International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2025, 15(1), 330-336.

Modelling Cambodia's Foreign Exchange Rate Dynamics: A Markov-Switching Autoregressive Model

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Received: 02 September 2024 **Accepted:** 22 November 2024 **DOI:** https://doi.org/10.32479/ijefi.17618

ABSTRACT

The analysis of the daily fluctuations in the foreign exchange rate between the Khmer Riel and the US dollar was performed utilizing a Markov-switching autoregressive model. This study covered a time frame from January 04, 2005, to August 22, 2024, encompassing a total of 4989 days of data. The research findings revealed that the MS(2)-AR(1) model emerged as the most appropriate model for the analysis. The empirical results from both state 1 and state 2 models demonstrated that the intercept term, along with the AR(1) component, exerted a statistically significant positive effect on the exchange rate at a 1% significance level. Furthermore, the intercept term, which represents the average exchange rate, along with the volatility of the exchange rate in the state 2 model, was found to be higher than that observed in the state 1 model. The analysis of the probability transition matrix indicated that there was a 15.53% likelihood for *FX* to transition from state 2 to state 1. In contrast, the probability of FX departing from state 1 and returning to state 2 was recorded at 29.34%. Additionally, the chance of *FX* maintaining its position in state 1 was assessed to be 70.66%, while the probability of it remaining in state 2 was significantly higher at 84.47%.

Keywords: Foreign Exchange Rate, Markov-Switching Model, Probability Transition Matrix
JEL Classifications: F31, C58, C51, C01

1. INTRODUCTION

As the values of currencies change in relation to each other, the consequences extend throughout financial markets, global trade, and domestic economic strategies. Prior to the onset of the Russia-Ukraine conflict, the Russian ruble (RUB) exhibited stability, largely attributed to the trade surplus that Russia consistently maintained throughout 2020 and 2021. However, during the war, there was a significant outflow of capital, coupled with a reduction in energy exports from Russia to Europe and other global markets, primarily due to sanctions and disrupted trade routes. These factors have undeniably affected the value of the RUB. In the early stages of the Russian-Ukraine conflict, the RUB experienced continued depreciation (Xu et al., 2023). The exchange rate of the RMB has exhibited a pattern of fluctuations, including both appreciation and depreciation, over the duration of the government's implementation of tariff restrictions in China (Guo and Chen, 2022). In addition to trade policy, the implementation of monetary policy conducted by The People's Bank of China also has significant influence on the RMB (Bahaj and Reis, 2024). The trade imbalance between the United States and several East Asian nations, including Japan, South Korea, Taiwan, China, Malaysia, and Thailand, has been observed to improve when the U.S. dollar experiences depreciation relative to the currencies of these countries (Thorbecke, 2023). Natural disasters can be categorized into two primary types of events: climatic and geological. Climatic events encompass phenomena such as droughts, floods, storms, and extreme temperature fluctuations, while geological events include volcanic activity, earthquakes, landslides, and wildfires (Raddatz, 2007; David, 2010). It has been observed that natural disasters exert a considerable influence on the fluctuations of exchange rates, particularly in emerging and developing economies. The extent of the response to the shock caused by such disasters is contingent upon the exchange rate regime adopted by the respective countries

(Nguyen and Nguyen, 2024). Political instability, variations in economic fundamentals, changes in government policies—such as fiscal, monetary, or trade policies—and even natural disasters can all play a significant role in the volatility of foreign exchange rates, leading to shifts from one state to another (Kumah, 2011; Phoong et al., 2022; Yamaka et al., 2023).

The fluctuations in exchange rates play a crucial role in the functioning of modern economies, influencing various elements of economic activity such as trade and investment. In particular, Cambodia, which has implemented a managed floating exchange rate system for nearly thirty years, presents a significant case for policymakers and investors to comprehend the intricacies of exchange rate movements, especially in different states of economy. Grasping the intricacies of exchange rate fluctuations among various states is crucial. Analyzing the probabilities associated with transitions between states, as well as the chances of departing from a particular state, is vital for a comprehensive understanding. The Markov-switching autoregressive (MSAR) model provides a solid framework for examining these variations by pinpointing specific states in the behavior of exchange rates (Lee and Chen, 2006; Korley and Giouvris, 2021; Kumar et al., 2024).

The dynamics of the nominal exchange rate between the Khmer Riel and the US dollar across various market conditions have not been explored in Cambodia to date. Investigating the behavior of exchange rates in the context of different market environments is essential for multiple reasons. Given that Cambodia is a developing economy with a significant dependence on trade, understanding the variations in exchange rates provides valuable insights that can assist policymakers in devising effective monetary policies aimed at stabilizing inflation and fostering economic growth.

This study is divided into five sections. The introductory section provides an insight into the background and aim of this study. The synthesis of the empirical literature reviews related to this research topic is discussed and processed in section two. The development of the research methodology, which includes Markov-switching modelling and the estimation method used to estimate all coefficients of the models under study, is described in section three. The research findings interacting with the presentation of descriptive statistics and graphical analysis, interpretation of empirical models and hypothesis testing are presented in section four. The conclusions and implications of the research are discussed in section five.

2. LITERATURE REVIEW

The Markov-switching (MS) model was first introduced by Goldfeld and Quandt in the early 1970s. By the late 1980s, it had gained significant traction in the analysis of structural changes within time series data, as noted by Goldfeld and Quandt in 1973 and Hamilton in 1989 (Goldfeld and Quandt, 1973; Hamilton, 1989). This model has been extensively utilized in examining various economic indicators, including inflation rates, interest rate, money supply, GDP, and exchange rates (Cheung and Erlandsson, 2005; Dai and Serletis, 2019; Ayinde et al., 2020; de Oliveira et al., 2024).

The behavior of nominal monthly exchange rate had be studied in the post-Bretton Woods using drift term using the two-state Markov switching stochastic segmented trend over a 12 nominal exchange rate series. The empirical finds of the study suggested that 9 out of 12, the prediction of exchange rate using MS(2) outperformed the random walk model (Nikolsko-Rzhevskyy and Prodan, 2012). The performance measurement of the out-of-sample forecast between the MS(2) and the random walk models, was carried out using the mean square prediction error (MSPE), so called the DMW test (Diebold and Mariano, 1995; West, 1996).

The findings derived from the Markov-Switching Autoregressive (MSAR) model revealed that the nominal exchange rate of the Indonesian rupiah against the US dollar transitioned between two distinct states, but this switching occurred solely during extreme events. Notable instances of such events include the significant mortgage crisis in the United States in 2008 and the current account deficit experienced by Indonesia in 2013. The alteration of the exchange rate not only affects the mean but also influences the variance, which quantifies the volatility of the Indonesian rupiah. Furthermore, two tests were conducted to evaluate the appropriateness of the nonlinear model for the Indonesian rupiah; these tests included the BDS test and the CUSUM of squares test (Mendy and Widodo, 2018). The BDS test, created by Brock, Dechert, and Scheinkman, evaluates the existence of nonlinearity and dependence within a time series (Broock et al., 1996), whereas the CUSUM of squares test is utilized to identify variations in variance over time. Both of these tests are essential instruments for researchers and analysts, aiding in the detection of structural breaks and confirming the reliability of their models (Page, 1961).

The exchange rate forecasting was performed utilizing a Markov-switching model, which posited the existence of multiple economic states rather than limiting the analysis to just one or two states. This approach was implemented for the exchange rates involving the British pound against the US dollar, the Canadian dollar against the US dollar, and the Japanese yen against the US dollar. It is important to highlight that the selection criteria for the models utilized was based on the Bayesian information criterion. The evaluation of the predictability of the exchange rate models involved a comparison with the random walk model of prediction. Even with the incorporation of multiple states within the model, the findings indicated that the forecasting efficiency of the exchange rate was superior in the random walk model compared to the Markov-switching model (Stillwagon and Sullivan, 2020).

To determine the pound sterling hedging forward exchange rates for 1-month, 2-month, and 3-month periods against five different currencies—namely the US dollar, Japanese yen, euro, Turkish lira, and Indian rupee—a regime-switching model was utilized. This model encompasses four distinct market conditions: very low, low, high, and very high. Although these conditions are categorized into four states, they can be further consolidated into two primary regimes: the normal regime, which includes low and high states, and the extreme states, which are defined as very low and very high (Adam et al., 2017; Zalachoris, 2022; Fatouh and Giansante, 2023). The empirical results of this research indicate that the foreign exchange risk was considerably mitigated through the application of the developed model, particularly in comparison to traditional hedging methods, especially when dealing with highly volatile currencies such as the Turkish lira. The conventional hedging strategies utilized in this study encompassed the calculation of the optimal hedging ratio via ordinary least squares (OLS) regression, as well as the generalized orthogonal approach of the generalized autoregressive conditional heteroscedasticity model (GO-GARCH) (Lee et al., 2023). The results of this study align with the empirical investigations carried out by Kroner and Sultan (1993), Myers and Thompson (1989), and Ricci (2020).

The analysis revealed that the Turkish foreign exchange market exhibited two distinct states during the period from January 2006 to December 2019, characterized as high and low states, as indicated by the Markov-switching model applied to monthly exchange rate data. Various factors were identified that exerted pressure on the Turkish exchange rate, prompting a transition from the low to the high regime. These factors included the industrial production index, bank credit levels, the general price level, short-term external debt, and the monthly volatility index derived from daily exchange rate data. This finding is consistent with the research conducted by Özatay (2016), Samba (2018), and Gevorkyan (2019), as noted by İlhan et al. (2022). This research distinguishes itself from other studies by incorporating control variables, as previously outlined, despite the application of the MS model of exchange rate with two states and the associated drift and variance inherent in the model.

The forecasting of exchange rates between the BRICS nations—Brazil, Russia, India, China, and South Africa—and the US dollar was performed using an out-of-sample approach grounded in the Markov-switching methodology. This analysis employed both the normal-gamma (NG) prior and the Litterman prior to accurately estimate the coefficients of the predictive models. Additionally, two other models, namely the random walk and the linear Bayesian Vector Autoregressive (BVA) models, were incorporated to assess the predictive performance of the various models in forecasting exchange rates. The empirical results of this study align consistently with the findings of Stillwagon and Sullivan (2020), demonstrating that the random walk model yielded greater forecasting accuracy than the MS model. Throughout the duration of the study, it was observed that the Russian ruble emerged as the most depreciated currency, while the African Rand was identified as the most appreciated currency (Kumar et al., 2024). The significant decline in the value of the Russian ruble can be attributed to the ongoing conflict between Russia and Ukraine (Xu et al., 2023).

A comprehensive examination of exchange rate fluctuations across various markets can assist businesses in making well-informed choices about their pricing and investment approaches. As Cambodia becomes increasingly integrated into the global economy, grasping the nuances of currency movements is vital for enhancing the nation's ability to withstand external economic disturbances. This understanding is crucial for fostering sustainable economic growth and ensuring that Cambodia remains competitive in both regional and international markets.

3. METHODOLOGY

The Markov-Switching Autoregressive (MS-AR) model enables a gradual adjustment in response to changes in the state of a process, such as the fluctuation of exchange rate. This model, referred to as the Markov-switching dynamic regression, was developed by Krolzig (2013) as an extension of the work by Hamilton (1993). This model is commonly used to analyze lower-frequency time series datasets, including daily data. The aim of this research study is to implement the MS-AR model, which incorporates two state-dependent autoregressive terms for the dependent variable, specifically when it is in state s at time t.

$$FX_t = \alpha_{s_t} + \sum_{i=1}^{p} \varphi_{i,s_t}\left(FX_{t-i} - \alpha_{s_{t-i}}\right) + \varepsilon_{s_t} \tag{1}$$

The variable denoted as FX_t serves as the dependent variable, representing the foreign exchange rate between Khmer Riel (KHR) and US dollar at a specific time t. The constant or intercept that varies with the state is represented by α_{s_t}. The time periods under consideration are t and $t-i$, where i ranges from 1 to n. The parameter for the autoregressive term is represented as φ_{i,s_t}. Additionally, the residual term, ε_{s_t}, is characterized as independent and identically distributed (i.i.d), possessing a mean of zero and a variance that is dependent on the state. It is important to mention that the optimal lag length of the model is established using the Akaike Information Criterion (AIC) (Akaike, 1981). This study utilizes daily data spanning from January 04, 2005, to August 22, 2024, encompassing a total of 4989 days. The data has been sourced from the Bloomberg terminal. The Augmented Dickey-Fuller (ADF) test, recognized as the most prominent unit root test (Dickey and Fuller, 1979), is utilized to evaluate the stationarity of the *FX* data series, given that the data incorporated in the model consists of time series. This test is conducted on two distinct sets of *FX* data series: the *FX* at their original level and those at the first difference.

The probability that the present state, denoted as s_t, corresponds to $j \in (1,\ldots,k)$ is contingent upon the most preceding state, s_{t-1}.

$$Pr\,(s_t = j | s_{t-1} = i) = p_{ij} \tag{2}$$

Given that this study centers on the Markov-switching model with two states, the transition probability from one state to another can be represented using a 2×2 transition matrix as follows.

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{3}$$

It is important to point out that $p_{11} + p_{12} = 1$, as well as $p_{21} + p_{22} = 1$.

The technique employed for estimating all coefficients, denoted as θ, will be the maximum likelihood estimation method. This approach can be applied once the likelihood function that includes latent states has been formulated, which will be elaborated upon in the subsequent discussion. The expression $f\,(FX_t|s_t = i;\, FX_{t-1};\, \theta)$ denotes the conditional density of FX_t for $i=1,\ldots,k$. These conditional densities are adjusted according to their associated probabilities, which exhibit a specific functional structure.

$$f\left(FX_t \mid \theta\right) = \sum_{i=1}^{k} f\left(FX_t \mid s_t = i; FX_{t-1}; \theta\right) \Pr\left(s_t = i; \theta\right) \tag{4}$$

A vector of conditional densities, characterized by $k \times 1$, represented as ξ_t, is outlined as follows.

$$\xi_t = \begin{bmatrix} f\left(FX_t \mid s_t = 1; FX_{t-1}; \theta\right) \\ f\left(FX_t \mid s_t = 2; FX_{t-1}; \theta\right) \\ \vdots \\ f\left(FX_t \mid s_t = k; FX_{t-1}; \theta\right) \end{bmatrix} \tag{5}$$

In order to construct the likelihood function, it is essential to assess the probability of the state variable taking on a specific value, based on the data accessible up to time t and the parameters of the model. The conditional probability of the state variable s_t being equal to i, given the information available at time t, can be represented as Pr ($s_t = i|FX_t; \theta$) and the likelihood of FX_t denoted as f ($FX_t|FX_{t-1}; \theta$).

$$\Pr\left(s_t = i \mid FX_t; \theta\right) = \frac{f\left(FX_t \mid s_t = i; FX_{t-1}; \theta\right) \Pr\left(s_t = i \mid FX_{t-1}; \theta\right)}{f\left(FX_t \mid FX_{t-1}; \theta\right)} \tag{6}$$

Since Pr ($s_t = i|FX_{t-1}; \theta$) represents the predicted likelihood of the state s_t being equal to i, based on the observations available up to time t-1. Then

$$\Pr\left(s_t = 1 \mid FX_{t-1}; \theta\right) = \sum_{j=1}^{k} \Pr\left(s_t = i \mid s_{t-1} = j, FX_{t-1}; \theta\right) \Pr\left(s_{t-1} = j \mid FX_{t-1}; \theta\right) \tag{7}$$

The log-likelihood function is

$$L\left(\theta\right) = \sum_{t=1}^{T} \log f\left(FX_t \mid FX_{t-1}; \theta\right) \tag{8}$$

Where

$$f\left(FX_t \mid FX_{t-1}; \theta\right) = 1'\left(\psi_{t|t-1} \cdot \xi_t\right) \tag{9}$$

The log-likelihood in (8) can be derived by applying the following iterative equations:

$$\psi_{t|t} = \frac{\left(\psi_{t|t-1} \cdot \xi_t\right)}{1'\left(\psi_{t|t-1} \cdot \xi_t\right)} \tag{10}$$

Where ξ_t is a vector of conditional densities, characterized by $k \times 1$, which indicates in (5) $\psi_{t|t}$ and $\psi_{t|t-1}$ represent vectors of conditional probabilities of $k \times 1$ of Pr ($s_t = i|FX_t; \theta$) and Pr ($s_t = i|FX_{t-1}; \theta$) and 1 is a k×1 vector of 1s (Hamilton, 1994; Tijms, 2003; Frühwirth-Schnatter, 2006).

4. EMPIRICAL RESULTS

The study encompasses a total of 4989 days of observations, spanning from January 4, 2005, to August 22, 2024. The daily average exchange rate, expressed in terms of Khmer Riel per US dollar, is calculated to be 4078.64, with an estimated standard deviation of approximately 56.03. The exchange rate exhibits a skewness of 0.18 and a kurtosis of 4.79. Within the duration of the study, the 5th percentile of the exchange rate is recorded at 3995 KHR, the median at 4074 KHR, and the 95th percentile at 4187 KHR per US dollar, as detailed in the summary statistics presented in Table 1.

Before proceeding to the subsequent phase of model estimation, it is essential to conduct a unit root test to determine whether the foreign exchange series is devoid of a unit root or exhibits stationarity, given that the data utilized in this research comprises time series data.

Stationarity denotes the characteristic of a time series in which its statistical attributes, including mean and variance, do not change over time. This attribute is essential for accurate modeling, forecasting, and drawing inferences. The ADF test, widely regarded as a prominent unit root test, was selected to conduct a unit root analysis of the foreign exchange series. This test can be executed using three distinct models: one that includes a constant, another that incorporates both a constant and a trend, and a third that excludes both a constant and a trend. It should be emphasized that the null hypothesis of the ADF test states that a series has unit root. As shown in Table 2, the results of the ADF tests conducted for all models except the ADF model without constant and trend, regardless of whether they were examined at the level or in the first difference, consistently showed a strong rejection of the null hypothesis at the 1% significance level. This finding suggests that the *FX* series displays stationarity, which is generally defined as a mean-reverting process. This conclusion aligns with the illustration presented in Figure 1.

The analysis of foreign exchange dynamics was categorized into two distinct states, referred to as state 1 and state 2, to examine the behavioral characteristics of the exchange rate in Cambodia. In this context, autoregressive (AR) terms were incorporated into the two-state Markov-Switching model, denoted as MR(2), with the optimal lag lengths being established through the AIC. A lower AIC value indicates a more effective estimation model. This research has sought to conduct a comprehensive analysis of the foreign exchange behavior in the two states by not only altering the estimation coefficients but also by modifying the intercept terms and the estimated volatility, represented by sigma, σ_i.

As the AIC result suggests, the best fitting Markov-Switching-*FX* model is the MS(2)-AR(1) model. The empirical result of the model estimated using the method of maximum likelihood estimation (MLE) is shown in Table 3. In Panel A, the regression

Table 1: Summary statistics

Percentiles	fx	Smallest		
1%	3970.5	3843		
5%	3995	3844.5		
10%	4011.9	3845	Observations	4989
25%	4046	3845	Sum of wgt.	4989
50%	4074		Mean	4078.64
		Largest	Standard deviation	56.03
75%	4110	4241		
90%	4146	4241	Variance	3139.89
95%	4187	4241	Skewness	0.18
99%	4231	4275	Kurtosis	4.79

Table 2: ADF unit root test

Models	At Level	
	t-Statistic	FX
With Constant	*t*-Statistic	−6.2201
	Prob.	0.0000 ***
With Constant and Trend	*t*-Statistic	−6.4073
	Prob.	0.0000 ***
Without Constant and Trend	*t*-Statistic	0.3657
	Prob.	0.7901 n0
	At First Difference	
		d (FX)
With Constant	*t*-Statistic	−12.1886
	Prob.	0.0000 ***
With Constant and Trend	*t*-Statistic	−12.2098
	Prob.	0.0000 ***
Without Constant and Trend	*t*-Statistic	−12.1815
	Prob.	0.0000 ***

(*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1% and (no) Not Significant, Lag Length based on AIC. Probability based on MacKinnon (1996) one-sided P-values.

Table 3: MS (2)-AR (1) of FX modeling

fx	Coefficient	Standard error	z
Panel A: State 1			
AR (1)	0.9149***	0.0096	95.36
α_1	4078.2***	5.2493	776.91
Panel B: State 2			
AR (1)	1.0001***	0.0008	1314.63
α_2	4078.4***	5.2628	774.95
Panel C: Sigma			
σ_1	18.26	0.3668	
σ_2	2.39	0.0640	

***, **, * indicate statistically significant at 1%, 5%, and 10% level

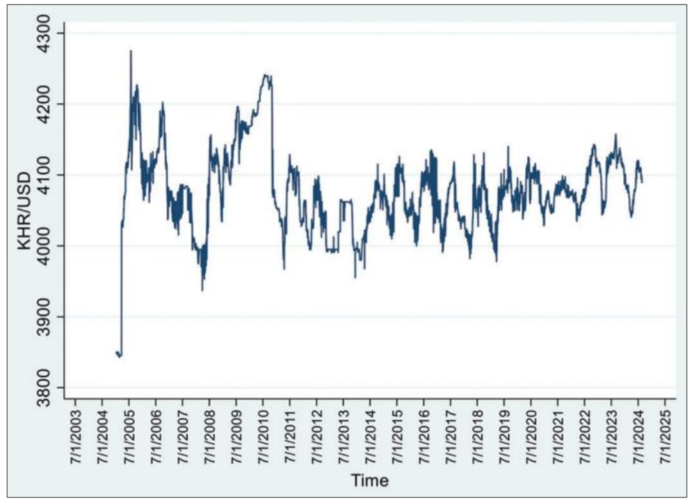
result of the model for state 1 shows that the coefficient of the first-order autoregressive term is 0.9149, which is positive and significant and explains the exchange rate at 1% level.

The coefficient of the intercept of the model for state 1 is also positive at 4078.2 and has a highly statistically significant impact on the exchange rate at 1% level. The result in Panel B of Table 3 shows that the slope coefficient of the first-order autoregressive term of the regression model for state 2 is estimated to be 1.0001, with a statistically significant explanatory factor of 1%. In addition,

Table 4: Probability transition matrix

pij	Regime 1, *t*	Regime 2, *t*
Regime 1	0.7066	0.1553
Regime 2	0.2934	0.8447

Figure 1: FX, KHR/USD



the estimated mean or intercept parameter of the state 2 model is also positive at 4078.4 and has a highly significant impact on *FX* at the 1% level. Comparing the two mean values of the Markov switching model for state 1 and state 2, it can be observed that the mean value of *FX* in state 2 is slightly higher than the mean value of *FX* in state 1, namely 4078.4 versus 4078.2. In contrast, the estimated AR(1) coefficient in the state 1 model is larger than the estimated AR(1) coefficient in the state 2 model (18.26 vs. 2.39). Interestingly, the volatility of foreign exchange in the state 1 model is estimated to be 18.16, which is a higher volatility than the volatility of foreign exchange in the state 2 model, as it is only estimated to be 2.39, as showed in Panel C.

The likelihood of remaining in state 1 during the subsequent period, given that the current state is 1, is estimated at 70.66%. Consequently, the probability of moving from state 2 to state 1 can be calculated as 100% minus 70.66%, resulting in a transition probability of 29.34%. In contrast, the probability of remaining in state 2 is significantly higher at 84.47%, suggesting that state 2 exhibits greater persistence compared to state 1. These results further reveal a 15.53% chance of transitioning from state 2 to state 1, while the probability of leaving state 1 stands at 29.34%.

The study, which spanned a duration of 4989 days, categorized the foreign exchange into two distinct states, referred to as states 1 and 2. Alongside the differentiation of the *FX* into these two states, modifications were also made to the intercept and standard deviation within the two-state models. The estimation parameters corresponding to states 1 and 2 were employed for in-sample forecasting, facilitating a comparative analysis of the predicted exchange rates across the two states. As can be seen from Figure 2, the forecasted foreign exchange in state 2 is significantly higher than in state 1. The transition of the exchange rate from a lower to a higher state can be attributed to various specific factors inherent in the autoregressive Markov switching model.

Figure 2: Prediction of FX in State 1 and State 2

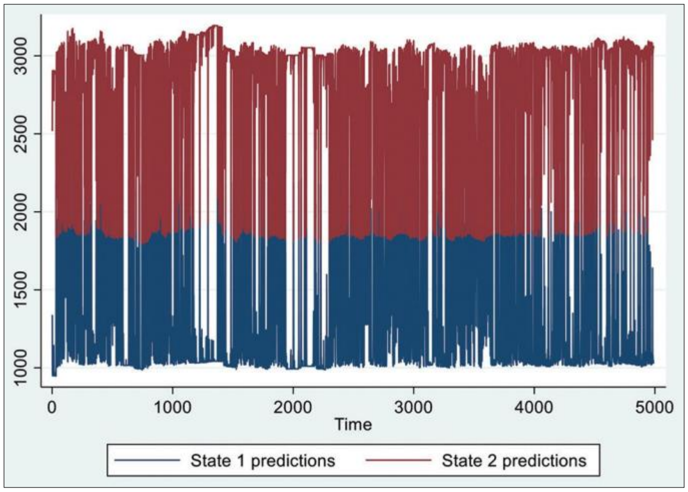
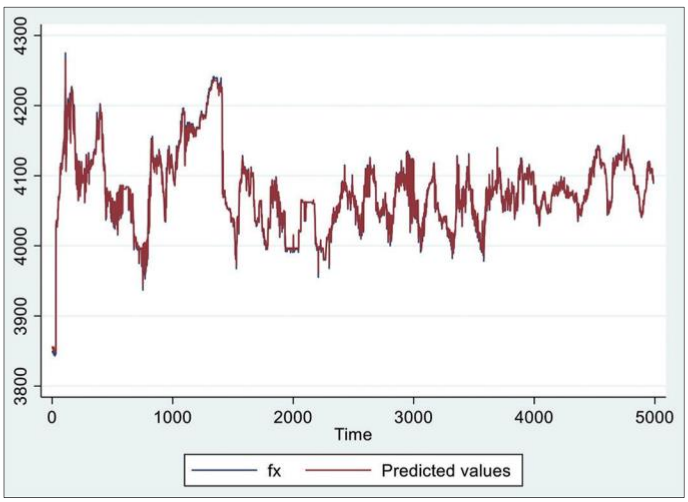


Figure 3: Observed and predicted *FX*



5. CONCLUSION

Analyzing the behavior of foreign exchange provides investors with valuable insights that help them make informed investment decisions. To study the behavior of foreign exchange in two different states, the autoregressive Markov switching model was used. The optimal lag length for the model was determined using AIC. Based on the AIC results, the MS(2)-AR(1) model proved to be the best choice. The empirical investigation conducted for both state 1 and state 2 indicated that the AR(1) component exhibited a substantial positive influence on the foreign exchange at the 1% significance level in both models. It is important to highlight that the variations in *FX* can be linked to the anticipated results of the intercept term in both state 1 and state 2, which is identified as the average return. The mean *FX* values in the models for state 1 and state 2 were determined to be 4078.2 and 4078.4, respectively. The volatility of *FX* for state 1 was estimated at 18.26, whereas for state 2, it was significantly lower at 2.39. This analysis suggests that state 2 not only provided a higher mean *FX* value than the model for state 1 but also demonstrated greater volatility. The probability transition matrix revealed a 15.53% chance for *FX* to move from state 2 to state 1, while the probability of leaving state 1 to revert to state 2 stood at 29.34%. Furthermore, the likelihood of *FX* sustaining its status in state 1 was estimated to be around 70.66%, whereas there was an approximately 84.47% probability that it would persist in state 2.

This research employed a Markov-switching autoregressive model to examine the dynamics of foreign exchange, concentrating exclusively on two states with daily time series data. To enhance the understanding of the financial intricacies associated with *FX*, it is highly recommended that subsequent studies integrate policy variables, including the monetary aggregate managed by the National Bank of Cambodia and government expenditure overseen by the Ministry of Economy and Finance. Furthermore, a more engaging analysis could be achieved by exploring *FX* fluctuations through the lens of additional states, such as three or four.

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