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Application of the Threshold Model for Modelling and Forecasting of Exchange Rate in Selected ASEAN Countries

(Aplikasi Model Ambang untuk Permodelan dan Peramalan Kadar Pertukaran di Negara ASEAN Terpilih)

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ABSTRACT

Linear time series models are not able to capture the behaviour of many financial time series, as in the cases of exchange rates and stock market data. Some phenomena, such as volatility and structural breaks in time series data, cannot be modelled implicitly using linear time series models. Therefore, nonlinear time series models are typically designed to accommodate for such nonlinear features. In the present study, a nonlinearity test and a structural change test are used to detect the nonlinearity and the break date in three ASEAN currencies, namely the Indonesian Rupiah (IDR), the Malaysian Ringgit (MYR) and the Thai Baht (THB). The study finds that the null hypothesis of linearity is rejected and evidence of structural breaks exist in the exchange rates series. Therefore, the decision to use the self-exciting threshold autoregressive (SETAR) model in the present study is justified. The results showed that the SETAR model, as a regime switching model, can explain abrupt changes in a time series. To evaluate the prediction performance of SETAR model, an Autoregressive Integrated Moving Average (ARIMA) model used as a benchmark. In order to increase the accuracy of prediction, both models are combined with an exponential generalised autoregressive conditional heteroscedasticity (EGARCH) model. The prediction results showed that the construct model of SETAR-EGARCH performs better than that of the ARIMA model and the combined ARIMA and EGARCH model. The results indicated that nonlinear models give better fitting than linear models.

Keywords: *EGARCH; exchange rate; nonlinearity; SETAR*

ABSTRAK

Model siri masa linear tidak mampu menghuraikan tingkah laku kebanyakan data siri masa pasaran tukaran asing dan pasaran saham. Fenomena seperti kemeruapan dan perubahan struktur dalam data kadar pertukaran tidak dapat dipadankan dengan baik menggunakan model siri masa linear. Justeru, model tak linear diperlukan bagi mengambil kira ciri-ciri ketaklinearan. Dalam kajian ini, ujian ketaklinearan dan perubahan struktur digunakan bagi mengesan kewujudan kedua-dua ciri tersebut menggunakan data kadar pertukaran bagi tiga negara ASEAN terpilih, iaitu Indonesia Rupiah, Ringgit Malaysia dan Baht Thailand. Kajian ini mendapati bahawa hipotesis nol kelinearan ditolak dan bukti pecah struktur wujud dalam siri kadar pertukaran. Oleh itu, keputusan untuk menggunakan model sendiri-rangsang ambang autoregresi (SETAR) dalam kajian ini adalah dibenarkan. Kajian menunjukkan bahawa model SETAR, sebagai model pensuisan rejim, dapat menjelaskan perubahan mendadak dalam siri masa. Untuk menilai prestasi ramalan model SETAR, satu model autoregresi bersepadu purata bergerak (ARIMA) digunakan sebagai penanda aras. Dalam usaha untuk meningkatkan ketepatan ramalan, kedua-dua model digabungkan dengan eksponen model am autoregresi heteroskedastisiti bersyarat (EGARCH). Keputusan ramalan menunjukkan bahawa model konstruk daripada SETAR-EGARCH adalah lebih baik daripada model ARIMA serta gabungan model ARIMA dan EGARCH. Keputusan menunjukkan bahawa model tak linear memberi pemasangan lebih baik daripada model linear.

Kata kunci: *EGARCH; kadar pertukaran; ketaklinearan; SETAR*

INTRODUCTION

In recent years, more consideration has been given to modelling and forecasting using nonlinear models, especially for financial market series. For this purpose, models, such as the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) and regime switching models, such as the threshold autoregressive model and the Markov switching autoregressive model have been applied. Among nonlinear models, regime switching models are comparatively more popular and have received more attention recently (Franses & Van Dijk 2000). However, from a forecasting perspective, no clear conclusion exists concerning whether allowing for nonlinearity leads to an improvement in forecast performance (De Gooijer & Kumar 1992). In the present study, the prediction performance of the Self-Exciting Threshold Autoregressive (SETAR) model, a nonlinear time series model proposed in existing literature for the modelling of gross domestic product (GDP), exchange rates and other time series data (Peel & Speight 1998; Potter 1995) is investigated.

After fitting the preferred SETAR model to the data, it is combined with an Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) model to increase the accuracy of prediction. The prediction performance of the constructed model is compared with that of the linear Autoregressive Integrated Moving Average (ARIMA) model and the AR-EGARCH model for in-sample and out-of-sample forecasting ability (Feng & Liu 2002). The objectives of the present paper were to compare the prediction performance of the regime switching model with linear models using three ASEAN countries exchange rates and to determine whether the regime switching model is a useful tool to explain the nonlinearity characteristics of exchange rates.

The most important aspect of the SETAR model is that regime switching that occurs in the past and present are known using statistical methods. The works provided by Chappell et al. (1996) and Hendry et al. (2001) are the motivation for using this model to investigate the behaviour of exchange rates. The assumption of the possibility of two or more regimes in a financial time series motivates the use of regime switching models. The assumption of the SETAR model is that the changes between regimes occur endogenously and are discrete. In the present paper, a nonlinearity test and a structural break test are used to justify the decision to apply the regime switching models.

The organisation of the paper is as follows. The next section considers the extant empirical studies regarding the threshold model. The section after that three introduces the ARIMA and regime switching model specifications. Next, we present the empirical results and a discussion of the results. Last section summarises and concludes the paper.

Empirical Studies for Threshold Model

Regime switching models are designed to detect discrete changes in the series that generates the data. A glance at the application of regime switching models showed that a large number of empirical studies use such models in the analysis of exchange rate markets and macroeconomic variables (such as GDP) instead of simply stock markets. For example, Engle (1994), Bergman and Hansson (2005) and Ismail and Isa (2006) develop regime switching models for exchange rates and find that these models provide more precise forecasting results in both in-sample and out-of-sample forecasting. Likewise, De Gooijer and Kumar (1992), Peel and Speight (1998) and Potter (1995) developed the SETAR model for modelling the GDP of different countries, including the UK and the US. The experimental results indicated that regime switching models outperform linear model approaches.

Moreover, Clements and Smith (1999) investigate the multi-period forecast performance of a number of empirical SETAR models proposed for modelling exchange rates and gross national product (GNP). The findings demonstrate the higher performance of the SETAR model compared with the linear Autoregressive (AR) and Moving Average (MA) models. Feng and Liu (2002) utilise the SETAR model to examine Canadian real GDP and compare the out-of-sample forecasting performance of the SETAR model with the ARIMA model for one step ahead and multi-steps ahead predictions. The SETAR model performs better than the ARIMA model in regards to both in-sample prediction and out-of-sample forecasting performance.

Boero and Marrocu (2004) apply the SETAR to Euro exchange rates and find that the SETAR model performs better than ARIMA model. Ismail and Isa (2006) apply the regime switching model to exchange rates in ASEAN countries and find that the regime switching models are superior to linear models. Furthermore, Chong et al. (2011) compare the performance of the SETAR model with two models, an autoregressive model and a moving average model, on four major indices, namely the Shanghai A and B shares indices; and the Shenzhen A and B share indices. The results of the study indicated that the SETAR model outperforms the AR and MA models.

Methods

In this section, the ARIMA model is introduced for the fitting comparison. The SETAR model is then considered as a regime-switching model. Finally, the EGARCH component is introduced and combined with the other two models to establish a new tool for prediction.

AUTOREGRESSIVE INTEGRATED MOVING AVERAGE

The Box-Jenkins (1976) methodology, which is known as ARIMA, includes four steps: model identification; parameter estimation; diagnostic checking and forecasting. During model identification, data transformation is required to make the time series stationary. Stationarity is a necessary condition in building an ARIMA model used for forecasting. For a stationary time series, the mean and the autocorrelation structure is constant over time. When the collected time series shows trend and heteroscedasticity, one way to remove the trend and stabilise the variance is differencing and power transformation, which is performed before an ARIMA model can be fitted. Once a tentative model is identified, the model parameters are estimated. The parameters are estimated in such a manner that the overall measure of errors is minimised (Zhang 2003).

The third step in model building, in accordance with the ARIMA process, is the diagnostic checking of the adequacy of the model. The diagnostic check is performed to determine whether the model assumptions for the errors are satisfied. Several diagnostic statistics and plots of the residuals can be utilised to examine the goodness of fit of the selected model to the historical data. If the model is not adequate, a new tentative model should be identified, which will require the model verification and parameter estimation processes to be repeated. Diagnostic information may assist in determining an alternative model(s). The three-step model building process is repeated several times until a satisfactory model is finally selected. The final selected model can then be used for prediction purposes in step four. The assumption underlying the

ARIMA model is that the error is homogenous. The model utilised in the present study is represented as follows:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t . \quad (1)$$

Equation 1 implies that the forecasted value of y depends to the past value of y and the previous shocks on y.

THRESHOLD AUTOREGRESSIVE

Regime switching models are designed to capture discrete changes in the data generating process (DGP) of observations under consideration. Threshold Autoregressive (TAR) models generally refer to piecewise linear models or regime switching models. The TAR model is a type of nonlinear time series model that was introduced by Tong (1978) and further refined by Tong and Lim (1980) and Tong (1983). Such models are addressed to z number of autoregressive components, in which one process switches to another due to the special value of a variable included in model, referred to as a threshold. When the series under consideration crosses over the threshold value, the process will shift to another regression line. During the TAR procedure, the regime switching of a dependent variable is based upon the threshold value(s) of the independent variable(s) in a given equation.

Self-exciting threshold autoregressive The SETAR model, which is a type of autoregressive model, is applicable to time series data sets and allows for greater flexibility in model parameters that involve regime switching behaviour (Watier & Richardson 1995).The SETAR model is a special example of the TAR model in which regime switching is based upon the self-dynamics of the dependent variable(s) (i.e. self-exciting). As a result, the SETAR model is considered to be a univariate procedure. In other words, unlike the TAR model where the threshold value is related to an exogenous variable, the SETAR model threshold value is related to the endogenous variable. Motivated by the study of complex nonlinear discrete systems, Tong (1983) develops a special type of time series model that can regenerate the properties of the original DGP of a sample set. The model hypothesises a different autoregressive process based on different threshold values. The advantages of using SETAR models lie in their ability to produce several commonly observed phenomena that cannot be captured by naive linear models, such as the autoregressive moving average (ARMA) model. Such phenomena include irreversibility, jumps and limit cycles.

The TAR model becomes a SETAR model when the threshold variable is taken to be a lagged value of the time series itself. Two regimes of SETAR model are specified in the following equation, where $\boldsymbol{\alpha}_i$ and β_i are coefficients; τ is the value of threshold; p is the order of the SETAR model; y_{t-d} is the threshold variable; d is the delay parameter and ε_t is a sequence of independent and identically distributed random variables with mean 0 and variance σ_ε^2 ,

$$y_t = \begin{cases} \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \varepsilon_t & if \;\; y_{t-d} \le \tau \\ \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t & if \;\; y_{t-d} > \tau \end{cases} . \quad (2)$$

If the value of threshold (τ) is known, the observations can be separated according to whether y_{t-d} is above or below the threshold. The AR model is then estimated for each segment using the ordinary least square method (Ismail & Isa 2006). In most cases, the threshold is unknown and must be determined alongside other parameters of the SETAR model.

The present study adopts the following procedure proposed by Tsay (1989) for SETAR modelling: Select the autoregressive order and a set of possible values for the delay parameter d. In the present study, d has the same value as the order of AR (d=p); perform a recursive local fitting and consider the possible values of the thresholds; estimate the SETAR for each possible threshold value entertained in step 2; select the threshold value that yields the minimum value of the selection criteria of the Akaike information criterion (AIC), the Schwartz Criterion (SC) and the Hannan Quinn (HQ) criterion; evaluate the adequacy of the adopted SETAR model using diagnostic tests and refine the estimated model, if necessary, to provide a proper model for prediction.

GENERALISED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY

Volatility in time series data can be estimated by employing the GARCH model developed by Bollerslev (1986). In the GARCH model, the conditional variance of a time series depends upon the squared residuals of the process. The incorporation of heteroscedasticity into the estimation procedure of the conditional variance is an advantage of the GARCH model. The model can be viewed as a reduced form of a more complicated dynamic structure for the time varying conditional second order moments. The GARCH (1,1) model can be represented as follows (Choudhry 2005):

$$y_t = \mu + \varepsilon_t . \quad (3)$$

$$\varepsilon_t = v_t \sigma_t ,\;\; v_t \sim N(0, \sigma_t^2). \quad (4)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 , \quad (5)$$

where y_t is equal to log form of (e_t / e_{t-1}); e_t is the real exchange rate; μ_t is the mean of y_t conditional on past information and σ_t^2 is the conditional variance. The size and significance of α_1 indicate the magnitude of the effect imposed by the lagged error term (ε_{t-1}) on the conditional variance. The size and significance of α_1 indicate the ARCH process in the residuals. The non-negativity conditions may be violated by the estimated method, since the coefficients of model are probably negative. The GARCH model also cannot be accounted for the leverage effects. Therefore, the EGARCH model introduced by Nelson (1991) as an extension of the GARCH model overcomes the aforementioned problems in the GARCH model, as explained below.

EGARCH MODEL

If $r_{j,t}$ represents the return on a market index at time t, EGARCH (1,1,1) can be written as follows:

$$r_{j,t} = \delta_j' I_{j,t-1} + \xi_{j,t}, \tag{6}$$

$$\xi_{j,t} = \sigma_{j,t} Z_{j,t}, \tag{7}$$

$$Z_{j,t} \big| \Omega_{t-1} \sim \psi(0,1,v). \tag{8}$$

$$\ln \sigma_{j,t}^2 = \omega_j + \alpha_j \left(\left| \varepsilon_{j,t-1} / \sigma_{j,t-1} \right| \right) + \gamma_j \left(\varepsilon_{j,t-1} / \sigma_{j,t-1} \right) + \beta_j \ln \left(\sigma_{j,t-1}^2 \right), \tag{9}$$

where $Z_{j,t}$ is the standardised residual; $\Psi(.)$ marks a conditional density function; and v denotes a vector of parameters needed to specify the probability distribution. The significant advantage of this model is that even if the parameters are negative, σ_i^2 will be positive. α represents a magnitude effect of the model (i.e., the ARCH effect); β measures the persistence in conditional volatility disregard of market news; and γ measures the asymmetry or the leverage effect.

APPLICATION TO ASEAN EXCHANGE RATES

The present section provides a description of the data and modelling of the data as an AR process to test for nonlinearity. The data is then modelled using three models: the regime switching model of SETAR-EGARCH; the AR-EGARCH model; and the ARIMA model. Since all three models utilise autoregressive components, more than one model may fit the data. Following the application of the model selection criteria, the best fitted model is chosen for the purpose of prediction. Diagnostic tests are applied to the selected models to ensure that they are adequate for prediction and finally, forecasting results are given.

DATA

The exchange rate data sets for the Indonesian Rupiah (IDR), Malaysian Ringgit (MYR) and Thai Baht (THB) are collected from the *International Financial Statistics* data base. The data consist of monthly frequency spanning from January 1985 until September 2010, with a total of 309 observations divided into two parts. The first group of data (297 observations) is utilised for estimation (training) purposes and the second group (12 observations) is utilised for prediction purposes. Monthly series are utilised because it is assumed that structural breaks can be observed more clearly when a low frequency period is used. In the present study, the return of exchange rate is calculated as follows:

$$Y_t = \log\left(e_t / e_{t-1}\right), \tag{10}$$

where e is the real exchange rate. The plot of monthly returns for all of the series is provided below. In Figure 1, a significant structural break for all series can be detected during 1997-1998.

NON-LINEARITY TEST

The BDS nonlinearity test, proposed by Brock et al. (1987) is used to detect serial dependence in the time series under consideration. The null hypothesis tested under the BDS test claiming that the time series has linear dependency. Therefore, its data generating process will be linear. Applying the BDS test assists researchers to determine whether or not the data set is nonlinear. The null hypothesis for this test assumes that the data is independently and identically distributed (*i.i.d*), while the alternative hypothesis assumes that the data is not independently and identically distributed. This implies that the time series is nonlinearly dependent when the first difference of the natural logarithm is examined. Table 1 shows the results of the BDS test for IDR.

The hypothesis that the series is *iid* will be rejected if the reported *z*-statistic is high (or the probability of *z*-statistics is small). Since all of the probabilities in Table 1 are small (less than 5%), the data series of *IDR* is determined to be nonlinear. Therefore, the finding suggests that nonlinear models are expected to have greater efficiency than linear models. However, Tables 2 and 3 present the BDS results for MYR and THB, respectively. The reported *z*-statistics are sufficiently large to reject the null of linearity in the two series.

UNIT ROOT RESULTS

In order to model the return of exchange rate, performing a unit root test is necessary to ensure that the data is stationary. For this purpose, the Augmented Dickey Fuller (ADF) and the Phillips-Perron (PP) unit root tests are employed. The null hypothesis for both unit root tests state that the data are non-stationary or the 'series has a unit root', while the alternative hypothesis states that series is stationary. The results of the unit root tests are presented in Table 4 and showed that all exchange rate series are stationary at the first difference (i.e., the return series of selected exchange rates are stationary at level). To save space, the ADF and PP procedures are not presented.

STRUCTURAL BREAK TEST

The test developed by Zivot and Andrew (1992) is a serial endogenous structural break test that is applied to time series data to determine whether any break(s) exist inside the sample using different dummy variable(s) for each possible break. Based on the above, a break point is selected where the t-statistic calculated from ADF test is at minimum. Zivot and Andrew assume that the exact time of break is unknown. A data dependent algorithm is used

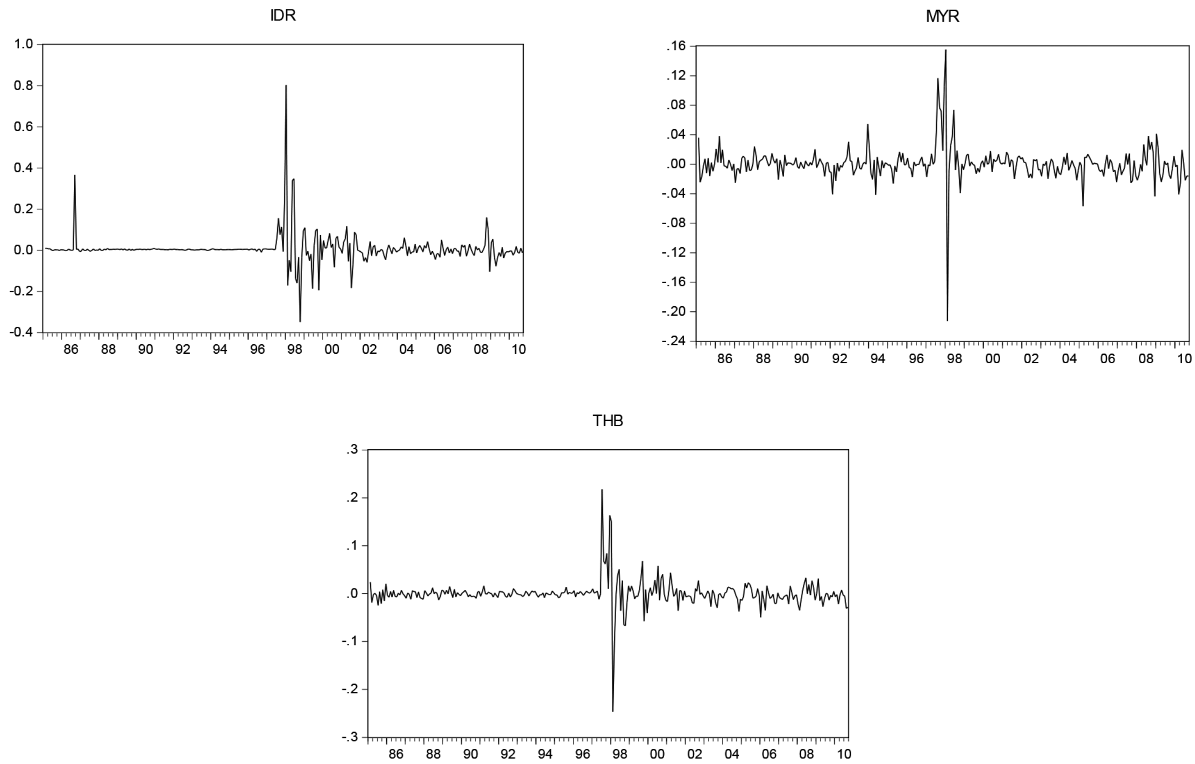

FIGURE 1. Return Series of selected exchange rates

TABLE 1. BDS results for Indonesian Rupiah

Dimension	Price Series			Return Series		
	BDS Stat.	z-Stat.	Prob.	BDS Stat.	z-Stat.	Prob.
2	0.179	75.63	0.000	0.092	10.69	0.000
3	0.303	81.14	0.000	0.174	12.60	0.000
4	0.389	88.10	0.000	0.229	13.76	0.000
5	0.449	98.23	0.000	0.261	14.91	0.000
6	0.488	111.49	0.000	0.284	16.61	0.000

TABLE 2. BDS result for Malaysian Ringgit

Dimension	Price Series			Return Series		
	BDS Stat.	z-Stat.	Prob.	BDS Stat.	z-Stat.	Prob.
2	0.197	68.92	0.000	0.035	5.74	0.000
3	0.333	73.84	0.000	0.063	6.49	0.000
4	0.427	80.06	0.000	0.076	6.51	0.000
5	0.491	89.04	0.000	0.084	6.87	0.000
6	0.534	101.08	0.000	0.081	6.83	0.000

TABLE 3. BDS result for Thai Baht

Dimension	Price Series			Return Series		
	BDS Stat.	z-Stat.	Prob.	BDS Stat.	z-Stat.	Prob.
2	0.192	61.59	0.000	0.050	6.78	0.000
3	0.326	65.90	0.000	0.090	7.62	0.000
4	0.417	71.15	0.000	0.120	8.47	0.000
5	0.476	78.48	0.000	0.139	9.39	0.000
6	0.516	88.67	0.000	0.153	10.67	0.000

TABLE 4. Unit root test for exchange rates

Exchange rates	Test	Level		1st Difference	
		Intercept	Trend & Intercept	Intercept	Trend & Intercept
IDR	ADF	-1.51	-2.97	-14.36*	-14.34*
	PP	-1.42	-2.87	-16.34*	-16.31*
MYR	ADF	-1.36	-0.92	-17.15*	-17.16*
	PP	-1.41	-1.05	-17.17*	-17.18*
THB	ADF	-1.44	-1.44	-13.76*	-13.76*
	PP	-1.52	-1.59	-15.36*	-15.35*

* denotes significance at 1%

to proxy Perron's subjective procedure to determine the break points. Zivot and Andrew proceed with the following model that combines onetime changes in the level and onetime change in the slope of the trend function of the series. The null hypothesis for the Zivot-Andrew test is $\alpha = 0$, which indicates the absence of a structural break, against the alternative hypothesis $\alpha < 0$, which indicates a onetime structural break occurring at an unknown time (Glynn et al. 2007).

$$\Delta y_t = c + \alpha y_{t-1} + \beta t + \theta DU_t + \gamma DT_t + \sum_{j=1}^{k} d_j \Delta y_{t-1} + \varepsilon_t, \qquad (11)$$

where DU_t is an indicator dummy variable for a mean shift occurring at each possible break date (BD) and DT_t represents the corresponding trend shift variable, which are represented as follows:

$$DU_t = \begin{cases} 1 & if \;\; t > BD \\ 0 & otherwise \end{cases}$$

$$DT_t = \begin{cases} t - TB & if \;\; t > BD \\ 0 & otherwise \end{cases}.$$

The application of the Zivot-Andrew test for detecting possible structural breaks in the time series under consideration showed that breaks exist for all series. The identified break date for the IDR occurred in December 1997, while the identified break for the MYR and the THB occurred in July 1997. Figure 2 shows the plot of the break date according to the Zivot-Andrew test.

The CUSUM of squares test, developed by Brown et al. (1975) is based upon a plot of the cumulative sum of the squared one-step-ahead forecast error that results from recursive estimation between two critical values. Any

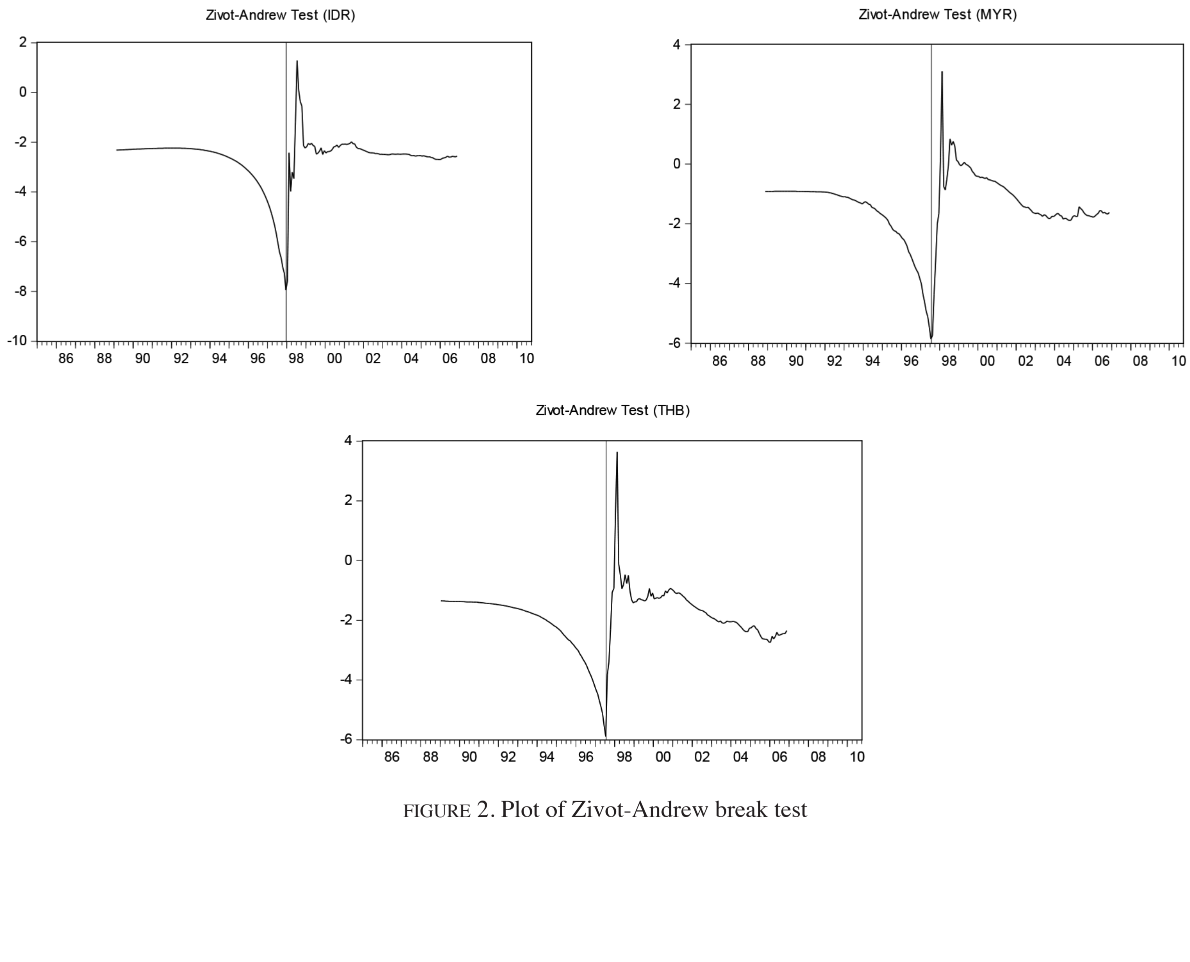

FIGURE 2. Plot of Zivot-Andrew break test

movement outside the critical line represents parameter or variance instability. In Figure 3, the CUSUM of squares test showed instability of variances in all return series.

SETAR MODEL AS A REGIME SWITCHING MODEL

In order to reduce the degree of model complexity of the SETAR model, an equal number of lags are assumed for every regime. Furthermore, the delay parameter, *d*, is assumed to have the same value as the order of the autoregressive (Ismail & Isa 2006). In the present study, the SETAR model is combined with an EGARCH model to yield a hybrid SETAR-EGARCH model to be utilised for modelling and forecasting the exchange rate. Therefore, the different structures of the SETAR model must be constructed to obtain the best fitted model. A controversial issue in relation to the SETAR model concerns threshold value determination. As mentioned earlier, an initial group of threshold values must be introduced and the final model selection will be based on the smaller value of information criteria. The information criteria utilised in the present study are the AIC, the SC and the HQ. Recursive local fitting plot is also employed to provide some raw and initial inferences about the threshold values.

As shown in Figure 4, three threshold values can be seen for IDR, namely 0.01 in September 1986; 0.08 in January 1998 and 0.15 in March 1998. Following attempts to model these threshold values, only one threshold value,

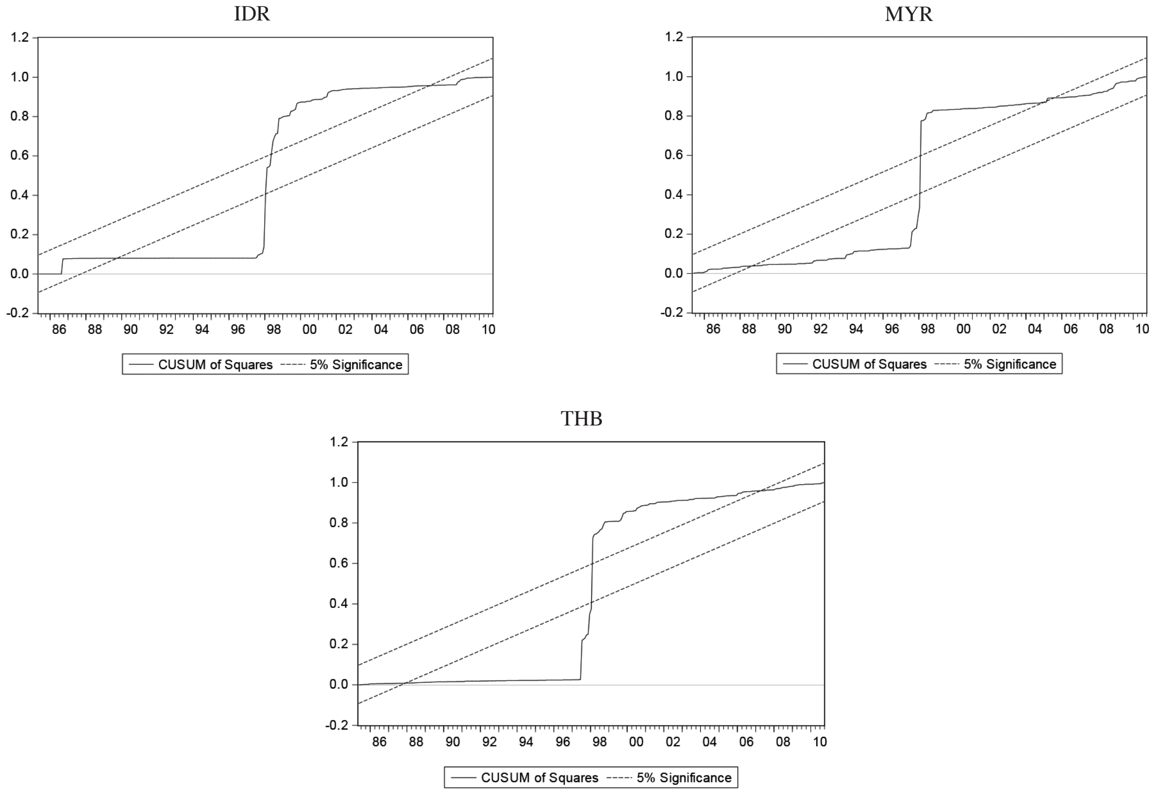

FIGURE 3. CUSUM of square test

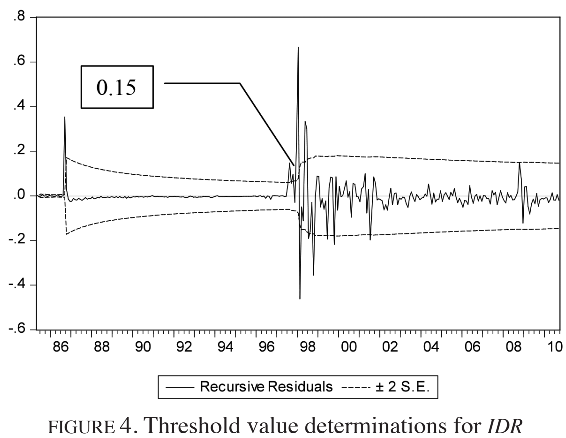

FIGURE 4. Threshold value determinations for *IDR*

which is 0.15 and occurring on March 1998, is significant and can be modelled. The threshold value of the IDR is due to the financial crisis in south East Asia in 1997. Therefore, the constructed SETAR model has two regimes, with one AR order in each regime and one delay parameter with a threshold value of 0.15. For the variance of the equation, an EGARCH structure is developed. Three different structures of the SETAR-EGARCH model can be found using the threshold value of 0.15, which are identified in Table 5. To select the best fitted model, the information criteria are used.

Using the information criteria calculated in Table 5, the SETAR(1)-EGARCH(2,0,1) model is selected because it has the lowest value in terms of the above-mentioned criteria. The selected model includes the SETAR part and the EGARCH part. The model is represented by the following equations:

$$Y_t = \begin{cases} \begin{matrix} 0.0078 + 0.0430(Y_{t-1}) \\ std.E.\ (0.0017)(0.0916) \end{matrix} & if \quad Y_{t-1} \geq 0.15 \\ \begin{matrix} 0.0078 - 0.1244(Y_{t-1}) \\ std.E.\ (0.0017)(0.0631) \end{matrix} & if \quad Y_{t-1} < 0.15 \end{cases}$$

$$\begin{matrix} \ln\sigma_t^2 = -7.3344 + 1.0343(|\varepsilon_{t-1}/\sigma_{t-1}|) + 1.2597(|\varepsilon_{t-2}/\sigma_{t-2}|) + 0.5266(\varepsilon_{t-1}/\sigma_{t-1}) \\ Std.E.\ \ (0.0958)(0.1054) \qquad (0.1025) \qquad (0.0969). \end{matrix}$$

In the case of the MYR, as depicted in Figure 5, three threshold values are detected: 0.02 in January 1986; 0.03 in August 1997 and 0.04 in January 1998. Out of these values, only one threshold value can be modelled, which is the threshold value of 0.03. The three EGARCH components can be combined with the SETAR model as presented in Table 6.

The calculated information criteria presented in Table 6 shows that the lowest value of the information criteria correspond with the SETAR(1)-EGARCH(1,1,1) model, so this model is selected for prediction purposes as represented in the following equations:

$$Y_t = \begin{cases} \begin{matrix} -0.0004 + 0.1441(Y_{t-1}) \\ std.E.\ (0.0014)(0.1171) \end{matrix} & if \quad Y_{t-1} \geq 0.03 \\ \begin{matrix} -0.0004 - 0.0427(Y_{t-1}) \\ std.E.\ (0.0014)(0.1234) \end{matrix} & if \quad Y_{t-1} < 0.03 \end{cases}$$

$$\begin{matrix} \ln\sigma_t^2 = -1.9433 + 0.3038(|\varepsilon_{t-1}/\sigma_{t-1}|) + 0.3207(|\varepsilon_{t-2}/\sigma_{t-2}|) + 0.7946(\varepsilon_{t-1}/\sigma_{t-1}^2) \\ Std.E.\ \ (0.3684)(0.0537) \qquad (0.0486) \qquad (0.0421). \end{matrix}$$

TABLE 5. Value of the information criteria for Indonesian Rupiah

Model / Criteria	SETAR(1)-EGARCH(0,1,1)	SETAR(1)-EGARCH(1,0,1)	SETAR(1)-EGARCH(2,0,1)
AIC	-3.17	-2.93	-3.43
SC	-3.08	-2.84	-3.33
HQ	-3.13	-2.89	-3.39

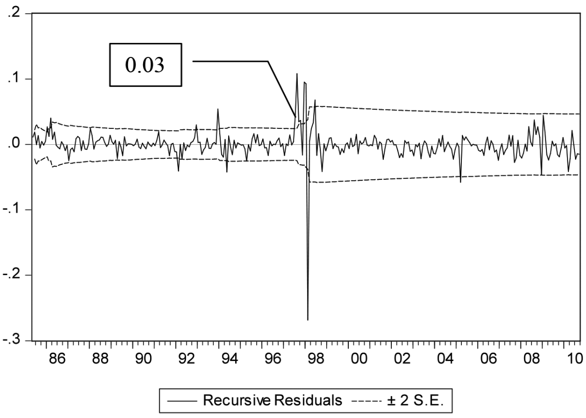

FIGURE 5. Threshold value determinations for *MYR*

TABLE 6. Value of the information criteria for Malaysian Ringgit

Model / Criteria	SETAR(1)-EGARCH(1,1,1)	SETAR(1)-EGARCH(0,1,1)	SETAR(1)-EGARCH(0,2,1)
AIC	-5.57	-5.49	-5.50
SC	-5.47	-5.41	-5.40
HQ	-5.53	-5.46	-5.46

In the case of THB, shown in Figure 6, three threshold values are detected: 0.01 in July 1997; 0.04 in December 1997 and 0.05 in February 1998. Of the three values, only the threshold value of 0.05 can be modelled. Four different EGARCH structures are combined with the selected SETAR model as depicted in Table 7.

According to the value of the information criteria in Table 7, the SETAR(1)-EGARCH(2,0,2) model is selected since it has the lowest value for all information criteria and is represented as follows:

$$Y_t = \begin{cases} \left.\begin{array}{l} \quad -0.0021 + 0.3141(Y_{t-1}) \\ std.E.\ (0.0012)(0.0460) \end{array}\right\} & if \quad Y_{t-1} \geq 0.05 \\ \left.\begin{array}{l} \quad 0.0021 + 0.0694(Y_{t-1}) \\ std.E.\ (0.0012)(0.1543) \end{array}\right\} & if \quad Y_{t-1} < 0.05 \end{cases}$$

$$\begin{aligned} \ln \sigma_t^2 &= -10.0773 + 0.8314\left(\left|\varepsilon_{t-1}/\sigma_{t-1}\right|\right) + 1.4607\left(\left|\varepsilon_{t-2}/\sigma_{t-2}\right|\right) + 0.1378\left(\varepsilon_{t-1}/\sigma_{t-1}\right) \\ &\quad -0.3112\left(\varepsilon_{t-2}/\sigma_{t-2}\right) \\ Std.E &\quad (0.1156)(0.0710) \qquad (0.0721) \qquad (0.0364) \\ &\quad (0.0483). \end{aligned}$$

To save space, the results of information criteria for the ARIMA and AR-EGARCH models are reported in Appendix A.

DIAGNOSTIC TESTS

In order to validate the appropriateness of the selected ARIMA, AR-EGARCH and SETAR-EGARCH models, a correlation test is performed utilising the Ljung-Box test and heteroscedasticity is tested utilising the ARCH test. The results of the aforementioned diagnostic tests for IDR are presented in Tables 8 and 9.

The insignificance of the estimated Q-statistics within 24 periods indicates the acceptance of hypothesis in favour of no correlation problems within the models. Therefore, based upon the correlation test, the constructed models are deemed to be correct. The results of the ARCH test for heteroscedasticity are summarised in Table 9.

As indicated in Table 9, the value of the computed F-statistics and the Chi-square statistics are sufficiently large in the case of the ARIMA model to reject the null hypothesis, which indicates the existence of heteroscedasticity in the model. Therefore, the selected ARIMA model suffers from a heteroscedasticity problem. In order to remove the ARCH effect from the ARIMA model, the volatility and asymmetry of the exchange rate is considered by including an EGARCH component in the ARIMA model. The constructed AR-GARCH model is then free from heteroscedasticity problems. The developed

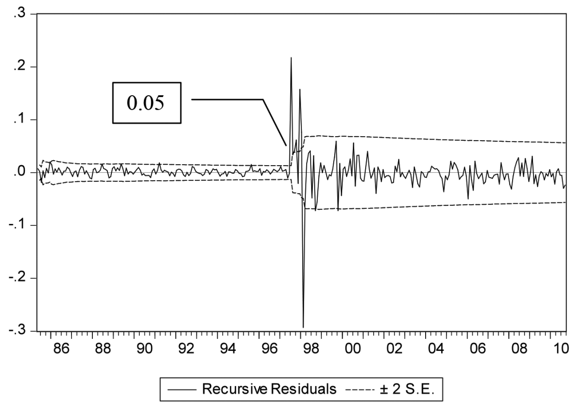

FIGURE 6. Threshold value determinations for *THB*

TABLE 7. Value of the information criteria for Thai Baht

Criteria \ Model	SETAR(1)-EGARCH(1,0,1)	SETAR(1)-EGARCH(1,0,2)	SETAR(1)-EGARCH(0,1,2)	SETAR(1)-EGARCH(2,0,2)
AIC	-4.96	-4.97	-4.80	-5.37
SC	-4.87	-4.87	-4.70	-5.25
HQ	-4.92	-4.93	-4.76	-5.32

TABLE 8. Ljung-Box correlation Q-statistic (IDR)

Models	Periods				
	1	6	12	18	24
ARIMA(2,1,2)	0.1402	9.9994	18.564	23.564	28.926
AR(1)-EGARCH(2,1,1)	0.0078	0.0489	0.1497	0.2586	0.2698
SETAR(1)-EGARCH(2,0,1)	0.0208	0.0493	0.1288	0.2237	0.2362

*, **, *** denotes significant at 1, 5 and 10%, respectively

TABLE 9. ARCH heteroscedasticity test (IDR)

Models	F-statistic	Prob.	Chi square-statistic	Prob.
ARIMA(2,1,2)	15.4270*	0.0001	14.7511*	0.0001
AR(1)- EGARCH(2,1,1)	0.00790	0.9198	0.00857	0.9198
SETAR(1)-EGARCH(2,0,1)	0.0203	0.8867	0.0204	0.8862

*, **, *** denotes significant at 1, 5 and 10%, respectively

SETAR-EGARCH model is free from heteroscedasticity as the value of computed F-statistic and the Chi square statistics are not large enough to reject the null hypothesis, indicating no heteroscedasticity problems exist in the model.

Tables 10 and 11 present the diagnostic tests for the MYR, while Tables 12 and 13 present the tests for the THB. In both cases, the developed SETAR-EGARCH and AR-EGARCH models are free from correlation and heteroscedasticity problems.

PERFORMANCE COMPARISON

After finding the best fitted models, they are utilised for forecasting purpose. In order to compare the forecasting performance of the selected models, the criteria summarised in Table 14 are employed.

TABLE 10. Ljung-Box correlation Q-statistic (MYR)

Models	Periods				
	1	6	12	18	24
ARIMA(1,1,1)	0.0001	7.4911	12.384	13.834	14.131
AR(1)-EGARCH(0,3,1)	0.1398	0.1556	0.1861	0.1899	0.1971
SETAR(1)-EGARCH(1,1,1)	1.2221	3.8765	5.8554	7.4832	13.678

*, **, *** denotes significant at 1, 5 and 10%, respectively

TABLE 11. ARCH heteroscedasticity test (MYR)

Models	F-statistic	Prob.	Chi square-statistic	Prob.
ARIMA(1,1,1)	51.7592*	0.0000	44.2671*	0.000
AR(1)-EGARCH(0,3,1)	0.1344	0.6975	0.1244	0.7120
SETAR(1)-EGARCH(1,1,1)	1.2345	0.2687	1.1912	0.2643

Note: *, **, *** denotes significant at 1, 5 and 10%, respectively

TABLE 12. Ljung-Box correlation Q-statistic (THB)

Models	Periods				
	1	6	12	18	24
ARIMA(1,1,1)	0.0070	6.0290	18.803	19.757	25.005
AR(1)-EGARCH(2,1,1)	0.1722	2.8432	9.6581	9.7542	10.075
SETAR(1)-EGARCH(2,0,2)	0.0097	0.5245	0.9153	1.2367	1.5911

*, ** and *** denotes significance at 1, 5 and 10%, respectively

TABLE 13. ARCH Heteroscedasticity Test (THB)

Models	F-statistic	Prob.	Chi square-statistic	Prob.
ARIMA(1,1,1)	7.6336**	0.0061	7.4901**	0.0062
AR(1)-EGARCH(2,1,1)	0.1876	0.5768	0.1722	0.6134
SETAR(1)-EGARCH(2,0,2)	0.0044	0.9271	0.0077	0.8654

*, ** and *** denotes significance at 1, 5 and 10%, respectively

TABLE 14. Performance criteria

Criteria	Formula
Root mean square error	$RMSE = \sqrt{\dfrac{\sum_{t=1}^{n}(X_t - F_t)^2}{n}}$
Mean absolute error	$MAE = \dfrac{1}{n}\sum_{t=1}^{n}\lvert X_t - F_t\rvert$
Mean absolute percentage error	$MAPE = 100 \times \left[\sum_{t=1}^{n}\left\lvert\dfrac{X_t - F_t}{X_t}\right\rvert\right] / n$

where F denotes forecasted value and X denotes actual value. The root mean square error (RMSE) and the mean absolute error (MAE) criteria depend on the scale of the dependent variable, while MAPE is scale invariant. The criteria should be used as relative measures to compare the forecasts of the same series across different models. A smaller value indicates stronger forecasting power for the respective model. The RMSE and MAE are a measure of fit, which indicates how well model fits with the historical data.

FORECASTING

Applying the above mentioned models for exchange rate return forecasting provides the following values for both in-sample and out-of-sample forecasting. Table 15 presents the results for in-sample and out-of-sample forecasting for the IDR, while Tables 16 and 17 present the forecasting results for the MYR and the THB, respectively.

TABLE 15. In-sample and out-of-sample forecasting (IDR)

Model	RMSE	MAE	MAPE
In-sample			
SETAR(1)-EGARCH(2,0,1)	0.07480	0.02876	100.1
AR(1)-EGARCH(2,1,1)	0.07483	0.02880	101.5
ARIMA (2,1,2)	0.07486	0.02998	217.4
3 step ahead			
SETAR(1)-EGARCH(2,0,1)	0.01512	0.01470	153.2
AR(1)-EGARCH(2,1,1)	0.01935	0.01621	153.8
ARIMA (2,1,2)	0.03262	0.02298	194.5
6 steps ahead			
SETAR(1)-EGARCH(2,0,1)	0.01726	0.01563	191.7
AR(1)-EGARCH(2,1,1)	0.01753	0.01579	162.1
ARIMA (2,1,2)	0.02894	0.02138	353.0
12 steps ahead			
SETAR(1)-EGARCH(2,0,1)	0.01674	0.01537	155.0
AR(1)-EGARCH(2,1,1)	0.01633	0.01479	136.0
ARIMA (2,1,2)	0.02349	0.01783	234.8

The results for in-sample forecasting (in the case of IDR) show that prediction performance is improved when the EGARCH component is utilised. As demonstrated, the difference between the two models utilising the EGARCH component is significant, which indicates that incorporating the volatility and asymmetry of exchange rates improves the prediction performance. In the case of out-of-sample prediction (for IDR), generally the models that include the EGARCH component perform better than the ARIMA model. Specifically, in the shorter horizons (3 and 6 steps ahead), the threshold model performs better than the AR-EGARCH model. However, in the longer horizon (12 steps ahead), the AR-EGARCH model performs better than the threshold model. The conclusion can be made that the threshold model is a better model for predictions in shorter horizons for the Indonesia Rupiah.

Table 16 presents the prediction results for the MYR. In-sample forecasting results showed that the SETAR-EGARCH model performs well compared with the other two models. However, the ARIMA and the AR-EGARCH models also provide reasonable results. In relation to out-of sample prediction, the prediction performance of the SETAR-EGARCH model is the strongest. Including the EGARCH component in the linear ARIMA model (AR-EGARCH) has improved the results.

TABLE 16. In-sample and out-of-sample forecasting (MYR)

Model	RMSE	MAE	MAPE
In-sample			
SETAR(1)-EGARCH(1,1,1)	0.02341	0.01183	99.9
AR(1)-EGARCH(0,3,1)	0.02347	0.01189	113.5
ARIMA(1,1,1)	0.02388	0.01199	107.6
3 step ahead			
SETAR(1)-EGARCH(1,1,1)	0.01254	0.01093	85.9
AR(1)-EGARCH(0,3,1)	0.01328	0.01199	96.6
ARIMA(1,1,1)	0.01352	0.01250	108.1
6 steps ahead			
SETAR(1)-EGARCH(1,1,1)	0.01875	0.01287	71.2
AR(1)-EGARCH(0,3,1)	0.01896	0.01313	77.0
ARIMA(1,1,1)	0.01973	0.01438	122.0
12 steps ahead			
SETAR(1)-EGARCH(1,1,1)	0.01817	0.01459	92.1
AR(1)-EGARCH(0,3,1)	0.01832	0.01473	93.0
ARIMA(1,1,1)	0.01925	0.01566	107.1

Table 17 presents the prediction results for THB. The results showed that the SETAR-EGARCH model remains the best fitted model for in-sample forecasting. In relation to out-of-sample prediction, the threshold model performs well in the shorter horizon (3 steps), while the AR-EGARCH model performs better than other models for prediction in longer horizons (6 and 12 steps ahead).

CONCLUSION

In the present study, the monthly returns of the exchange rates series of three ASEAN countries (Indonesia, Malaysia and Thailand) are examined. The BDS nonlinearity test utilised in the present study suggests that nonlinear models are more appropriate than linear models for all series being

TABLE 17. In-sample and out-of-sample forecasting (THB)

Model	RMSE	MAE	MAPE
In-sample			
SETAR(1)-EGARCH(2,0,2)	0.02923	0.01341	379.2
AR(1)-EGARCH(2,1,1)	0.02946	0.01359	581.4
ARIMA(1,1,1)	0.02988	0.01399	196.6
3 step ahead			
SETAR(1)-EGARCH(2,0,2)	0.0041	0.0043	61.1
AR(1)-EGARCH(2,1,1)	0.0057	0.0061	120.0
ARIMA(1,1,1)	0.0060	0.0067	81.3
6 steps ahead			
SETAR(1)-EGARCH(2,0,2)	0.01049	0.0073	92.4
AR(1)-EGARCH(2,1,1)	0.0098	0.0071	87.2
ARIMA(1,1,1)	0.01060	0.0077	97.3
12 steps ahead			
SETAR(1)-EGARCH(2,0,2)	0.01545	0.01110	108.4
AR(1)-EGARCH(2,1,1)	0.01334	0.0097	77.6
ARIMA(1,1,1)	0.01473	0.01052	103.1

analysed. A visual inspection of the plot of returns series shows the existence of structural break in the series. The structural breaks are justified by the two structural change tests conducted, which provide evidence of structural breaks in all of the returns of the exchange rate series. The best model to fit the data is determined based upon the AIC, SC and HQ values. From the prediction results, the SETAR-EGARCH model is found to outperform the ARIMA and AR-EGARCH models in in-sample fitting of all the returns series due to the significant results of performance criteria. Out-of-sample prediction results showed that the threshold model performs best in the cases of the IDR and the THB in shorter horizons, while this model performs well for both shorter and longer horizons in the case of the MYR. When the EGARCH component is combined with the ARIMA model, the prediction performance of the constructed AR-EGARCH model improves. The finding implies that when nonlinear features of exchange rates are examined, nonlinear models perform better than linear models. Finally, it can be concluded that the SETAR-EGARCH model is a possible alternative model that can be used under conditions of nonlinearity and structural change. The consideration of three different exchange rates provides support for the appropriateness of the threshold model as a nonlinear model for time series prediction.

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APPENDIX A

TABLE (A). Value of the information criteria for (IDR), ARIMA

Model	ARIMA(2,1,2)	ARIMA(3,1,4)	ARIMA(4,1,3)
AIC	-2.42	-2.41	-2.40
SC	-2.35	-2.31	-2.30
HQ	-2.39	-2.37	-2.36

TABLE (B). Value of the information criteria for (IDR), AR-EGARCH

Model	AR(1) EGARCH(1,1,1)	AR(1) EGARCH(0,1,1)	AR(1) EGARCH(2,1,1)
AIC	-3.43	-3.17	-3.45
SC	-3.35	-3.11	-3.36
HQ	-3.40	-3.15	-3.41

According to table A and B, ARIMA(2,1,2) and AR(1)-EGARCH(2,1,1) is selected respectively

TABLE (C). Value of the information criteria for (MYR), ARIMA

Model	ARIMA(1,1,1)
AIC	-4.69
SC	-4.65
HQ	-4.67

TABLE (D). Value of the information criteria for (MYR), AR-EGARCH

Model	AR(1) EGARCH(1,0,1)	AR(1) EGARCH(0,3,1)	AR(2) EGARCH(0,1,1)
AIC	-5.21	-5.51	-5.50
SC	-5.15	-5.42	-5.42
HQ	-5.19	-5.48	-5.45

According to the table C and D, ARIMA(1,1,1) and AR(1)-EGARCH(0,3,1) is selected respectively

TABLE (E). Value of the information criteria for Thai Baht-ARIMA

Model	ARIMA(1,1,1)	ARIMA(2,1,2)	ARIMA(4,1,3)
AIC	-4.28	-4.27	-4.29
SC	-4.24	-4.20	-4.19
HQ	-4.26	-4.24	-4.25

TABLE (F). Value of the information criteria for Thai Baht-AR-EGARCH

Model	AR(1) EGARCH(0,1,1)	AR(1) EGARCH(2,0,1)	AR(1) EGARCH(2,1,1)
AIC	-5.02	-5.34	-5.37
SC	-4.95	-5.27	-5.29
HQ	-4.99	-5.31	-5.34

According to the table E and F, ARIMA(1,1,1) and AR(1)-EGARCH(2,1,1) is selected respectively