FORECASTING MODELS FOR SECTOR-WISE STOCK PRICE INDICES: COLOMBO STOCK EXCHANGE

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ABSTRACT

The stock markets of a country play a vital role in its economy. Stock market indices are vital fragments of information for investors. It is very important to develop models that reflect the pattern of the stock price movements for different sectors since it becomes very significant to investors and policymakers. Therefore, the aim of this research study was to develop models to forecast different sector indices in Colombo Stock Exchange and to compare sector-wise models. The investigation was performed using secondary data for a sample of ten listed sectors in the Colombo Stock Exchange (CSE) for the thirty-four years from 2nd January 1985 to 31st March 2019. Secondary data were collected by using the data library maintained by Colombo Stock Exchange. Financial time series data analysis techniques were used to analyze the collected data. It was applied the ARCH family models in this research study, which included the Autoregressive conditional heteroscedasticity model (ARCH), Generalized Autoregressive conditional heteroscedasticity model (GARCH), Threshold Autoregressive conditional heteroscedasticity model (TARCH), Exponential generalized autoregressive conditional heteroscedastic model (EGARCH), Integrated Generalized Autoregressive conditional heteroscedasticity model (IGARCH) and Power Autoregressive conditional heteroscedasticity model (PARCH) since the sector indices are financial time series data. Findings revealed that the appropriate model to forecast the sector indices of Oil Palms sector, Services sector and Stores & Supplies sector as PARCH (2,1) model, Beverage, Food & Tobacco sector as PARCH (1,1) model, Chemicals & Pharmaceuticals sector as PARCH (2,2) model, Banking Finance & Insurance sector and Investment Trusts sector as IGARCH (2,2) model, Footwear & Textiles sector as EGARCH (1,1) model, the Manufacturing sector as EGARCH (1,3) model and Hotels & Travels sector as TARCH (1,1) model. The findings of this research study are useful to policymakers and investors for their decision-making.

Keywords: Colombo Stock Exchange, Stock price indices, Time series analysis

1. INTRODUCTION

The stock markets of the country play a significant role in the economy. The combination of buyers and sellers of stocks which represent ownership claims on businesses can be identified as a stock market. It includes publicly listed securities on the stock exchange and privately traded securities. Therefore, it can be identified that the stock market is the best method for raising funds for companies, where most probably debt markets do not trade publicly.

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The stock marketplace offers a chance for companies to trade shares publicly and to increase their financial ability by expanding the capital to enlarge their businesses. The companies can sell the ownership of shares in the public market. Investing in stock is a liquidity opportunity. It means that a securities exchange provides a chance for the investors who are holding securities to sell their securities as soon as possible. This is the most striking chance of investing in stocks compared to other investments such as estates, gold and other non-moveable assets. Some of the companies themselves enthusiastically rise liquidity by trading their shares.

Stock prices and the price of other properties are a substantial part of the dynamic economic actions, and can impact or can be an indicator of societal moods. It is well-known that the economic strength and development of a country indicates by the stock market. By the efficient market hypothesis by changing the essential factors, like the margins, profits or dividends, long term share prices, which casual sound in the system may overcome. Further, it says that the hard efficient-market hypothesis does not explain some situations such as the crash in 1987. Share prices can be decreased intensely without a fixed reason. None of the advanced searches was able to perceive any rational expansion that might have caused the crash. It says the Stock markets play a vital role in rising businesses which eventually touch the economy by moving existing capital from the parties which have excess to those who are suffering from capital shortages (Padhi and Naik, 2012).

The Colombo Stock Exchange comprises 290 listed business organizations as of 30th September 2019 which represent 20 business sectors. The prices of shares will change rapidly. Investors invest money in the capital market to earn profits. The stockholders purchase the shares of diverse businesses on the precedence base. Investors will select the shares of diverse businesses based on the diverse aspects. Most investors have no information regarding the market investigation and regarding the appropriate forecast of the forthcoming prices of diverse kinds of shares existing in the market. Therefore, most probably investors employ their funds to buy shares of diverse corporations based on error presumptions, deprived of any knowledge of data analysis and estimation. Most stockholders lose their investment in this unbalanced capital marketplace. Then, the universal investors will not pay attention to capitalizing their funds in the capital marketplace and it will cause to rise a disaster in the capital market. Changes in share prices of the capital market are seized in price indices called stock indices. Stock market indexes are vital fragments of information for investors. Therefore, it is required to develop models that reflect the pattern of the stock price movements for different sectors listed in CSE since it becomes very significant to investors and policymakers. Therefore, in this research study, the researcher developed models to forecast different sector indices and compared them with two objects to develop financial time series models to forecast Sector Indices for different sectors listed in CSE & to identify the most suitable model for forecasting sector indices by comparing different sectors.

The stock market of a country is a very crucial part of its economy. Most investors are gathering in the stock market of a particular country to buy or sell their securities. Out of the buying and selling securities stock transactions are major in CSE and some

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other countries. When deciding on stock transition stock prices and indices are the most important factors to be concerned about. Therefore, studying stock indices is very important for investors. Investors most probably invest their money in any investment opportunity seeking a profit. They have to select a suitable sector and suitable company or companies to invest their money in. Stock prices are fluctuating with time. Earnings of a particular investment will be depending on the future fluctuations of stock prices. Therefore, forecasting future stock prices and stock indices is very important for investors to make better decisions.

Some investors are familiar with stock transactions and they are engaging very frequently with stock transactions. Therefore, they have good experience and knowledge about the behavior of the stock market. But some of the investors are new to stock market transactions and they have no sound knowledge and experience in it. Therefore, they will ask for help from stock brokerage firms. Stock brokerage firms should have to obtain better knowledge about the behavior of the stock market. Therefore, this study is also significant for stock brokerage firms. For the students or future researchers who are interested in studying the stock market, the behavior of stock prices and stock indices, financial time series modeling and forecasting techniques are also very important in this research study.

The Colombo Stock Exchange (CSE) is an authorized party to compute and issue the ASPI, Sector-wise Indices and Total Return Indices. ASPI is the comprehensive marketplace index of CSE. It is calculated to amount to the activities of the complete marketplace. The ASPI is designed for weighted market capitalization indices that establish total elective and non-elective ordinary shares which are listed on Colombo Stock Exchange. CSE has mentioned that the Elective Ordinary Shares and Non-Elective Ordinary Shares from 19th June 2017 listed on Colombo Stock Exchange are eligible for index calculation. It has been further mentioned by the CSE when upsurges or reductions in the present marketplace price because of fluctuations in the stock price activities, the Colombo Stock Exchange will do essential modifications to the Base Market Capitalization to remove all belongings other than price fluctuations. By altering the Base Market Capitalization, the index worth holds its steadiness previously and later the incident.

According to the Colombo Stock Exchange, the CSE Sector Wise Indices contains directories shaped by separating the residents of All Share Price Indices into twenty Sectors. Sector indices replicate price changes of businesses in twenty individual sectors. All the base values which are used to compute the sector-wise indices are similar to the values used to compute the All Share Price Indices.

Simply forecasting can be introduced as an effort to estimate future events. The key impartial of forecasting is to support for decision makers to end up with good conclusions. Theoretically, there are two key tactics of forecasting, one is explanatory forecasting and the other one is time series analysis. Explanatory forecasting accepts a cause and effect association among the contributions and production. Further, it emphasizes the varying inputs will impact the production of the organization in a foreseeable manner. Here it assumes the cause and effect association is as fixed. Time series forecasting is considered the organization as a black box and activities to

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determine the influences affecting the performance. According to the theory, two motives influence to consideration of a scheme as a black box. The initial reason is the scheme may not be unstated and smooth if it were unspoken it may be tremendously hard to amount associations supposed to rule its behavior. The next reason is the chief consideration only for forecast what will occur and why not it occurs. Financial time series is the least stated method. Therefore, the attention of this research study is on time series forecasting.

Numerous studies have been conducted to create a suitable model for predicting stock price with different models comprise with autoregressive models, moving average models, nutral networks and some of ARCH family models. Most studies are conducted outside of Sri Lanka. Even the models used in the studies are extremely challenging for investors to comprehend and use to forecast stock prices. Therefore, the aim of this research study was to develop models to forecast different sector indices in Colombo Stock Exchange and to compare sector-wise models.

2. LITERATURE REVIEW

2.1. Linear modeling

It has been shown that linear regression forecasting models are effective at forecasting returns in both developed and developing markets (Champbell, 1995). Over 55–65 percent of the time, tested linear regression models can accurately forecast the market's direction. According to research, the random walk hypothesis, which holds that the present price is the best indicator of the direction of market prices 50% of the time, can do so (Champbell, 1995). At this point, it may be safe to speculate that stock market price nonlinearities are to blame for the linear approaches' inability to significantly outperform the random walk hypothesis.

Because of this, investors have not been able to obtain adequate results with linear regression techniques. As a univariable model, the autoregressive-integrated moving average (ARIMA) is one of the linear techniques that has been widely applied to try to forecast the direction of market prices. Using a technique known as differencing, the ARIMA model may convert non-stationary time series into stationary time series. Higher order statistical methods were found to be preferable to ARIMA models by (Hamilton and Lin, 1996). Because linear models are straightforward, they naturally seek to simplify complex systems like the behavior of the financial markets. However, the simplicity of linear models is their main benefit. Only when a model's predictions closely match the result of the underlying process is it considered to be useful. There is a trade-off between predictability and simplicity with linear models.

2.2. Non-linear modeling

According to prevailing wisdom, linear forecasting models do a terrible job of capturing the underlying dynamics of financial time series. The identification of non-linear movements in the financial markets has received significant attention in recent years from a variety of researchers and financial experts (Abhyankar, Copeland, and Wong, 1997). In comparison to linear models, non-linear models are far more complex and challenging to build. There are many different models available, and the

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number of various models is higher for non-linear models, which makes it challenging to select an appropriate model. A few techniques for identifying non-linear models have been developed through research, including non-linear regression, parametric models like GARCH, non-linear volatility models, and nonparametric models.

Many researchers have predicted the volatility of the stock marketplace, and most of this research was carried out on overseas stock markets. Most of these findings inversely affect the Sri Lankan stock market. Therefore, the findings of these researches cannot be straight functional to Colombo Stock Exchange. Ng and McAleer 2004 stated that the extrapolative estimating ability of the GARCH (1,1) model introduced by Bollerslev in the year 1986 and an asymmetry accommodating GJR (1,1) model presented by Glosten, Jagannathan, and Runkle for the S&P 500 indices and Nikkei 225 indices in the year 1993. Ng and McAleer 2004 observed predicting the ability of each model GJR (1,1) and GARCH (1,1). They found that forecasting performance was reliant on the data applied. Further, Ng and McAleer 2004 identified that to forecast the S&P 500 data the GJR (1,1) is mostly applicable and to predict the Nikkei 225 data the GARCH (1,1) model is more applicable.

Regularly evaluating the volatility of the stock market and the projecting performance of the conditional movements of the stock marketplace is very much important. Stock market indices change dynamically. DSE 20 and DSE general are two stock market indices in Bangladesh. Alam et al. in the year 2013 investigate the Bangladesh stock indices by using five ARCH family models. They concluded that from their research findings historical changes significantly influenced future changes when considering both stock indices mention above in Bangladesh with ARCH family models. The authors further identified that the EGARCH model has an asymmetric performance in volatility. Alam et al. in the year 2013 assessed models grounded on within-sample and out-of-the-sample statistical as well as trading ability.

Alam et al. (2013) study found mean absolute error, mean absolute percentage error, root mean squared error, and the inequality coefficient statistical performance from their research study. Based on the annual returns, annual volatility, the Sharpe ratio, and maximum reductions it may depend on trading ability. Though the research of Alam et al. (2013) submitted a tough model for measuring the ability of conditional volatility models, its findings were rather inconclusive. Further less interpretation of research and more practical errors has provided plenty of chances for further research.

AL-Najjar in the year 2016 focused on the Stock Market movements of Jordan. She has applied ARCH and GARCH Models in her research work. She modeled ARCH, GARCH, and EGARCH to examine the performance from Jan. 1 2005 to Dec.31 2014 time period of the Amman Stock Exchange. Further, she found that the behavior of the Amman Stock Exchange can be identified by ARCH and GARCH models. AL-Najjar (2016) further deliver more signals while EGARCH results disclose that for the survival of the leverage effect it will not be reinforced by the stock indices of the Jordan stock market. Mahmoud and Dawalbait in the year 2015 measured the predicting ability of different conditional volatility models by using Saudi Arabia's Tadawul All Share Index daily data returns for the twelve years. They have

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considered GARCH (1,1), EGARCH (1,1), and GRJ-GARCH (1,1) models for predicting Saudi Arabia's Tadawul All Share Index. Ljung-Box Q statistics were functional to the choice volatility model and both the standardized and squared standardized residuals and ARCH-LM test. Further, Mahmoud and Dawalbait in the year 2015 applied Akaike information criteria and maximum log-likelihood values to select the best output. They have evaluated the performance of the out-sample. To measure, the statistical performance and find the best model they have used mean absolute error, the mean absolute percentage error, the root mean squared error and the Theil-U statistic in their research study.

Further to select the best model for forecasting the stock market changes Mhmoud and Dawalbait (2015) used Akaike information criteria and maximum log-likelihood values. They found that GRJ-GARCH (1,1) model is most suitable when the selection criteria are Akaike information. And also researcher found that EGARCH (1,1) is most suitable with LL value. They conclude that GRJ-GARCH (1,1) model is the best for forecasting volatility of the Saudi Arabia's Tadawul All Share Index for statistical forecasting performance.

Alam et al. (2013) investigated the stock indices of Bangaladesh it is different from the approach of Mhmoud and Dawalbait (2015). Alam et al. (2013) and Mhmoud and Dawalbait (2015) used equally statistical prediction performance assessments. Further Mhmoud and Dawalbait (2015) included extra appraisals through information criteria, though Alam et al. (2013) extended the assessment measures through trading performance procedures. The selection process of Mhmoud and Dawalbait (2015) was promoted from out-of-sample trading ability assessments. That research can be further expanded by increasing data. They applied daily stock indices from January 1, 2005, to December 31, 2012. Mhmoud and Dawalbait (2015) applied 124 data points to the out-of-sample prediction from a total of 2,317 data points. Predicting models have grown period from the period. The complication of the market increased and therefore complexity of the forecasting models has also increased. There are diverse models applied by different researchers and some of the models are currently using and some of the models are still under research.

3. METHODOLOGY

3.1. Population & Sample

The Colombo Stock Exchange (CSE) has 290 companies which are representing 20 sectors as of 30th September 2019. Though the population of this research is 20 business sectors, the sample was limited to 10 sectors because unavailability of data for six sectors including Diversified Holdings, Health Care, Information Technology, Plantations, Power & Energy and Telecommunications for the entire period considered for this research study and another four sectors cannot apply the ARCH family models since they have not ARCH effect including Construction & Engineering, Motor, Land & Property and Trading. Therefore, the sample of this research was 10 sectors listed in CSE for the thirty-four years from 2nd January 1985 to 31st December 2018 and for forecasting 99 days used from 2nd January 2019 to 29th

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March 2019. This is the maximum period that the researcher could find secondary data archived from the Colombo Stock Exchange data library.

3.2. Data Collection

The secondary data was collected for the study for thirty-four years from 2nd January 1985 to 29th March 2019 using a data library maintained by Colombo Stock Exchange.

3.3. Data Analysis

Since this research is based on financial time series to analyze the data it used conditional variance analysis techniques such as ARCH and GARCH models and the extensions of the ARCH and GARCH models. The collected data was analyzed in Eviews – 08 statistical package by using Time Series Analysis techniques.

3.3.1. Unit Root Test

Unit root test can be used to find whether to apply differencing or not for a time series. It is a statistical hypothesis test to test the stationarity of a time series. Unit root test is intended to identify whether it is required to differentiate time series or not. There are many tests to select to check the unit root. In this research study to check the stationarity of the data series Augmented Dickey-Fuller test (ADF) was used. The Augmented Dickey-Fuller Test is one major test of the unit root which can be used to check stationarity. If there are unit roots it is difficult to predict by using the output of time series. Though there is a serial correlation with series *Augmented* Dickey-Fuller test can be applied. The ADF test is better used to test more complicated series than the Dickey-Fuller test. The Augmented Dickey-Fuller test is more powerful. It is said Augmented Dickey-Fuller test should be applied to test the stationary series very carefully since it may include a high Type I error rate like other tests. Time series has no unit root is the null hypothesis for the Augmented Dickey-Fuller test and the basic alternative hypothesis is that the time series is stationary or has no unit root. The model is as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where;

α is a constant,

β coefficient of time trend

p lag order of autoregressive method

3.3.2. Autocorrelation

The series values of the series can be forecasted grounded on previous data of time series, the series is supposed to display autocorrelation. It is denoted as serial correlation or serial dependence. If there is autocorrelation with residuals of a model that is not a symbol and that may be unreliable. Autocorrelation can be identified by using a correlogram / Autocorrelation function (ACF) plot and autocorrelation can be confirmed by the Durbin-Watson test.

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It is said that the autocorrelation function is the coefficient of correlation among two values within a series. For example, if we consider the autocorrelation function of the time series "Y_t".

Y_t can be defined as Correlation (Y_t, Y_t −k)

Here "k" represents the time gap and that is named lag. If we consider a lag 1 autocorrelation, it is a correlation among values of the considered period. Here we can define lags k autocorrelation as the correlation among data of the "k" period.

The autocorrelation function is the mechanism to measure the linear association among data at time "t" and the data at the preceding period. A partial autocorrelation function (PACF) can be found after computing the association of converted time series. By using the PACF, it can be identified in order of an autoregressive model.

We can use ACF and PACF graphs to assess the lag of an autoregressive model. If the series is serially correlated, we can see a large ACF amount and a fixed pattern of lag values. Normally in a PACF plot with lag values, we can see an arbitrary pattern. After confirming the stationary and the autocorrelation of the data series it tested the ARCH effect.

3.3.3. ARCH Model

Autoregressive conditional heteroscedasticity (ARCH) models are used if there are error terms of series in typical size or variance of the series. ARCH modes assume that the variance of the existing error term of a series is a function of the actual sizes of the error terms of the prior period of a series. The ARCH model is nonlinear. It does not assume that the series has a constant variance.

The basic model of linear ARCH is as follows:

$$Y_t = \emptyset X_t + \varepsilon \quad (2)$$

The error terms can be presented as follows and it divided into stochastic sections and a standard deviation:

$$\varepsilon_t = \sigma_t z_t \quad (3)$$

The random variable and the series changes over time can be modeled as follows:

$$\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + \cdots + a_q\varepsilon_{t-q}^2 = a_0 + \sum_{i=1}^{q} a_i\varepsilon_{t-i}^2 \quad (4)$$

Where $a_0 > 0$ and $a_i > 0$

3.3.4. GARCH Model

Bollerslev 1986 independently recognized the Generalized Autoregressive conditional heteroscedasticity (GARCH) model. It has presented a moving average

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term and fixed lag structure in the ARCH model. In GARCH (p, q) model p represents the order of the GARCH terms σ^2 and q denote the order of the ARCH terms ε^2.

$$\sigma_t^2 = w + a_1\varepsilon_{t-1}^2 + \cdots + a_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_q\sigma_{t-q}^2 = w + \sum_{i=1}^{p} a_i\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2 \ldots\ldots (5)$$

The GARCH (1,1) can be presented as follows:

$$\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \ldots\ldots (6)$$

3.3.5. ARCH Effect

To test the ARCH effect of the data series it used the ARCH-LM test. Only if there was an ARCH effect of data series it has applied ARCH family models for analysis.

3.3.6. Extension of ARCH Models

EGARCH model

Nelson 1991 introduced the EGARCH model and it has developed to solve the problem of estimating negative variance parameters. The log form of the model confirms that the conditional variance is positive and sometimes parameters may take negative values. The EGARCH (p,q) can be presented as follows:

$$log\sigma_t^2 = w + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \ldots\ldots (7)$$

Engle and Ng. 1993 permit from the EGARCH model for positive and negative return shocks. Most of the previous studies prove that the coefficient γ is frequently negative and it proposes a huge influence on return volatility by negative return shocks.

TARCH model / GJR GARCH model

Zakoian in 1994 Threshold Autoregressive conditional heteroscedasticity (TARCH) model was presented. This is based on conditional standard deviation but not based on conditional variance. The TARCH model identifies the impact of good and bad news. It will identify independently by α and γ, coefficients correspondingly. TARCH model is presented as follows:

$$\sigma_t^2 = w + \sum_{i=1}^{p} a_i\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k\varepsilon_{t-k}^2\overline{I_{t-k}} \ldots\ldots (8)$$

TARCH (1,1) model can be presented as follows:

$$\sigma_t^2 = w + a_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \gamma_1\varepsilon_{t-1}^2\overline{I_{t-1}} \ldots\ldots (9)$$

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If $\gamma = 0$ the TARCH model converts as a linear Generalized Autoregressive conditional heteroscedasticity model. If $\gamma \neq 0$, there is an unbalanced effect.

IGARCH model

Integrated Generalized Autoregressive conditional heteroscedasticity (IGARCH) models are the unit root Generalized Autoregressive conditional heteroscedasticity models. IGARCH model is presented as follows:

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2 \ldots\ldots (10)$$

PARCH model

Power Autoregressive conditional heteroscedasticity (PARCH) model, parameter δ of the standard deviation can be projected. PARCH model is presented as follows:

$$\sigma_t^\delta = w + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^\delta + \sum_{i=1}^{p} \alpha_i\left(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i}^2\right)^\delta \ldots\ldots (11)$$

3.3.7.Model Selection

After applying the six ARCH models including ARCH, GARCH, TARCH, EGARCH, IGARCH and PARCH it was selected the best model by using the Akaike information criterion (AIC) and Schwarz criterion (SC) values. According to the AIC and SC criteria, the model which has the lowest value of AIC and SC was recognized as the appropriate model for the forecasting sector indices.

3.3.8.Residual analysis

After selecting a tentative model, it was done the residual analysis for the selected model for checking the autocorrelation, Heteroscedasticity and ARCH effect. To check the autocorrelation of the residuals it was used the correlogram of squired standardized residual and to check the ARCH effect of the residuals it was used the ARCH-LM test. To check the heteroscedasticity of the residuals Breusch – Pagan - Godfrey test was used.

4. RESULT AND DISCUSSION

Ten sector indices are satisfied with the preliminary analysis and the ARCH effect test. After applying the six ARCH family models including ARCH, GARCH, TARCH, EGARCH, IGARCH and PARCH for different ten sector indices, it was selected the best model by using the Akaike information criterion (AIC) and Schwarz criterion (SC) values. The model comparison of different sector indices is presented in table 1 to table 10.

4.1. Banking Finance & Insurance Sector

It employed the ARCH family models after passing the preliminary analysis and the ARCH effect test for the Banking, Finance, and Insurance Sector Indices. Only three of the six ARCH family models that were chosen, as shown in Table 1, the GARCH

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(2,2), EGARCH (1,2), and IGARCH (2,2) models were satisfied for the Banking Finance & Insurance Sector Indices.

Table 1 Banking Finance & Insurance Sector Indices

Model	AIC Value	SC value
GARCH (2,2)	-6.042503	-6.035588
EGARCH (1,2)	-6.520517	-6.512738
IGARCH (2,2)	-6.520104	-6.514053

Source: The author developed

Table 1 shows that the lowest AIC & SC values are with the IGARCH (2,2) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Banking, Finance and Insurance sector indices is the IGARCH (2,2) model.

4.2. Beverage, Food & Tobacco Sector

It used the ARCH family models after passing the preliminary analysis and the ARCH effect test for the Beverage, Food, and Tobacco Sector Indices. It satisfied five models from the selected six ARCH family models, as shown in Table 2, ARCH (1), GARCH (1,1), EGARCH (1,2), IGARCH (1,2), and PARCH (1,1) for Beverage, Food, and Tobacco Sector Indices.

Table 2 Beverage, Food & Tobacco Sector Indices

Model	AIC Value	SC value
ARCH (1)	-3.607250	-3.603793
GARCH (1,1)	-3.475911	-3.471590
EGARCH (1,2)	-6.237918	-6.230139
IGARCH (1,2)	-6.189736	-6.184550
PARCH (1,1)	-6.297611	-6.290696

Source: The author developed

Table 2 shows that the lowest AIC & SC values are with the PARCH (1,1) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting the Beverage, Food & Tobacco sector indices is the PARCH (1,1) model.

4.3. Chemicals & Pharmaceuticals Sector

It passed the preliminary analysis as well as the ARCH effect test for the Chemicals and Pharmaceuticals Sector Indices before employing the ARCH family models.

It satisfied five of the selected six ARCH family models, as shown in Table 3, ARCH (2), GARCH (1,1), TARCH (1,1), IGARCH (1,2), and PARCH (2,2) for the Chemicals & Pharmaceuticals Sector Indices.

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Table 3 Chemicals & Pharmaceuticals Sector Indices

Model	AIC Value	SC value
ARCH (2)	-5.021614	-5.016428
GARCH (1,1)	-5.023121	-5.017935
TARCH (1,1)	-5.177166	-5.171115
IGARCH (1,2)	-6.073752	-6.068566
PARCH (2,2)	-6.169184	-6.161405

Source: The author developed

Table 3 shows that the lowest AIC & SC values are with the PARCH (2,2) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting of Chemicals & Pharmaceuticals sector indices is the PARCH (2,2) model.

4.4. Footwear & Textile sector

It used the ARCH family models after passing the preliminary analysis and the ARCH effect test for the Footwear and Textile sector Indices. It satisfied four models from the selected six ARCH family models, as shown in Table 4, ARCH (2), GARCH (1,2), TARCH (1,2), and EGARCH (1,1) for Footwear & Textile sector Indices.

Table 4 Footwear & Textile sector Indices

Model	AIC Value	SC value
ARCH (2)	-4.738264	-4.733942
GARCH (1,2)	-4.772248	-4.767062
TARCH (1,2)	-4.785997	-4.779083
EGARCH (1,1)	-5.588103	-5.581188

Source: The author developed

Table 4 shows that the lowest AIC & SC values are with the EGARCH (1,1) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Footwear & Textile sector indices is the EGARCH (1,1) model.

4.5. Hotels & Travel Sector

After passing the preliminary analysis and the ARCH effect test for the Hotels & Travel Sector Indices, it used the ARCH family models. It satisfied only three of the six ARCH family models that were chosen, as shown in Table 5, ARCH (6), GARCH (1,1), and TARCH (1,1) for Hotels & Travel Sector Indices.

Table 5 Hotels & Travel Sector Indices

Model	AIC Value	SC value
ARCH (6)	-5.816166	-5.807523
GARCH (1,1)	-5.802212	-5.797026
TARCH (1,1)	-5.834313	-5.828262

Source: The author developed

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Table 5 shows that the lowest AIC & SC values are with the TARCH (1,1) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Hotels & Travel sector indices is the TARCH (1,1) model.

4.6. Investment Trusts Sector

It used the ARCH family models after passing the initial analysis and the ARCH effect test for the Investment Trusts Sector Indices. Only three of the six ARCH family models—ARCH (1), GARCH (1, 2), and IGARCH (2, 2) for Investment Trusts Sector Indices—were satisfied, as shown in Table 6.

Table 6 Investment Trusts Sector Indices

Model	AIC Value	SC value
ARCH (1)	-3.992654	-3.988333
GARCH (1,2)	-3.786784	-3.786784
IGARCH (2,2)	-6.040602	-6.034552

Source: The author developed

Table 6 shows that the lowest AIC & SC values are with the IGARCH (2,2) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Investment Trusts sector indices is the IGARCH (2,2) model.

4.7. Manufacturing Sector

It made use of the ARCH family models after passing the Manufacturing Sector Indices' preliminary analysis and ARCH effect test. Only three of the six ARCH family models—GARCH (2,1), EGARCH (1,3), and IGARCH (2,2) for Manufacturing Sector Indices—were satisfied.

Table 7 Manufacturing Sector Indices

Model	AIC Value	SC value
GARCH (2,1)	-6.143782	-6.137732
EGARCH (1,3)	-6.615324	-6.606681
IGARCH (2,2)	-6.608206	-6.603020

Source: The author developed

Table 7 shows that the lowest AIC & SC values are with the EGARCH (1,3) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Manufacturing sector indices is the EGARCH (1,3) model.

4.8. Oil Palms Sector

After passing the preliminary analysis and the ARCH effect test for the Oil Palms Sector Indices, it used the ARCH family models. As shown in Table 8, it satisfied only two of the six ARCH family models chosen: IGARCH (2,1) and PARCH (2,1) for Oil Palms Sector Indices.

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Table 8 Oil Palms Sector Indices

Model	AIC Value	SC value
IGARCH (2,1)	-9.964241	-9.959055
PARCH (2,1)	-16.27446	-16.26668

Source: The author developed

Table 8 shows that the lowest AIC & SC values are with the PARCH (2,1) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Oil Palms sector indices is the PARCH (2,1) model.

4.9. Service Sector

It used the ARCH family models after passing the preliminary analysis and the ARCH effect test for the Service Sector Indices. It satisfied only two of the six ARCH family models chosen, as shown in Table 9: IGARCH (2,2) and PARCH (2,1) for Service Sector Indices.

Table 9 Service Sector Indices

Model	AIC Value	SC value
IGARCH (2,2)	-6.113642	-6.108456
PARCH (2,1)	-6.271048	-6.263269

Source: The author developed

Table 9 shows that the lowest AIC & SC values are with the PARCH (2,1) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Service Sector Indices is the PARCH (2,1) model.

4.10. Stores & Supplies

It tested the ARCH family models after passing the Stores & Supplies Sector's preliminary analysis and ARCH effect test. As indicated in Table 10, it complied with five of the six ARCH family models selected for the Stores & Supplies Sector: ARCH (1), GARCH (1,1), TARCH (1,2), EGARCH (1,3), and PARCH (2,1).

Table 10 Stores & Supplies Sector

Model	AIC Value	SC value
ARCH (1)	-4.413492	-4.410035
GARCH (1,1)	-4.308365	-4.304044
TARCH (1,2)	-4.514740	-4.507825
EGARCH (1,3)	-7.273141	-7.265362
PARCH (2,1)	-8.446055	-8.438276

Source: The author developed

Table 10 shows that the lowest AIC & SC values are with the PARCH (2,1) model. Therefore, considering the AIC and SC values prove that the appropriate model for forecasting Stores & Supplies sector indices is the PARCH (2,1) model.

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4.11. Residual Analysis

After selecting tentative models for each sector, it was done the residual analysis for the selected models for checking the autocorrelation, heteroscedasticity and ARCH effect. The correlogram of squired standardized residual was used to check the autocorrelation and to check the ARCH effect of the residuals it was used the ARCH-LM test and to check the heteroscedasticity of the residuals Breusch – Pagan - Godfrey test were used.

4.12. Forecasting Models

Banking Finance & Insurance sector

According to the finding of the research study, it can conclude that to forecast the Banking Finance & Insurance sector indices the appropriate model is IGARCH (2,2) model. IGARCH (2,2) model is as follows:

Mean Equation

$$dlogbfi = 0.500755 dlogbfi_{t-1} - 0.277170\varepsilon_{t-1} \qquad (12)$$

Variance Equation

$$\sigma_t^2 = 0.338277\varepsilon_{t-1}^2 - 0.337221\varepsilon_{t-2}^2 + 1.592963\sigma_{t-1}^2 - 0.594019\sigma_{t-2}^2 \qquad (13)$$

Beverage, Food & Tobacco sector

For the Beverage, Food & Tobacco sector, PARCH (1,1) model is a suitable model to predict the sector indices. PARCH (1,1) model is as follows:

Mean Equation

$$dlogbft = 0.715425 dlogbft_{t-1} - 0.661127\varepsilon_{t-1} \qquad (14)$$

Variance Equation

$$\sqrt{\sigma_t} = 0.001569 + 0.380192(|\varepsilon_{t-1}| + 0.082423\varepsilon_{t-1}) + 0.759004\sqrt{\sigma_{t-1}} \qquad (15)$$

Chemicals & Pharmaceuticals sector

PARCH (2,2) model is the appropriate model to forecast the Chemicals & Pharmaceuticals sector indices. PARCH (2,2) model is as follows:

Mean Equation

$$dlogcp = -0.00000556 + 0.037023 dlogcp_{t-1} \qquad (16)$$

Variance Equation

$$\sqrt{\sigma_t} = 0.002686 + 0.308823(|\varepsilon_{t-1}| + 0.181683\varepsilon_{t-1}) + 0.297016|\varepsilon_{t-2}| -$$

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$0.128725\sqrt{\sigma_{t-1}} + 0.773333\sqrt{\sigma_{t-2}}$…………………………………………..…(17)

Footwear & Textile sector

According to the results of the research, it reveals that to forecast the Footwear & Textile sector indices the appropriate model is the EGARCH (1,1) model. EGARCH (1,1) model is as follows:

Mean Equation

$dlogft = 0.990503 dlogft_{t-1} - 0.990502\varepsilon_{t-1}$…………………………….…(18)

Variance Equation

$log\sigma_t^2 = -1.057854 + 0.192010\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right| - 0.023769\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} +$
$0.885735 log\sigma_{t-1}^2$…………………………………………………………..…(19)

Hotels & Travel sector

For the Hotels & Travel sector, TARCH (1,1) model is the appropriate model to forecast the sector indices. TARCH (1,1) model is as follows:

Mean Equation

$dloght = -0.000327 - 0.315544 dloght_{t-1} + 0.577610\varepsilon_{t-1}$……………..…(20)

Variance Equation

$\sigma_t^2 = 0.0000411 + 1.800594\varepsilon_{t-1}^2 - 1.385955\varepsilon_{t-1}^2(\varepsilon_{t-1} < 0) +$
$0.354888\sigma_{t-1}^2$…………………………………………………………..……..(21)

Investment Trusts sector

IGARCH (2,2) model is the appropriate model to forecast the Investment Trusts sector indices. IGARCH (2,2) model is as follows:

Mean Equation
$dlogit = 0.000000462 + 0.571702 dlogit_{t-1} - 0.531030\varepsilon_{t-1}$…………..…(22)

Variance Equation

$\sigma_t^2 = 0.189203\varepsilon_{t-1}^2 - 0.089555\varepsilon_{t-2}^2 + 1.371560\sigma_{t-1}^2 - 0.471209\sigma_{t-2}^2$……(23)

Manufacturing sector

To forecast the sector indices of the Manufacturing sector, the appropriate model is EGARCH (1,3) model. EGARCH (1,3) model is as follows:

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Mean Equation

$$dlogmfg = 0.361102 dlogmfg_{t-1} - 0.263043\varepsilon_{t-1} \ldots\ldots(24)$$

Variance Equation

$$log\sigma_t^2 = -1.117555 + 0.464428\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}\right| + 0.061227\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} + 0.387869 log\sigma_{t-1}^2 + 0.185518 log\sigma_{t-2}^2 + 0.337846 log\sigma_{t-3}^2 \ldots\ldots(25)$$

Oil Palms sector

Findings of the research study show that to forecast the Oil Palms sector indices, the appropriate model is the PARCH (2,1) model. PARCH (2,1) model is as follows:

Mean Equation

$$dlogop = 0.0000000182 - 0.656569 dlogop_{t-1} + 0.655339\varepsilon_{t-1} \ldots\ldots(26)$$

Variance Equation

$$\sqrt{\sigma_t} = 0.000000094 + 0.893621(|\varepsilon_{t-1}| - 0.088837\varepsilon_{t-1}) + 0.391437|\varepsilon_{t-2}| + 0.641324\sqrt{\sigma_{t-1}} \ldots\ldots(27)$$

Service sector

To forecast the Service sector indices, the appropriate model is the PARCH (2,1) model. PARCH (2,1) model is as follows:

Mean Equation

$$dlogss = 0.794241 dlogss_{t-1} - 0.794239\varepsilon_{t-1} \ldots\ldots(28)$$

Variance Equation

$$\sqrt{\sigma_t} = 0.0000793 + 0.274587(|\varepsilon_{t-1}| + 0.089843\varepsilon_{t-1}) + 0.874119\sqrt{\sigma_{t-1}} \ldots\ldots(29)$$

Stores & Supplies sector

PARCH (2,1) model is the appropriate model to forecast the sector indices of the Stores & Supplies sector. PARCH (2,1) model is as follows:

Mean Equation

$$dlogsts = -0.933461 dlogsts_{t-1} + 0.933461\varepsilon_{t-1} \ldots\ldots(30)$$

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Variance Equation

$$\sqrt{\sigma_t} = 0.00000105 + 0.935005(|\varepsilon_{t-1}| + 0.410339\varepsilon_{t-1}) + 0.250160|\varepsilon_{t-2}| + 0.611487\sqrt{\sigma_{t-1}} \qquad (31)$$

4.13. Sector Wise Comparison

Table 11 presents the sector-wise appropriate forecasting models for all the selected ten sectors.

Table 11 Sector-wise appropriate forecasting models

Sector	Appropriate forecasting model
Banking Finance & Insurance	IGARCH (2,2)
Beverage, Food & Tobacco	PARCH (1,1)
Chemicals & Pharmaceuticals	PARCH (2,2)
Footwear & Textiles	EGARCH (1,1)
Hotels & Travels	TARCH (1,1)
Investment Trusts	IGARCH (2,2)
Manufacturing	EGARCH (1,3)
Oil Palms	PARCH (2,1)
Services	PARCH (2,1)
Stores & Supplies	PARCH (2,1)

Source: The author developed

According to Table 11 for the Oil Palms sector, Services sector and Stores & Supplies sector the appropriate model for forecasting sector indices is PARCH (2,1) model while for the Beverage, Food & Tobacco sector the appropriate model for forecasting sector indices is PARCH (1,1) model and for Chemicals & Pharmaceuticals sector is PARCH (2,2) model. Banking Finance & Insurance sector and Investment Trusts sector the appropriate model for forecasting sector indices is IGARCH (2,2) model. To forecast sector indices of the Footwear & Textiles sector the appropriate model is EGARCH (1,1) model while for the Manufacturing sector is EGARCH (1,3) model. The appropriate model to forecast sector indices of the Hotels & Travels sector is TARCH (1,1) model.

5. CONCLUSION

The stock market of a country is a very crucial part of the economy. Developing models which reflect the pattern of the stock price movements for different sectors listed in CSE is very significant to investors and policymakers. Therefore, in this research study, the researcher developed models to forecast different sector indices and compared them. The forecasting models comprise ARCH, GARCH, TARCH, EGARCH, IGARCH and PARCH. Out of these ARCH family models researcher selected the appropriate model to forecast the sector indices by using Akaike information criterion (AIC) and Schwarz criterion (SC) values.

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According to the finding of the research study, it can conclude that to forecast the Banking Finance & Insurance sector indices the appropriate model is IGARCH (2,2) model. For the Hotels & Travel sector, TARCH (1,1) model is the appropriate model to forecast the sector indices. IGARCH (2,2) model is the appropriate model to forecast the Investment Trusts sector indices. To forecast the sector indices of the Manufacturing sector, the appropriate model is EGARCH (1,3) model. Findings of the research study show that to forecast the Oil Palms sector indices, the appropriate model is the PARCH (2,1) model. To forecast the Service sector indices, the appropriate model is the PARCH (2,1) model. PARCH (2,1) model is the appropriate model to forecast the sector indices of the Stores & Supplies sector.

It can be concluded that PARCH model is appropriate to forecast five sectors out of ten sectors. Oil Palms sector, Services sector and Stores & Supplies sector the appropriate model for forecasting sector indices is PARCH (2,1) model while for the Beverage, Food & Tobacco sector the appropriate model for forecasting sector indices is PARCH (1,1) model and for Chemicals & Pharmaceuticals sector is PARCH (2,2) model. For two sectors including Banking Finance & Insurance sector and the Investment Trusts sector, the appropriate model for forecasting sector indices is IGARCH (2,2) model. To forecast sector indices of the Footwear & Textiles sector the appropriate model is EGARCH (1,1) model while for the Manufacturing sector is EGARCH (1,3) model. The appropriate model to forecast sector indices of the Hotels & Travels sector is TARCH (1,1) model.

5.1. Recommendations & Limitations

It can be recommended that the most appropriate model forecast the sector indices of Oil Palms sector, Services sector and Stores & Supplies sector as PARCH (2,1) model, Beverage, Food & Tobacco sector as PARCH (1,1) model, Chemicals & Pharmaceuticals sector as PARCH (2,2) model, Banking Finance & Insurance sector and Investment Trusts sector as IGARCH (2,2) model and Manufacturing sector as EGARCH (1,3) model. These findings are contradicted by Ng and McAleer (2004), Mhmoud and Dawalbait (2015) and AL-Najjar (2016). Further, it can be recommended that the most appropriate model forecast the Footwear & Textiles sector indices are EGARCH (1,1) model. This is similar to the findings of Mhmoud and Dawalbait (2015). TARCH (1,1) model is more appropriate to forecast the Hotels & Travels sector. This is similar to the findings of Ng and McAleer (2004), and Mhmoud and Dawalbait (2015) and contradict the findings of AL-Najjar (2016).

This research study was carried out with some limitations therefore future researchers can further develop this. It has selected only the Colombo Stock Exchange for this research study and other stock markets in foreign countries have not been considered. This research study was limited only to thirty-four years from 2nd January 1985 to 29th March 2019. The sample of this research was limited only to daily market indices. All the previous studies on forecasting market indices have not been considered.

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