DOI: 10.20472/IAC.2016.024.096

DITEBOHO XABA
North West University , South Africa

TSHEPISO TSOKU
North West University, South Africa

TEBOHO MOSIKARI
North West University , South Africa

IDENTIFYING REGIME SHIFTS IN SOUTH AFRICAN EXCHANGE RATES

Abstract:

Linear time series models are not able to capture the behaviour of many financial time series, as in the cases of inflation rates, exchange rates and stock prices data. To overcome this problem, nonlinear time series models are typically designed to capture these nonlinear features in the data. In this paper, we use portmanteau test and likelihood ratio test (LR) test to detect nonlinear feature and to justify the use of 2-regime Markov switching autoregressive model (MS-AR) in South Africa exchange rate between 1995 and 2013. For model selection criteria (AIC and SBC) were used and for identifying best model error matrix such as MEA and MSE were used. The study compared the in-sample fitting between linear model and Markov switching model. From the error matrix (MEA and MSE) values, it is found that the MS –AR(3) model is the best fitted model for exchange rate. 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:

stationarity; nonlinear model; exchange rates

JEL Classification: C19, C50

1. Introduction

In recent years, literature has revealed that most linear models are relatively poor in terms of capturing certain financial data behaviour, or economic performance at certain times. Several studies have proved that conventional models are good in term of modelling and forecasting, but the models are incapable of reveal same attributes that can be found in financial and economic data. For instance, studies by Yarmohammadi et al, (2012), Amiri (2012), Ismail & Isa (2007) revealed that conventional models cannot explain the business cycles behaviour. In support of the mentioned studies, Medereios and Sobral (2011) pointed out that the analysis of business cycles have been restricted to linear methods, which are incapable to follow the fast and accelerated rhythm of constant change of the countries' economies. This led to an increasing interest in studies using nonlinear models which are capable of dealing with switching regimes associated with financial and economic data. Xaba et al., (2016) provide evidence that the stock price of banks were nonlinear in nature, while finding a better Markov-switching model. The study used daily data obtained from the Johannesburg Stock Exchange over the period from January 2010 to December 2012. An extension of Markov Switching with autoregressive model was used for empirical analysis.

Amiri (2012) compared the forecasting performance of linear and nonlinear univariate time series models for GDP. The evaluation of the forecasting performance of their set of nonlinear models using real time data proved that the nonlinear models are able to capture the underlying processes of GDP as opposed to linear models. Cruz and Mapa (2013) also contributed to the literature by developing an early warning system for predicting the occurrence of high inflation in the Philippines with MS model. The study successfully managed to identify episodes of high and low inflation with this model.

Yarmohammadi et al,.(2012) Markov switching autoregressive (MS-AR) model and six different time series modeling approaches are considered. These models are compared according to their performance for capturing the Iranian exchange rate series. The series has dramatic jump in early 2002 which coincides with the change in policy of the exchange rate regime. Their criteria were based on the AIC and BIC values. The results indicate that the MS-AR model can be considered as useful model, with the best fit, to evaluate the behaviours of Iran's exchange rate. Ismail & Isa (2007) in their study used a univariate 2-regime Markov switching autoregressive model (MS-AR) to capture regime shifts behaviour in both the mean and the variance in Malaysia ringgit exchange rates against four other countries namely the British pound sterling, the Australian dollar, the Singapore dollar and the Japanese yen between 1990 and 2005. The MS-AR model is found to successfully capture the timing of regime shifts in the four series and this regime shifts occurred because of financial crises such as the European financial crisis in 1992 and the Asian financial crisis in 1997.

Ismail & Isa (2006) employed Markov switching model to capture regime shifts behaviour in Malaysian exchange rates and other four ASEAN countries from year 1993 to 2005. The objective of their study was to test which model was efficient between regime switching model and the linear model using few of ASEAN countries exchange rates. The results of the study revealed that MS-AR model outperformed linear model. Ismail & Isa (2007) detected the behaviour of regime shifts in Malaysian exchange rates from 1990 to 2005. The authors used a univariate 2-regime Markov switching model to capture this behaviour in both mean and variance.

The objective of the paper is to find the best models which are capable of describing and forecasting the South African exchange rate. Furthermore, the study intends to compare the performance of each of the two models in modeling and forecasting exchange rate.

Our paper is organized as follows. Section 2 outlines the methodology. Section 3 presents the empirical results and discussion on the results and Section 4 conclusion.

2. Methodology

This section discusses the data and method used in the study.

2.1. Data

The data under investigation is quarterly exchange rate from South Africa. The period that has been sampled is from 1995 Q1 to 2015Q4, with 84 observations. The time series dataset was accessed from World Bank database. A time series plot for this exchange rate is shown a Figure 1.

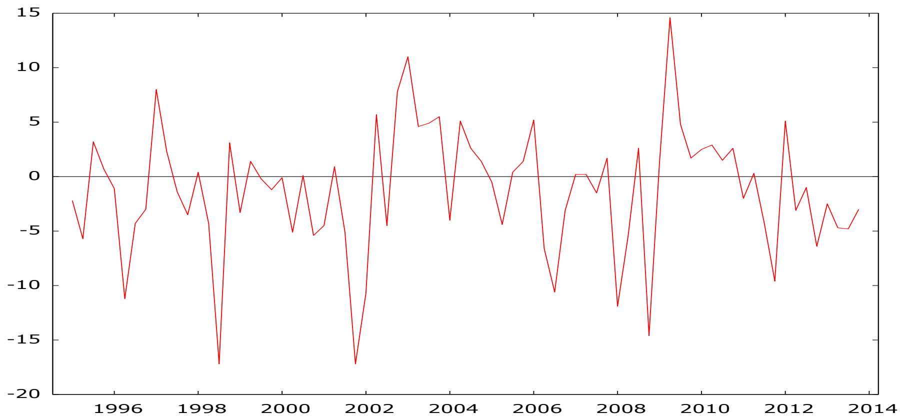

Figure 1: Graphical Representation of the Exchange rate

2.2 Markov Switching Autoregressive Models (MS-AR)

In this section study consider a univariate autoregressive process, AR which is subject to regime shifts. Study extends the conventional Hamilton's model with a focus on one time regime shifts in the mean by allowing the mean and the variance to shift simultaneously across the regime. The variable under investigation is the quarterly exchange rates changes. Therefore, a Markov switching autoregressive model of two regimes with an AR process of order p is given as follow:

$$X_t - \mu(S_t) = \varphi_1[X_{t-1} - \mu(S_{t-1})] + \varphi_2[X_{t-2} - \mu(S_{t-2})] + ... + \varphi_p[X_{t-p} - \mu(S_{t-p})] + \varepsilon_t$$

which, when re-parameterised yields:

$$X_t = c + \varphi_1 X_{t-1} + \varphi_2 + ... + \varphi_p X_{t-p} + \varepsilon_t$$

or

$$X_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad (2.1)$$

where $\varphi_1, \varphi_2, ..., \varphi_p$ represent the coefficients of the AR(p) process, $\varepsilon_t \sim \mathrm{iid}(0, \sigma_\varepsilon^2)$ and $\mu(S_t)$ are constants that are dependent on the states/regimes S_t and represent μ_1 if the process is in state/ regime 1 ($S_t = 1$), μ_2 if the process in state/regime 2 ($S_t = 2$), …, and μ_R if the process is in state/regime R ($S_t = R$, the last state/regime). The change from one state to another is governed by the R-state first-order Markov Chain with transition probabilities, expressed as:

$$p_{ij} = P(S_t = j | S_{t-1} = i), \quad i, j = 1, 2 \qquad (2.2)$$

where p_{ij} is the probability of moving from state i at time t-1 to state j at time t. Using the fact that:

$$p_{1i} + p_{2i} + ... + p_{Ri} = 1, \qquad (2.3)$$

the probability of state i being followed by state j (also known as the transition matrix) is given by:

$$P = \begin{pmatrix} p_{11} & p_{21} & \cdots & p_{R1} \\ p_{12} & p_{22} & \cdots & p_{R2} \\ . & & & \\ . & & & \\ p_{1R} & p_{2R} & \cdots & p_{RR} \end{pmatrix} \qquad (2.4)$$

In the current study, two states or regimes assumed that R=2 and the underlying MS-AR (p) model is given by:

$$X_t = \begin{cases} c_1 + \sum_{i=1}^{p} \varphi_{1,i} X_{t-i} + \varepsilon_{1,t}, & \text{if } S_t = 1 \\ c_2 + \sum_{i=1}^{p} \varphi_{2,i} X_{t-i} + \varepsilon_{2,t}, & \text{if } S_t = 2 \end{cases} \qquad (2.5)$$

The transition matrix is, thus, given by:

$$P = \begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix} \qquad (2.6)$$

so that $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$. P represents the probability of change in regime. For this two-regime MS-AR model, there are four transition probabilities given by:

$$
\begin{aligned}
&P(S_t = 1 | S_{t-1} = 1) = p_{11} \\
&P(S_t = 2 | S_{t-1} = 1) = p_{12} = 1 - p_{11} \\
&P(S_t = 2 | S_{t-1} = 2) = p_{22} \\
&P(S_t = 1 | S_{t-1} = 2) = p_{21} = 1 - p_{22}
\end{aligned}
\tag{2.7}
$$

The MS-AR allows one to make inferences about the value of the observed regime, s_t, through the observed behaviour of x_t.

3. Results of the study

In this section, a preliminary data analysis of data is conducted with the aim to identify the broad characteristics of the measured variables used in the study. This covers includes basic descriptive statistics and stationary tests.

3.1. Descriptive Statistics

Table 3.1: Summary Statistics of Exchange rate

Observation	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Prob.
84	-1.28	5.77	-0.39	3.92	4.60	0.10

A lot of things can be learned from a preliminary analysis of the data before econometric modelling and main analysis of the data is carried out, factors such as normality of the actual data have to carry out. Descriptive statistics such as the mean and standard deviations of the variables are analysed. Table 3.1 consists of the summary of these measures. The range of the data falls within the minimum and maximum values of the data, the actual values are this is an indication that the data is normally distributed. This might also suggest that the mean is the best value to report on the central tendency of the data. Skewness and kurtosis are measure which can decide on the normality of the data. The negative value of skewness suggests that the data is negatively skewed and normally distributed. Kurtosis is the measure of peakedness of the data, the value of kurtosis falls within standard errors so the data is considered normally distributed. The mean of exchange rates is explained by a symmetric distribution due to the closeness of the value of the mean and median.

Table 3.2: Results of the Tests for Stationarity

Types	Lag	t-stat	5% cv	AIC	SBC	Conclusion
Constant	0	-7.0123	-1.9452	6.3406	6.3716	Stationary
	1	-5.5498		6.3746	6.4369	Stationary
	2	-4.0711		6.3894	6.4835	Stationary
	3	-3.9664		6.4225	6.5490	Stationary
	4	-3.7271		6.4624	6.6217	Stationary
Constant and Term	0	-7.0743	-3.1100	6.3336	6.3645	Stationary
	1	-5.6217		6.3668	6.4291	Stationary
	2	-4.1329		6.3536	6.4778	Stationary
	3	-4.0458		6.4150	6.5415	Stationary
	4	-3.8293		6.4534	6.6128	Stationary

The table 3.2 reveals the results of stationarity test, at 5% level of significance the data is stationary at both constant and constant and term with a lag length of 0 and the lowest values of both AIC and SBC. The data is stationary at levels and therefore does not need any differencing.

3.2. Regime Identification using the Markov-switching model

Markov switching model parameters were estimated using OxMetrics software. Four of two-regime Markov switching models, MS-AR(1) to MS-AR(4), are estimated using different lags. Akaike Information Criterion (AIC) and various diagnostic tests are performed for model selection, normality and linearity tests also included. The results in Table 3.3 suggest that MS-AR(3) is best model that can be used to predict exchange rate.

Table 3.3 Diagnostic Tests – MS-AR models

Test		Models			
		AR(1)	**AR(2)**	**AR(3)**	**AR(4)**
AIC		6.378	6.432	6.197	6.336
Linearity test (Likelihood Ratio)	Test Stat	13.146	13.598	33.633	28.090
	P-Value	0.022	0.034	0.000	0.001
Normality test (Chi-Square)	Test Stat	2.869	0.501	0.973	0.642
	P-Value	0.238	0.778	0.056	0.726
ARCH 1-1 test (F)	Test Stat	0.001	2.621	0.117	0.028
	P-Value	0.971	0.111	0.734	0.867
Portmanteau test (Chi-Square)	Test Stat	6.060	5.543	6.010	2.615
	P-Value	0.641	0.698	0.646	0.956

The estimated parameters of the MS-AR(3) model are shown in Table 3.4. The values shown are rounded to the first three decimal places. Results show that the mean exchange rate in state 0 using the formula $\frac{c}{(1-\varphi_1-\varphi_2-\varphi_3)}$ is 0.021 percent while that in state 1 is 0.017 percent. This implies that state 1 refers to a depreciation exchange rate regime while state 0 refers to an appreciation exchange rate regime.

Table 3.4 Estimated Model of MS-AR(3)

Regime 0 (Depreciation)						
Parameter	c_1	φ_1	φ_2	φ_3	σ_1	p_{01}
Estimate	0.754	0.346	0.192	0.106	7.408	0.241
Standard Error	0.472	0.021	0.021	0.019	0.809	
Regime 1 (Appreciation)						
Parameter	c_2	φ_1	φ_2	φ_3	σ_2	p_{10}
Estimate	1.062	-0.511	0.162	0.735	0.477	0.450
Standard Error	0.170	0.065	0.060	0.062	0.088	

Based on the transition probabilities of the Markov-Switching model, the probability that the country will shift from a "appreciation exchange rate" state to "depreciation exchange rate" state ($p_{10} = 0.450$) is about twice the probability of shifting from a depreciation exchange rate regime to an appreciation regime ($p_{01} = 0.241$). Another interesting result is the expected duration of a state which is estimated as the reciprocal of the transitional probability. The expected duration of a period of depreciation exchange rate is estimated to be 4 quarters while that of appreciation exchange rate is about 2 quarters. This implies that, on average, once the South Africa enters a period of "appreciation" exchange rate, it will stay in that state for about 2 quarters. The estimated duration of depreciation exchange rate is about 4 quarters, more than twice that of depreciation exchange rate. Overall, the relatively depreciation probability of shifting from a depreciation exchange rate regime to an appreciation exchange rate regime and the duration of a depreciation exchange rate regime lend support to the effectiveness of monetary policy in managing exchange rate in South Africa.

3.3. Model Comparison and Forecast Accuracy

One of the objectives of this study is to compare forecasting ability of linear ARIMA and MS-AR. Predicting future values is essential for the sake of decision making and formulation of policies. Both models satisfy the terms of assumptions. If models satisfy the assumptions, they can then be used for future predictions. Error metrics, including MAE and MSE were used to measure forecast accuracy of the models. Table 3.5 summarizes the results of the in-sample forecast accuracy measures of the two models for the exchange rate.

Table 3.5: Forecast Comparison among AR and MS-AR Models

Measure	Method	Exchange rate
MSE	ARIMA	31.424
	MS-AR	21.251
MAE	ARIMA	4.374
	MS-AR	1.413

According to the results, the two performance-selection criteria select the MS-AR(3) model for exchange rate accordingly. Both MSE and MAE, selected the MS-AR model for exchange rate, Based on the findings by Dacco and Satchell (1999), the exchange rate is best modelled by the MS-AR(3) model.

4. Conclusion

The study explored the performance of the ARIMA and the MS-AR models in modelling and forecasting the quarterly exchange rate of South Africa. The suggested models perform better when applied to exchange rate series. Appropriate test for this assumption proved that the series is nonlinear in nature. The estimation of the two models was based on an optimal lag five suggested by the AIC and SBC. The two models were successfully estimated using this lag. To evaluate the performance of the two models, the study used the two forecast error metrics which were in favour of the MSAR model. Generally, the results proved that the MS-AR performed better compared to the linear models.

5. Reference

Akaike, H. (1974) A New Look at the Statistical Model Identification, I.E.E.E. Transactions on Automatic Control, AC 19, 716-723

AMIRI, E. (2012) Forecasting GDP Growth rate with Nonlinear Models.1st International Conference of Econometrics Methods and Applications.1-18.

CRUZ, C. J. F. & MAPA, D. S. (2013) An Early warning system for Inflation in the Philippines using Markov-Switching and Logistic Regression Models. Theoretical and Practical Research in Economic Fields 2, 137-152.

Dacco, R, & Satchell, S. (1999) Why Do Regime-Switching Models Forecast So Badly? Journal of Forecasting, 18: pp. 1-16

Hamilton, J.D. (1989) A new approach to the econometric analysis of nonstationary time series and business cycle". Econometrica, 57: pp. 357-384.

ISMAIL, M.T. & ISA, Z. (2006) Modelling Exchange Rates Using Regime Switching Models. Sains Malaysiana 35(2): 55-62.

ISMAIL, M.T. & ISA, Z. (2007) Detecting Regime Shifts in Malaysian Exchange Rates. Journal of Fundamental Sciences, 3, 211-224.

MEDEIROS O.R & SOBRAL Y.D (2007) A Markov Switching Regime Model of the Brazilian Business Cycle

RAMSEY, J. B. (1969) Test for Specification error in Classical Linear Least Squares Regression Analysis, Journal of the Royal Statistical Society, Series B. 31, pp. 350-371

Schwarz, G. (1978) Estimating the Dimension of a Model, Annals of Statistics, 6, pp. 461-464.

Xaba,D, Moroke, N.D, Arkaah, J & Pooe, C (2016) Modeling South African Banks closing stock prices: a Markov-Switching Approach, Journal of Economics and Behavioral Studies (ISSN: 2220-6140) Vol. 8, No. 1, pp. 36-40, February 2016

YARMOHAMMADI, M, MOSTAFAEI, H & SAFAEI, M. (2012) Markov Switching Models for Time Series Data with Dramatic Jumps, Sains Malaysiana 41(3): 371–377