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# EVALUATING THE PERFORMANCE OF ARCH AND GARCH MODELS IN MODELING VOLATILITY AND SHOCK DYNAMICS OF THE CAMBODIA SECURITIES EXCHANGE INDEX

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## ABSTRACT

*In this study, we concentrate on constructing an accurate predictive model for Cambodia Securities Exchange (CSX) index and its returns with the high-frequency time series data. Through the Box-Jenkins procedure, the ARMA (1,1) model was the most adequate in terms of model selection criteria and diagnostic analysis. The importance of both AR and MA coefficients implies that short-term dependence in the return series demonstrates that prior returns and forecast errors contain predictive information. Besides the mean modeling, this paper investigates the volatility behavior by ARCH and GARCH models. The ARCH Lagrange Multiplier (LM) test confirms ARCH effects, suggesting that return volatility is conditionally heteroskedastic and that it is also influenced by past shocks. The ARCH model emphasizes on volatility clustering, a common phenomenon in financial time series, particularly in emerging markets. The GARCH model also suggests that average and variance of CSX returns is highly persistent, which are at the heart of both the short-run autocorrelations and long-run volatility dynamics. Non-negligible AR (1) and MA(1) coefficients along with persistent volatilities explain the model's capability of capturing the financial time series structure. These findings endorse the recommended role of ARMA-GARCH models as useful instruments in risk-return prediction in the emerging capital market of Cambodia.*

**KEYWORDS:** CSX index, Return of CSX index, ARMA model, ARCH model, GARCH model.

## 1. INTRODUCTION

Opened in April 2012, the Cambodia Securities Exchange (CSX) diversified the financial landscape in Cambodia and enabled businesses to tap the capital market for expansion, allaying the economy's over-dependence on bank lending. It allows for greater market efficiency, wider financial inclusion and stronger long-term economic resilience in Cambodia. However, with volatile stock prices it is important to know one's exposure to risk. Nevertheless, to capture the behavior of stock market returns, it is necessary to apply advanced econometric models. The Autoregressive Moving Average (ARMA), Autoregressive Conditional Heteroskedasticity (ARCH) as well as the Generalized ARCH (GARCH) models are among the most popular applied methods. With time-dependent return patterns, ARMA models represent the dynamics well as they are constituted by autoregressive and moving average components (Box & Jenkins, 1976). ARCH models generalize this by permitting conditional error variances to be a function of lagged squared errors, modelling volatility clustering, a prevalent feature of financial returns (Engle, 1982). Extending ARCH, GARCH models include lagged predictions of the variance in addition to the lagged squared errors in order to formulate a smoother and persistent model of time varying volatility (Bollerslev, 1986).

Lack of empirical researches in Cambodia's nascent stock market on using alternative advanced econometric techniques to cover volatility and return behavior of the CSX index. A prior study by Lim (2017) applied the GARCH(1,1) model examining the dynamics of returns as well as the risk in the CSX index but confronted an inherent methodological limitation. The study, more to the point, commenced with the GARCH(1,1) in place rather than grinding as Box and Jenkins (1976) advocated that the model itself should be subject to steps of model identification, estimation, and checking diagnostic-execution before integrating any volatility model. To fill in this research gap, the present study follows a more comprehensive and methodologically rigorous process. It is based on the Box-Jenkins modelling approach to estimate and build a set of econometric models to account for linear dependence in the returns series (ARMA) time-varying volatility (ARCH) and persistent volatility clusters (GARCH). Using a controlled modeling technique of high-frequency CSX data, this paper attempts to enhance understanding of the return dynamics and volatility aspect of the CSX, and provide support for academic research as well as real-world trading analysis of the frontier financial market.

This research is organized into five chapters in order to offer a coherent and complete discussion of its purpose and results. In the introductory part includes background, motivation, and significance of the study. The next section provides a review of the relevant literature with an emphasis on applied literature in financial return behavior and volatility modeling. The methodology is described in the third section: the econometric model used in the analysis (ARMA, ARCH and GARCH model). It also includes methods of data collection, sample size, the estimation of parameters and diagnostic tests to examine the model adequacy and quality of fit. The fourth section contains empirical findings and analyzes the statistical results and discusses their implications on predicting volatility, as well as returns in the CSX. Finally, in the fifth section some recommendations and practical suggestions on future research are addressed to conclude the paper.

## 2. LITERATURE REVIEW

Ausloos (2020), through the application of a TGARCH model to China's CSI-300 index, found that futures market activity serves to moderate spot index volatility. Furthermore, a bidirectional effect of Granger causality between the futures and spot market was established, proving the usefulness of time varying variance models to capture dynamical interplays between markets. Analogous to this, Setiawan et al. (2021) used a GARCH(1,1) model to study the impact of the COVID-19 pandemic on the Jakarta Composite Index and the Budapest Stock Exchange, which also serves to demonstrate the utility of analyzing volatility in the context of market reactions to exogenous shocks. Their findings indicated that the pandemic led to a stronger volatility upsurge than the 2007–08 financial crisis, offering insights into the GARCH capacity in modelling reactions to extreme, unexpected shocks. Building on the one of the model structure, Sent et al. (2021) applied GARCH models to Indian sectoral indices and showed that asymmetric GARCH model, especially EGARCH model, was more preferable than symmetric model. This result underscored the necessity of accommodating volatility clustering and leverage effects across industries. Broadening the interpretation, Li et al. (2023) used the ARMA models under the GARCH and EGARCH frameworks to predict the values of the CSI□300 and S&P500 indices. They found that model pairings such as ARMA(0,6)–GARCH(1,1) and ARMA(2,6)–EGARCH(1,1) obtained greater forecast accuracy and adequately measured financial risks via Value at Risk

(VaR) and Expected Shortfall (ES). This demonstrated the advantages of integrating models for both the mean and variance in conducting a more comprehensive analysis of stock market behavior.

Arashi and Rounaghi (2022) applied an ARMA-GARCH model to assess the daily stock index volatility of the NASDAQ Stock Exchange over the period from 2000 to 2016. The out-of-sample forecast generating from the model demonstrated strong model performance, with a forecasting error of just 1%. The choice of model began at the process of selecting the appropriate ARMA structure, where an ARMA(1,1) was the best lag selected. However, the study ignored the performance of the ARCH process test to assess whether the ARCH effects existed before fitting the GARCH(1,1) model. Such an omission suggests a procedural deficiency and suggests that the future challenge, as to the volatility modelling, will be to provide the diagnostic testing motivation (Reza et al., 2020; Khan et al., 2021).

Over the study period from May 2013 to May 2015, 502 daily observations of the S&P 500 index were incorporated into the Alpha-stable GARCH, Alpha-stable Power-GARCH, and ARMA-GARCH-M models to produce out-of-sample forecasts and evaluate model performance. The Alpha-stable distribution, defined as a non-parametric distribution, was introduced by Chen et al. (2011). In addition, the optimal lag length was determined using the autocorrelation function (ACF) and was found to be GARCH(1,1). The study also tested the goodness of fit using the Kolmogorov–Smirnov non-parametric test. The empirical results demonstrated that Alpha-stable distributions provided a more accurate fit than Gaussian innovations. Forecasts were generated for 40 out-of-sample points, and model accuracy was assessed using the MSE, which indicated that the ARMA-GARCH-M model was computationally tractable (Mohammadi, 2017).

The market efficiency hypothesis has been an issue of many empirical researches since Fama (1970), and one of them tested the efficiency of the S&P 500 and SSE Composite indices by using the Sharpe ratio in an ARMA–GARCH framework according to a metric for evaluating market efficiency in combination with conditional entropy. The findings suggest that the impact of Sharpe ratio was dominated by AR and MA parts rather by the GARCH component. Specifically, the R-squared value exhibited a monotonic increase as sample size grew, indicating greater explanatory power. The study presented three stochastic simulation models: AR(1), ARMA(1,1), and AR(1)-GARCH(1,1) (Liu & Chen, 2020).

A further analysis of the Chinese stock market was studied using GARCH, ARMA-GARCH, and EGARCH introduced by Nelson (1991), which are applied, and TGARCH proposed by Zakoian (1994). Data between January 4, 2000, and March 4, 2020, were used to estimate model parameters and evaluate forecasting performance. The main aim of this study was to find the most accurate models in predicting Chinese key indexes; Shanghai and Shenzhen indexes. Based on the RMSE as performance measures, it was observed that the ARMA(4,4)-GARCH(1,1) model generated the best estimation for the Shanghai index, while the ARMA(1,1)-TGARCH(1,1) gave the best estimation for the Shenzhen Index. These results highlight the importance of adapting model forms to the specific nature of the indices for enhancing the forecasting accuracy in China's fluctuating financial markets. It is worth mentioning that the study followed the Box–Jenkins approach for modeling (Wang et al., 2022).

High-frequency data from January 2008 to November 2019 have been used to analyze the volatility patterns in three ASEAN members include Indonesia, Malaysia, and Thailand, using the ARMA-GARCH model based on the Box–Jenkins approach with the EGARCH model for potential asymmetries in the return behavior, and the Granger causality test was performed using the Vector Autoregressive (VAR) framework. The best lag length of VAR model was determined by the various information criteria, including the AIC, SBIC, FPE, and HQ. The EGARCH(1,1) model was found to be the best in determining the asymmetric effects and the existence of leverage effects in all three indices. These results pointed to the dynamic and nonlinearity behavior of return volatility in ASEAN markets (Toong et al., 2023), which in line with Byström (2016) who also found evidence of volatility clustering and that periods of high volatility prolong over a considerable time after a market disturbance.

Volatility of the Jordanian Amman Stock Exchange (ASE) has been analyzed for three key periods: pre- / in-crisis and post- COVID-19 crises. This study employed daily return of the ASE20 index for the period January 1, 2019, to March 26, 2024 and employed the ARMA-GARCH model for the Box–Jenkins framework. Results showed that the ARMA-GARCH(1,1) model fitted volatility in ASE20 returns well. Moreover, to detect the asymmetrical effects in data the ARMA-EGARCH(1,1) model was used. ARMA and GARCH parameters were statistically significant under two models in three periods, supporting their robustness and predictability. Notably, the results show that the market shows the largest positive anomaly during the COVID crisis, indicating its higher responsiveness during the crisis periods (Saqfalhait & Alzoubi, 2024).

From 2000 to 2024, the volatility of Bulgaria's SOFIX stock index was examined by employing the set of models such as ARMA-GARCH, EGARCH, IGARCH, CGARCH, and GJR-GARCH, with GARCH estimation based on Perlin et al. (2020). This period included dramatic short-term economic disruptions. Based on the Bayesian and Akaike Information Criterion (BIC and AIC), the best specification resulted to be the ARMA(1,1)-CGARCH(1,1) model based on the Student's t-distribution. It was found that long-run shocks had a larger effect on SOFIX volatility than the short-run ones. Moreover, results suggested that volatility was asymmetric, with negative shocks having greater effects on return changes. The asymmetry indicates that the index is more sensitive under longstanding market unrests (Petkov et al. 2024).

The GARCH Mixed Data Sampling (GARCH-MDS) and Additional Outlier-Corrected GARCH-MIDAS (AO-GARCH-MIDAS) models was used to predict the volatility of Chinese (3,278 data points) and Japanese (3,298 data points) stock markets that ranging from 1 October 2009 to 31 March 2023 adjoined by employing in-sample and out-of-sample prediction using Root Mean Square Error (RMSE) and Theil's U statistic. In-sample results showed that the AO-GARCH-MIDAS model provided robust and reliable estimates. For forecasting out of sample, which was important to investors to investigate the behavior of time series (Ma et al., 2019; Wang et al., 2020), the GARCH-MIDAS-RV-X model had a better fitting performance in predicting volatility for the Chinese market when compared to that of GARCH-MIDAS-X. On the other hand, for the Japanese market, it was found that GARCH-MIDAS-X produced more accurate forecasts than GARCH-MIDAS-RV-X. These disparate findings thus illustrated how market-specific attributes determined the performance of models and stressed the significance of hybrid models to improve the forecasting of volatility in international stock markets (Liu et al., 2024).

Data from the NSE from January 30, 2012, to October 16, 2024 representing 3,176 number of observations were applied in evaluating the NSE using EGARCH and GJR-GARCH model specifications. Those were the models whose distributions were non-Gaussian, such as Student's t-distribution and the GED. The findings indicated that the GJR-GARCH model provided accuracy volatility forecasts. Siaplay (2016) also found evidence of clustering of volatility especially during turbulent market conditions. These conclusions are consistent with Chunga and Yu (2024) and Lahboub and Benali (2024) works that studied the stock market volatility of Malawi and Morocco.

## 3. METHODOLOGY

The methodology of this study describes in this section include econometric analysis and data collection to evaluated the volatility of the return of CSX index, which denoted as RCSX. A high frequency data, daily data, are applied in the development of the volatility models, over a time span covering from April 18, 2012, to February 18, 2025, which extracted from the Bloomberg terminal. A key assumption for most econometric models, to compress the scale of the daily data series and to stabilize the variance, which enhance the likelihood of homoscedasticity, the series is equipped with the natural logarithm (Gujarati & Porter, 2009). After the transformation natural logarithm, the series has become LNCSX. In addition, the first difference of the log-transformed series will interpret as percentage change or growth rate (Stock & Watson, 2015). Taking the first difference of the LNCSX yields the daily return series of the CSX index, which can be calculated using the following formula:

$$RCSX_t = LN(CSX_t/CSX_{t-1}) = LNCSX_t - LNCSX_{t-1} \quad (1)$$

To begin with an initial understanding of the behavior and distribution of the return of CSX index, prior get in-depth into the analysis of the econometric models, it is started with a graphical analysis and the presentation of descriptive statistics. The next process is the discussion of ARMA, ARCH, and GARCH models specification, estimation methods, and hypothesis testing. The sequential processes of modeling for instance model identification, parameter estimation, and diagnostic evaluation to ensure the accuracy and reliability of the results following structural framework established by Box and Jenkins (1976). A systematic approach of model analysis involves with three key stages such as identification, estimation, and diagnostic checking. It is initiated with the estimation of ARMA model, which regarded as the mean equation and later expanded to include volatility models framework like ARCH and GARCH.

It begins with reviewing whether the return of CSX series has stationary or non-stationary. It is critical to get a stationary data series to avoid spurious regression results before proceed with model estimation. One of the most famous unit root tests is the Augmented Dickey-Fuller (ADF), where the null hypothesis of the test suggests that a series is non-stationary or has unit root. The test is initiated with RCSX, if the series is non-stationary; differencing is applied to achieve stationarity.

The next process is related to the determination of lag lengths of ARMA model, which combined between autoregressive (AR) and moving average (MA) components. The optimal lag lengths are evaluated through the analyzing of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which found to be an effective way in capturing the series' dynamics. After determine lag lengths of ARMA model, the next step involves estimating parameters of the model employing Maximum Likelihood Estimation (MLE) technique. The optimal lags of AR and MA terms are represented by p and q, where the combination of both terms generates ARMA(p, q) model. The estimated parameters of the ARMA model will be incorporated in the ARCH and GARCH models to measure CSX volatility behaviour.

$$RCSX_t = \mu + \sum_{i=1}^{p} \delta_i RCSX_{t-i} + \sum_{j=1}^{q} \varphi_i \epsilon_{t-j} + \epsilon_t \quad (2)$$

**Where**

$RCSX_t$ : return of the CSX index at time t,
$\mu$ : constant mean term,
$\delta_i$ : coefficients of the AR terms (lags of the dependent variable),
$\varphi_i$ : coefficients of the MA terms (lags of the error term),
$\epsilon_t$ : white noise error term,
$p$ : order of the AR component,
$q$ : order of the AR component.

The estimation of the ARCH and GARCH models will be implement, if the predicted residuals extracted from the ARMA model display time-varying variance, which can be assessed by performing the ARCH Lagrange Multiplier (LM) test on the residuals. The development of the ARCH(q) model is to modeling the variance of the error terms of the ARMA model which accounts for changing volatility over time

$$\epsilon_t = z_t\sqrt{h_t} \rightarrow z_t \sim N(0,1) \quad (3)$$

$$h_t = \theta_0 + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}^2 \quad (4)$$

**Where**

$h_t$ : conditional variance at time t,
$\theta_0 > 0$ and $\theta_i \geq 0$ are parameters,
$q$ : number of lagged squared residuals.

The ARCH framework is extended by including both past squared residuals and previous conditional variances to derive GARCH(p, q) model, which is specification as follow.

$$\epsilon_t = z_t\sqrt{h_t} \rightarrow z_t \sim N(0,1) \quad (3)$$

$$h_t = \theta_0 + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \vartheta_j h_{t-j} \quad (6)$$

**Where**

$h_t$ : conditional variance at time t,
$\theta_0, \theta_i, \vartheta_j$ are parameters (with $\theta_0 > 0$ and $\theta_i, \vartheta_j \geq 0$),
$q$ : number of ARCH terms (lagged squared residuals)

The model section criterion of ARCH and GARCH frameworks is relied on information criteria for instance the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where lower values suggest a better model fit. To conduct performance evaluation of both models, the in sample forecasting of return of CSX index, will be carried out for the period spanning February 7 to February 18, 2025. Over the forecasted time horizon, the predicted data will be compared with the actual data. The deviation between actual and predicted results will be applied in the calculation of two standard statistical metrics include Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) in order to examine predictive accuracy of the models. A quantitative assessment of ARCH or GARCH model is forecasting capability reflecting by the MSE and RMSE, with lower values indicating higher accuracy.

## 4. EMPIRICAL RESULTS

The empirical results and data analysis are discussed in this section, starting with visual exploration and summary statistics of the CSX index return series. To assess the normality of the data, both the Jarque-Bera test and Quantile-Quantile (Q-Q) plot are utilized. Before proceeding with the estimation of ARMA, ARCH, and GARCH models, the stationarity of the return series must first be evaluated to ensure the appropriateness of the time series models. To ensure valid and unbiased estimations and to avoid spurious regression results, the ADF test is conducted. Following this, the mean equation of the ARCH or GARCH models is defined as ARMA model, if the return of CSX index is integrated of order zero, I(0), or ARIMA model if it integrated of order one, I(1). However, either ARMA or ARIMA model, to support model specification, it is necessary to assess the optimal lag length of the model. Next step is the estimation of model parameters, interpretation of the results, and hypothesis testing related to the study's objectives. The analysis concludes by reviewing the performance of forecast accuracy of the models, how well they predict returns of CSX index.

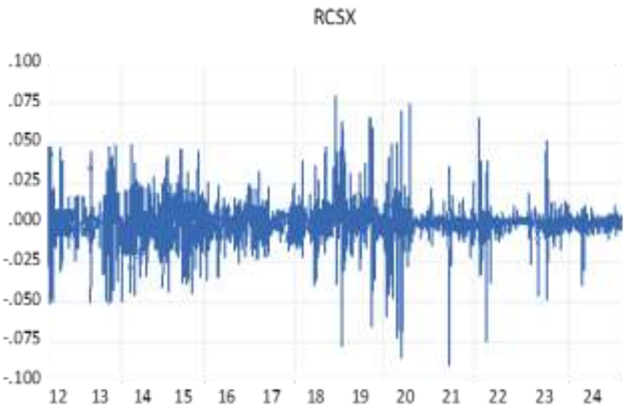


*Figure 1: Return of CSX Index.*
*Source: Constructed by the Authors Using EViews 13.*

The plot of the return of CSX index is illustrated in Figure 1, showed that the series exhibit a cyclical pattern which moving around a constant average throughout the observation period. This fluctuation of the data reflects the behavior of a mean reverting process, which is a fundamental trait of stationary time series. The fluctuation of returns of CSX index deviations from the average level are temporary, with the series eventually returning to its long-term equilibrium. However, the judgement of a stationary of the data is based on visual pattern of the graph, where the conclusion does not derive from a formal statistical test, which is necessary to determine whether it is truly stationary (lacking a unit root) or non-stationary (possessing a unit root). The ADF test for unit root, which offers more definitive evidence regarding the stationarity of the series, must be applied to establish the data's statistical properties with greater accuracy.

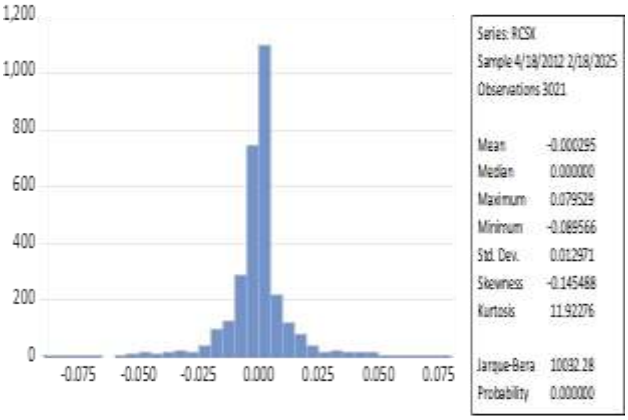


*Figure 2: Histogram of Return of CSX Index.*
*Source: Constructed by the Authors using EViews 13.*

The period of the study is covering from April 18, 2012 to February 18, 2025, which accounted for 3,021 trading day observations of the Cambodia Securities Exchange. The daily data is considered one of the most suitable series for the analysis and measuring the behavior of the return of the CSX index, as it defined as a high-frequency data. The histogram of the CSX index returns shows in Figure 2, visually resembles a normal distribution, however, formal statistical testing provides a different conclusion. To examine whether the series of CSX returns are distributed as normal distribution or not, the Jarque-Bera normality test is applied, with a null hypothesis stated that the series are distributed as normal. As suggested by its test statistic of 10,032.28 and a p-value of 0.000, the null hypothesis is highly rejected at 1% significance level, which concluded that the returns of CSX index are not normally distributed.

Over the period of the study, the average daily return of the CSX index is estimated to be -0.000295, indicating a modest downward trend in returns. The returns fluctuated in the range between minimum return at 0.089566 and the maximum return at 0.079529. Additionally, it is concluded that the return has a moderate return volatility as indicated by a standard deviation of 0.012971. The values of kurtosis and skewness of returns of CSX index indicate in Figure 2 show the present of leptokurtosis, which is generally observed in financial time series data. The leptokurtosis behavior interpreted that the distribution of the index returns exhibit fat tails and asymmetry, which are not in line with the key assumptions of normal distribution. The violation of the normality assumptions provides strong justification for employing heteroskedasticity-consistent models, such as the ARMA-ARCH and ARMA-GARCH models. Since the two models are suitable in applying with the analysis of time series financial data which are non-normality and time-varying volatility.

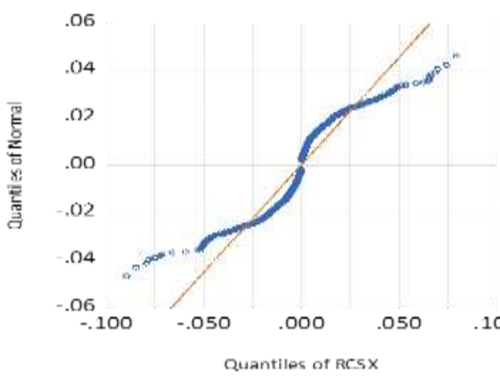


*Figure 3: Q-Q plot of RCSX.*
*Source: Constructed by the authors using EViews 13.*

In addition to a formal statistical test, the Jarque-Bera test, which has been discussed earlier to evaluate the normality of the CSX return series, this study also incorporates a Q-Q plot, which considered being a visual diagnostic approach to examine the distributional properties of the index returns. The feature of the Q-Q plot is to compare between a theoretical normal distribution and the empirical distribution of the time series data, which is the return of CSX index. The Q-Q plot presented in Figure 3 displays the quantiles of the CSX return distribution and its corresponding quantiles in horizontal and vertical axis, respectively. As indicated in Figure 3, the diagonal orange line represent a reference line, if the data are perfectly normally distributed, the data points will lie on the line. In contrast, if they are not lie on the reference line, it is concluded that the return series are discrepancies from normality, providing intuitive insight into the shape, skewness, and kurtosis of the data distribution.

The Q-Q plot showed that the data points are exhibit a pronounced S-shaped pattern, which deviated from the diagonal reference line at both ends of the distribution, specifically, on the left tail of distribution (below the reference line), which consist extremely negative returns, while on the right tail (above the reference line), which lies about the reference line, indicate with extreme positive returns. The curved shape of the plot is a recognized sign of non-normality, indicating leptokurtosis, which is marked by fat tails and a more pronounced peak than that of a normal distribution. The observed deviations imply that the CSX return series is more prone to extreme fluctuations, both upward and downward, than would be predicted under a normal distribution assumption. The visual analysis of returns of CSX index using the Q-Q plot revealed that the data series are non-normality, which characterized by fat tails and potential skewness, aligned with the result drawn from the Jarque-Bera test.

The non-normality of the data series demonstrated that to investigate the volatility behavior of CSX index returns, it is not appropriate to apply traditional econometric models because the results derived from those models may underestimation of extreme market volatility. In view of these findings, it may be useful to apply more flexible econometric models, which are able to capture non-normality and volatility clustering. An alternative is the GARCH model, which is specially made for estimating time-varying volatility. GARCH models are extensively known for good job they do in capturing the return process and the risk structure of financial time series, especially in an emerging market like Cambodia. Accordingly, their use provides a more genuine, and resilient, basis to analyze and predict CSX returns.

The Augmented Dickey-Fuller (ADF) unit root test was employed to reflect on stationarity in the CSX index return series for three specifications: with constant; constant and trend; none. Both the level and the first-difference form of the series were estimated for each specification. In levels, the return series was clearly stationary as all the ADF test statistics (-48.5162 to -48.5555) were less than the critical values, and had p-values less than 0.0001, so that the null hypothesis could be rejected at the 1% significance level. These results verify that differencing is not needed for further analysis. For completeness, we have also investigated the first-differenced series (DRCSX), and as expected stationarity was established for all the specifications with extremely significant estimates. With or without drift, the daily return series was stationary.

***Table 1: ADF Unit Root Tests.***

| **Model** | **At Level** | |
|---|---|---|
| | Statistic | RCSX |
| With Constant | t-Statistic | -48.5333 |
| | *Prob.* | *0.0001* |
| | | *** |
| With Constant & Trend | t-Statistic | -48.5555 |
| | *Prob.* | *0.0000* |
| | | *** |
| Without Constant & Trend | t-Statistic | -48.5162 |
| | *Prob.* | *0.0001* |
| | | *** |
| **Model** | **At First Difference** | |
| | Statistic | DRCSX |
| With Constant | t-Statistic | -26.9301 |
| | *Prob.* | *0.0000* |
| | | *** |
| With Constant & Trend | t-Statistic | -26.9287 |
| | *Prob.* | *0.0000* |
| | | *** |
| Without Constant & Trend | t-Statistic | -26.9335 |
| | *Prob.* | *0.0000* |
| | | *** |
| | | |
| Probability based on MacKinnon (1996) one-sided p-values. | | |

**Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1% and (no) Not Significant.**
**Source: Derived by the authors using EViews 13 for Windows.**

In order to estimate a GARCH model, it is sensible to find an adequate ARMA model for the conditional mean equation first. This initial processing ensures that the final model for the conditional variance adequately captures the serial correlation structure of the return series. The selection of the appropriate lag length is a crucial step in the specification of an ARMA model. This procedure is based on the use of diagnostic tools such as ACF, PACF and the Ljung-Box Q-statistic, to check for serial correlation in the residuals. These diagnosis facilitate in choosing appropriate autoregressive (AR) and moving average (MA) terms at each lag as the order in an ARIMA model implementing real structure of time series (Box et al., 2015).

The Table 2 reveals that both the initial lags of the Autocorrelation (AC) and the Partial Autocorrelation (PAC) functions deviates significantly from zero which shows the presence of serial dependence in case of CSX return series. The autocorrelation at lag 1 is 0.126, which indicates strong short-term correlation. This is also confirmed by the Ljung-Box Q-statistic (lag 1 = 47.648; p = 0.000) which strongly rejects the null hypothesis of no autocorrelation. The joint evidence from AC, PAC and lags 1 of Ljung-Box test suggests that there is indeed autocorrelation, hence the use of one lag AR- and MA-term is reasonable and that ARMA(1,1) is an appropriate model form. Furthermore, the Q-statistics are statistically significant for all 15 lags, all with p-values of 0.000, indicating the presence of autocorrelation throughout the series. Although individual AC and PAC coefficients are volatile and gradually decrease after the first few lags, the overall Q-test statistics reveal a lingering serial dependence up to lag 15. This pattern indicates that the CSX return series is not strictly random, which violates the white noise assumption commonly imposed on classical time-series modeling. The existence of self-correlation means that the past return values have predictive information towards future return.

***Table 2: AC and PAC Results with Ljung-Box Q-Statistic for CSX Index Returns.***

| Autocorrelation | Partial Correlation | Lag | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| \|* \| | \|* \| | 1 | 0.126 | 0.126 | 47.648 | 0.000 |
| \| \| | \| \| | 2 | 0.059 | 0.044 | 58.267 | 0.000 |
| \| \| | \| \| | 3 | -0.033 | -0.046 | 61.543 | 0.000 |
| \| \| | \| \| | 4 | -0.041 | -0.035 | 66.631 | 0.000 |
| \| \| | \| \| | 5 | -0.006 | 0.007 | 66.755 | 0.000 |
| \| \| | \| \| | 6 | -0.001 | 0.002 | 66.756 | 0.000 |
| \| \| | \| \| | 7 | -0.012 | -0.016 | 67.208 | 0.000 |
| \| \| | \| \| | 8 | -0.010 | -0.008 | 67.488 | 0.000 |
| \| \| | \| \| | 9 | 0.037 | 0.042 | 71.591 | 0.000 |
| \| \| | \| \| | 10 | 0.029 | 0.020 | 74.137 | 0.000 |
| \| \| | \| \| | 11 | 0.071 | 0.060 | 89.402 | 0.000 |
| \| \| | \| \| | 12 | 0.008 | -0.008 | 89.614 | 0.000 |
| \| \| | \| \| | 13 | 0.015 | 0.013 | 90.300 | 0.000 |
| \| \| | \| \| | 14 | -0.005 | -0.002 | 90.385 | 0.000 |
| \| \| | \| \| | 15 | 0.059 | 0.064 | 100.90 | 0.000 |
| Source: Calculations were made with EViews 13 for Windows. | | | | | | |

The dynamic properties of the CSX index return series were investigated by fitting ARMA model using maximum likelihood method with the BHHH/OPG algorithm for parameter estimations. The model was fitted to a high-frequency daily dataset with 3,021 observations from April 19, 2012, to February 18, 2025. Convergence to a solution was obtained after 66 iterations, suggesting the stability and certainty of the parameter estimates. According to these estimates, the intercept (C) is -0.000292, a test for equality of this coefficient with zero gives −1.058 with a p-value of 0.2903, that is, the average return of the CSX index is not significantly different from zero. By contrast, we find that the AR(1) term is statistically significant, with an estimate of 0.306 whose p-value is less than 0.01. This implies a significantly positive association between current and previous period returns, which is the evidence of short-term returns persistence in CSX index. This indicates that there exists short-term momentum in the returns series. The first lag moving average term MA(1) is also found to be statistically significant with an estimated coefficient of -0.181 while the associated p-value is 0.0083. It means that the past forecast errors have a negative effect on the present returns, which suggests the existence of short-run adjustment or reversal process in the CSX index return series. The estimated SIGMASQ is 0.000165 with a very large t statistic of 83.73, which verifies the accuracy of the variance estimate. The results in Table 3 pave the way to the modelling in what follows for the realized volatility.

***Table 3: ARMA(1,1) Model.***

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000292 | 0.000276 | -1.057710 | 0.2903 |
| AR(1) | 0.305996 | 0.064557 | 4.739934 | 0.0000 |
| MA(1) | -0.180891 | 0.068468 | -2.641995 | 0.0083 |
| SIGMASQ | 0.000165 | 1.97E-06 | 83.73310 | 0.0000 |

The ARMA(1,1) model describes the CSX return series quite well by appropriately capturing serial correlation and short-term dependence in the data, indicating good statistical significance. The importance of the autoregressive and moving average parts is evidence of a time-dependent structure, which supports the decision to establish the ARMA model as a benchmark specification for the models in which volatility will follow. A test for ARCH effects is necessary before applying the ARCH model but it is for whether the return series have time varying conditional heteroskedasticity. Therefore, this step suggests that ARCH type model is appropriate to be used to model volatility structure in the CSX index.

***Table 4: ARCH Lagrange Multiplier (LM) Test.***

| Heteroskedasticity Test: ARCH | | | |
|---|---|---|---|
| F-statistic | 587.9822 | Prob. F(1,3018) | 0.0000 |
| Obs*R-squared | 492.4334 | Prob. Chi-Square(1) | 0.0000 |

Heteroskedasticity in the CSX index return series was tested using the ARCH Lagrange Multiplier (LM) test; the results are shown in Table 4. This diagnostic test checks whether the residual variance is constant over time or conditionally changes when past shocks are experienced (i.e., this is a feature of many financial time series). For the regression run, we obtained the F-statistic as 587.9822 with a p-value of 0.0000 and an Obs*R-squared value of 492.4334 with a Chi-square p-value at 0.0000. Both statistics are significant at a strong level and reject the null hypothesis of no ARCH effects. These results indicate that volatility in the return series is not a constant but a function of past errors, and so equally upholds the existence of time varying conditional variance. These results justify the use of ARCH type structures in an attempt to parsimoniously represent this conditional heteroskedasticity and that such models are appropriate in modeling the dynamic aspects of the volatility patterns of the CSX index. Table 5 shows the estimation results of the ARCH model.

***Table 5: ARMA(1,1)-ARCH Model.***

| ARMA(1,1) model | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| C | -0.000248 | 0.000134 | -1.850667 | 0.0642 |
| AR(1) | -0.136496 | 0.061127 | -2.233000 | 0.0255 |
| MA(1) | -0.006429 | 0.057360 | -0.112077 | 0.9108 |
| **Variance Equation** | | | | |
| **Variable** | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| C | 7.26E-05 | 9.47E-07 | 76.61145 | 0.0000 |
| RESID(-1)^2 | 0.740285 | 0.031260 | 23.68128 | 0.0000 |

The ARCH model was also estimated by MLE assuming normal errors. Estimation was carried out by the BFGS/Marquardt optimization algorithm, which converged after 52 iterations, with 3,020 adjusted observations. The mean model includes both an AR(1) and MA(1) component. The AR(1) coefficient is also statistically significant in Table 2 (coefficient = -0.136, p = 0.0255), showing that past returns have a negative and significant impact on current returns. By comparison, the MA(1) coefficient is statistically indeterminate (p = 0.9108); if anything past forecast errors have no statistically significant short-run impact on current returns. In the mean equation, the constant term is only slightly insignificant with a p-value of 0.0642, indicating that the mean return is not statistically different from zero at the 5% confidence level. Looking at the variance equation, all results strongly indicate the presence of ARCH effects. Both the constant (C = 7.26E-05) and the lagged squared residual term ($RESID(-1)^2$ = 0.7403) are significant at 1% level (p = 0.0000) so as the lag is still positive and significant, indicating a significant influence of past squared shocks on the current volatility. This can be interpreted as an evidence of volatility clustering a very well known phenomenon of financial time series in which high and low volatility periods cluster together.

Results of the ARCH model suggest that the CSX return series is with volatility changing in time and with large effect of past shocks. The lagged square residual term has a statistically significant large coefficient, showing that big shocks beget more big shocks of around same size regardless of sign. In addition, the AR(1) effect in the mean equation is also significant, indicating that there is some predictability in the returns which means previously strong return periods provide valuable information about the future behavior of the market. In general, these results confirm the appropriateness ARCH-type models for the estimation and forecasting of volatility as well as for the risk in the Cambodian stock market and for the further development of more sophisticated models like GARCH model, which are flexible enough to model the long run volatility patterns.

Fitting of the GARCH model utilized maximum likelihood estimation with normally distributed error terms assumption. The estimation was performed with use of the BFGS/Marquardt optimization algorithm, which converged after 43 iterations. We used 3; 020 adjusted observations in the analysis, the resulting empirical results are shown in Table 6. The average equation of the model contains AR(1) and MA(1) components. With autoregressive coefficient AR(1) = 0.7448 and is highly significant at the 1% level (p = 0.0000) thus showing strong positive autocorrelation in the CSX index returns. It indicates that past returns exercise a significant influence on current returns and therefore reflects persistent dynamic behavior in returns. The estimated coefficient of MA(1) is -0.7855, which is also significant (p = 0.0000), indicating that past forecast errors have a negative effect on current returns. Meanwhile, the constant term in the mean equation is not statistically significant (p = 0.3298), which means the average return is not significantly different from zero. Where in the variance equation the GARCH has a constant, an ARCH term (lagged squared residual) and a GARCH term (lagged conditional variance). The constant is 7.84E-06 and statistically significant (p = 0.0000) and is the baseline level of volatility. The above ARCH coefficient (RESID(-1)$^2$) is 0.3253, while the GARCH coefficient (GARCH(-1)) is 0.6873, both significant at the 1% level. Together, these components add up to around 1.01, showing that there is strong volatility persistence.

***Table 6: ARMA (1,1)-GARCH(1,1) Model.***

| ARMA(1,1) model | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| C | -0.000108 | 0.000111 | -0.974462 | 0.3298 |
| AR(1) | 0.744828 | 0.095617 | 7.789670 | 0.0000 |
| MA(1) | -0.785485 | 0.083805 | -9.372768 | 0.0000 |
| **Variance Equation** | | | | |
| **Variable** | **Coefficient** | **Std. Error** | **z-Statistic** | **Prob.** |
| C | 7.84E-06 | 2.87E-07 | 27.27836 | 0.0000 |
| RESID(-1)^2 | 0.325270 | 0.012357 | 26.32238 | 0.0000 |
| GARCH(-1) | 0.687312 | 0.007936 | 86.60212 | 0.0000 |

The importance of ARCH and GARCH parameters is a strong indication of volatility clustering in the returns of stock indexes that the high returns or low returns are followed by high or low return in the returns. In addition, the fact that the GARCH effect is bigger than the ARCH term indicates that historical volatility has a greater effect on current volatility than recent ones. This behavior reveals the existence of long-range dependence in volatility, which is a common property of financial time series. The GARCH(1,1) model adequately captures the dynamics of volatility of CSX index returns. The importance of AR(1) and MA(1) components indicates return predictability, and strong persistence of conditional variance emphasizes the importance of volatility modeling in financial markets.

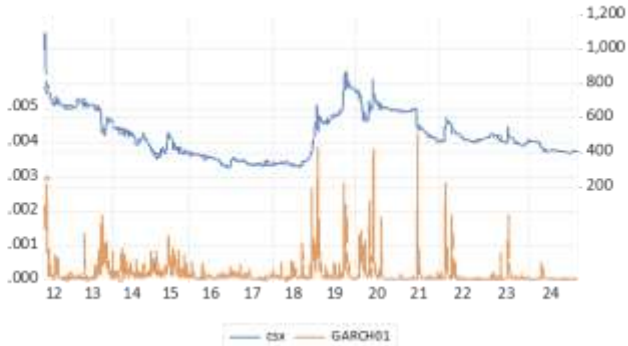


***Figure 4: CSX Index and Volatility of ARMA(1,1)-GARCH(1,1) Model.***
**Source: Derived by the Authors Using EViews 13 for Windows.**

As shown in Figure 4, the blue line displays the development of the CSX index over time with periods characterized by stability and some remarkable volatility. Specifically, the index surged in late-2017 and in before 2020, when investor speculations bull runs or policy-based events were observed. Afterwards, the index starts taking a more neutral (less extreme) stand and the eventual downturn now becomes evident, with lesser peaks in returns. The orange line, which depicts the conditional variance estimates produced by the GARCH model, indicates clear signs of volatility clustering a pattern in which high volatility levels are followed by long stretches of time during which volatility remains high, and in which low volatility levels are followed by extended periods of low volatility. This is particularly evident between 2018 and 2020; the GARCH estimates display large spikes that correspond to major changes in the CSX index. By contrast, the return series and volatility estimates in 2021 and later decrease the entire time, indicating a relatively less volatile and less turbulent market environment. The figure demonstrates that it is good to represent fluctuations of volatility through the CSX over time using the GARCH (1,1), and frequencies of significant market instability. The empirical association of rising index movements and GARCH volatility spikes provides support for the model's capacity to identify and measure market uncertainty and risk.

Besides the investigation of the volatility patters of the stock returns of the CSX index, one important contribution of this study is to estimate the efficacy of ARCH and GARCH models in formulating forecast. To identify the best model, several model selection criteria are used, such as the log-likelihood ratio, AIC, SC, HQC, etc. Together, the criteria measure goodness-of-fit and forecasting accuracy of each model and should be able to help select the most appropriate model to model the volatility of CSX. A model is better if it has a larger log-likelihood and smaller values across the information criteria as these indicate more explanatory power with fewer parameters. Table 7 reports the comparison findings, which indicate that the GARCH model significantly outperforms the ARCH model in terms of all the four criteria. It can be interpreted that GARCH is a more suitable approach in modeling the nature of time-varying volatility and persistence, which is often seen in financial markets such as the CSX.

***Table 7: Log-likelihood and Information Criterion of ARCH and GARCH Models.***

| Criteria | ARCH Model | GARCH Model | Model Selection |
|---|---|---|---|
| Log likelihood | 9,383 | 9,696 | GARCH |
| Akaike Information Criterion (AIC) | -6.210 | -6.418 | GARCH |
| Schwarz Criterion (SC) | -6.200 | -6.406 | GARCH |
| Hannan-Quinn Criterion (HQC) | -6.207 | -6.413 | GARCH |

To test if the GARCH model is superior to the ARCH model (which are based on the values calculated by the means of the log-likelihood and information criteria) we perform one-step ahead in-sample forecasting for the period February 7–18, 2025 (Figure 5). Up to the time of forecasting, the forecasted returns of each model would be assessed against the realized returns over the same period. In assessing the precision of these predictions, the following popular metrics MSE and RMSE are utilized. These are baseline measures for predictive accuracy (lower is better). The model having the smallest MSE and RMSE is hence considered to be more useful in describing the volatility of CSX index returns.

***Table 8: MSE and RMSE of ARCH and GARCH Models.***

| Model | MSE | RMSE |
|---|---|---|
| ARCH model | 6.5511E-06 | 0.00256 |
| GARCH model | 6.3210E-06 | 0.00251 |

Table 8 compares between the ARCH and GARCH models in terms of predictive accuracy using two commonly used performance measures: Mean Squared Error (MSE) and Root Mean Square Error (RMSE). The GARCH model based method also has lower MSE of 6.3210E-06 comparing to 6.5511E-06 of ARCH model. The RMSE outcomes show the same trend; GARCH model 0.00251 and ARCH model 0.00256. Although the differences are quite small by number, the lower values of absolute errors for the GARCH model supports the higher efficiency of prediction. These results are consistent with prior results controlling for the selection of criteria including the log-likelihood, AIC, and SC that also support the GARCH model. The improved forecasting ability may be due to the ability of the GARCH model to capture time variation in volatility and persistence. Briefly, the findings suggest that the GARCH model makes more reliable forecasts of the CSX index return volatility than the ARCH model.

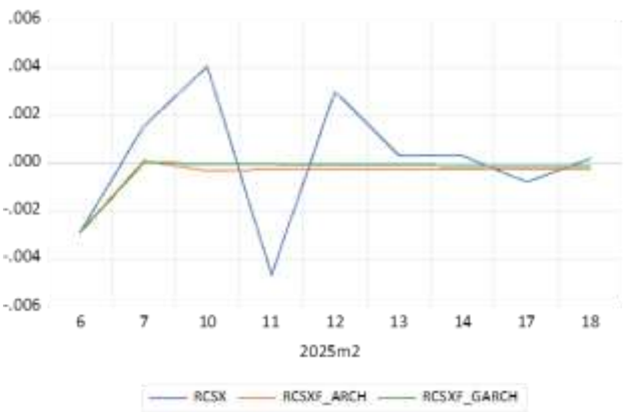


***Figure 5: Forecasting of Return of CSX Index.***

## 5. CONCLUSION

The ARMA (1,1) model was determined to be the most suited forecasting model to the CSX after utilizing high-frequency time series data, employing the Box-Jenkins methodology supported by diagnostic checks and model selection criteria, and validating its ability to capture the return series in a statistically significant manner that demonstrated that autoregressive and moving average components play a crucial role in explaining return patterns.

Empirical findings from the ARCH modeling approach strongly indicate the presence of time-varying volatility in the CSX index return series.

Results from the ARCH Lagrange Multiplier (LM) test reveal significant ARCH effects, suggesting that return variance shifts over time in response to previous shocks alongside evidence of volatility clustering, a common trait in emerging market financial data. Moreover, the AR (1) term in the mean equation is statistically significant, which implies some predictability in returns. This implies that past returns shed some light on predicting future returns showing short-term dependence in the CSX index return dynamics. The mean equation in which it is included both the important AR (1) and MA (1) terms, demonstrates that returns are autocorrelated and depend on previous forecast errors. In particular, the positive AR (1) coefficient suggests strong return persistence, while the negative MA (1) coefficient indicates the presence of a corrective mechanism with past shock. The fact that the constant is not significantly different from zero indicates that there is no significant difference between zero and average return, a condition that captures the behavior of financial return series that may be efficient markets. The findings of the variance equation provide evidence in favor of employing the GARCH model for capturing the time varying volatilities of the CSX index. The ARCH and GARCH coefficients are statistically significant, and their sum, 1.01, indicates a strong level of volatility persistence. This implies that the impact of a volatility shock does not vanish immediately, but is transmitted over several periods, thereby reflecting the financial market's tendency towards the clustering of volatility.

This paper contributes to the explanation of returns and volatility of Cambodia Securities Exchanges. The results of the ARMA(1,1) model indicate significant short-term predictability in returns, while the ARCH and GARCH models show evidence for non-constant volatility and persistence shock effects: investors should use forecasting tools (like ARMA-GARCH models) to time strategies and hedge models. Since the GARCH model suggests long-term volatility, investors are recommended to pay extra attention on managing the risks. If average return in not significantly different from zero then passive strategies can be inadequate. Rather, active investment strategies using living, real-time information and model-derived judgments are more suitable for the Cambodia Securities Exchange.

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