Two Stage Markov Switching Model: Identifying the Indonesian Rupiah Per US Dollar Turning Points Post 1997 Financial Crisis

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Abstract:

This paper aims to identify the Indonesia rupiah per US dollar turning points using a regime switching model. Firstly, to detect if nonlinear model suits the data at hand, the BDS test and CUSUM of square test was used and the results indicates that a nonlinear model suits the data. The paper then proceeds by using a univariate two state Markov Switching autoregressive model (MSAR) developed by Hamilton (1989), Engel and Hamilton (1990) to capture regime shifts behaviour in both the mean and the variance of the Indonesian rupiah per US dollar exchange rate between 2000 to 2015. The empirical evidence indicates strong transition probabilities suggesting that only extreme events can switch the series from an appreciation regime to a depreciation regime vice versa. Moreover, the results of the MSAR model was found to successfully capture the timing of the regime shifts of the Indonesian rupiah per US dollar exchange rate because of government intervention, Indonesian presidential elections, US financial crises of 2008, and the Indonesian current account deficit in 2013. Finally, the non-linear exchange rate dynamic of the Indonesian rupiah implied that regime-switching models have potential important implication for the macroeconomic literature documenting the effect of monetary policy shock and political environment on the economic aggregates. Furthermore, regime-switching models is well suited to capture the non-linearities in exchanges rate.

Keywords: Exchange rates (Indonesian Rupiah per US Dollar), Nonlinearity, Markov switching model(MSAR)
JEL Classification: E3,E5.

1. Introduction

Exchange rate, which measures the price of one currency in term with others, is one of the most important topics in international finance and policy making (Stephane Goutte, 2011). This currency relationship has received a lot of attention among many researchers on its role in affecting economic growth of a nation as investors take into account the effect of exchange rate fluctuation on their international portfolios to minimise risk and maximise returns. Moreover, a stable exchange rate is often considered to be a sign of economic strength and a symbol of national pride. Thus, politicians are worried if they see a weakening in the exchange rate. They would point to exchange rate as a symbol of economic success. Consequently, the behaviour of the exchange rate is considered to be a key indicator for central bank performance (Hutabarat, 2006). The Purchasing Power Parity (PPP) theorem states that the exchange rate between two countries' currencies equals the ratio of the two countries' price level. The variation in prices between the two countries will be adjusted by the exchange rate. In other words, the nominal exchange rate will reveal the differences in inflation among countries. The theorem therefore envisages that the fall in a currency's domestic purchasing power (as indicated by an increase in the domestic price level) will be associated with the proportional currency depreciation in the foreign exchange market.

Empirical evidence suggested that excessive exchange rate movement depreciation or appreciation has detrimental impacts on its domestic economy as well as monetary and financial stability. For instance, the risk of currency depreciation in the case of a large amount of external debt held by various sectors within an economy is unfavourable. A sharp reduction of the value of a currency gives rise to the cost of imported good thus resulting in higher inflation. As such, according to Calvo and Reinhart (2002), emerging market economies are often reluctant to allow their currencies to freely fluctuate because of the possibility of exchange rate movement to exacerbate inflationary pressure and financial sector vulnerabilities. Because of these, much professional attention is devoted to analysing both what determines exchange rate? Moreover, how a government wants to maximise its national growth rate should approach the issue of exchange rate determination.

Exchange Market Pressure (EMP) is sometimes defined as sum of exchange rate depreciation and foreign reserve outflows, which will provide a measure of the volume of intervention needed to attain any favored exchange rate target through adjusting in reserve or exchange rate level. Following the works of Mess and Rogoff (1983) seminar paper, numerous studies have attempted to forecast exchange rate. Alvarez, Atkeson, and Kehoe (2005) argued that if the exchange rate is a random walk, then everything we say about monetary policy based on models is wrong. Flood and Rose (1995) note that nominal exchange rates are much more volatile (at low frequencies) than the macroeconomic fundamentals to which they are linked in theoretical models purchasing power parity (PPP) and Uncovered interest parity (UIP). According to Sarno and Taylor (2001:135), this instability could be the result of policy regime changes, implicit instability in key equations that underlie the econometric specification such as; the money-demand or PPP equations. This excess volatility implies that exchange rate models based on macroeconomic fundamentals are less likely to be very successful either at explaining or forecasting nominal exchange rates, and that there are other important variables that may be omitted from standard exchange rate models such as; irrationality of market participant, speculative bubbles, and the herding behaviours (Bailliu and King, 2005). However, according to Bailliu and king (2005), forecasting exchange rate based on macroeconomic fundamental can be improved if the exchange rate is modelled as nonlinear.

Moreover, regime switching models are designed to capture discrete changes in the economic mechanism that generate the data. In recent papers, Engel and Hamilton (1990) and Engel (1994) use time series approach with two regimes and applied their models to their different currencies, and the result indicated a success in capturing the dynamic evolution of exchange rate. Also, among other empirical studies, the successful use of Markov switching models to study exchange rate has been documented by Evans and Lewis (1995). Engel and Hakkio (1996) investigated the behaviour of European monetary system on exchange rate using the Markov switching model, and the results indicated that changes in the exchange rates matched periodic extreme volatility. Again, Bollen, Gray, and Whaley (2000) studied the ability of the regime-switching model to capture the dynamic of foreign exchange rates, and the results were, a regime-switching model with an independent shift in the mean and variance displays a closer fit and more accurate variance forecast than a range of other models. Similarly, Bergman and Hansson (2005) concludes that the Markov switching model is suitable to describe the exchange rates of six industrialised countries against the US dollar. More recently, Ismail and Isa (2007) employ Markov switching model to capture regime shifts behaviour in Malaysia Ringgit exchange rates against four other currencies between 1990 and 2005. They concluded that the Markov Shifting model is found to successfully capture the timing of regime shifts in the four series.

Unlike previous studies on exchange rates in Indonesia (see Saxena, 2002; Warjiyo, 2013), the aim of this paper is to examine exchange rate of the Indonesia rupiah value to the US dollar from 2000 to 2015 by employing the two-state Markov switching model developed by Hamilton (1989), Engel and Hamilton (1990). The choice of the Indonesian rupiah against the US dollar is because the US dollar is the most traded international currency in the world. Again, as noted by Goeltom (2008) in Indonesia the relationship among macroeconomic environment, structural changes, and the objective of the monetary policy in broad sense can be divided into three periods, namely before during and after the 1997-2000 financial crises. This paper contributes to the monetary literature in three broad fronts; firstly, the study of exchange rate dynamic of the Indonesian rupiah against the US dollar using a two-stage Markov switching model has not been investigated and yet this paper bridges this gap. Secondly, it defines episodes of sharp changes in exchange rate dynamics reflecting government interventions (monetary or fiscal), political environment, and major shocks around the world. Finally, this paper specifies and estimates Markov switching probabilities of being in an appreciation regime or depreciation regime.

2. Literature Review

2.1. The Markov switching model

The Markov switching (MS) model was pioneered by Hamilton (1989). A Markov switching autoregressive (AR) model (MS-AR) of states with an AR process of order p is written as follows;

$$y_t = \begin{cases} c_1 + \alpha_{11}\gamma_{t-1} + \ldots\ldots\ldots + \alpha_{p1}\gamma_{t-p} + \varepsilon_t & S_t = 1 \\ c_2 + \alpha_{12}\gamma_{t-1} + \ldots\ldots\ldots\ldots + \alpha_{p2}\gamma_{t-p} + \varepsilon_t & S_t = 2 \end{cases} \tag{1}$$

Where the regime in equation (1) are index by S_t . In this model, the parameters of the autoregressive part and the intercept are dependent on the regime at time t .The regimes are assumed to be discrete unobservable variable. Thus, in this study, regime one (1) describes the periods of downward trending of the exchange rate and regime two (2) denotes period of upward trending of the exchange rates. The transition between the regimes is assumed to follow an ergodic and irreducible a first order Markov process. This implies influences of all past observations for the variables and the state is fully encapsulated in the current observation of the state variable as denoted below;

$$\rho_{ij} = \Pr\,(S_t = j/s_{t-1} = i) \qquad \forall i,j = 1,2, \textstyle\sum_{i=1}^{2} \rho_{ij} = 1 \tag{2}$$

The probability of switching is captured in the matrix P known as a transition matrix.

$$P = \begin{bmatrix} P11 & P12 \\ P21 & P22 \end{bmatrix} \tag{3}$$

Where the $P11 + P12 = 1$ and $P21 + P22 = 1$

The maximum likelihood estimator MLE was used to estimate the parameters of the MS-AR. Thus, the log likelihood function is written as follows;

$$\text{In } L = \textstyle\sum_{t-1}^{T} In \left\{ \sum_{s_t-1}^{2} f(y_t/S_{t,}\Psi_{t-1})\, P(s_t/\Psi_{t-1}) \right\} \tag{4}$$

Where $\Psi_{t-1} = \{y_1,.....y_{t-1}\}$ and $P(s_t/\Psi_{t-1})$ denotes the filtered probabilities. Given that the MS- AR allows in making an inference about the observe regime value, through the behaviour of exogenous y_t . Thus using γ_t as observe at the end of the t-th iteration, the calculated filtered probabilities by a simple iterative algorithm is written as;

$$P(S_t = j/\Psi_t) = \sum_{s_{t-1}=1}^{2} P(s_t = j, s_{t-1} = i/\Psi_t) \text{ for } t = 1,......,T \qquad (5)$$

Similarly, the smoothed probabilities are obtained if the data set is used as a whole. Therefore, using all the information in the sample that is $\Psi_T = \{y_1,.....,y_T\}$, the calculated smoothed probabilities are written as;

$$P(S_t = j/\Psi_T) = \sum_{k=1}^{2} P(s_t = j, s_{t+1} = k/\Psi_T)$$

$$= \sum_{k=1}^{2} \frac{P(S_{t+1}=k/\Psi_t)\, P(S_t=j/\Psi_t)\, P(S_{t+1}=k/s_t=j)}{P(S_{t+1}=k/\Psi_t)} \text{ for t} = T-1, T-\ 2,.... \qquad (6)$$

Finally, from the transition matrix in equation (3) above, the expected duration of the i^{th} regime is extracted. This implies that the closer the probability P_{ij} is to one, it takes long time to shift to the next regime. In short, the expected duration written as

$$Expected\ duration = \frac{1}{1-p_{ij}} \qquad (7)$$

Furthermore, the empirical procedure used in this paper supports Granger (1993) and is outlined in Franses and Dijk (2000: P.83): Firstly, Specification of an appropriate autoregressive (AR) model of the lag order p which includes all of the time series data under investigation. Secondly, test the null hypothesis of linearity against the alternative of nonlinearity that is typically done through the use of the likelihood-ratio (LR) statistic i.e. through the linearity χ2 LR-test in which the null and alternative hypothesis of linearity is denoted as follows;

H0: $\alpha_{1,1} = \alpha_{1,2}$ and $\alpha_{2,1} = \alpha_{2,2}$ and $\alpha_{k,1} = \alpha_{k,2}$

H1: $\alpha_{1,1} \neq \alpha_{1,2}$ and $\alpha_{2,1} \neq \alpha_{2,2}$ and $\alpha_{k,1} \neq \alpha_{k,2}$

where $\alpha_{1,1}$, $\alpha_{2,1}$ and $\alpha_{k,1}$ represent the coefficients for regime 1, while $\alpha_{1,2}$, $\alpha_{2,2}$ and $\alpha_{k,2}$ represent the coefficients for regime 2. Thirdly, Estimate the parameters in the selected model and evaluate the model using diagnostic tests. These parameters include the AR parameters, transition probabilities as well as the probabilities with which each state occurs at time t.

However, for model selection, this study employs both the Akaike information criterion (AIC) and the log likelihood ratio. Again, arguably the Akaike information criterion is one of the most widely used criterion by researchers(Pan, 2001). The AIC was first developed by Akaike (1973) a way to compare different model on a given outcome. Thus, given several models for a set of data the preferred model is the model with minimum AIC value. Similarly, the log likelihood ratio popularised by was used to test for the goodness of fit between models. Thus, for the log likelihood ratio, the preferred model is the model with the highest log likelihood ratio value.

2.2. Theoretical Framework

Following Lee and Chen (2006), the logical process of the exchange rate is tied closely into empirical time series process; i.e., exchange rate process is state dependent and approximated by an autoregressive representation in each state. Thus following the works of Lee and Chen, (2006) an equilibrium exchange rate in the foreign exchange market with no government intervention is given as;

$$e_t = \alpha_0 + \beta E_t{}^n e_{t+1} + \alpha_1 F_t \quad /\beta/< 1 \tag{8}$$

Where e_t is the logarithm of exchange rate, F_t denotes the fundamental variable, ${E_t}^n$ denotes the expectation based on information not set by the central bank at time t. Thus, assuming that the operation follows an AR (1) the fundamental variable is represented as;

$$F_t = a + bF_{t-1} + \varepsilon_t \qquad /b/< 1 \tag{9}$$

Where ε_t denotes serial uncorrelated disturbance. The exchange rate calibrated forward is hence denoted as follows;

$$e^* = \frac{\propto_0}{1-\beta} + \alpha_1 F_t + \alpha_1 {E_t}^n \sum_{i=1}^{\infty} \beta^i F_{t+1}$$

$$= c + \frac{\alpha_1}{1-\beta b} F_t \tag{10}$$

Where e^* is the fundamental rate of exchange, and the constant term c $\equiv [\alpha_o + \alpha_1 \alpha\beta/(1-\beta b)]/(1-\beta)$. However, in a country with a dirty float regime, at any point of time the central banks switches stochastically between intervening and non-intervening in the foreign exchange market. Thus, whether or not the central banks intervene or not intervene will depend on a persistently changing environment. Thus, it seems more appropriate to model the central bank's intervention behaviours as a Markov chain rather than to assume independent non-intervention. It follows, let q_o be the probability that the central banks continuously intervene in the foreign exchange market at time $t+1$ if it intervenes at time t, and let q_1 be the probability that the central bank still allows the exchange rate to freely adjust at time $t+1$ if it does not intervene in the foreign exchange market at time t. Thus, the expected exchange rate under intervention is written as follows;

$${E_t}^i e_{t+1} = (1-q_0){E_t}^i {e^n}_{t+1} + q_0 {E_t}^i {e^i}_{t+1} \tag{11}$$

Where $e_t{}^i$ is the exchange rate under intervention at time t, $e_t{}^n$ is the market determined exchange rate at time t, and $E_t{}^i$ is the expectations operator based upon the information set when the central bank intervenes at time t, similarly, in the case of non- intervention the expected exchange rate written as follows;

$$E_t{}^n e_{t+1} = (1 - q_1) E_t{}^n e^i{}_{t+1} + q_1 E_t{}^n e^n{}_{t+1} \tag{12}$$

Also, assuming that the given country intervenes to peg the currency to promote export so as to influence economic growth, therefore, set its target as follows;

$$e_t{}^i = d + e_t{}^* \tag{13}$$

Where d denotes a discretionary parameter. If the central banks want to its money to be under-valued/over-valued, then the parameter d is positive or negative, otherwise if the central bank just wants to target the value of its money to be consistent with the economic fundamentals, then d is zero.

Thus, if the central bank does not intervene, then the market exchange rate $e_t{}^n$ is determined by the market fundamentals and the expected exchange rate for the next period is denoted as follows;

$$e_t{}^n = \alpha_o + \beta E_t{}^n e_{t+1} + \alpha_1 F_1 \tag{14}$$

Thus, combining eq (8), eq (9), eq (10), eq (11), eq (13), yield an equilibrium exchange rate under dirty floating regime as (see Lee and Chu (2006));

$$e_t{}^n = \frac{\beta(1-q_1)d}{1-\beta q_1} + e^*{}_t \tag{15}$$

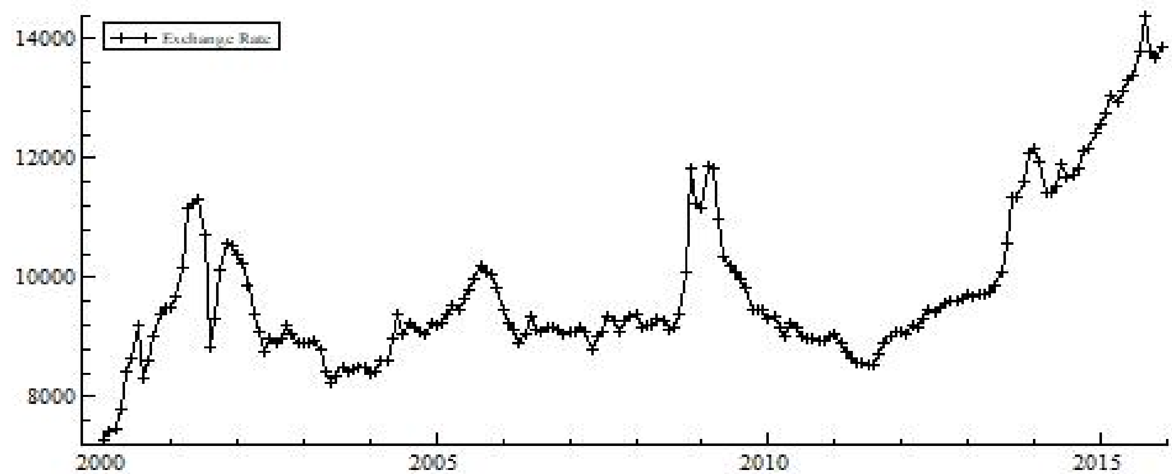
Here, a higher probability of central bank intervention raises the rational expectation discrepancy between the exchange rate and its fundamentals, even though the central banks do not step in the foreign exchange market during this period. Thus, assuming that intervention or no intervention States follows a first order Markov chain. A regime switching model can thus be applied to estimate the exchange rate dynamics (Lee and Chen, 2006).

3. Methodology

3.1. Data

The data consists of monthly observations on the exchange rate of the Indonesian rupiah per US dollar taken from the www.OECDiLibrary.com. The sample runs from the first month of the year 2000 to the last month of the year 2015 comprising of a sample of 192 observations, accounting for behaviour of the rupiah against the US dollar after the Asian financial crises of 1997-2000. A plot of the exchange rate is depicted in Fig 1.

Fig. 1 A Plot of The Indonesian Rupiah Per US Dollar Exchange Rate



Source: Author's Graphical Representation

In Fig. 1 above, the Indonesian rupiah per US dollar exchange rate indicate a large amount of variability over time, with an upward trending from 2000 until 2001, and then a sharp falling trend which was broken lately in 2005. Notably, the long swing in nominal exchange rate documented in Engle and Hamilton 1990 also show up here graphically. In which Engle and Hamilton (1990) defines long swing in the dollar, a situation in which the dollar appears to increase in one direction for an extended period. Thus, the plot indicates that the Indonesian rupiah per dollar exchange rate exhibit a pattern of depreciation as well as appreciation. An upward-trending implies a depreciation of the Indonesian rupiah against the US dollar exchange rate while a downward trending indicates an appreciation of the rupiah against the US dollar exchange rate. Also, Shen and Chen (2004) showed that developed countries experience asymmetric swings in the exchange rate, while developing countries may experience an asymmetric speed of adjustment; i.e., long swings in appreciation and short swings in depreciation (Nikolsko and Prodan, 2011).

3.2. Test of Nonlinearity

To determine whether a nonlinear model is suitable for the data. According to Brooks (2008), the decision should come from the financial theory; nonlinear model should be used where financial theory suggests that the relationship between the variable requires a nonlinear model. Notwithstanding, linear vs. nonlinearity choice can be made partly on statistical grounds deciding whether a linear specification is sufficient to describe all of the most important features of the data at hand. Although there are quite some tests for detecting a nonlinear pattern in time series data for researchers. This paper focuses on the most widely used tests known as BDS test name after the three authors that developed it.

To test for a nonlinear effect of Indonesian rupiah per US dollar exchange rate, this paper used the nonparametric method known as the BDS test. The BDS test developed by Brock, Dechert and Scheinkman (1987) is arguably the most popular test for nonlinearity (Zivot and Wang, 2006). Many studies have shown that BDS test has power against a wide range of linear versus nonlinear alternatives, for example (see Brock, Dechert, Scheinkman, 1987; Barnett, Gallant, Hinich, and Kaplan, 1997). The BDS test is based on an integral correlation of the series and is defined as follows;

$$BDS_{m.M}(r) = \sqrt{M}\frac{c_m(r)-c_1{}^r(r)}{\sigma_{m.M}(r)} \quad (16)$$

Where M is the surrounded points of the space with m dimension, r denotes the radius of the sphere centred on the X_i, C is the constant and $\sigma_{m.M}(r)$ is the standard deviation of $\sqrt{M}C_m(r) - C^r{}_1(r)$. Thus, the null and alternative hypothesis of the BDS test for detecting nonlinearity is as follows;

H_0: the series are linearly dependent

H_1: the series are not linearly dependent.

Also, for detecting structural breaks, this paper similar to Ismail and Zaidi (2007), employed the CUSUM of squares test developed by Brown, Durbin and Evan (1975) based on a plot of the cumulative sum of the squared one-step-ahead forecast error resulting from recursive estimation between two critical lines. In which any movement outside the critical line is an indication that the of parameter or variance is unstable.

4. Results

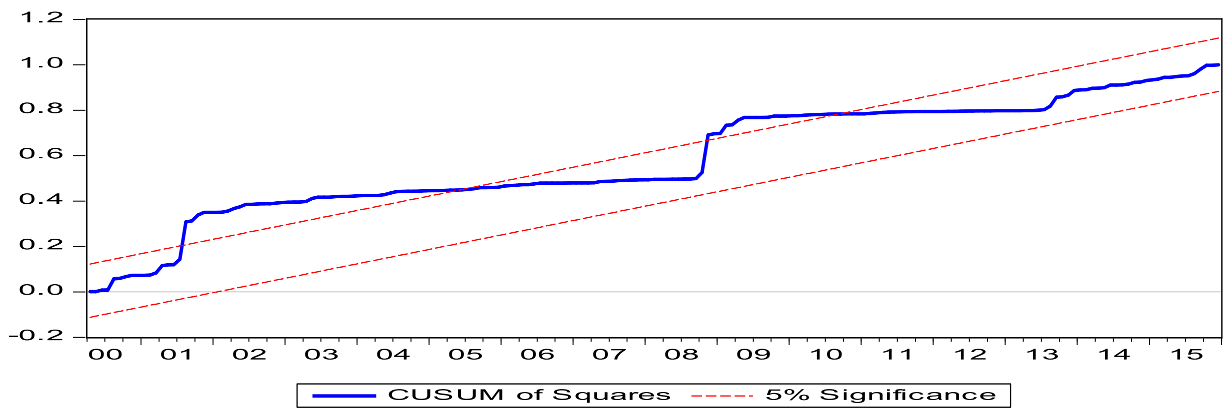
Before the estimation of the Markov switching models, a nonlinearity test might still be necessary to describe the important features of the data at hand. Table 1 below, reports the results of the nonlinearity test developed by Brock, Dechert, and Scheinkman (1987), whereas Fig 2 reports the results of the structural break test developed by Brown et al. (1975).

Table 1. BDS Test for Nonlinearity

Dimension	BDS Statistic	Std. Error	Z-statistic	Probability
2	0.172501	0.007468	25.10014	0.0000
3	0.285056	0.011942	23.87100	0.0000
4	0.357166	0.014315	24.95065	0.0000
5	0.402537	0.015021	26.79848	0.0000
6	0.429984	0.014585	29.48099	0.0000

Source: www.OECDiLibrary.com Database, *Authors' estimates using Eviews9*

Figure 2 CUSUM of Squares Test



Source: www.OECDiLibrary.com Database, *Authors' estimates using Eviews9*
Note: The CUSUM test was derived by estimating an AR (2) model

The BDS test results in Table 1 indicates that there is nonlinearity effect in the Indonesian rupiah per US dollar exchange rate. Table 1 shows that the probabilities are less than 5%, thus implying a rejection of the null hypothesis that the series is linearly dependent. While in Fig 2, the results indicate that some the cumulative sums of squares are outside the boundary of 5% significant level which implies instability. The results (in Table 1 and Fig. 2) suggest that the Indonesian rupiah per US dollar exchange rate are nonlinear and unstable which is an indication of the messy behaviour of financial time series data hence the data can be estimated using a nonlinear model.

Next, the study proceeds with the estimation of the Markov switching model (MS-AR). However, before obtaining the final form of the models used in this paper, various form of lagged values of the Indonesian rupiah per US dollar exchange rate was considered. Table 2 compares the appropriateness of the various estimated two-state Markov switching models.

Table 2. Model Estimation and Selection

Model [MS-AR]	Number of states	Number of lags	Log likelihood	AIC
1	2	1	-1336.6408	14.080
2	2	2	-1318.4602	13.984
3	2	3	-1315.2567	14.045
4	2	4	-1307.5516	14.059
5	2	5	-1273.0499	13.787*

Source: www.OECDiLibrary.com Database*, Authors' estimates using PcGive in OxMetrics 6*
[Note the asterisk * denotes the chosen model]

From Table 2 above , using the specification measures such as the log likelihood and the Akaike information criteria, among the five estimated Markov switching model i.e. MS (2)- AR (1) to MS (2)- AR (5) The selected model was MS (2)- AR (5) with the lowest Akaike information criteria of (13.789) and the highest log likelihood of (-1273.0499). After model estimation and selection, the model MS (2)- AR(5) was then tested for serial correlation, ARCH, and normality (see Table 3). The portmanteau tests concluded that the error terms are not serially correlated. The ARCH test reported no issues of homogeneity of the variance of the error term. Finally, the normality test indicates that the residuals were found to be normally distributed. Also, the LR test indicated that hypothesis of linearity can be rejected in favour of a model a Markov switching model.

Table 3. Estimation results of MS (2) – AR (5) model for the period 2000(1) – 2015(12)

	Regime 1[Appreciation]			Regime2[Depreciation]	
	Coefficient	**p-value**		**Coefficient**	**P-value**
Regime-dependent intercepts					
c	10073.4	(0.000)		102254.4	(0.000)
Autoregressive coefficients					
AR_{t-1}	1.37979	(0.000)		1.25939	(0.000)
AR_{t-2}	-0.362003	(0.000)		-0.378038	(0.000)
AR_{t-3}	0.0545023	(0.532)		0.117801	(0.145)
AR_{t-4}	-0.143282	(0.088)		0.259486	(0.001)
AR_{t-5}	0.0756737	(0.037)		-0.134091	(0.007)
Variances					
$\boldsymbol{\sigma^2}$	137.553	(0.000)		652.243	(0.000)
Log likelihood			- 1273.0499		
AIC			13.787		
LR-test χ^2			132.99 (0.000)		
Portmanteau test χ^2 **(36 lags)**			24.18 (0.9333)		
Normality test χ^2			2.6377 (0.2674)		
ARCH 1-6 test			0.98492 (0.4374)		
Transition probability					
			Regime 1	**Regime 2**	
Regime 1			0.956619	0.19801	
Regime 2			0.043392	0.80199	

Source: www.OECDiLibrary.com Database*, Authors' estimates using PcGive in OxMetrics 6*
[Note: the numbers indicated in parenthesis indicates P-values]

Notably**,** in Table 3 above, almost all the estimated coefficient of the MS (2)- AR(5) model is found to be significant at conventional level. However, the estimated model was not able to capture the long swing documented by Hamilton and Engels (1990) since the regime dependent intercepts for appreciation regime and depreciation regime are positive. As such, it is hard to make economic interpretation using the regime dependent intercepts. An Interesting part of Table 3 is the transition probabilities Matrix. The estimated transition probabilities shows that there is a higher probability that the system stays in the same regime thus implying few switches in the regime. For example, the results indicated a 96% probability of staying in an appreciation and a lower probability of 19.8 % switching to the depreciation regime. Correspondently, when the system is in a depreciation regime, there is an 80 %probability of staying in a depreciation regime and again a lower probability of 4.3 % switching to the appreciation regime. This shows that only an extreme event can switch the series from appreciation regime to a depreciation regime, or from a depreciation regime to an appreciation regime. Further, the estimated transition probabilities indicated that none of the regime is permanent since all the estimated transition probabilities are less than one.

Also, there have been more episodes of appreciation of the Indonesian rupiah against the US dollar than the counterpart depreciation during the period 2000(1) to 2015(12). The average duration of each regime supports this. Based on expected duration, the appreciation regime has an average duration 22.43 month while depreciation has only 5.00 months duration. It implies that Indonesian rupiah per US dollar exchange rate will be in an appreciation regime for an average 22.43 months and depreciation regime for an average of 5 months (see Table 4).

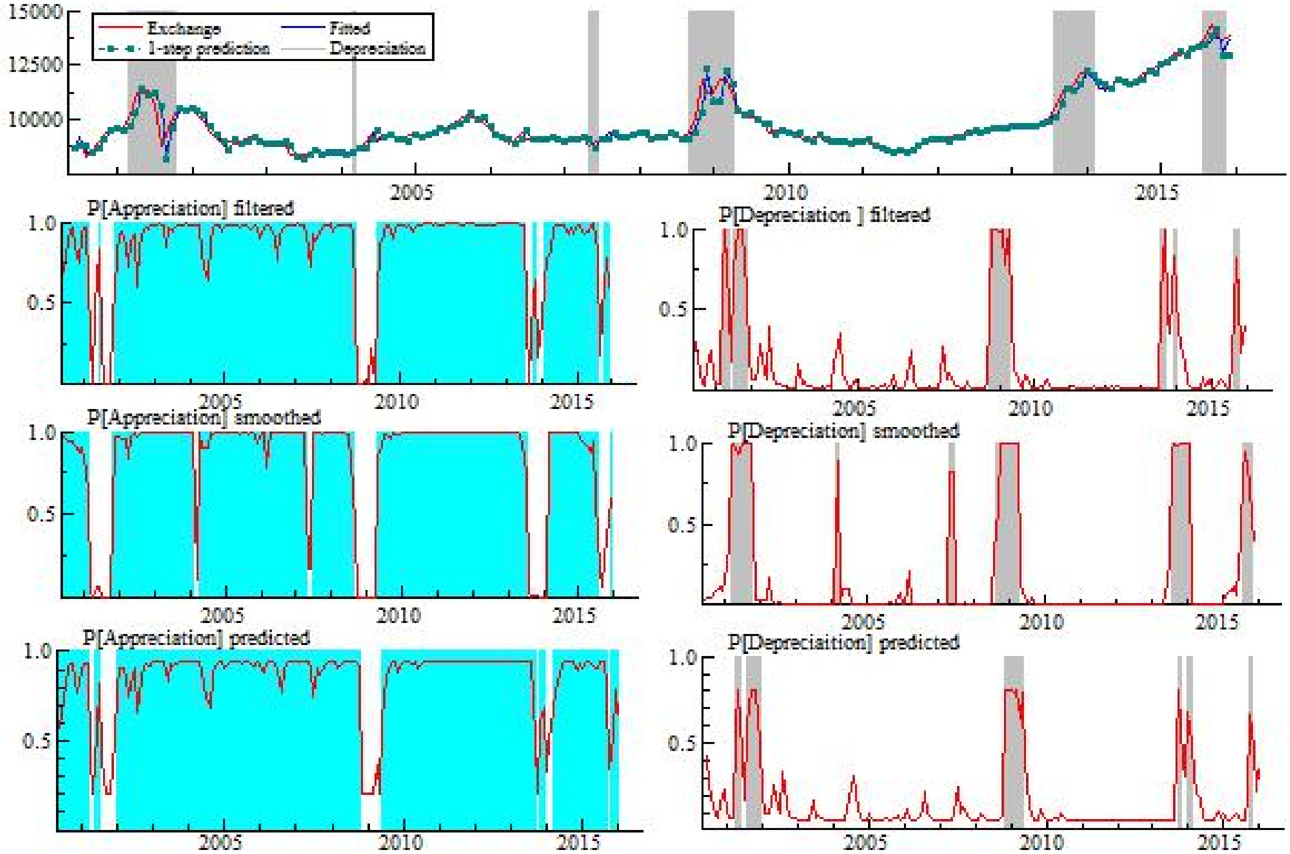
Table 4 Regime Classification: Episodes of Appreciation and Depreciation from 2000(1) to 2005(12) (Smoothed Probabilities)

Regime1[Appreciation]			**Regime2[Depreciation]**		
Period	**Months**	**Average probability**	**Period**	**Months**	**Average probability**
2000(6) – 2001(2)	9	0.890	2001(3) – 2001(10)	8	0.980
2001(11) – 2004(2)	28	0.985	2004(3) – 2004(3)	1	0.898
2004(4) – 2007(4)	37	0.980	2007(5) – 2007(6)	2	0.828
2007(7) – 2008(8)	14	0.971	2008(9) – 2009(4)	8	0.949
2009(5) – 2013(7)	51	0.986	2013(3) – 2014(2)	7	0.992
2014(3) – 2015(7)	17	0.951	2015(8) – 2015(11)	4	0.762
2015(12) – 2015(12)	1	0.598			
Total: 157 months (83.96%) with an average duration of 22.43 months.			Total: 30 months (16.04%) with an average duration of 5.00 months.		

Source: www.OECDiLibrary.com Database*, Authors' estimates using PcGive in OxMetrics 6*

To further assist with the interpretation of the MS (2)- AR(5) model, in Fig.3 the first panel shows the evolution of exchange rate of the Indonesian rupiah per US dollar exchange rate, while the second, third and fourth panel denotes the filtered smoothed and predicted probabilities of being in an appreciation regime and depreciation regime respectivley. From Fig.3 below, it can be observed that the appreciation regime dominates the counterpart of depreciation regime which confirms the statistical analysis reported in Table 4.

Fig. 3 Graphical Representation of The Regime Probabilities



Source: www.OECDiLibrary.com Database, *Authors' estimates using PcGive in OxMetrics 6*

As noted in Table 4 and Fig. 3 above, referring to the depreciation regime results, the MSAR model manages to identify accurate turning points of the Indonesia rupiah per US dollar exchange rate. The approach also identifies six periods of depreciation of the Indonesians rupiah per US dollar exchange rate. It appears that the respective tuning point varies in length periods corresponding to economic and financial crisis, and shocks. The occurrence of these turning point is explained as follows; From Edward and Sahminan (2008), this paper finds that the turning point in 2001 happened due to the uncertainty stemming from accusations of presidential graft, further debt downgrades and forecasts of lower growth which all in all resulted in a reduction in investors and corporate confidence. Again, from Edwards and Sahminan (2008), this paper finds that the turning point in 2004 happened due to the interest rate differentials affecting the flow of capital in and out of the country with corresponding implication for the domestic currency. This was in the case of Indonesia when the decline interest rate differentials was due to the monetary policy tightening in the United States (US) which caused the short-term capital outflows. Also, concerns about the Indonesian presidential elections in July 2004 added to the depreciation of the Indonesia rupiah per dollar exchange rate. However, for the appreciation regime, with the aftermath of the Bank Indonesia adoption of August 2005 depreciation policy, the Indonesia rupiah per US dollar exchange rate was observed to be stable (see Panel 1 in Fig. 3 above).

Moreover, from Edward and Sahminan (2008), this paper finds the depreciation of the rupiah in 2007 was due to the Sub- prime mortgage in the United States (US) in which the impact spread to emerging markets as global investors reassessed their holding of the risky asset. Along with the Federal Reserve decision to cut interest rate triggered the return of capital inflows into the rupiah asset thus putting pressure on the Indonesian rupiah. However, lately in 2007, the Indonesian rupiah was notably in an appreciation regime (see Panel 1 in Fig. 3 above). The results of the Indonesian rupiah being in an appreciation regime corresponded to the monetary policy interventions undertaken by Bank Indonesia in which the Governor of BI at the end of August 2007 reported that Indonesian rupiah pegged at 9000 per US dollar was best for the Indonesian economy. Finally, in 2008 the Indonesian rupiah depreciated against the US dollar.

The timing of this turning exactly corresponded to the US 2008 financial crisis. However, after the 2008 US financial crisis, the Indonesian rupiah appreciated against the US dollar in 2009, 2010 and 2011. From Warjiyo (2013) this paper finds the appreciation of the Indonesian rupiah against the US dollar was due to the sizeable balance of payment surplus in the current account and capital inflows into the Indonesian economy. Again, from early, 2012 to mid-2013, the Rupiah steadily weaken (depreciates) against the US dollar, as Indonesia current account shifted into a deficit. Also, notably, in 2015 the Indonesian rupiah depreciated against the US dollar.

5. Conclusions

This paper uses a univariate two-state Markov switching autoregressive model (MS-AR) model developed by Hamilton (1989), Engel and Hamilton (1990) to capture regime shifts behaviour in both the mean and the variance of the Indonesian rupiah per US dollar exchange rate between 2000 and 2015. The BDS test and CUSUM of squares test were used, and both tests suggested that a nonlinear model was appropriate for modelling the Indonesia rupiah per dollar exchange rate. A visual inspection of the Indonesian rupiah per US dollar exchange rate suggested evidence of a regime-switching behaviour. A plot of the smoothed probability was able to report a timing of appreciation or depreciation of Indonesian rupiah per US dollar exchange rate corresponding to major government intervention, political environment, and shocks around the world. Finally, the study concludes that significant events not incorporated within the standard exchange rate models do affect the behaviour of the Indonesian rupiah per US dollar exchange rate.

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