	(3.241)
α_2		-0.176	
		(-2.417)	
McLeod-Li (20)	0.001	0.000	0.000
RESET	0.000	0.609	0.061
BDS	0.002	0.004	0.000

Figures in the parenthesis are t-values

TABLE 2. Estimated MS-AR model for monthly returns series

Currency Parameters	Malaysia Ringgit	Singapore Dollar	Thailand Bath
α_0	0.0792	0.0739	5.597
	(0.4165)	(0.4789)	(1.6801)
α_1	0.2669	0.3679	1.1004
	(3.3575)	(5.1634)	(2.1137)
α_2		-0.1917	
		(-2.3031)	
β_0	2.1036	-3.2536	0.2243
	(0.9528)	(-.2.4519)	(0.9590)

Figures in the parenthesis are t-values

MODEL SELECTION CRITERIA

For each model fitted, we calculate the Akaike (1973) information criterion (AIC), Schwartz Bayesian criterion (SBC) by Schwartz (1978) and Hannan-Quinn criterion by Hannan and Quinn (1979) and Hannan (1980). Below we show the formulae to compute the AIC, SBC and HQC value:

$$\text{AIC} = T \ln(\text{sum of squared residuals}) + 2n$$
$$\text{SBC} = T \ln(\text{sum of squared residuals}) + \ln(T)$$
$$\text{HQC} = \ln(\text{sum of squared residuals}) + nc \ln [\ln(T) / T]. \tag{6}$$

where n is the numbers of parameter estimated, c is a constant to be selected (we use 2 in the calculation) and T is the number of usable observation. From Equation 6, the first term measure the lack of fit of the model and the second is a penalty term to prevent over-fitting. The residuals are the within-sample one-step ahead forecast error. Thus, the minimization of a criterion will lead to a model with superior in-sample fitting.

TABLE 3. Estimted SETAR model for monthly returns series

Figures in the parenthesis are t-values

Using Equation 6, the AIC, SBC and HQC values for all the exchange rates are given in Table 4. We found that the best fitted model is the MS-AR model for all the returns series because it has the smallest AIC, SBC and HQC values. When we compare the AIC, SBC and HQC values of MS-AR model and SETAR model with the AR model, the MS-AR and the SETAR model fit the returns series better than the linear AR model i.e. lower AIC, SBC and HQC values. Based on likelihood ratio test developed by Garcia and Perron (1996), the null hypothesis of AR linear model is rejected against regime switching models (MS-AR model and SETAR model) for all the exchange rates series. This is because the Davies (1987) p-value suggested by them showed significant results (see Table 4).

TABLE 4. THE AIC, SBC, HQC and likelihood ratio statistic value

Currency Model		Malaysian Ringgit	Singapore Dollar	Thailand Bath
AR		5.0386	4.2832	5.3617
	SBC	5.0910	4.3116	5.4141
	HQC	5.0598	4.3534	5.3829
SETAR	AIC	4.8367	4.2232	5.1800
	SBC	4.9590	4.3810	5.3023
	HQC	4.8863	4.2871	5.2296
MS-AR	AIC	4.7170	4.2371	4.6784
	SBC	4.8393	4.3206	4.8007
	[illegible]	[illegible]	[illegible]	[illegible]

Figures in the parenthesis are Davies p-values

IV. CONCLUSIONS

We have examined the monthly returns of exchange rates series of three ASEAN countries against the British pound. The three ASEAN currencies we considered are the Malaysian ringgit, the Singapore dollar and the Thailand bath from 1990 until 2005. The three portmanteau tests we used in this paper suggest that a nonlinear models are more appropriate as compared to linear models for all series being analysed but did not give information regarding the nature of the nonlinearity. Visual inspection against the returns series plot, show the existent of structural breaks in the series. This was justified by the three structural change tests we conducted where there is evidence of structural breaks in all the returns of exchange rates series. From the AIC, SBC and HQC values we found that the model fit of the Markov switching autoregressive models (MS-AR) is superior to the self-exciting threshold autoregressive models (SETAR) and the linear AR models. We also found that the regime switching models outperform linear model in fitting the returns series through the significant results of likelihood ratio statistics. This finding shows that nonlinear time series models give good in-sample fits to exchange rates as suggested by Dacco and Satchell (1999). It is also found that the regime switching models are possible alternative models that can be used under the nonlinearity and structural change condition. Therefore it is recommended that any future studies involving economic and financial time series data, should take into consideration the nonlinearity of the series and the structural change/break that exist.

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