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Analyzing Cambodia Securities Exchange Index Returns using the Markov-Switching Autoregressive Model

Siphat Lim*, Edman Flores, Casey Barnett, Md Monirul Islam

CamEd Business School, Phnom Penh, Cambodia. *Email: lsiphat@cam-ed.com

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ABSTRACT

The examination of the weekly return behavior of the Cambodia securities exchange (CSX) index, spanning from 2012 to 2024, was categorized into two distinct states or regimes using the Markov-Switching Autoregressive model. The research findings indicated that the MS (2)-AR (1) model, which includes two states or regimes and a first-order autoregressive component, was the most suitable model. The empirical results showed that both the first-order lag of the dependent variable and the intercept term had a significant positive effect on the return of the CSX index at a 1% significance level, applicable to both Regime 1 and Regime 2 models. In contrast, the first-order autoregressive variable in the Regime 1 model demonstrated a significant negative effect on the return of the CSX index at the same 1% significance level, a relationship not observed in the Regime 2 model. The empirical results indicated a 38.35% likelihood of the CSX index transitioning from Regime 2 to Regime 1, while the probability of exiting Regime 1 was notably lower at 17.39%, as shown by the probability transition matrix. Additionally, the volatility of the CSX index returns in Regime 2 was found to be greater than that observed in Regime 1.

Keywords: Cambodia Securities Exchange Index, Markov-Switching Autoregressive Model, Probability Transition Matrix
JEL Classifications: C51, C58, A23

1. INTRODUCTION

Understanding stock market behavior is essential for investors, policymakers, and researchers in financial economics. Traditional models often fail to capture the complex dynamics of financial time series data, especially during market instability. The Markov-switching (MS) model, also known as the Markov-chain, offers significant advantages in this context (Mathlouthi and Bahloul, 2022). Stock markets exhibit variations in volatility and return characteristics, influenced by economic conditions, investor attitudes, and geopolitical events (Bouattour and Miloudi, 2024). The MS model effectively detects transitions in market regimes by allowing data to move between different states, each characterized by distinct parameters. This ability to capture non-linearity and changing market behaviors over time significantly enhances the understanding of market dynamics (Mallikarjuna and Rao, 2019). Incorporating regime changes within the Markov-switching autoregressive (MSAR) model greatly improves prediction accuracy compared to traditional autoregressive models. These models better manage the autocorrelation in financial time series, leading to more reliable and adaptable forecasts (Segnon et al., 2024).

The Cambodia securities exchange (CSX) is a key player in the Cambodian economy, facilitating capital formation and economic development. It enables the trading of securities issued by public and private entities, contributing to economic growth and stability. As an emerging market, the CSX experiences significant volatility and rapid price changes, often influenced by shifts in domestic and international economic conditions. Understanding these price fluctuations is crucial for investors to manage risk and make informed decisions. The MSAR model, a powerful tool for capturing complex stock price dynamics, is a key focus of this research. This model identifies different market states and reflects structural changes in the market (Inayati et al., 2024). It is particularly useful for understanding regime-switching behaviors in emerging markets like Cambodia.

Previous research has demonstrated the usefulness of the MSAR model in analyzing financial markets (Adejumo et al., 2020). However, few studies have applied this model to the CSX index. This research makes a unique and significant contribution to the literature by comprehensively analyzing the CSX index's return dynamics using the MSAR framework. By applying the MSAR model to the CSX Index, this study explores the underlying regime-switching behaviors of stock prices (Korley and Giouvris, 2021) in Cambodia, providing valuable insights into market stability, investor strategies, and the development of predictive models tailored to emerging economies (Chang et al., 2024). The findings of this study have significant practical implications for investors, policymakers, and researchers. By understanding different regimes and their characteristics, investors can make more informed decisions about asset allocation and risk management. Additionally, policymakers can use these insights to develop effective regulatory policies and promote the growth of the CSX.

2. LITERATURE REVIEW

Financial time series analysis has long relied on traditional models such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) to predict market behaviors and volatility. These models have been foundational in understanding linear relationships and capturing volatility clustering in financial data. The ARIMA model is particularly effective in capturing linear relationships within financial time series. It is built on three components: Autoregression (AR), differencing (I), and moving average (MA). These components help in understanding underlying patterns in the data and making future predictions based on past values and errors. However, ARIMA models have limitations. They assume that time series data is linear, which can be a significant limitation during periods of market instability when financial data often exhibit nonlinear behaviors (Huang, 2021; Yu, 2022). Additionally, ARIMA models are not designed to handle the volatility clustering commonly observed in financial markets, making them less effective in predicting sudden market changes or periods of high volatility (Huang, 2021; Akhtar et al., 2022).

The GARCH model extends the capabilities of ARIMA by addressing its inability to capture volatility. GARCH models are particularly useful for modeling and forecasting the volatility of financial time series. They account for the changing variance over time, which is a common characteristic of financial data. However, GARCH models are more complex and computationally intensive compared to ARIMA models. This complexity can make them difficult to implement and interpret, especially for high-frequency data (Mani and Thoppan, 2023). Additionally, there is a risk of overfitting with GARCH models, particularly when too many parameters are included, leading to poor out-of-sample forecasting performance (Akhtar et al., 2022; Mani and Thoppan, 2023).

During periods of market instability, both ARIMA and GARCH models face significant challenges. The linear nature of ARIMA models makes them less effective in capturing the nonlinear dynamics and sudden shifts that often occur during market instability, resulting in large forecasting errors and reduced predictive accuracy (Li et al., 2020; Yu, 2022). While GARCH models are better at capturing volatility, their performance can still be hindered by complexity and potential overfitting issues. Additionally, during extreme market conditions, the assumptions underlying GARCH models may not hold, leading to inaccurate volatility predictions (Huang, 2021; Mani and Thoppan, 2023).

The MSAR model addresses some of the limitations of traditional models by incorporating regime-switching mechanisms. This allows the model to switch between different states or regimes, each with its own set of parameters, thus capturing structural changes and nonlinear dynamics in financial time series (Hossain and Ismail, 2022). The MSAR model is particularly useful in environments where market conditions can change abruptly, such as during financial crises or significant economic events.

Several studies have demonstrated the superiority of the MSAR model over traditional linear models. For instance, one study compared the forecasting performance of linear models (AR and ARMA) with nonlinear models (self-exciting threshold autoregressive and MSAR) for macroeconomic variables such as GDP growth, consumer price inflation, and exchange rates. The results indicated that the MSAR model outperformed linear models in terms of forecast accuracy, as measured by root mean square error (RMSE), mean absolute error (MSE), and mean absolute percentage error (Fraz et al., 2020). Another study highlighted the importance of incorporating nonlinearity in both the conditional mean and variance to capture volatility dynamics more precisely. This study proposed a hybrid model combining exponential autoregressive with Markov-switching GARCH and found that this approach outperformed traditional GARCH models in both simulation and real-world financial data (Hossain and Ismail, 2022). Moreover, the MSAR model has been applied to multivariate time series data, where it accounts for the heterogeneous influence of different variables through a network topology. This approach allows for the modeling of complex system variations and multimodal marginal distributions, further demonstrating the versatility and effectiveness of the MSAR model in financial applications (Li and Zhang, 2023).

The effectiveness of the MSAR model in forecasting stock market returns has been demonstrated through various studies, highlighting its ability to capture regime-switching behavior and improve forecasting accuracy. One study applied the MSAR model to Nigeria's stock market using the all share index (ASI) as a proxy. The analysis identified three distinct regimes: accumulation/distribution, big-move, and excess/panic phases. The optimal model, MS (3)-AR (2), was selected based on the minimum AIC value. The study found that extreme events trigger regime switches and that the model provided accurate forecasts based on RMSE and MSE metrics. The findings suggest that the MSAR model is effective in capturing regime-switching behavior and forecasting stock market returns in Nigeria (Adejumo et al., 2020).

Another study focused on the relationship between exchange rates and stock market returns using the Markov switching vector autoregressive model, providing insights into regime-switching behavior in emerging markets. The study found that exchange rate movements did not significantly impact stock returns in all emerging countries, but the regime-switching model was useful in understanding the dynamic relationships during different market conditions (da Silva, 2023).

Research on enhancing portfolio performance and VIX futures trading timing with Markov-switching GARCH models tested the use of these models to forecast high volatility episodes in the S and P 500 index. The study found that the MS-GARCH models, combined with VIX futures, led to better performance compared to a buy-and-hold strategy, particularly during high and extreme volatility periods. This indicates the effectiveness of regime-switching models in improving investment strategies and forecasting market conditions (De la Torre-Torres et al., 2021).

Further extending the use of MS-GARCH models in algorithmic trading, another paper incorporated asymmetric log-likelihood functions and variance models. The study simulated portfolios and found that using the suggested trading algorithm with symmetric homogeneous GED LLF and an asymmetric E-GARCH variance model allowed institutional investors to outperform the S and P 500 index. This further supports the effectiveness of MSAR models in forecasting and trading strategies (De la Torre-Torres et al., 2021).

A study on the Gulf Arab countries (Kuwait, Qatar, Saudi Arabia, and UAE) using an MSAR model identified two distinct regimes in stock returns: low-volatility and high-volatility. The study found that while exchange rate changes do not influence stock market returns, stock returns significantly impact exchange rates, especially during high-volatility regimes. This suggests that the MSAR model is effective in identifying regime shifts and understanding the dynamic linkages between stock and exchange markets in these countries (Thai Hung, 2020).

Furthermore, a study on the stock markets of Nigeria, South Africa, and Egypt applied the MSAR model to examine volatility from January 1997 to September 2019. The study identified regime-switching behavior in the ASI of these countries, finding that extreme events could switch the series between appreciation and depreciation regimes. It also revealed that Nigeria's stock market was more sensitive to external shocks compared to South Africa and Egypt, indicating a need for policy intervention (Umar et al., 2020).

Lastly, a study investigated the role of geopolitical risks in forecasting stock market volatility using an autoregressive Markov-switching GARCH mixed data sampling (ARMS-GARCH-MIDAS) framework. The findings showed that incorporating geopolitical risks as explanatory variables improved the accuracy of volatility forecasts. This highlights the robustness of regime-switching models in accounting for external factors and enhancing forecast precision (Segnon et al., 2024).

The Cambodian capital markets have evolved considerably since the Paris Peace Agreements in 1991, which marked the end of the nation's civil war. The CSX was officially launched in 2012, much later than expected given Cambodia's strong GDP growth of 10.8% annually between 2000 and 2018, a dollarized economy, and favorable investment policies (Sisowath et al., 2021). Despite this, the CSX remains small compared to other Asian markets and has not yet fully met the urgent funding needs of local corporations. Historically, returns on stocks and bonds listed on the CSX have been lower compared to less risky bank deposits or higher-yielding real estate investments (Sisowath et al., 2021).

Recognizing these challenges, the Royal Government of Cambodia has implemented several measures to accelerate the development of the Cambodian capital market. These measures include efforts to educate both investors and corporations about the benefits and mechanisms of the capital market, the introduction of accounting standards, audit requirements, and licensing for market actors such as fund management companies, securities brokers, and custodian banks. Additionally, the government is encouraging the listing of private companies with high growth potential and introducing new investment vehicles like real estate investment trusts, private equity, and mutual funds. Furthermore, a government bond market has been established to attract institutional investors seeking safe, long-term assets for asset-liability management (Sisowath et al., 2021). These initiatives are designed to provide the necessary infrastructure and support for the long-term growth of Cambodia's capital markets, with the successful implementation expected to renew investor interest and provide local corporations with more accessible and cost-effective funding options.

While the MSAR model has been utilized in various emerging markets, its application to the CSX is limited. This study aims to fill this gap by providing specific insights into the dynamics of a nascent market like the CSX, thereby enhancing the understanding of regime-switching in this context. Previous studies have highlighted the difficulties of capturing volatility during extreme market conditions using traditional models. This study will explore how the volatility dynamics of the CSX index differ between identified regimes, contributing to the literature on the effectiveness of the MSAR model in emerging markets, particularly within Cambodia's evolving financial landscape.

3. METHODOLOGY

The MSAR model allows for a smooth adaptation to changes in the state of a process, such as stock market index returns. Known as the Markov-switching dynamic regression, this model was developed by Krolzing (1997), building on Hamilton's (1993) work. It is often used to analyze lower-frequency data, like weekly datasets. This research aims to apply the MSAR model, which includes two state-dependent autoregressive terms for the dependent variable when it is in state s at time t.

$$rcsx_t = \alpha_{s_t} + x_t\vartheta + z_t\delta_{s_t} + \sum_{i=1}^{p}\varphi_{i,s_t}\left(rcsx_{t-i} - \alpha_{s_{t-i}} - x_{t-i}\vartheta - z_{t-i}\delta_{s_{t-i}}\right) + \varepsilon_{s_t} \tag{1}$$

$$rcsx_t = \left| ln\left(csx_t \big/ csx_{t-1} \right) \times 100 \right| \tag{2}$$

The variable $rcsx_t$ acts as the dependent variable, indicating the absolute return of the CSX index at time t. The state-dependent constant or intercept is denoted by α_{st}. The matrices x_t and z_t include independent variables, which also encompass lagged dependent variables. The coefficients for x_t and z_t are represented by ϑ and δ_{st}, respectively. The time periods considered are t and t-i, where i ranges from 1 to n. The autoregressive term parameter is $\varphi_{i,st}$. The residual term ϵ_{st} is independent and identically distributed (i.i.d) with a mean of zero and state-dependent variance. The optimal lag length of the model is determined using the Akaike information criterion (AIC) (Akaike, 1981). This study uses weekly data from April 2012 to August 2024, covering 588 weeks, sourced from the Bloomberg terminal. The augmented Dickey-Fuller (ADF) test, a prominent unit root test (Dickey and Fuller, 1979), is used to assess the stationarity of the CSX index returns, considering the time series nature of the data. This test is applied to two sets of CSX index data: The original level returns and the first differences. The probability that the current state s_t is $j \in (1,\ldots,k)$ depends on the previous state s_{t-1}.

$$\Pr(s_t = j|s_{t-1} = i) = p_{ij} \tag{3}$$

Since this study focuses on a Markov-switching model with two states, the transition probabilities between states can be depicted using a 2 × 2 transition matrix.

$$\mathrm{P} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{4}$$

It is crucial to note that $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$. The method used to estimate all coefficients, represented as θ, will be maximum likelihood estimation. This method can be applied once the likelihood function, which includes latent states, has been formulated. This will be discussed further. The expression $f(rcsx_t|s_t = i;\, rcsx_{t-1};\theta)$ represents the conditional density of $rcsx_t$ for $i = 1,\ldots,k$. These conditional densities are adjusted based on their associated probabilities, which follow a specific functional structure.

$$f\left(rcsx_t \mid \theta\right) = \sum_{i=1}^{k} f\left(rcsx_t \mid s_t = i; rcsx_{t-1};\theta\right)\Pr\left(s_t = i;\theta\right) \tag{5}$$

A vector of conditional densities, denoted as $k \times 1$, is described as a ϱ_t vector, as follows.

$$\tilde{n}_t = \begin{bmatrix} f\left(rcsx_t \mid s_t = 1; rcsx_{t-1};\theta\right) \\ f\left(rcsx_t \mid s_t = 2; rcsx_{t-1};\theta\right) \\ \vdots \\ f\left(rcsx_t \mid s_t = k; rcsx_{t-1};\theta\right) \end{bmatrix} \tag{6}$$

To build the likelihood function, it is crucial to evaluate the probability of the state variable assuming a particular value, based on the data available up to time t and the model parameters. The conditional probability of the state variable s_t being equal to i, given the information at time t, is represented as $\Pr(s_t = i|rcsx_t;\, \theta)$. The likelihood of $rcsx_t$ is denoted as $f(rcsx_t|rcsx_{t-1};\, \theta)$.

$$\Pr\left(s_t = i \mid rcsx_t;\theta\right) = \frac{f\left(rcsx_t \mid s_t = i; rcsx_{t-1};\theta\right)\Pr\left(s_t = i \mid rcsx_{t-1};\theta\right)}{f\left(rcsx_t \mid rcsx_{t-1};\theta\right)} \tag{7}$$

Given that $\Pr(s_t = i|rcsx_{t-1});\, \theta)$ represents the predicted probability of the state s_t being equal to i, based on the observations up to time t-1, then

$$\Pr\left(s_t = 1 \mid rcsx_{t-1};\theta\right) = \sum_{j=1}^{k}\Pr\left(s_t = i \mid s_{t-1} = j, rcsx_{t-1};\theta\right)$$
$$\Pr\left(s_{t-1} = j \mid rcsx_{t-1};\theta\right) \tag{8}$$

The function for the log-likelihood is

$$L(\theta) = \sum_{t=1}^{T}\log f\left(rcsx_t \mid rcsx_{t-1};\theta\right) \tag{9}$$

Where

$$f(rcsx_t|rcsx_{t-1};\, \theta) = 1'(\psi_{t|t-1} \odot \varrho_t) \tag{10}$$

The log-likelihood in equation (8) can be obtained using the following iterative equation:

$$\psi_{t|t} \frac{\left(\psi_{t|t-1} \odot \varrho_t\right)}{1'\left(\psi_{t|t-1} \odot \varrho_t\right)} \tag{11}$$

Where ϱ_t is a $k \times 1$ vector of conditional densities. As indicated in equation (6), $\psi_{t|t}$ and $\psi_{t|t-1}$ represent $k \times 1$ vectors of conditional probabilities for $\Pr(s_t = i|rcsx_t;\, \theta)$ andm $\Pr(s_t = i|rcsx_{t-1};\, \theta)$, respectively. Additionally, 1 is a $k \times 1$ vector of 1s (Hamilton, 1994; Tijms, 2003; Frühwirth-Schnatter, 2006).

4. EMPIRICAL RESULTS

Over the study period from April 2012 to August 2024, there were 588 observations of the CSX index and its absolute returns. The average weekly value of the CSX index was 506.26, with a standard deviation of 131.5. The minimum and maximum values of the CSX index were 310.18 and 903.23, respectively. During the same period, the average, standard deviation, minimum, and maximum of the absolute weekly returns of the CSX index were 1.93%, 2.73%, 0.00%, and 22.29%, respectively.

The results of the Jarque-Bera test suggest that the CSX index and its returns do not follow a normal distribution. The hypothesis that the series under investigation is normally distributed is rejected at the 1% significance level. These summary statistics are presented in Table 1.

Before proceeding to estimate all parameters of the model, it is essential to conduct a unit root test to determine whether the absolute return of the CSX index has a unit root. This assessment is crucial because the data used in this research is time series data, and it helps to prevent spurious results. The ADF test, one of the most prominent unit root tests, has been chosen for this analysis.

Table 1: Summary statistics

Variable	Obs.	Mean	Standard deviation	Min.	Max.	Skewness	Kurtosis	Jaque-bera test	
								Adj. Chi^2 (2)	Prob.>Chi^2
csx	588	506.29	131.50	310.18	903.23	0.4147	2.2088	48.10	0.0000
rcsx	588	1.9275	2.7266	0.0000	22.290	3.4232	18.640	339.44	0.0000

Figure 1: Cambodia securities exchange index, April 2012 to August 2024

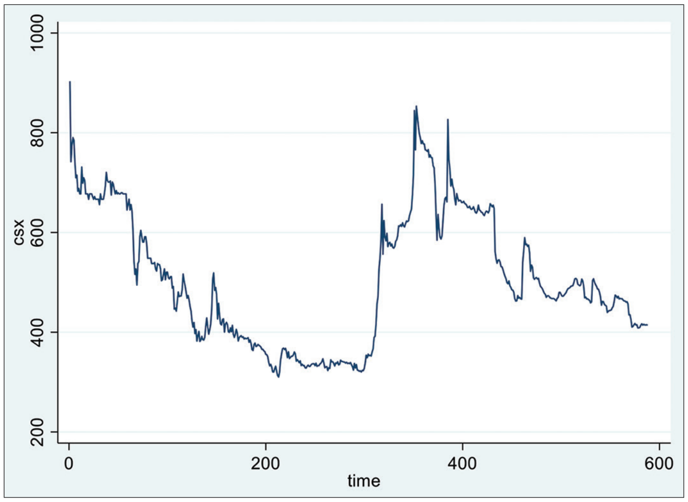
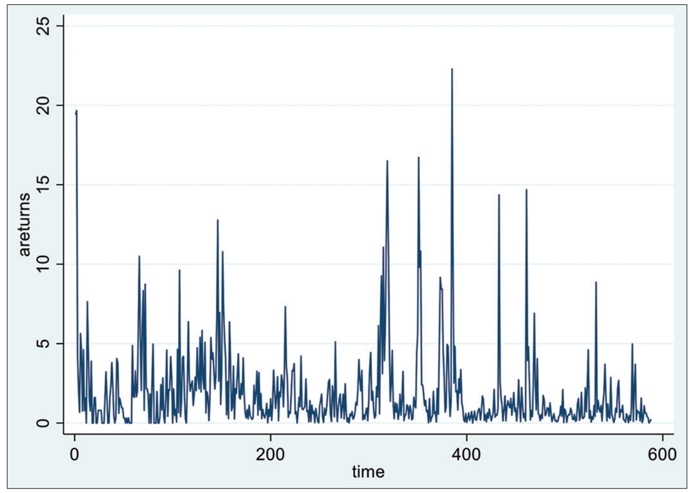


Figure 2: Absolute returns of Cambodia securities exchange index, April 2012 to August 2024



The ADF test can be implemented using three distinct models: one with a constant, one with both a constant and a trend, and one without either a constant or a trend. The CSX index for the period of April 2012 to August 2024, is presented in Figure 1.

The results of the ADF tests performed on all models, whether analyzed at the level or first difference, consistently demonstrate a robust rejection of the null hypothesis at the 1% significance level (Table 2). This outcome suggests that the absolute return of the CSX index exhibits stationarity, typically characterized as a mean-reverting process. This finding aligns with the illustration presented in Figure 2.

The empirical results from the MSAR model, as shown in Table 3, indicate that the model is divided into two distinct regimes: Regime 1 and Regime 2. The optimal lag lengths for the model in each regime are determined using the AIC, where a lower AIC value signifies a more accurate model estimation. The analysis of the information criteria reveals that the optimal lag length for the model is one lag. This research explores the two-state Markov-switching model, concluding that the optimal lag length for the analysis is one. This finding indicates that the appropriate specification of the MSAR model is the MS (2)-AR (1) model.

The empirical findings from the Regime 1 model reveal that the estimated parameter for the lag of the dependent variable, specifically the absolute return of the CSX index, is 0.2571, indicating a positive relationship. This parameter is statistically significant at the 1% level. Additionally, the estimated coefficient for the autoregressive component in this model is −0.231, which is also statistically significant at the 1% level. The estimated intercept for Regime 1 is 0.4820, and it is statistically significant at the 1% level.

In the Regime 2 model, the estimated slope parameter for the lagged dependent variable is 0.4473, which is significant at the 1% level, and its sign aligns with the findings from the Regime 1 model. However, the estimated coefficient for the autoregressive term in the Regime 2 model, while maintaining a consistent sign with that of the Regime 1 model, does not achieve statistical significance. The estimated intercept for Regime 2 is 2.6583, and this value is statistically significant at the 1% level.

The return volatility of the CSX index is assessed to be 0.6079 in Regime 1. In contrast, the estimated volatility of the return for the CSX index in Regime 2 is 3.2599, representing an increase of approximately 5 times compared to Regime 1. This suggests that the return of the CSX index in Regime 2 is more volatile than in Regime 1.

This research outlines the mechanism that facilitates the transition from one regime to another. This transition is enabled through the use of the Markov transition matrix, which encapsulates the probabilities associated with shifting from one regime to another. The likelihood of transitioning from state j in one period (e.g., Regime 2) to state i in the subsequent period (e.g., Regime 1) depends solely on the preceding state.

As illustrated in Table 4, the study presents the matrix of transition probabilities, where the conditional probabilities in the columns sum to one for all examined parameters. The findings indicate a 38.35% probability of transitioning from Regime 2 to Regime 1, while exiting Regime 1 is notably easier, with a weekly probability of 17.39%. The analysis of the transition matrix reveals that Regime 1 exhibits greater persistence compared to Regime 2, with probabilities of 82.61% and 61.65%, respectively.

Table 2: Unit root test

Models	t-statistic	At level
		RCSX
With constant	t-statistic Prob.	−13.0566 0.0000 ***
With constant and trend	t-statistic Prob.	−13.1633 0.0000 ***
Without constant and trend	t-statistic Prob.	−4.9585 0.0000 ***
		At first difference d (RCSX)
With constant	t-statistic Prob.	−19.9918 0.0000 ***
With constant and trend	t-statistic Prob.	−19.9705 0.0000 ***
Without constant and trend	t-statistic Prob.	−20.0088 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) modeling results

$rcsx_t$	Coefficient	Standard error	z
Panel A: State 1			
$rcsx_{t-1}$	0.2571***	0.0370	6.95
AR (1)	−0.2310***	0.0590	−3.92
α_1	0.4820***	0.0531	9.07
Panel B: State 2			
$rcsx_{t-1}$	0.4473***	0.0918	4.87
AR (1)	−0.1413	0.1281	−1.1
α_2	2.6583***	0.4112	6.46
Panel C: Sigma			
σ_1	0.6080	0.0383	
σ_2	3.2600	0.1817	

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

Table 4: Transition probability matrix

p_{ij}	Regime 1, *t*	Regime 2, *t*
Regime 1	0.8261	0.3835
Regime 2	0.1739	0.6165

Figure 3: Prediction of return of Cambodia securities exchange index in Regime 1 and Regime 2

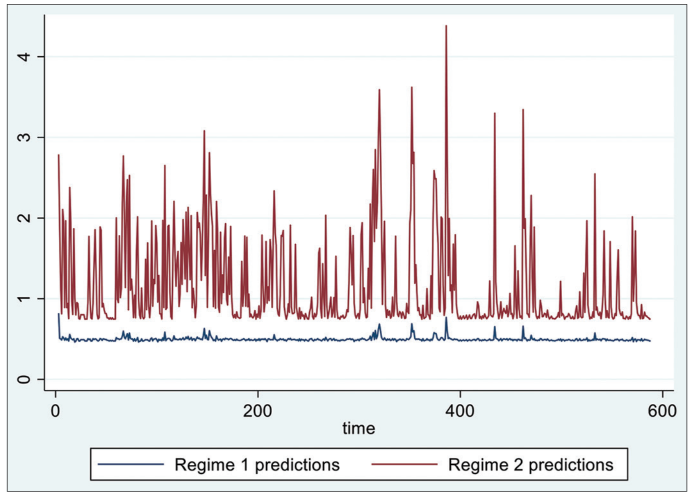
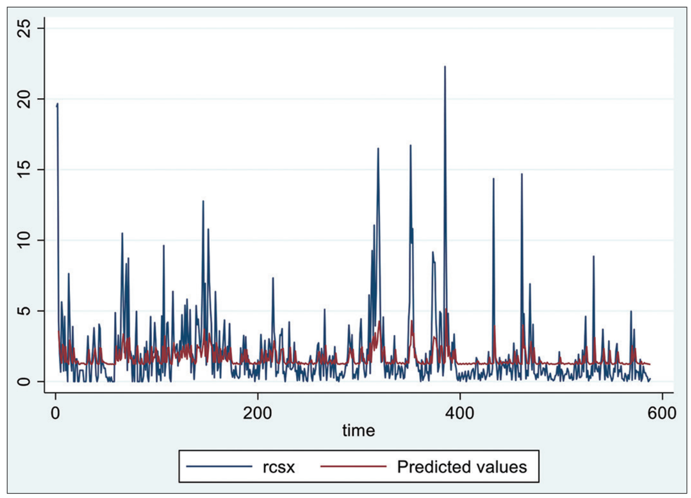


Figure 4: Actual and predicted return of Cambodia securities exchange index



Over the 588-week study period, the returns of the CSX index were divided into two states or regimes, Regime 1 and Regime 2. In addition to the switching states of returns, the intercept and standard deviation of the two-state models also switched. The estimated parameters of the model in Regime 1 and Regime 2 were used to make in-sample forecasts, allowing for a comparison between the predicted returns of the CSX index in the two states. As indicated in Figure 3, the predicted returns of the CSX index in Regime 2 are much higher than those in Regime 1. The resurgence of stock market indices from a low to a high state can be attributed to various specific factors within the framework of the MSAR model.

The resurgence of the stock market index, particularly as it transitions to a phase characterized by high returns, can be attributed to various factors, including economic indicators, investor sentiment, external shocks, and market corrections. Understanding these transitions allows investors and analysts to anticipate potential changes in market dynamics, facilitating more strategic investment decisions in a constantly evolving financial and economic environment. By recognizing the cyclical nature of the market and the factors driving these fluctuations, stakeholders are better equipped to navigate the complexities of stock market behavior (Rehman and Apergis, 2020; Fu and Wu, 2021; Agyemang-Badu et al., 2024). The actual and predicted return of CSX index results are presented in Figure 4.

5. CONCLUSION

The analysis of stock market index behavior provides valuable insights for investors, aiding them in making informed investment decisions. This study utilized the MSAR model to explore the return behavior of the CSX index across two distinct states or regimes. The optimal lag length for the model was determined using the AIC, with the MS (2)-AR (1) model emerging as the most suitable choice.

Empirical analysis for both Regime 1 and Regime 2 revealed that the lag of the dependent variable had a statistically significant positive effect on the returns of the CSX index at the 1% significance level, indicating persistence in returns across both regimes. In contrast, the AR component demonstrated a significant negative impact on CSX index returns at the same level within Regime 1, a relationship that was absent in Regime 2. The average returns for the CSX index in Regime 1 and Regime 2 were calculated to be 0.4820 and 2.6583, respectively, with return volatility showing a similar pattern—0.608 in Regime 1 compared to 3.26 in Regime 2. These findings align with prior research indicating that increased volatility often accompanies higher average returns, supporting the notion that investors might expect higher risks to yield higher returns (Hossain and Ismail, 2022).

The probability transition matrix indicates a 38.35% likelihood for the CSX index to transition from Regime 2 to Regime 1, whereas the chance of exiting Regime 1 to return to Regime 2 was merely 17.39%. The likelihood of the CSX index maintaining its position in Regime 1 was approximately 82.61%, whereas there was about a 61.65% probability that it would continue to remain in Regime 2. This transition probability suggests that while Regime 1 offers stability, the characteristics of Regime 2 warrant caution for risk-averse investors.

Considering these dynamics, several policy implications emerge. First, the Royal Government of Cambodia could enhance its capital market development strategies by incorporating educational initiatives focusing on the significance of understanding market regimes. Investors must be equipped with the tools to navigate the implications of switching states, aligning with previous calls for better investor education in emerging markets (Sisowath et al., 2021). Additionally, regulatory adjustments that encourage transparency and provide clearer guidelines for measuring market volatility could further enhance investor confidence in the CSX, aligning with the insights from successful regime-switching applications in other contexts (Thai Hung, 2020).

This study utilized the MSAR model to analyze the return behavior of the CSX index based on weekly time series data. For a more comprehensive understanding of the financial dynamics of the CSX index, it is strongly suggested that future research incorporate daily data and explore additional states, such as three or four. Insights gleaned from such research can significantly contribute to better regulatory frameworks and investment strategies, thereby fostering the growth of Cambodia's emerging capital markets.

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