DETERMINISTIC BEHAVIORAL STOCK MARKET MODEL TO EXAMINE THE VOLATILITY IN COLOMBO STOCK INDICES

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DECLARATION

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The above candidate has carried out research for the Masters Dissertation under my supervision.

Supervisor 's Name

Mr. T. M. J. A. Cooray ……………………… …………………

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ABSTRACT

The study “Deterministic behavioral Stock Market Model to Examine the Volatility in Colombo Stock Indices” is done using daily stock market price indices of Colombo Stock Exchange (CSE) from 2000 to 2016. The main objective of the study is to build an appropriate model to estimate market volatility based on All Share Price Index (ASPI) and price indices of the selected sectors.

Stationarity and variance patterns of the ASPI are inspected by using descriptive time series plots of the original series, log transformed series and returns series. Box-pierce LM Test and ARCH Effect Test are used to check the existing of volatility clusters in returns series**.** Further Statistical Tests are applied to identify the asymmetric volatility clusters. Two distinct EGARCH models are built to examine the volatility in ASPI before and after the ending of war which was occurred till May 2009, Sri Lanka. The Diagnostic Checking of the fitted models is done by using Heteroskedasticity Test, Correlogram of the squared residuals. Assumptions of the Error distribution are validated by Q-Q plot.

Further, existence of volatility clusters and asymmetric patterns of price indices of Bank Finance & Insurance (BFI), Construction & Engineering (CE) and Manufacturing (MFU) sectors are tested using proper statistical tests. Diverse GARCH family models are used to inspect the variance of sector price indices. Diagnostic checking is performed for each built model and volatility of the sector indices are estimated by appropriate models.

Key Words: ASPI,Volatility, GARCH, Heteroskedasticity

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AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving average
ASPI	All Share Price Index
ASTRI	All Share Total Return Index
BFI	Bank Finance & Insurance
CE	Construction & Engineering
CSE	Colombo Stock Exchange
DW	Durbin-Watson Value
EGARCH	Exponential Generalized Autoregressive Conditional Heterotedasticity
GARCH	Generalized Autoregressive Conditional Heterotedasticity
GDP	Gross Domestic Product
GED	Generalized Error Distribution
JB	Jarque-Bera
MAPE	Mean Absolute Percentage Error
MFU	Manufacturing
MPI	Milanka Price Index
MSCI	Morgan Stanley Capital International
SBC	Schwartz's Bayesian Criterion
TGARCH	Threshold Generalized Autoregressive Conditional Heterotedasticity
TRI	Total Return Index

CHAPTER 1: INTRODUCTION

This chapter is based on providing a general introduction to the study of performing "Deterministic behavioral Stock Market Model to Examine the Volatility in Colombo Stock Indices". It contains essentially, Background of the study, Significance of the study, Objectives and Outline of the thesis.

1.1 Background of the Study

The Colombo Stock Exchange (CSE) is the only licensed stock exchange in Sri Lanka. It is one of the exchanges in South Asia, providing a fully automated trading platform. There are several indices to reflect the stock market behavior of CSE such as All Share Price Index (ASPI), S & P SL 20 Index, Total Return Index (TRI) and sector indices. For investors, indices give the direction of the entire market. They use indices to track the performance of the stock market. Ideally, a change in the price of an index represents an exactly proportional change in the stocks included in the index. The ASPI is one of the principal stocks Index of the CSE and it measures the movement of share prices of all listed companies based on market capitalization.

The most basic purpose of the stock market indices is to provide a measure to understand the direction or the movements of the market as a whole. An increase in the index indicates a rising market and decrease indicates a falling market. Market indices enable us to calculate market return. Share market investment is considered as high return, but high risk investment. Thus predictability of share returns in a secondary market is greatly helpful to the investors.

The objective of this study is to develop a deterministic behavioral model for the CSE to examine the volatility in the areas of clustering, leverage effects and sudden shocks in CSE.

1.1.1 Financial Market Volatility

The study of (Morawakage & Nimal, July-December 2015) explained that financial markets are getting dynamic day by day. New instruments and trading methodologies such as derivative are introduced. Investor preferences are continuously changing over different markets. This situation always encourages the academicians and practitioners

in financial markets to innovate new models as well as validate, compare and contrast the existing models for the purpose of explaining different market phenomena.
Volatility, as measured by the standard deviation or variance of returns, is often used as a basic measure of the total risk of financial assets. The volatility is derived as the results of unequal variances of the error terms of the return series. Volatility clustering occurs when large stock price changes are followed by large price change, of either sign, and small price changes are followed by periods of small price changes.

As mentioned in the study of (Jegajeevan) Volatility in stock return is often perceived as a measure of risk, thus increasingly used in asset pricing, hedging, risk management and portfolio selection. Accurate modeling and forecasting of the variance receive a lot of attention in the investment community. Therefore, studying the stock market for identifying the persistence in volatility and its dynamics to the impact of news is valuable. Studies on this area usually focus on diverse properties of the return series such as volatility clustering, leptokurtosis and asymmetric effect.

1.1.2 Types of Stock Market Indices

There are three types of stock market indices. They are price-weighted, value-weighted and equally weighted indices. They differ according to the weighting scheme used in their construction.
A price –weighted index is an index where the price of each stock receives the same weight. It is constructed as an arithmetic mean of current prices of the stock that constitute the index. The best example of a price weighted index is the Dow Jones Industrial Average (DJIA), which is a price-weighted average of 30 well-known industrial stocks in the U.S. There is no weighted market index in Sri Lanka.

A value-weighted index is an index where each stock is given a weight equal to its value. The value of a stock is the market capitalization of the common stocks, as measured by the number of listed shares times the market prices per share. This is the most widely used index construction method. In the Sri Lankan market the ASPI, MPI, and the MBSL Mid Cap index are all value weighted indices. The most popular value weighted index in the U.S. is the S&P 500 Index.

An equally –weighted index is an index in which the change of each stock is given the same weight. Sometimes this is referred to as an un-weighted index. In the construction of an equally weighted index, all stocks carry equal weight regardless of price or market value.

1.1.3 All Share Price Index (ASPI)

It is a value-weighted price index, which incorporates all the voting ordinary shares listed on the CSE. The base year is 1985, and the base value of the index is 100. ASPI showed 7,811.82 points as its highest value on 14th February 2011. Current ASPI value is the broadest and the longest measure of the level of the Sri Lankan stock market.

As explained above the ASPI is a value weighted index based on market capitalization where the weight of any company is taken as the number of ordinary shares listed in the market. This weighting system allows the price movements of larger companies to have a greater impact on the index. Such a weighting system was adopted on the assumption that the general economic situation has a greater influence on larger companies than on smaller ones.

The ASPI indicates the price fluctuations of shares of all the listed companies and covers all the traded shares of companies during a market day. The ASPI is calculated using the following formula.

$$\text{All Share Price Index} = \frac{\text{Market Capitalization of All Listed Companies}}{\text{Base Market Capitalization}} \times 100$$

Where,

$$\text{Market Capitalization} = \sum_{i=1}^{n} \text{Current Number of Listed Shares of Company}_i \times \text{Market Price}_i$$

$$\text{Base Market Capitalization} = \sum_{i=1}^{n} \text{Number of Listed Shares of Company}_i \times \text{MarketPrice}_i$$

Base values are established with average market value on year 1985. Hence the base year becomes 1985.

$$\text{Opening Base Market Capitalization} = \frac{\text{Total Market Capitalization in 1985}}{\text{Number of Trading Days in 1985}}$$

1.1.4 S&P Sri Lanka 20 (S&P SL20)

The S&P SL20, or the Standard & Poor's Sri Lanka 20, is a stock market index, based on market capitalization, that follows the performance of 20 leading publicly traded companies listed in the Colombo Stock Exchange. The 20 companies that make up the index is determined by Standard & Poor's global index methodology, according to which the index's listing is reviewed each year. All S&P SL20 listed stocks are classified according to S&P and MSCI's Global Industry Classification Standard, thereby enabling better comparison of performance of Sri Lanka's largest and most liquid stocks with other global indices.

The S&P Sri Lanka 20 aims to provide investors with an easily replicable, yet representative benchmark of the Sri Lankan equity market. The index is designed to measure the performance of 20 leading Sri Lankan companies and was developed in partnership with the Colombo Stock Exchange (CSE).

1.1.5 Sector Indices

The listed companies of CSE are divided into 20 sectors and a price index for each sector is calculated on a daily basis using the same formula used to construct the ASPI. Each index indicates the direction of the price movement of the sector. By referring to these indices investors can get an idea of the stock price levels of particular business sectors. The 20 Business sectors are as follows;

1. Bank Finance and Insurance – (BFI)
2. Beverage Food and Tobacco – (BFT)
3. Chemicals and Pharmaceuticals – (C&P)
4. Construction and Engineering – (C&E)
5. Diversified Holdings –(DIV)
6. Footwear and Textile – (F&T)
7. Health Care – (HLT)
8. Hotels and Travels – (H&T)
9. Information Technology – (IT)
10. Investment Trusts – (INV)
11. Land and Property – (L&P)
12. Manufacturing – (MFG)

13. Motors – (MTR)
14. Oil Palms – (OIL)
15. Plantations – (PLT)
16. Power & Energy –(P&E)
17. Services – (SRV)
18. Stores Supplies – (S&S)
19. Telecommunications – (TLE)
20. Trading –(TRD)

These price indices reflect the price movements of companies in the twenty respective sectors. The base dates and base values of these indices are the same as of ASPI (i.e. base date is January 02, 1985 and base value is equal to 100). Additions, deletions and adjustments for corporate actions for these indices follow the same rules of ASPI.

1.2 Significance of the Study

Literature for the past decade has been acknowledged on modeling stock market indices in Sri Lanka. According to the ASPI during 2000-2016, it can be seen a significant fall in price indices corresponding to the 2008 and 2009 years. This decreasing pattern due to the critical time period of the war had occurred in Sri Lanka. There is no study available for investigate the market price variations of ASPI before and after the war. The purpose of this study therefore, is to investigate the existence of the volatility patterns in the CSE by using distinct models for before and after the ending of the war which occurred till 18th May 2009. This study also attempts to realize the suitability of diverse models in explaining the volatility and return behavior of sector-wise price indices. The results of this study should present vital insights on the investing environment and also serve as valuable information for devising investment strategies for stock market participants.

1.3 Objectives

The main objective of the study is to build an appropriate model to estimate market volatility based on ASPI and price indices of the selected sectors. So the following sub objectives can be structured to achieve the main objective of the study.

- To investigate the volatility pattern of ASPI of the CSE using symmetric and asymmetric models before and after the war.
- To analyze the appropriateness of Generalized Autoregressive Conditional Heteroscedastic (GARCH) family models that capture the important facts about the index returns and fits more appropriate models.
- To estimate the volatility of the ASPI and sector-wise price indices through appropriate Generalized Autoregressive Conditional Heteroscedastic (GARCH) family models.

1.4 Outline of the Thesis

There are six chapters including in this thesis and organization of those chapters is as follows.

Chapter 1 provides an elementary move towards the study. It consists Background of the Study, Significance of the Study and Objectives of the Study. This gives a general idea about this research. The Chapter 2 reviewed literature related to this study. It provides basic idea about the related researches of Stock Market Data. Theories and Techniques which are applied in this study explained through chapter 3. Chapter 4 consists descriptive analysis of the monthly and daily ASPI and sector-wise stock market data. Modeling of the daily ASPI and sector-wise indices by applying various techniques will be discussed through chapter 5. Finally chapter 6 briefly summarized the findings of the whole study and discussed the overview of the study, significant areas of model fitting, problems encountered in the study, improvements and conclusions.

CHAPTER 2: LITERATURE REVIEW

This chapter provides reviews of literature related to modeling Stock market data of Colombo Stock Exchange (CSE). Previous researches which were carried out based on stock market data has been discussed through this chapter. Some researches related to this study have been compared respective to techniques which were used.

2.1 Review on previous studies

The study on “Equity Market Volatility Behavior in Sri Lankan Context” (Morawakage & Nimal, July-December 2015) have been examined the volatility behavior of Colombo Stock Exchange with advanced econometric models. GARCH, EGARCH and TGARCH models have been used to capture the complex volatility features. It is observed that volatility clustering and leverage effect exists in Colombo Stock Exchange. Further, negative shocks were created more volatility compared to a positive shocks generated in the market. TGARCH model assuming student-t probability distribution function was more suitable to explain the volatility in Colombo Stock Exchange among the models described above according to the Akaike and Schwarz information criteria.

(Konarasinghe, Abeynayake, & Gunaratne, 2015) have stated in their research paper on use of the ARIMA models on forecasting Sri Lankan share market returns. Stationary of the series were tested by Auto Correlation Functions and Partial Auto correlation Functions. ARIMA models were tested on total market returns, sector returns and individual company returns of CSE. Mean Square Error, Mean Absolute Deviation, residual plots and Anderson Darling test were used in model validation. Based on the results of this study, it was concluded that ARIMA models are suitable in forecasting Sri Lankan stock market returns.

The study on “Volatility Models for World Stock Indices and Behavior of All Share Price Index˝” (Samayawardena, Dharmarathne, & Tilakaratne, 2015) Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models have been used to capture the characteristics of volatility in the stock price series. Many GARCH family models were considered in this study. All Share Price Index of Colombo stock exchanges (ASPI), S & P 500 index of New York stock exchange, FTSE 100 of the London stock exchange and BSE SENSEX index of Bombe stock exchange have been considered in this study and the study period is from 1st January 2004 to 1st January 2014. All four stock price indices had contained the volatility clusters and ASPI of Colombo Stock Exchange illustrates the symmetric volatility clusters and other three series have asymmetric volatility clusters. GARCH (1,1) model had been fitted for

ASPI , EGARCH(1,1) model had been developed for BSE SENSEX and FTSE 100 series, and EGARCH (2,1) had been fitted for S & P 500 series.

(Konarasinghe & Chandrapala, July - December, 2013) have been conducted a study on “Modeling Stock Returns and Trading Volume of Colombo Stock Exchange” to test causal relationship between returns and trading volumes in the Sri Lankan share market and to model the relationship. Further, it was intended to identify patterns of trading volume. Results of multivariate tests reveal that there is no causal relationship between market returns and trading volumes. Therefore, time series techniques were used on returns and trading volume. Ljung-Box Q (LBQ) statistic reveals that stock returns are auto-correlated and stationary while trading volumes are auto-correlated but not stationary. Finally concluded that ARIMA (0, 0, 1) is the best model for forecasting stock returns and Quadratic Trend model is the best for forecasting trading volume.
The study “Empirical Investigation of Stock Market” used to apply multivariate statistical methods and economic data forecasting techniques to identify the directions and movements of market prices and trade volume rates in CSE during 2006 to 2012. Stocks from the banking, finance & insurance, manufacturing, hotel & travels, beverage, food & tobacco, plantation, IT and telecommunications were important in explaining the variations in the CSE. Moreover, Principal component results suggest that GDP rates, inflation and consumer spending rates directly involve changing stock market prices and trade volume rates in the Colombo Stock Exchange (Rathnayaka, Seneviratna, & Nagahawatta, 2014) .

2.2 Financial Time Series Modeling

A time series is defined as a set of data values of a certain variable generates sequentially in time. The time series models assume that, in the absence of major disruptions to critical factors of a recurring event, the data of this event in the future will be related to that of the past events and can be expressed via models developed from the past events (Rani & Kaur, 2011).

Financial time series analysis is concerned with theory and practice of asset valuation over time. It is a highly empirical discipline, but like other scientific fields theory forms the foundation for making inference. There is, however, a key feature that distinguishes financial time series analysis from other time series analysis. Both financial theory and its empirical time series contain an element of uncertainty. For example, there are various definitions of asset volatility, and for a stock return series, the volatility is not directly observable. As a result of the added uncertainty, statistical theory and methods play an important role in financial time series analysis (TSAY, 2002).

Returns from financial market variables measured over short time intervals (i.e. intra-daily, daily, or weekly) are uncorrelated, but not independent. In particular, it has been observed that although the signs of successive price movements seem to be independent, their magnitude, as represented by the absolute value or square of the price increments, is correlated in time. This phenomena is denoted volatility clustering, and indicates that the volatility of the series is time varying (Aas & Dimakos, 2004).

2.3 GARCH Family Models

Financial economists are concerned with modeling volatility in asset returns. Volatility measures the size of the errors made in modeling returns and other financial variables. It has been discovered that, for vast classes of models, the average size of volatility is not constant but changes with time and is predictable.

Autoregressive conditional heteroscedasticity (ARCH)/generalized autoregressive conditional heteroscedasticity (GARCH) models and stochastic volatility models are the main tools used to model and forecast volatility. ARCH model proposed by Engle and its extension; GARCH model by Bollerslv and Taylor were found to be the first models introduced into the literature and have become very popular in that they enable the analysts to estimate the variance of a series at a particular point in time (Enders, 2004).

(Zakaria, 2012) has described volatility means “the conditional variance of the underlying asset return”. A special feature of this volatility is that it is not directly observable, so that financial analysts are especially keen to obtain a precise estimate of this conditional variance process, and consequently, a number of models have been developed that are especially suited to estimate the conditional volatility of financial instruments, of which the most well-known and frequently applied model for this volatility are the conditional heteroscedastic models.

Furthermore a GARCH model has been fitted to electricity demand series to obtain more accurate forecast for the variance of the return series if the series consist volatility clusters. The study on "Daily Load Forecasting and Maximum Demand Estimation using ARIMA and GARCH" discussed the model incorporates the concept of GARCH to model the residual in the student-t distribution and to estimate the maximum load demand that would be likely to occur within a finite time series with each estimated demand level corresponding to accepted levels of risk. The model has been fitted to an in-sample training data from 1970 - 1998 and the out of sample results were then verified with actual electricity data from 1999 - 2003. The mean absolute percentage error (MAPE) for each month generally lies within 1-3% (Hor, Watson, & Majithia, 2006).

2.4 Sector-wise Stock market Indices

The study on "Sector-Wise Stock Return Analysis: An Evidence from Dhaka Stock Exchange in Bangladesh (DSE)" is used to identify the sector-wise return characteristics of selected stocks of Dhaka Stock Exchange. In this study, 48 months return data of 126 stocks listed in the DSE have been used. The stocks had been divided in 10 different sectors and found individual sector's return and risk. Considering monthly return and risk analysis, stocks in the Garments Sector generated the highest return during this period. Stocks in the Banking and Insurance sectors also achieved higher return. Stocks of these two industries also have lower degree of risk compared to those of garments sector. Considering the risk – return trade off, has found that Banking Sector is the best place to invest. Negative return in the food & allied and service sectors was found. Macroeconomic factors impact on those selected industry return, following multi factor stock return analysis proposed in the Arbitrage Pricing Theory had also been tested. Out of the 10 sectors, used in this study, only return of the banking sector was significantly influenced by the macroeconomic condition (Hasan, 2011).

OLS regression techniques have been used to determine the relationship between changes in the federal funds rate and sector stock indexes. The study has been aimed to determine why particular sectors are more sensitive to interest rate changes than others. Weekly returns of the Dow Jones ICB classified financial, energy, utilities, materials, industrials, consumer goods, consumer services, information technology , healthcare and telecommunications sectors were analyzed using separate OLS regression models for each sector. The results had shown that the utilities, financials, telecom and basic materials sectors are the most interest rate sensitive in that order and that the relationship exhibited between the stock price and the federal funds rate is positive (Garg, 2008) .

CHAPTER 3: METHODOLOGY

The data set mainly consists daily market price data of three main indices from 2000 to 2016 and daily sector-wise stock market price indices data from 2000 to 2016. When creating different models, several time series techniques are used with different software. This chapter describes techniques, terms and theories which are used in all the analysis of this study and the procedure which has used in the analysis.

3.1 Arithmetic and Geometric returns

Direct statistical analysis of financial prices is difficult, because consecutive prices are highly correlated, and the variances of prices often increase with time. This makes it usually more convenient to analyze changes in prices. Results for changes can easily be used to give appropriate results for prices. Two main types of price changes are used: arithmetic and geometric returns. There seems to be some confusion about the two terms, in the literature as well as among practitioners.

Daily arithmetic returns are defined by

$r_t = y_t - y_{t-1}$, where y_t is the price of the asset at day *t*.

Daily geometric returns are defined by

$d_t = \log(y_t) - \log(y_{t-1})$, where y_t is the price of the asset at day *t*.

3.2 Auto Regressive Conditional Heterosedasticity (ARCH)

Autoregressive Conditional Heteroskedasticity (ARCH) models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modeled as a function of past values of the dependent variable and independent or exogenous variables.

ARCH models were introduced by Engle (1982) and generalized as GARCH (Generalized ARCH) by Bollerslev (1986) and Taylor (1986). These models are widely used in various branches of econometrics, especially in financial time series analysis.

3.2.1 GARCH(1,1) Model

The fundamental idea of the GARCH(1,1)-model (Bollerslev,1986) is to describe the evolution of the variance σ_t^2 as

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3.1}$$

The parameters satisfy $0 \ll \alpha \ll 1$, $0 \ll \beta \ll 1$, and $\alpha + \beta \ll 1$. The variance process is stationary if $\alpha + \beta < 1$, and the stationary variance is given by $\omega/(1 - \alpha - \beta)$.

The parameter $\eta = \alpha + \beta$ is known as persistence and defines how slowly a shock in the market is forgotten.

3.2.2GARCH (p,q) Model

Engle (1982) proposed a stationary non-linear model for y_t , which termed ARCH (Auto-Regressive Conditionally Heteroscedastic; it means that the conditional variance of y_t evolves according to an autoregressive-type process. Bollerslev (1986) and Taylor (1986) independently generalized Engle's model to make it more realistic; the generalization was called GARCH". GARCH is probably the most commonly used financial time series model and has inspired dozens of more sophisticated models.

The GARCH (p, q) model is defined by

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{3.2}$$

Where $\omega > 0$, $\alpha \geq_i 0, \beta_j \geq 0$, and the innovation sequence $\{\varepsilon_i\}$ is independent and identically distributed with $E(\varepsilon_0) = 0$ and $E(\varepsilon_0^2) = 1$

3.2.3 The Exponential GARCH (EGARCH) Model

The EGARCH or Exponential GARCH model was proposed by Nelson (1991). The specification for the conditional variance is:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \left| \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \right| \tag{3.3}$$

Note that the left-hand side is the *log* of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. The impact is asymmetric if $\gamma_i \neq 0$.

3.2.4 The Integrated GARCH (IGARCH) Model

If one restricts the parameters of the GARCH model to sum to one and drop the constant term,

$$\sigma_t^2 = \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (3.4)$$

such that

$$\sum_{j=1}^{q} \beta_j + \sum_{i=1}^{p} \alpha_i = 1 \qquad (3.5)$$

Then the model is identified as an integrated GARCH. This model was originally described in Engle and Bollerslev (1986).

3.2.5 The Threshold GARCH (TARCH) Model

TARCH or Threshold ARCH and Threshold GARCH were introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993). The generalized specification for the conditional variance is given by:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 \Gamma_{t-k} \qquad (3.6)$$

Where $\Gamma_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise.

In this model, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} < 0$, have differential effects on the conditional variance; good news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, bad news increases volatility, and say that there is a leverage effect for the i^{th} order. If $\gamma_i \neq 0$, the news impact is asymmetric.

3.3 Test for existing of Volatility

3.3.1 Box-pierce LM test:

Volatility clustering implies a strong autocorrelation in squared returns. Therefore a simple method for detecting volatility clustering is to calculate 1st order autocorrelation in squared returns. A basic test for the significance of is the Box-Pierce LM test.

$$\frac{\sum_{t=2}^{T} r_t^2 r_{t-1}^2}{\sum_{t=2}^{T} r_t^4} \approx \chi_1^2 \qquad (3.7)$$

This test statistics is asymptotically distributed as chi squared. However, this test is not very robust.

3.3.2 Test for an ARCH effect

The test for an ARCH effect was devised originally by Engle (1982) and is similar to the Lagrange Multiplier (LM) test for autocorrelation.

1) Run the regression of the model using Ordinary Least Squares (OLS) and collect the residuals. Square the residuals.
2) Run the following secondary regression:

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 ..... + \alpha_3 u_{t-p}^2 + v_t \qquad (3.8)$$

Where u is the residual from the initial regression and p lags are included in this secondary regression. The appropriate number of lags can either be determined by the span of the data (i.e. 4 for quarterly data) or by an information criteria. Collect the R^2 statistic from this regression.

3) Compute the statistic T* R^2, where T is the number of observations. It follows a chi-squared distribution with p degrees of freedom. The null hypothesis is that there is no ARCH effect present.

3.4 Testing for asymmetric volatilities

If volatilities is higher following a negative return than it is following a positive return then the autocorrelation between yesterday's return & today's squared return will be large & positive. This fact can be used to test the asymmetry in volatility.

$$\frac{\sum_{t=2}^{T} r_t^2 r_{t-1}}{\sqrt{\sum_{t=2}^{T} r_t^4 \sum_{t=2}^{T} r_{t-1}^2}} \qquad (3.9)$$

Value of the equation 3.16 is calculated. If this is negative and the corresponding Box-Pierce test is significantly different from zero, then there is an asymmetry in volatility clustering.

3.5 Model Selection Methods

3.5.1 Akaike Information Criterion (AIC)

The Akaike information criterion is a measure of the relative goodness of fit of a statistical model. It was developed by Hirotsugu Akaike, under the name of "an information criterion" (AIC), and was first published by Akaike in 1974. It is grounded in the concept of information entropy, in effect offering a relative measure of the information lost when a given model is used to describe reality. It can be said to describe the tradeoff between bias and variance in model construction, or loosely speaking between accuracy and complexity of the model.

AIC values provide a means for model selection. AIC does not provide a test of a model in the sense of testing a null hypothesis; i.e. AIC can tell nothing about how well a model fits the data in an absolute sense. In the general case, the AIC is

$$AIC = -2\ln(L) + 2k \qquad (3.10)$$

Where k is the number of parameters in the statistical model , and L is the maximized value of the likelihood function for the estimated model.

Given a set of candidate models for the data, the preferred model is the one with the minimum AIC value. Hence AIC not only rewards goodness of fit, but also includes a penalty that is an increasing function of the number of estimated parameters. This penalty discourages over fitting. (Increasing the number of free parameters in the model improves the goodness of the fit, regardless of the number of free parameters in the data-generating process).

3.5.2 The Schwarz's BC Criterion

Bayesian information criterion (BIC) or Schwarz criterion (also SBC) is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function, and it is closely related to Akaike information criterion (AIC).

$$SBC(K) = nln(\sigma_e^2) + kln(n) \qquad (3.11)$$

k = the number of free parameters to be estimated.
n=the number of observations, or equivalently, the sample size.

3.5.3 Durbin Watson statistic

The Durbin Watson Test is a measure of autocorrelation (also called serial correlation) in residuals from regression analysis. Autocorrelation is the similarity of a time series over successive time intervals. It can lead to underestimates of the standard error and can cause you to think predictors are significant when they are not. The Durbin Watson test looks for a specific type of serial correlation, the AR (1) process**.**
The Hypotheses for the Durbin Watson test are:
H_0 = No first order autocorrelation. $(\rho = 0)$
H_1 = First order correlation exists. $(\rho > 0)$
(For a first order correlation, the lag is one time unit).
Assumptions are:

- That the errors are normally distributed with a mean of 0.
- The errors are stationary.

The test statistic is calculated with the following formula:

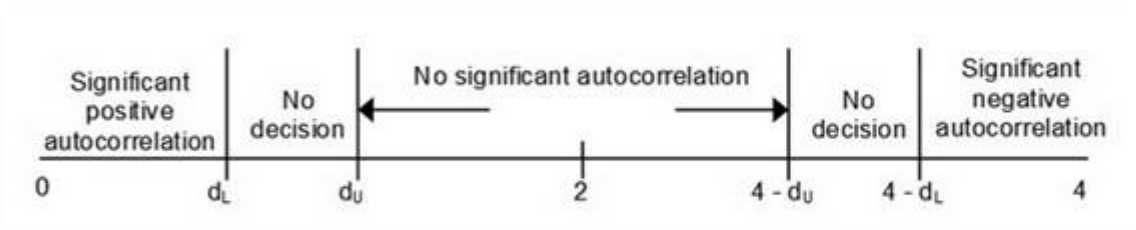
$$DW = \frac{\sum_{t=2}^{T}\left(e_t - e_{t-1}\right)^2}{\sum_{t=1}^{T} e_t^2} \qquad (3.12)$$

where $e_i = y_i - \hat{y}_i$ and y_i and $\hat{y}_i$ are, respectively, the observed and predicted values of the response variable for individual i. DW value becomes smaller as the serial correlations increase. Upper and lower critical values, d_U and d_L have been tabulated for different values of k (the number of explanatory variables) and t.

If DW < d_L reject $H_0 : \rho = 0$

If DW > d_U do not reject $H_0 : \rho = 0$

If d_L < d < d_U test is inconclusive



3.6 Residual Diagnostics

3.6.1 Ljung-Box Test

The Box-Ljung test (1978) is a diagnostic tool used to test the lack of fit of a time series model. The test is applied to the residuals of a time series after fitting an ARMA(p,q) model to the data. The test examines m autocorrelations of the residuals. If the autocorrelations are very small, we conclude that the model does not exhibit significant lack of fit.

In general, the Box-Ljung test is defined as:

Ho : The model does not exhibit lack of fit.

H_1 : The model exhibits lack of fit.

Test Statistic

Given a time series *Y* of length *n*, the test statistic is defined as:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-k} \quad (3.13)$$

Where $\hat{r}_k$ is the estimated autocorrelation of the series at lag *k*, and *m* is the number of lags being tested.

The test is applied to residuals, the degrees of freedom must account for the estimated model parameters so that *h* = *m*-*p*-*q*, where *p* and *q* indicate the number of parameters from the ARMA(*p*,*q*) model fit to the data.

Critical Region

The Box-Ljung test rejects the null hypothesis (indicating that the model has significant lack of fit) if $Q > x_{1-\alpha,h}^2$

where $x_{1-\alpha,h}^2$ is the chi-square distribution Table value with *h* degrees of freedom and significance level α.

3.6.2 Autocorrelation Test

For large sample T, the Box-Pierce test statistics

$$Q = T\sum_{n=1}^{p} Q(n)^{2} \sim \chi_{p}^{2} \qquad (3.14)$$

Where

$$Q(n) = \frac{\sum_{t=n+1}^{T} r_t^2 r_{tn}^2}{\sum_{t=1}^{T} r_t^4} \qquad (3.15)$$

If there is no autocorrelation in the squared standardized returns the GARCH model is well specified.

3.6.3 Jarque-Bera Test

The Jarque-Bera Test, a type of Lagrange multiplier test, is a test for normality. Normality is one of the assumptions for many statistical tests, like the t test or F test; the Jarque-Bera test is usually run before one of these tests to confirm normality. It is usually used for large data sets, because other normality tests are not reliable when n is large.

Specifically, the test matches the skewness and kurtosis of data to see if it matches a normal distribution. The data could take many forms, including:

- Time Series Data.
- Errors in a regression model.
- Data in a Vector.

A normal distribution has a Skewess of zero (i.e. it's perfectly symmetrical around the mean) and a kurtosis of three; kurtosis tells you how much data is in the tails and gives you an idea about how "peaked" the distribution is. It's not necessary to know the mean or the standard deviation for the data in order to run the test.

The formula for the Jarque-Bera test statistic (usually shortened to just JB test statistic) is:

$$JB = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4} \right) \qquad (3.16)$$

Where:

N is the sample size,

S is the sample Skewness Coefficient,

K is the kurtosis coefficient.

The null hypothesis for the test is that the data is normally distributed; the alternate hypothesis is that the data does not come from a normal distribution. In general, a large JB value indicates that errors are not normally distributed.

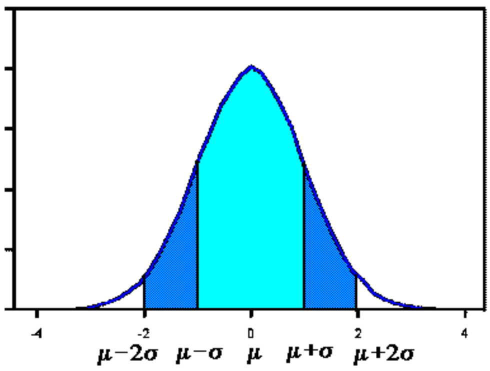
3.6.4 Histogram

In statistics, a histogram is a graphical representation showing a visual impression of the distribution of data. It is an estimate of the probability distribution of a continuous variable and was first introduced by Karl Pearson. A histogram consists of tabular frequencies, shown as adjacent rectangles, erected over discrete intervals, with an area equal to the frequency of the observations in the interval. The height of a rectangle is also equal to the frequency density of the interval. That is the frequency divided by the width of the interval. The total area of the histogram is equal to the number of data. A histogram may also be normalized displaying relative frequencies.

3.6.5 Normal Distribution

A normal distribution has a bell-shaped density curve described by its mean μ and standard deviation σ. The density curve is symmetrical, centered about its mean, with its spread determined by its standard deviation. The height of a normal density curve at a given point x is given by

$$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}} \quad (3.17)$$



The Standard Normal curve, shown here, has mean 0 and standard deviation 1. If a dataset follows a normal distribution, then about 68% of the observations will fall within σ of the mean μ, which in this case is with the interval (-1,1). About 95% of the observations will fall within 2 standard deviations of the mean, which is the interval (-2,2) for the standard normal, and about 99.7% of the observations will fall within 3 standard deviations of the mean, which corresponds to the interval (-3,3) in this case. Although it may appear as if a normal distribution does not include any values beyond a certain interval, the density is actually positive for all values,(-∞, +∞) Data from any normal distribution may be transformed into data following the standard normal distribution by subtracting the mean μ and dividing by the standard deviation σ.

3.6.6 Student-t Distribution

If $Z \sim N(0, 1)$ and $U \sim \chi^2(n)$ are independent, then the random variable:

$$T = \frac{Z}{\sqrt{U/n}} \qquad (3.18)$$

follows a *t*-distribution with *n* degrees of freedom. write $T \sim t(n)$. The p.d.f. of *T* is

$$f(t) = \frac{\tau((n+1)/2)}{\sqrt{\pi n}.\tau(n/2)(1+t^2/2)^{(n+1)/2}} \qquad (3.19)$$

for $-\infty < t < \infty$.

3.6.7 Normal Probability Plot

The normal probability plot is a graphical technique for assessing whether or not a data set is approximately normally distributed.

The data are plotted against a theoretical normal distribution in such a way that the points should form an approximate straight line. Departures from this straight line indicate departures from normality. The normal probability plot is a special case of the probability plot.

3.6.8 Q-Q Plot

A Q-Q plot is a plot of the quantiles of the first data set against the quantiles of the second data set. By a quantile, mean the fraction (or percent) of points below the given value. That is, the 0.3 (or 30%) quantile is the point at which 30% percent of the data fall below and 70% fall above that value.

A 45-degree reference line is also plotted. If the two sets come from a population with the same distribution, the points should fall approximately along this reference line. The greater the departure from this reference line, the greater the evidence for the conclusion that the two data sets have come from populations with different distributions.

The advantages of the Q-Q plot are:

1. The sample sizes do not need to be equal.
2. Many distributional aspects can be simultaneously tested. For example, shifts in location, shifts in scale, changes in symmetry, and the presence of outliers can all be detected from this plot. For example, if the two data sets come from populations whose distributions differ only by a shift in location, the points should lie along a straight line that is displaced either up or down from the 45-degree reference line.

The Q-Q plot is similar to a probability plot. For a probability plot, the quantiles for one of the data samples are replaced with the quantiles of a theoretical distribution.

3.6.9 Residuals

The "residuals" in a time series model are what is left over after fitting a model. For many (but not all) time series models, the residuals are equal to the difference between the observations and the corresponding fitted values.

$$e_t = y_t - \hat{y}_t \qquad (3.20)$$

Residuals are useful in checking whether a model has adequately captured the information in the data. A good forecasting method will yield residuals with the following properties:

- The residuals are uncorrelated. If there are correlations between residuals, then there is information left in the residuals which should be used in computing forecasts.
- The residuals have zero mean. If the residuals have a mean other than zero, then the forecasts are biased.

3.7 Methodology of the analysis

The techniques which have described in the previous sections of this chapter are used in preliminary analysis and in advanced analysis.

In chapter 4, descriptive plots are plotted to gain the basic idea about the All Share price Index (ASPI) and monthly demand variation in different sector-wise price indices. The behaviors of the stock market price indices in previous years are descriptively analyzed and the basis of the advanced analysis is built up under the preliminary analysis.

In chapter 5, further analysis is done based on four main sections. Section 5.1 & 5.2, is used to build a model for ASPI using different GARCH family models for bofore and after the ending of the war , which was occurred till may 2009 in Sri Lanka. Stationarity and variance patterns of the ASPI are inspected by using descriptive time series plots of the original series and returns series of the ASPI. Test for existing of volatility clusters in returns series of the ASPI is done using Box-pierce LM Test and Test for an ARCH effect**.** Further existence of asymmetric volatility clusters is statistically tested. Two distinct EGARCH models are identified to examine the volatility in ASPI. Diagnostic checking of the fitted models is done using Heteroskedasticity Test, Correlogram of the squared residuals. Error distribution assumption is tested by using Q-Q plot.

In section 5.3, variance patterns of the three selected sector price indices namely, Banking Finance & Insurance (BFI), Construction & Engineering (CE), Manufacturing (MFU) are investigated with time series plots of the original series, log transformed series and returns series over the period 2000-2016. Existence of volatility clusters and asymmetric patterns are tested using proper statistical tests and diverse GARCH family models are used to inspect the variance of sector price indices. Furthermore diagnostic checking is performed for each built model.

3.8 Data Description

The following data sets are used in this study. All data which have used for this study has been obtained from Colombo Stock Exchange (CSE), head office.

- Monthly market price indices of ASPI,S&P SL 20 (2000-2016)
- Daily market price indices of ASPI,S&P SL 20 (2000-2016)
- Daily market price indices of Bank Finance and Insurance, Construction & Engineering, Manufacturing sector (2000-2016)

CHAPTER 4: PRELIMINARY ANALYSIS

This chapter focuses on obtaining a fundamental idea of the monthly and daily stock market indices and other variables which can be affected on stock market indices. At the beginning, chapter provides the description of data. Graphical representations such as time series plots, ACF & PACF which are used to identify the existing of relationships & behaviors of the variables.

In summary, this chapter focuses on five main aspects as follows,

1. Monthly variation of three main market price indices
2. Daily variation of All Share Total Returns Index (ASTRI)
3. Descriptive Statistics of returns of the ASPI
4. Monthly variation of market price indices of selected sectors
5. Descriptive statistics of market price indices of selected sectors

4.1 Monthly variation of three main market price indices

4.1.1 Monthly Market Price of ASPI

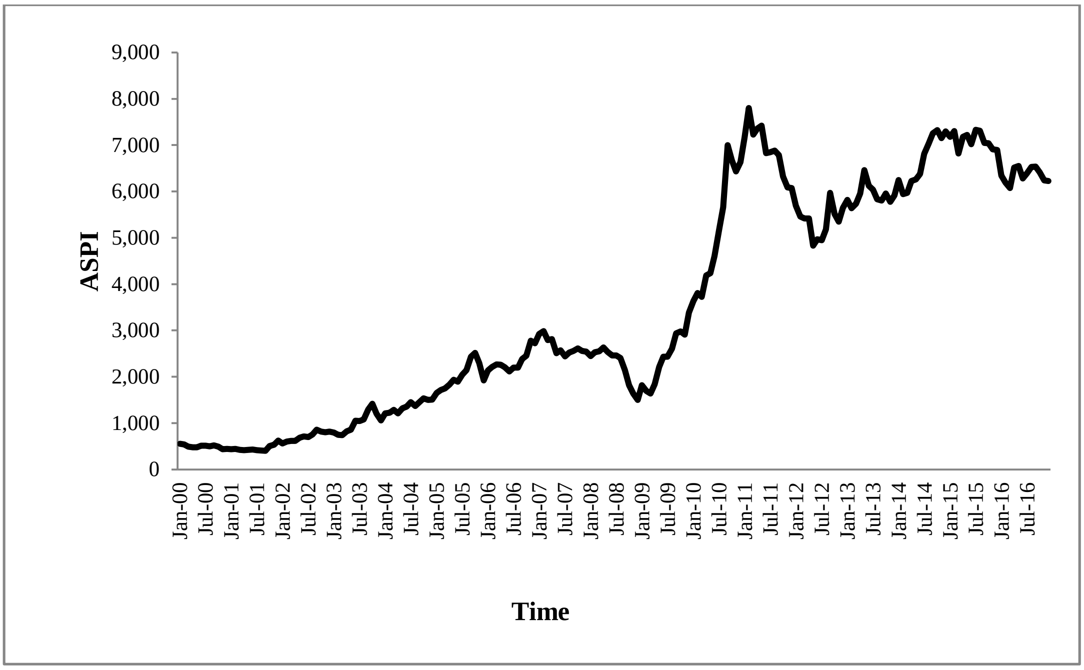


Figure 4.1: Monthly ASPI over 2000-2016

The time series plot depicts monthly variation of ASPI over 2000-2016. It can be clearly identified a positive trend over the time when considering overall data. However, it can be seen a significant fall in price indices corresponding to the 2008 and 2009 years. This decreasing pattern might be due to the critical time period of the war had occurred in Sri Lanka.

Thus, when developing model for ASPI, It is required to consider the data set before and after the ending of the war. Therefore two models to be fitted under the Further Analysis.

4.1.2 Monthly market price of S&P SL 20 Price Index

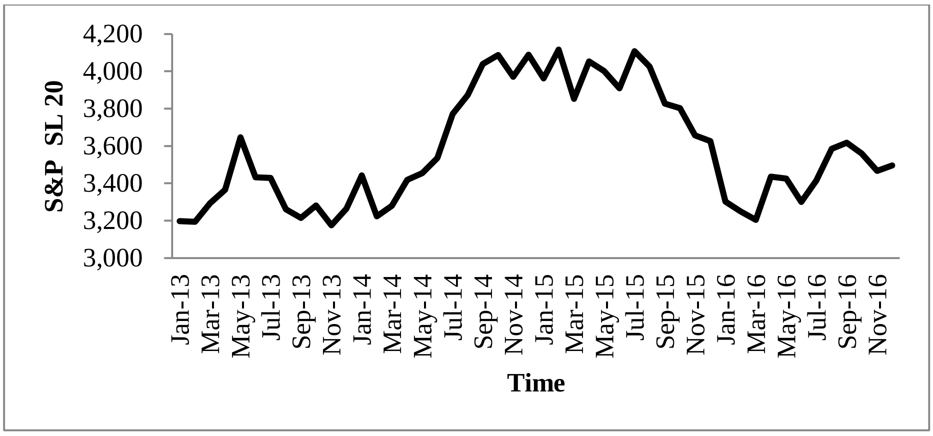


Figure 4.2: Monthly S&P SL 20 over 2013-2016

S&P SL 20 index has been included to CSE since January 2013. The Figure 4.2 illustrates the monthly variation patterns of the S&P SL 20 over 2013-2016. As the time series plot, there cannot be clearly identified negative or positive trend over time. It can be seen a rapid growth during 2014. However, S&P SL 20 price index has been declined to 3200 in 2016 which was the lowest price had recorded till 2016.

4.2 Daily variation of All Share Total Returns Index (ASTRI)

4.2.1 Daily return index of ASTRI

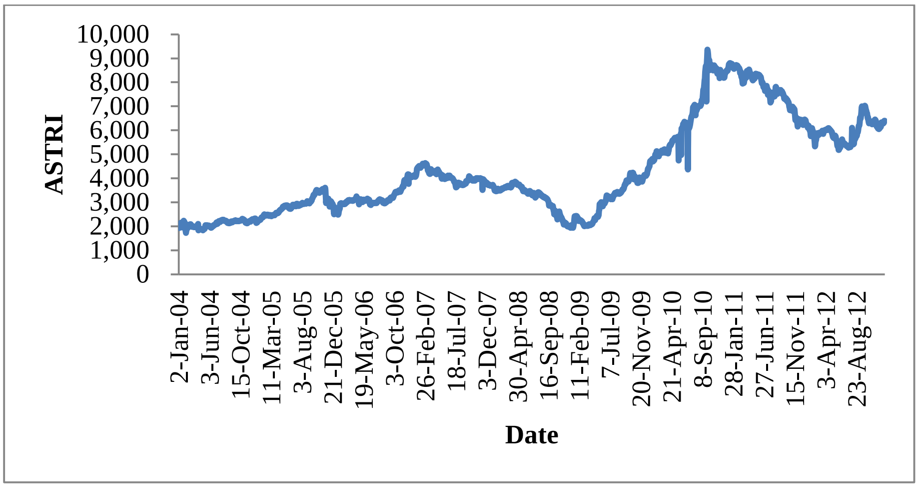


Figure 4.3: Daily ASTRI over 2004-2016

The Figure 4.3 illustrates that ASTRI has been increased steadily over the period 2004-2016. But It can be clearly identified some decrement patterns during 2007-2008 & mid of 2010 – mid of 2012 periods.

4.2.2 Comparison of total market returns by ASPI and ASTRI

Total market returns estimated by ASPI and market returns estimated by ASTRI are plotted for 2016.

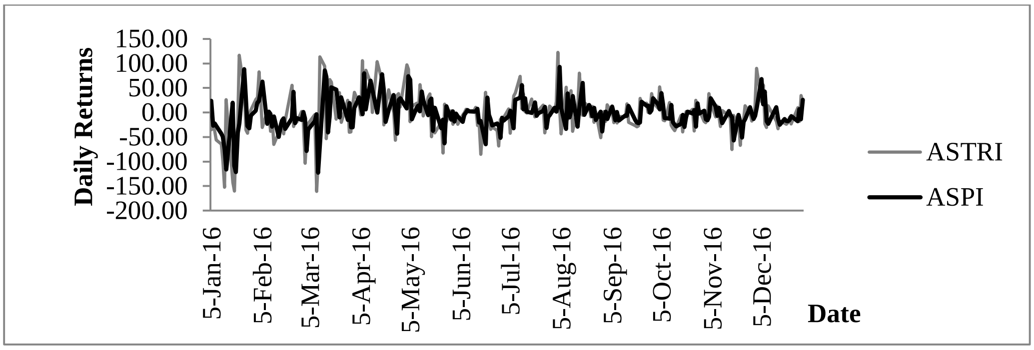


Figure 4.4: Time Series Plot of Returns of ASPI and Returns of ASTRI in 2016

The time series plot of Figure 4.4 shows that there is no significant difference in the variation pattern of the total market returns calculated for ASPI and ASTRI. Hence, for the rest of the study, the analysis was continued by using total market returns calculated by ASPI.

4.3 Descriptive Statistics of returns of the ASPI

4.3.1 Basic Statistics of the returns of ASPI

Table 4.1: Basic Statistics values of the returns of the ASPI

Statistics	Returns of ASPI
Mean	1.388236
Median	0.340000
Maximum	255.2900
Minimum	-300.5900
Std. Dev.	34.14064
Skewness	-0.057585
Kurtosis	12.39698
Jarque-Bera	14995.40
Probability	0.000000
Sum	5657.060
Sum Sq. Dev.	4748586.
Observations	4075

The return series of the ASPI indicates the negative skewness (-0.057585) that means series consist more decrements than the increments. The Jarque-berra statistics of the return series are highly significance (Probability=0.00). It rejects the null hypothesis that returns series is normally distributed. Thus returns series of the ASPI is not normally distributed. Further Skewness and Kurtosis values also indicates that the deviation of the returns from the normal distribution. Thus, when developing a GARCH model it is required to assume the error distribution away from the normal distribution.

4.3.2 Q-Q Plot of the returns of ASPI

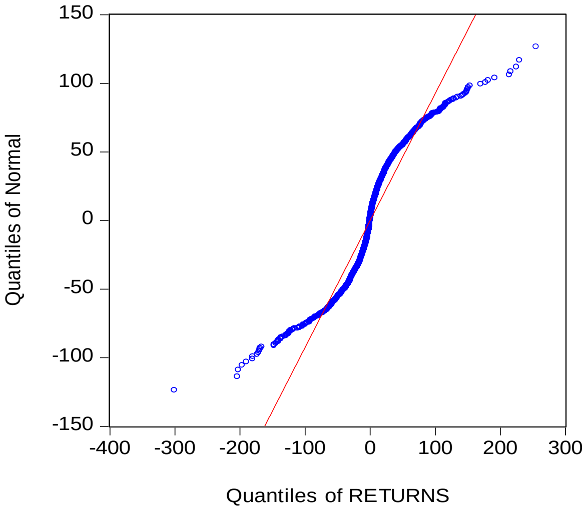


Figure 4.5 : Q-Q Plot of the Returns of ASPI

The Q-Q Plot illustrates that how the returns series of the ASPI deviates from the normal distribution graphically. If the sample is perfectly normally distributed all the points should fall on the 45 degree line or on other words if the data is normally distributed then the quantiles lie on a straight line. Thus the returns of the ASPI evidently violate the normality.

4.4 Monthly variation of market price indices of selected sectors

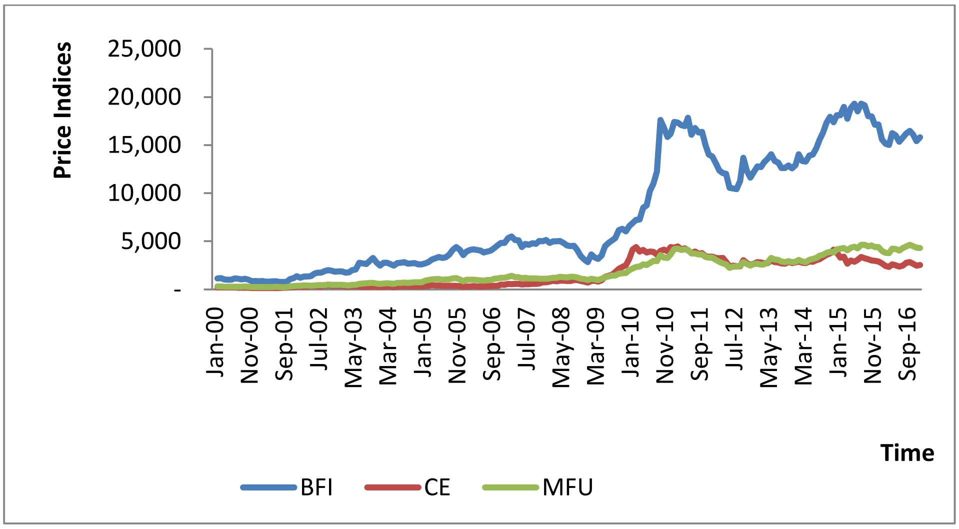


Figure 4.6: Time series Plot of three selected price indices

According to the Figure 4.6, BFI sector has recorded higher price indices at all considered time period when compared with other two sectors. Besides, BFI sector shows a significant positive trend of price index during the considered sixteen years period while other two sectors fluctuate simultaneously with a slight trend.

4.5 Descriptive statistics of market price indices of selected sectors

4.5.1 Basic Statistics of the returns of selected indices

Table 4.2: Basic Statistics values of the returns of the selected indices

Statistics	Bank Finance & Insurance(BFI)	Construction & Engineering(CE)	Manufacturing(MFU)
Mean	3.583642	0.571396	0.980304
Median	0.600000	0.000000	0.150000
Maximum	1086.480	676.2500	238.8600
Minimum	-743.6200	-303.1300	-160.6700
Std. Dev.	94.98927	36.33594	23.48700
Skewness	0.402267	2.417476	0.568166
Kurtosis	17.05431	48.55834	15.24901
Jarque-Bera	33647.75	356382.3	25694.50
Probability	0.000000	0.000000	0.000000
Sum	14603.34	2328.440	3994.740
Sum Sq. Dev.	36759543	5378903.	2247377.
Observations	4075	4075	4075

The Table 4.2 illustrates the basic statistics values of the returns of the three sector price indices of the bank Finance Insurance (BFI) sector, Construction & Engineering (CE) sector and Manufacturing (MFU) sector. Mean value and the standard deviation value of the returns of the BFI sector is noticeably high when compared with returns of the other two sectors. All the three return series indicate a positive Skewness values implies that all three series consist of more increments than decrements.

The Jarque-berra statistics of all the return series are highly significance. It rejects the null hypothesis that return series are normally distributed. And this result finally implies that the returns of the all series are not normally distributed. The Skewness, Kurtosis and the Jarque-Berra statistics (P value =0.00) indicates that the deviation of the returns from the normal distribution. The above kind of statistics assures the reliability of the predictions based on the standard deviation. Furthermore when developing volatility models, error distribution is required to be assume away from the normal distribution.

4.5.2 Q-Q Plot of the returns of the selected sector indices

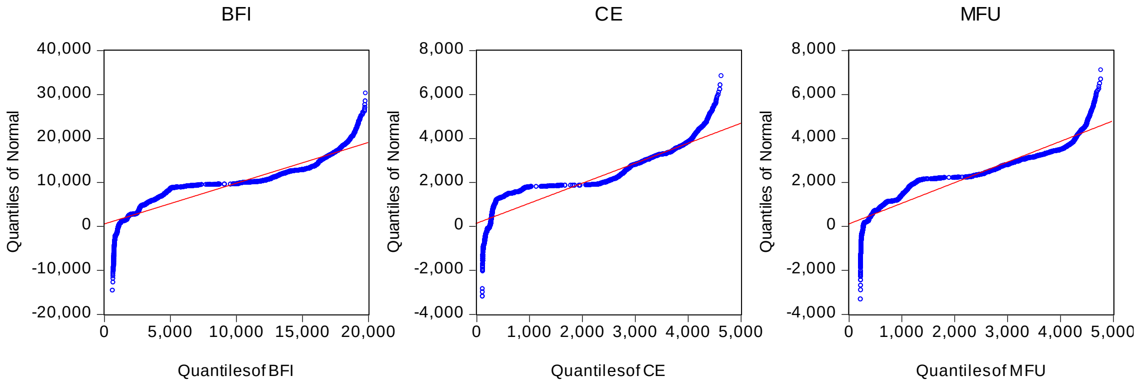


Figure 4.7: Q-Q Plot of the Returns of Selected Sector Indices

The Q-Q diagrams illustrate that how the each returns series of selected three sector indices deviate from the normal distribution graphically. If the sample is perfectly normally distributed all points should fall on the 45 degree line or on other words if the data is normally distributed then the quantiles will lie on a straight line. According to the Q-Q plots of return series of the three price indices, it can be clearly identified that three series are highly deviate from the normal distribution.

CHAPTER 5: FURTHER ANALYSIS

The behavior of the stock market price indices in previous years was descriptively analyzed and the basis of this advanced analysis was built up in chapter 4. A basic idea about the main stock price indices and sector-wise price indices can be obtained through chapter 4.

The further analysis consists in following main parts.

- Modeling daily ASPI using different GARCH family models before and after the ending of the war, to estimate the variance of ASPI.
- Modeling daily price indices of following three sectors.
  1. Banking Finance & Insurance (BFI)
  2. Construction & Engineering (CE)
  3. Manufacturing (MFU)

5.1 Modeling daily ASPI (2000-2009 May)

5.1.1 Identifying the Stationarity

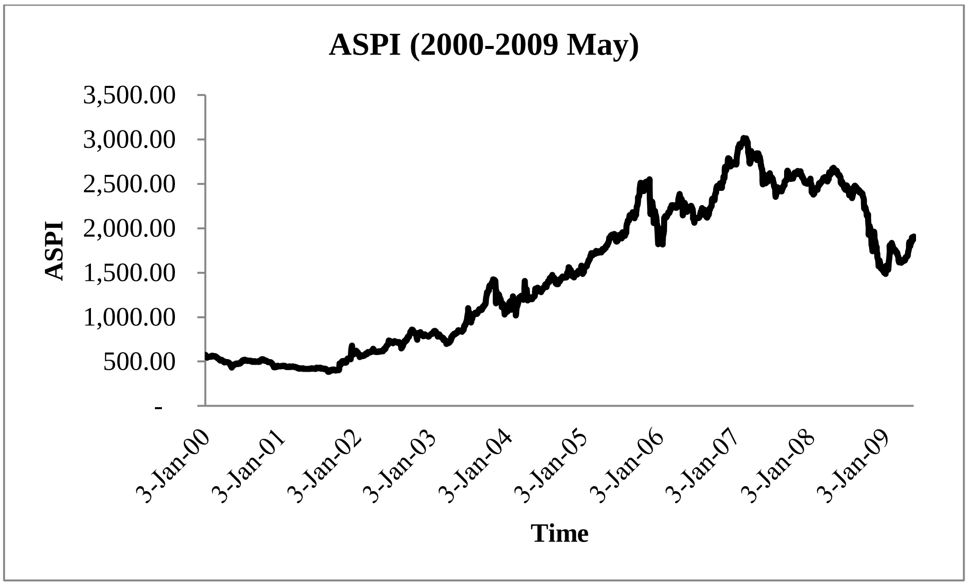


Figure 5.1: Time Series plot of the daily ASPI (2000-2009 May)

Figure 5.1 illustrates that there is a positive trend in the ASPI daily data series till 2007. Variance of the series is seems to be not constant. When fitting a time series model it is required that the variance of the series to remain constant.

Time series plot of the 1st differenced series of the ASPI is plotted.

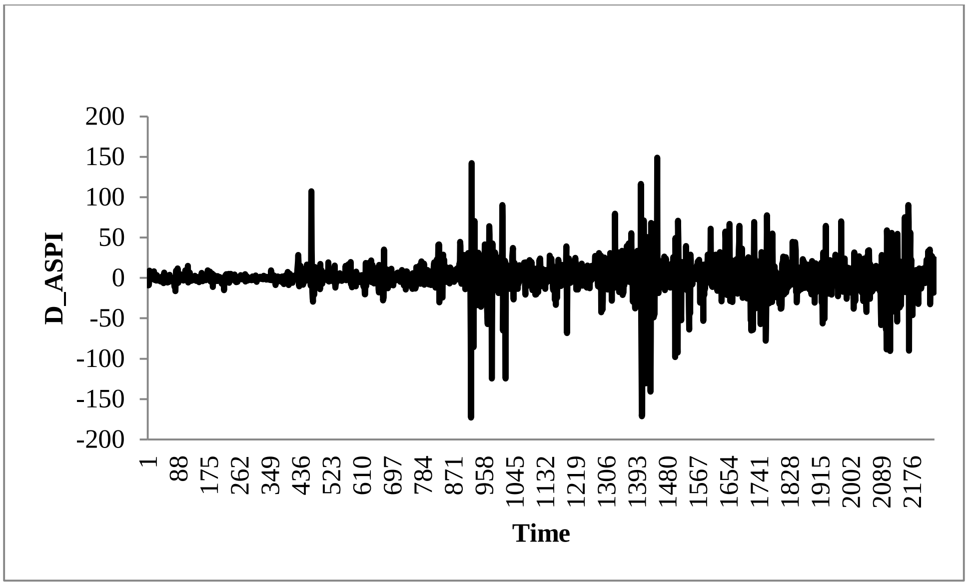


Figure 5.2: Returns Series of the ASPI (2000-2009 May)

According to the Figure 5.2, it can be seen that return series of the ASPI fluctuate significantly over the considered periods. Thus variance of the series seems to be non-constant.

Existence of the volatility clusters and nature of the volatility (Symmetric or Asymmetric) are examined using appropriate statistical tests.

5.1.2 Test for existing of volatility clusters in returns series of the ASPI

Box-pierce LM Test:

The value of the formula 3.7 is calculated.

$$\sum_{t=2}^{T} r_t^2 r_{t-1}^2 = 2,375,021,954.48$$

$$\sum_{t=2}^{T} r_t^4 = 6,818,940,404.47$$

1st order autocorrelation coefficient of squared return series = $\dfrac{\sum_{t=2}^{T} r_t^2 r_{t-1}^2}{\sum_{t=2}^{T} r_t^4} = 0.3482978$

T=2240, χ^2 = 3.871

Test statistic= Q =0.3482978×2240=780.1871

Since Q=780.1871 > χ^2 =3.871, reject H_0 and conclude that there exist volatility clustering in the return series of the ASPI at 5% level.

Since this test is not very robust one, Test for an ARCH effect is also applied.

Test for an ARCH effect

Step1: The regression of the returns series is run with intercept using Ordinary Least Squares (OLS) method and residuals are obtained.

Step2: Squared residuals are calculated. The following regression is run for the residuals series.

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + v_t$$

Where u is the residual from the initial regression and 1 lag term is included in this secondary regression.

Table 5.1: Results of the secondary regression run for the squared residuals

Method: Least Squares				
Included observations: 2239 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Squared Residuals	0.311678	0.020090	15.51438	0.0000
C	279.6354	35.16188	7.952800	0.0000
R-squared	0.097145	Mean dependent var		406.1553
Adjusted R-squared	0.096741	S.D. dependent var		1702.891
S.E. of regression	1618.426	Akaike info criterion		17.61719

Step 3: T*R^2 is calculated.

H_0: There is no ARCH effect present

H_1: There exists an ARCH effect.

T=2239 R^2 =0.096741

T*$R^2 = 216.60 \sim x^2(1)$

$x^2(1) = 3.871$ at 5% level of significance.

Since T*$R^2 = 216.60 \gg 3.871$ H_0 is rejected at 5 % level. Therefore, the returns series of the ASPI exists an ARCH effect.

5.1.3 Test for asymmetry in volatility clustering:

The value of the denominator of the formula 3.9 is calculated.

1st order autocorrelation coefficient between lag returns and current squared returns,

$$\nu = \sum_{t=2}^{T} r_t^2 r_{t-1} = -9261089.911$$

Since $\nu = \sum_{t=2}^{T} r_t^2 r_{t-1}$ has taken negative value, formula is a negative quantity here.

Corresponding Box-Pierce LM test is significant at 5% level. there exists asymmetric volatility clusters in the return series of the ASPI.

The asymmetric of the volatility is happened when volatility increases more when the stock prices were falling than when it was rising by the same amount. Asymmetric Volatility series can be modeled using asymmetric GARCH models such as EGARCH.

5.1.4 GARCH model for the ASPI (2000-2009 May)

As described in the Chapter 4, returns series of the ASPI is not normally distributed. In addition Skewness and Kurtosis values also indicates that the deviation of the returns from the normal distribution. Thus, when fitting a GARCH model it is required to assume the error distribution away from the normal distribution. Also, Q-Q Plot of the Returns of ASPI evidently violates the normality.

EGARCH(1,1) Model

Table 5.2 : Parameter Estimation of the E-GARCH(1,1) Model

	Coefficient	Std. Error	z-Statistic	Prob.
Mean equation				
θ	0.243838	0.020089	12.13767	0.0000
Variance Equation				
ω	-0.224414	0.028652	-7.832257	0.0000
α	0.506710	0.039232	12.91564	0.0000
β	0.975963	0.005052	193.1660	0.0000
γ	-0.039172	0.022076	-1.774439	0.0430
T-Distribution. DOF	3.645676	0.303466	12.01347	0.0000

According to the Table 5.2, all coefficient of the EGARCH (1,1) model are significant at 5% level. The mean and variance equations of the fitted model can be represented as follows.

The Mean Equation

$$r_t = C + \theta r_{t-1} + \varepsilon_t$$

$$r_t = 0.24 r_{t-1}$$

The Variance Equation

$$\log(\sigma_t^2) = \omega + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta log(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

$$\log(\sigma_t^2) = -0.22 + 0.51 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.98 log(\sigma_{t-1}^2) - 0.04 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

$$\alpha, \beta > 0$$

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative.

Here, it can be seen that the relatively small degrees of freedom parameter for the *t*-distribution (3.65) suggests that the distribution of the standardized errors departs significantly from normality.

Diagnostic checking

Heteroskedasticity Test (ARCH-LM test)

Table 5.3 : Heteroskedasticity Test for EGARCH (1,1) model

F-statistic	0.726268	Prob. F(1,2236)	0.3942
Observed R-squared	0.726682	Prob. Chi-Square(1)	0.3940

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Standard ε_{t-1}^{2}	0.018019	0.021144	0.852214	0.3942

According to the results of the Table 5.3, coefficient of the lag value of the squared standard error is insignificant. Thus errors don’t depend on the lag values of the errors. Both test statistics (F statistic & observed R-squared) do not reject the null hypothesis that standardized residuals exhibit additional ARCH effect. Hence, there is no heteroscedasticity in the standardized residuals.

The correlogram of the squared residuals

Table 5.4 : The correlogram of Standardized Residuals

Lag	ACF	PACF	Q-Stat	Prob*
1	0.018	0.018	0.7280	0.394
2	0.013	0.013	1.1187	0.572
3	-0.024	-0.024	2.3831	0.497
4	-0.019	-0.019	3.2214	0.521
5	-0.007	-0.006	3.3365	0.648
6	-0.026	-0.026	4.8837	0.559
7	-0.002	-0.002	4.8956	0.673
8	-0.006	-0.006	4.9662	0.761
9	-0.003	-0.004	4.9885	0.835
10	-0.007	-0.008	5.0936	0.885
11	-0.015	-0.015	5.5757	0.900
12	-0.006	-0.007	5.6688	0.932
13	0.010	0.010	5.8749	0.951
14	-0.013	-0.015	6.2707	0.959
15	-0.006	-0.007	6.3636	0.973
16	-0.021	-0.021	7.3833	0.965
17	-0.019	-0.019	8.1569	0.963

18	-0.015	-0.015	8.6684	0.967
19	-0.003	-0.004	8.6921	0.978
20	-0.015	-0.018	9.2122	0.980
21	-0.001	-0.003	9.2140	0.987
22	-0.021	-0.023	10.212	0.984
23	-0.010	-0.012	10.458	0.988
24	-0.007	-0.009	10.582	0.992
25	0.003	0.001	10.597	0.995
26	-0.012	-0.016	10.949	0.996
27	-0.003	-0.005	10.976	0.997
28	-0.011	-0.014	11.271	0.998
29	-0.009	-0.011	11.458	0.999
30	0.015	0.014	11.999	0.999
31	0.014	0.011	12.437	0.999
32	0.015	0.011	12.962	0.999
33	-0.009	-0.012	13.149	0.999
34	-0.013	-0.015	13.520	0.999
35	-0.020	-0.020	14.445	0.999
36	-0.011	-0.012	14.740	0.999

According to the Table 5.4, the correlogram of the squared residuals consists of the highly insignificance Q - Statistics values from lag 1 to 36. These results confirm that the selected variance equation is highly accepted to describe the error variance of the mean equation.

Q-Q plot:

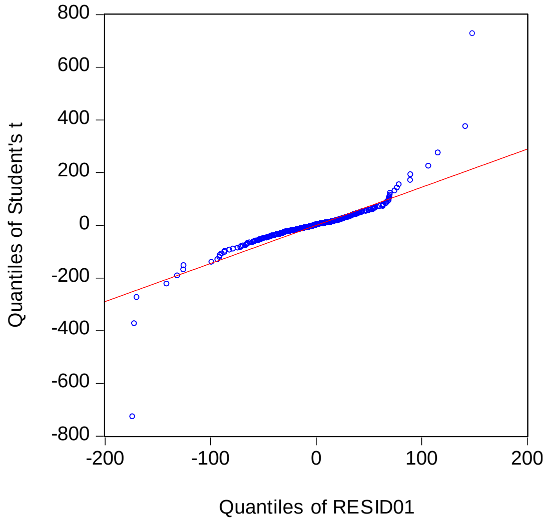


Figure 5.3 : Q-Q plot of the EGARCH (1, 1) model

The Figure 5.3 illustrates the Q-Q plot which has drawn with the assumption of the residuals follows t-distribution. As above plot, it can be seen that the residuals are much closed to the straight line. Thus the residuals of the fitted model follow the t-distribution.

Actual and fitted volatility

Since the actual volatility is unobservable, the squared return series will be used as a proxy for the realized volatility. A plot of the proxy against the fitted volatility provides an indication of the models ability to track variations in ASPI (2000-2016 May).

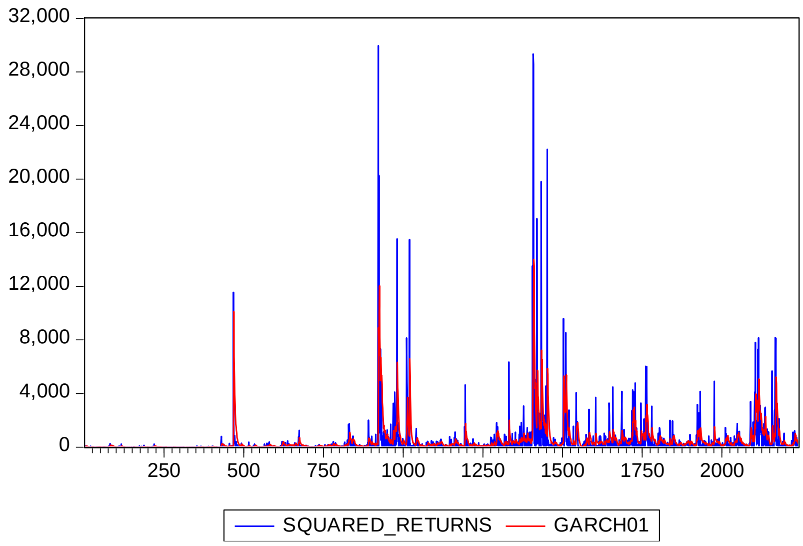


Figure 5.4 : Actual & fitted volatility in return series of the ASPI(2000-2016 May)

According to the Figure 5.4, the fitted volatilities have captured the patterns of the squared return series. Thus this model can be used to forecast the volatilities of the ASPI (2000-2016 May). Further it can be observed that estimated variance of the series fluctuated in the range 0- 16,000.

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5.2 Modeling daily ASPI (2009 May-2016)

5.2.1 Identifying the Stationarity

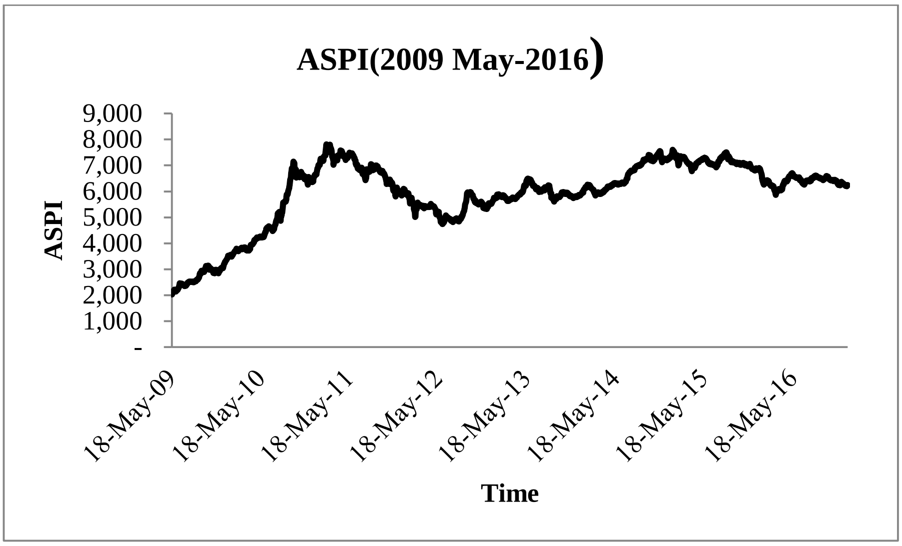

Figure 5.5 : Time Series plot of the daily ASPI (2009 May-2016)

Figure 5.5 illustrates that there is a slight positive trend in the ASPI daily data series of 2009 May-2016. Variance of the series is seems to be not constant. When fitting a time series model it is required that the variance of the series to remain constant.

Time series plot of the 1st differenced series of the ASPI is plotted.

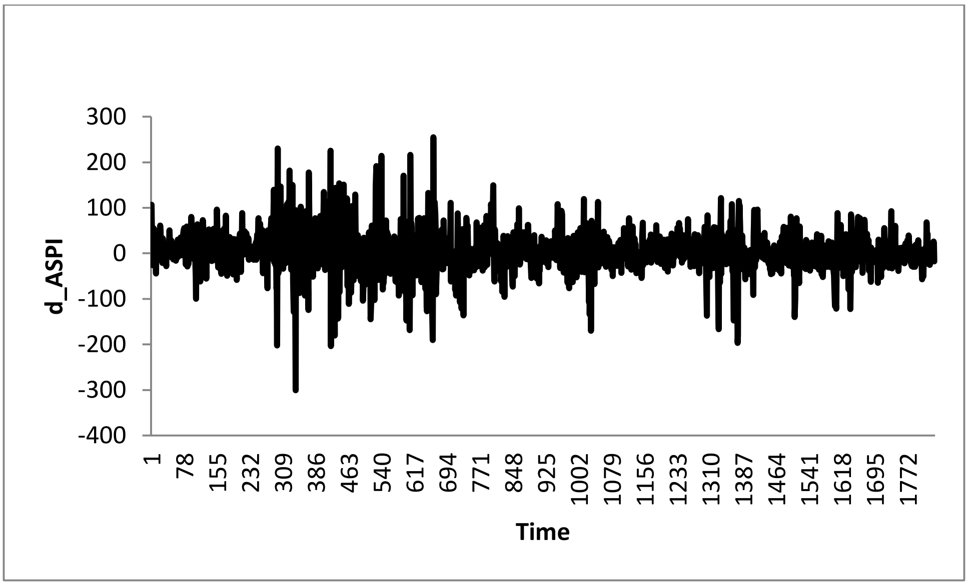

Figure 5.6 : Returns Series of the ASPI (2000-2009 May)

According to the Figure 5.6, it can be seen that return series of the ASPI fluctuate significantly over the considered periods. Thus variance of the series seems to be non-constant.

Existence of the volatility clusters and nature of the volatility (Symmetric or Asymmetric) are examined using appropriate statistical tests.

5.2.2 Test for existing of volatility clusters in returns series of the ASPI

Box-pierce LM Test:

The value of the formula 3.7 is calculated.

$$\sum_{t=2}^{T} r_t^2 r_{t-1}^2 = 21864363985.93$$

$$\sum_{t=2}^{T} r_t^4 = 61552416653.93$$

1st order autocorrelation coefficient of squared return series = $\frac{\sum_{t=2}^{T} r_t^2 r_{t-1}^2}{\sum_{t=2}^{T} r_t^4}$ = 0.355215

T=1836, χ^2 = 3.871

Test statistic= Q =0.355215×1836=652.175

Since Q=651.82 > χ^2 =3.871, reject H_0 and conclude that there exist volatility clustering in the return series of the ASPI(2009 May-2016) at 5% level.

Since this test is not very robust one, Test for an ARCH effect is also applied.

Test for an ARCH effect

Step1: The regression of the returns series is run with intercept using Ordinary Least Squares (OLS) method and residuals are obtained.

Step2: Squared residuals are calculated. The following regression is run for the residuals series.

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + v_t$$

Where u is the residual from the initial regression and 1 lag term is included in this secondary regression.

Table 5.5: Results of the secondary regression run for the squared residuals

Method: Least Squares				
Included observations: 1836 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Squared Residuals	0.260687	0.022555	11.55766	0.0000
C	1540.546	130.5564	11.79985	0.0000
R-squared	0.067959	Mean dependent var		2083.679
Adjusted R-squared	0.067451	S.D. dependent var		5401.708
S.E. of regression	5216.354	Akaike info criterion		19.95807

Step 3: T*R^2 is calculated.

H_0: There is no ARCH effect present

H_1: There exists an ARCH effect.

T=1836 R^2 =0.067959

T*$R^2 = 124.77 \sim x^2(1)$

$x^2(1) = 3.871$ at 5% level of significance.

Since T*$R^2 = 124.77 \gg 3.871$ H_0 is rejected at 5 % level. Therefore, the returns series of the ASPI (2009 May-2016) exists an ARCH effect.

5.2.3 Test for asymmetry in volatility clustering:

The value of the denominator of the formula 3.9 is calculated.

1st order autocorrelation coefficient between lag returns and current squared returns,

$$\nu = \sum_{t=2}^{T} r_t^2 r_{t-1} = -13054788.89$$

Since $\nu = \sum_{t=2}^{T} r_t^2 r_{t-1}$ has taken negative value, formula is a negative quantity here.

Corresponding Box-Pierce LM test is significant at 5% level. there exists asymmetric volatility clusters in the return series of the ASPI(2009 May-2016) .

The asymmetric of the volatility is happened when volatility increases more when the stock prices were falling than when it was rising by the same amount. Asymmetric Volatility series can be modeled using asymmetric GARCH models such as EGARCH.

5.2.4 GARCH model for the ASPI (2009 May-2016)

As described in the Chapter 4, returns series of the ASPI is not normally distributed. In addition Skewness and Kurtosis values also indicates that the deviation of the returns from the normal distribution. Thus, when fitting a GARCH model it is required to assume the error distribution away from the normal distribution. Also, Q-Q Plot of the Returns of ASPI evidently violates the normality.

EGARCH (2, 2) Model

Table 5.6 : Parameter Estimation of the EGARCH(2,2) Model

	Coefficient	Std. Error	z-Statistic	Prob.
Mean equation				
θ	0.236866	0.024031	9.856887	0.0000
Variance Equation				
ω	0.084382	0.089307	0.944853	0.0000
α_1	0.408360	0.062047	6.581509	0.0000
α_2	-0.152929	0.195887	-0.780700	0.0000
β_1	0.032850	0.027058	-1.214049	0.0000
β_2	1.149086	0.553858	2.074693	0.0000
γ	-0.186402	0.525933	-0.354422	0.0032
T-Distribution. DOF	5.364308	0.763544	7.025543	0.0000

According to the Table 5.5 all coefficients of the EGARCH (2, 2) model are significant at 5% level. The mean and variance equations of the fitted model can be represented as follows.

The Mean Equation

$r_t = C + \theta r_{t-1} + \varepsilon_t$

$r_t = 0.24 r_{t-1}$

The Variance Equation

$$\log(\sigma_t^2) = \omega + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha_2 \left|\frac{\varepsilon_{t-2}}{\sigma_{t-2}}\right| + \beta_1 log(\sigma_{t-1}^2) + \beta_2 log(\sigma_{t-2}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

$$\log(\sigma_t^2) = 0.084 + 0.41 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - 0.15 \left|\frac{\varepsilon_{t-2}}{\sigma_{t-2}}\right| + 0.033 log(\sigma_{t-1}^2) + 1.15 log - 0.19 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

$\alpha_1, \beta_1 > 0$

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative.

Here, also we see that the relatively small degrees of freedom parameter for the *t*-distribution (5.36) suggests that the distribution of the standardized errors departs significantly from normality.

Diagnostic checking

Heteroskedasticity Test (ARCH-LM test)

Table 5.7 : Heteroskedasticity Test for EGARCH (2,2) model

F-statistic	0.004944	Prob. F(1,1831)	0.9439
Observed R-squared	0.004950	Prob. Chi-Square(1)	0.9439

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Standard ε_{t-1}^2	-0.001643	0.023362	-0.070316	0.9439

According to the results of above Table 5.6, both test statistics (F statistic & observed R-squared) do not reject the null hypothesis that standardized residuals do not exhibit additional ARCH effect. Hence there is no heteroscedasticity in the standardized residuals of the fitted model.

The correlogram of the squared residuals

Table 5.8 : The correlogram of standardized residuals

Lag Value	AC	PAC	Q-Stat	Prob*
1	-0.002	-0.002	0.0050	0.944
2	0.012	0.012	0.2651	0.876
3	-0.007	-0.007	0.3620	0.948
4	-0.009	-0.009	0.5124	0.972
5	-0.012	-0.012	0.7916	0.978
6	0.006	0.006	0.8616	0.990
7	0.001	0.001	0.8622	0.997
8	0.001	0.000	0.8630	0.999
9	0.025	0.025	1.9846	0.992
10	-0.024	-0.024	3.0572	0.980
11	-0.001	-0.002	3.0606	0.990
12	0.028	0.028	4.4597	0.974
13	0.006	0.007	4.5331	0.984
14	0.036	0.035	6.8760	0.939
15	-0.046	-0.047	10.784	0.768
16	0.027	0.027	12.110	0.736
17	0.047	0.049	16.144	0.514
18	-0.021	-0.022	16.928	0.528
19	-0.020	-0.020	17.663	0.545
20	-0.019	-0.020	18.342	0.565
21	0.018	0.019	18.967	0.587
22	0.003	0.005	18.988	0.646
23	-0.034	-0.038	21.105	0.575
24	-0.029	-0.027	22.690	0.538
25	0.025	0.023	23.875	0.527
26	0.008	0.007	24.006	0.576
27	0.002	0.005	24.011	0.630
28	-0.017	-0.021	24.563	0.652
29	-0.025	-0.025	25.757	0.638
30	-0.000	-0.003	25.757	0.687
31	0.032	0.034	27.667	0.638
32	-0.029	-0.022	29.250	0.606
33	0.031	0.025	31.079	0.563
34	0.007	0.003	31.177	0.607
35	-0.007	-0.004	31.265	0.649
36	0.037	0.045	33.831	0.572

The correlogram of standardized residuals are shown in Table 5.7. Q statistics values of lag 1 to 36 are highly insignificant, hence selected variance equation is adequate to describe the error variance of the mean equation.

Q-Q plot:

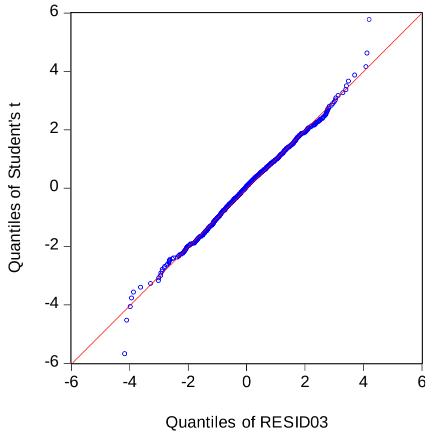

Figure 5.7 : Q-Q plot of the EGARCH (2, 2) model

The Q-Q plot depicts that apart from few large and small residuals most of the points are laid in the straight line. Therefore assumptions made for the error distribution is validated.

Actual and fitted volatility

Since the actual volatility is unobservable, the squared return series will be used as a proxy for the realized volatility. A plot of the proxy against the fitted volatility provides an indication of the models ability to track variations in ASPI(2009 May-2016).

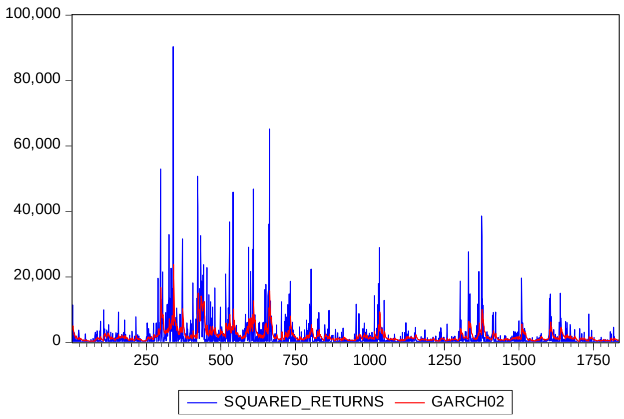

Figure 5.8: Actual & fitted volatility in return series of the ASPI

According to the Figure 5.8, the fitted volatilities have captured the patterns of the squared return series. Thus this model can be used to forecast the volatilities of the ASPI. Further it can be observed that estimated variance of the series fluctuated in the range 0- 20,000.

5.3 Modeling sector-wise daily price indices

This study also focuses on discussing the market performances of three sector price indices. Those are as follows.

1. Banking Finance & Insurance (BFI)
2. Construction & Engineering(CE)
3. Manufacturing(MFU)

These sectors are selected based on the GDP contribution of the sectors as mentioned in the annual reports of the central bank.

5.3.1 Banking Finance & Insurance (BFI) sector price index (2000-2016)

Identifying the stationarity of the BFI Series

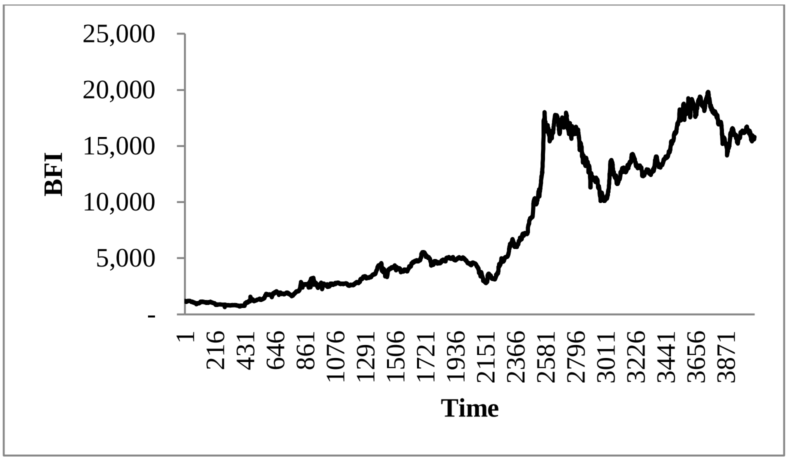

Figure 5.9 : Time Series plot of the Daily BFI

As depicts in Figure 5.9, there is a positive trend of the BFI series over the period 2000-2016. However BFI sector price index has been fall noticeably in some time intervals. Thus variance of the series seems to be non-constant.

Log transformed series of the BFI has used to inspect the variance stability.

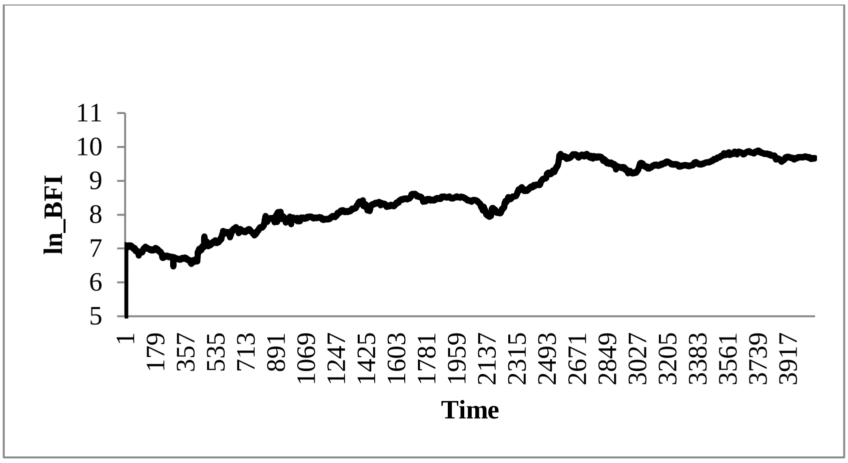

Figure 5.10 : Log Transformed series of the BFI

According to the Figure 5.10, log transformed series shows very little fluctuation patterns when compared with Figure 5.9. 1st difference series of the BFI is obtained for more assessment.

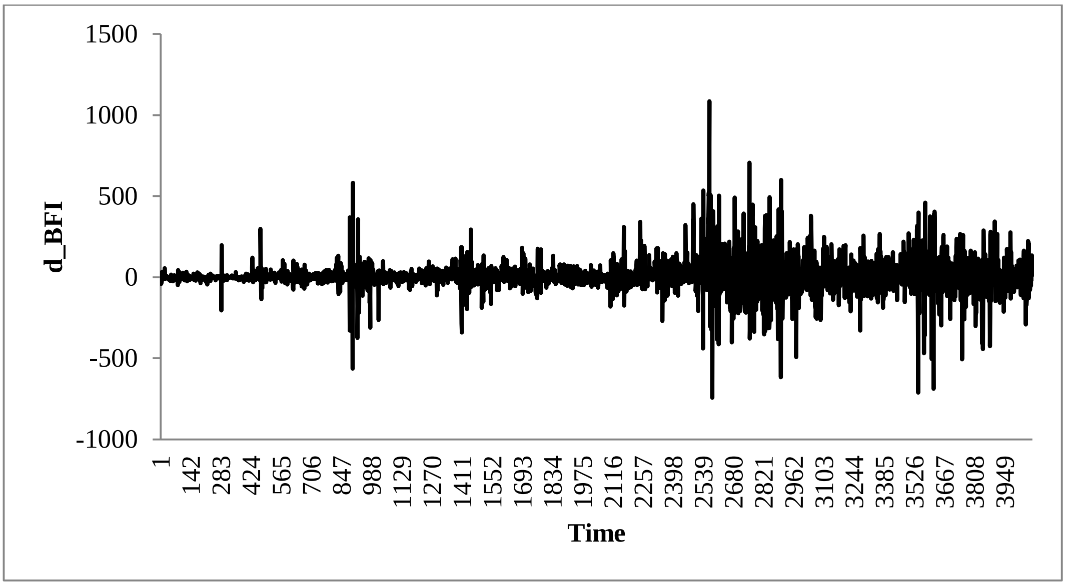

Figure 5.11 : Returns series of the BFI

According to the Figure 5.11, the variance of the series seems to be irregular with time. In some time periods returns of BFI has increased significantly while in other periods returns takes small values. Hence it can be suspected that returns series of the BFI exists volatility clusters.

Existence of the volatility clusters and nature of the volatility (Symmetric or Asymmetric) were examined using appropriate statistical tests.

Test for existing of volatility clusters in returns series of the BFI

Box-pierce LM Test:

The value of the formula 3.7 is calculated.

$\sum_{t=2}^{T} r_t^2 r_{t-1}^2$ = 1908570173059.71

$\sum_{t=2}^{T} r_t^4$ = 5678145584069.82

1st order autocorrelation coefficient of squared return series = $\frac{\sum_{t=2}^{T} r_t^2 r_{t-1}^2}{\sum_{t=2}^{T} r_t^4}$ = 0.336126

T=4075, χ^2=3.871

Test statistic = Q =0.336126×4075=1369.712

Box-pierce Q =1369.712 > χ^2 =3.871 H_0 is rejected and conclude that there exist volatility clustering in the return series of the BFI at 5% level.

Since this test is not very robust one, Test for an ARCH effect is also performed.

Test for an ARCH effect

Step1: The regression of the returns series is run with intercept using Ordinary Least Squares (OLS) method and residuals series is obtained.

Step2: Squared residuals are calculated. The following regression is run for the residuals series.

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + v_t$$

Where u is the residual from the initial regression and 1 lag term is included in this secondary regression.

Table 5.9 : Results of the secondary regression run for the squared residuals

Method: Least Squares				
Included observations: 4074 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.

Squared Residuals	0.293842	0.014979	19.61664	0.0000
C	6371.148	558.0870	11.41605	0.0000
R-squared	0.086343	Mean dependent var		9022.471
Adjusted R-squared	0.086118	S.D. dependent var		36152.88
S.E. of regression	34561.13	Akaike info criterion		23.73934

Step3:T*R^2 is calculated.

H_0: There is no ARCH effect present

H_1: There exists an ARCH effect.

T=4074 R^2 =0.086343

T*$R^2 = 351.761 \sim x^2(1)$

$x^2(1) = 3.871$ at 5% level of significance.

Since T*$R^2 = 351.761 \gg 3.871$ H_0 is rejected at 5 % level. Therefore the returns series of the BFI exists an ARCH effect.

Test for asymmetry in volatility clustering:

The value of the denominator of the formula 3.9 is calculated.

1st order autocorrelation coefficient between lag returns and current squared returns,

ν $= \sum_{t=2}^{T} r_t^2 r_{t-1}$ = 531536718.69

Since ν = $\sum_{t=2}^{T} r_t^2 r_{t-1}$ has taken positive value, formula 3.9 is a positive quantity.

Also, corresponding Box-Pierce LM test is significant at 5% level. Thus as the test described in Chapter 3, there is no asymmetric volatility clusters in the return series of the BFI.

GARCH model for the BFI

As described in Chapter 4, returns series of the BFI is not normally distributed. Skewness and Kurtosis values also indicates that the deviation of the returns from the normal distribution. Therefore, when fitting a GARCH model for the BFI returns it is required to assume the error distribution away from the normal distribution.

GARCH (1, 2) Model

Table 5.10 : Parameter Estimation of the GARCH(1,2) Model

	Coefficient	Std. Error	z-Statistic	Prob.
Mean equation				
θ	0.190849	0.015757	12.11176	0.0000
Variance Equation				
α_0	8.035175	2.657596	3.023475	0.0025
α	0.457763	0.060940	7.511734	0.0000
β_1	0.539784	0.116528	4.632241	0.0000
β_2	0.192801	0.095205	2.025116	0.0029
T-Distribution. DOF	3.091726	0.162197	19.06159	0.0000

According to the Table 5.10, all the coefficients of the GARCH(1,2) model are significant at 5 % level. The mean and variance equations of the fitted model can be written as follows.

The Mean Equation

$r_t = C + \theta r_{t-1} + \varepsilon_t$

$r_t = 0.19 r_{t-1}$

The Variance Equation

$\sigma_t^2 = a_0 + \alpha\varepsilon_{t-1}^2 + b\sigma_{t-1}^2$

$\sigma_t^2 = 8.04 + 0.46\varepsilon_{t-1}^2 + 0.54\sigma_{t-1}^2 + 0.19\sigma_{t-2}^2$

$a_0 > 0 \ and \ \alpha, \beta_1, \beta_2 > 0$

Here, also we see that the relatively small degrees of freedom parameter for the *t*-distribution (3.09) suggests that the distribution of the standardized errors departs significantly from normality.

Diagnostic checking

Heteroskedasticity Test (ARCH-LM test)

Table 5.11 : Heteroskedasticity Test for GARCH (1,2) model

F-statistic	0.006883	Prob. F(1,4071)		0.9339
Observed R-squared	0.006886	Prob. Chi-Square(1)		0.9339
Variable	Coefficient	Std. Error	t-Statistic	Prob.

Standard ε_{t-1}^2	0.001300	0.015673	0.082964	0.9339

According to the results of the Table 5.11, coefficient of the lag value of the squared standard error is insignificant. Thus errors do not depend on the lag values of the errors. F statistic and observed R-squared values are insignificant implies that standardized residuals do not exhibit additional ARCH effect. Hence there is no heteroscedasticity in the standardized residuals.

The correlogram of the squared residuals

Table 5.12 : The correlogram of standardized residuals

Lag	AC	PAC	Q-Stat	Prob*
1	0.001	0.001	0.0069	0.934
2	-0.002	-0.002	0.0284	0.986
3	-0.002	-0.002	0.0471	0.997
4	-0.004	-0.004	0.1031	0.999
5	-0.004	-0.004	0.1567	1.000
6	-0.003	-0.003	0.2019	1.000
7	-0.000	-0.000	0.2026	1.000
8	-0.004	-0.004	0.2591	1.000
9	-0.004	-0.004	0.3214	1.000
10	-0.004	-0.004	0.3860	1.000
11	-0.003	-0.003	0.4323	1.000
12	-0.004	-0.004	0.4928	1.000
13	-0.002	-0.002	0.5036	1.000
14	0.013	0.013	1.1851	1.000
15	-0.002	-0.002	1.2013	1.000
16	-0.002	-0.002	1.2193	1.000
17	-0.002	-0.002	1.2358	1.000
18	-0.004	-0.004	1.2899	1.000
19	-0.004	-0.004	1.3498	1.000
20	-0.003	-0.003	1.3984	1.000
21	-0.002	-0.002	1.4205	1.000
22	-0.003	-0.003	1.4544	1.000
23	-0.003	-0.003	1.4844	1.000
24	-0.003	-0.004	1.5338	1.000
25	-0.002	-0.002	1.5517	1.000
26	-0.002	-0.002	1.5693	1.000
27	-0.001	-0.001	1.5710	1.000
28	0.007	0.006	1.7521	1.000
29	-0.004	-0.004	1.8165	1.000
30	-0.003	-0.003	1.8443	1.000

31	-0.003	-0.003	1.8844	1.000
32	-0.004	-0.004	1.9408	1.000
33	-0.003	-0.003	1.9897	1.000
34	-0.003	-0.003	2.0306	1.000
35	-0.001	-0.001	2.0374	1.000
36	-0.000	-0.000	2.0375	1.000

The correlogram of standardized residuals of the GARCH(1,2) model are shown in Table 5.12. Q-statistics values of the correlogram of the squared residuals are greater than to 0.05 for lag 1 to 36 at 5% level. Thus ACF and PACF values of the squared residuals are insignificant up to lag 36 illustrated that chosen variance equation can be used to describe the error variance of the mean equation.

Q-Q plot:

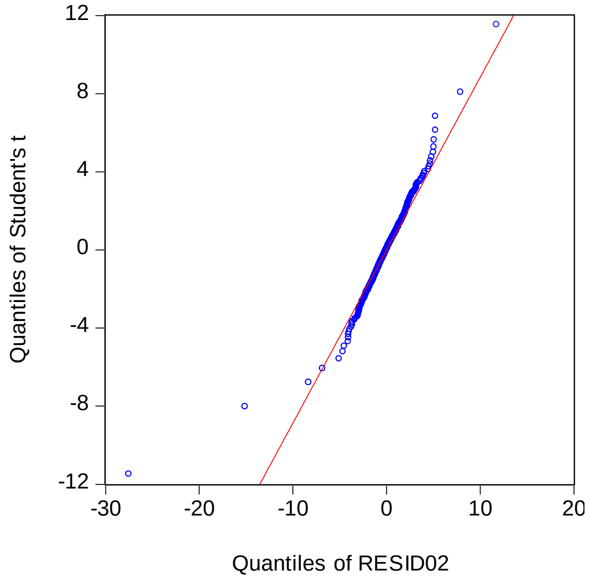

Figure 5.12 : Q-Q plot of the GARCH (1, 2) model

The Figure 5.12 depicts the Q-Q plot which has drawn with the assumption of the residuals follows t-distribution. Accordingly, apart from few large and small outliers data points residuals lie nearly in a straight line prove that error distribution has been correctly specified.

Actual and fitted volatility

Since the actual volatility is unobservable, the squared return series will be used as a proxy for the realized volatility. A plot of the proxy against the fitted volatility provides an indication of the models ability to track variations in BFI.

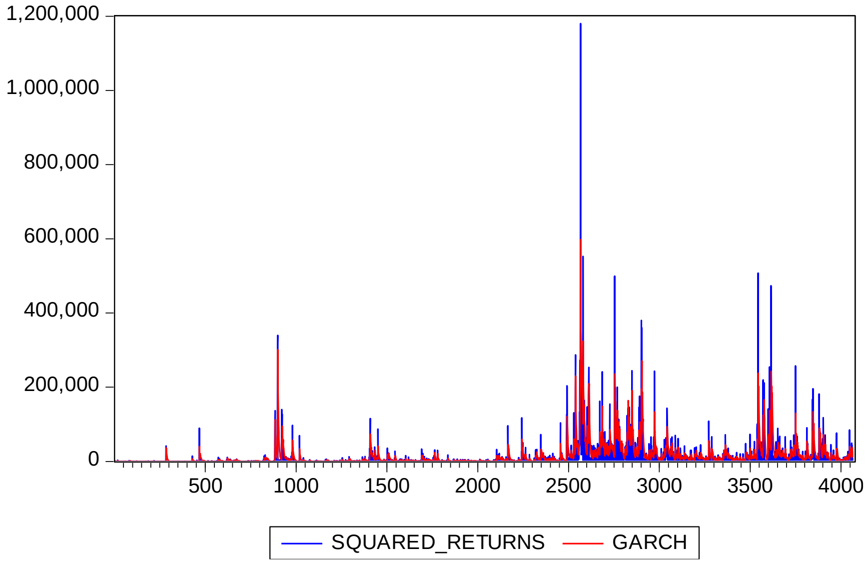

Figure 5.13 : Actual & fitted volatility in return series of the BFI

According to the Figure 5.13, the fitted volatilities have captured the patterns of the squared return series. Thus this model can be used to forecast the volatilities of the BFI.

5.3.2 Construction & Engineering (CE) Sector Price Index (2000-2016)

Identifying the Stationarity of the CE Series

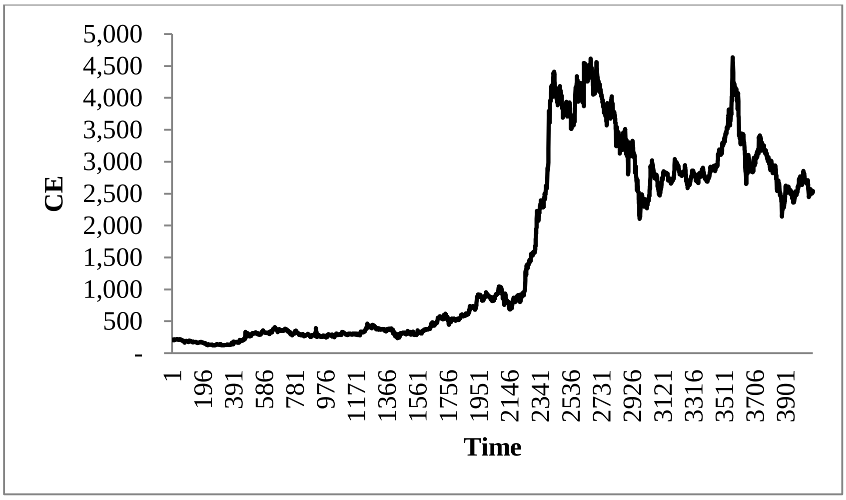

Figure 5.14 : Time Series plot of the daily CE

The Figure 5.14 shows the time series plot of the daily price index of the Construction & Engineering (CE) sector over the period (200-2016). The series consists a positive trend when considering initial and final data points. However there can be seen many sudden increments and decrements of the price index during the considered period. Thus variance of the CE price index series seems to be non-constant.

Log transformed series of the CE sector index has been obtained to inspect the variance stability.

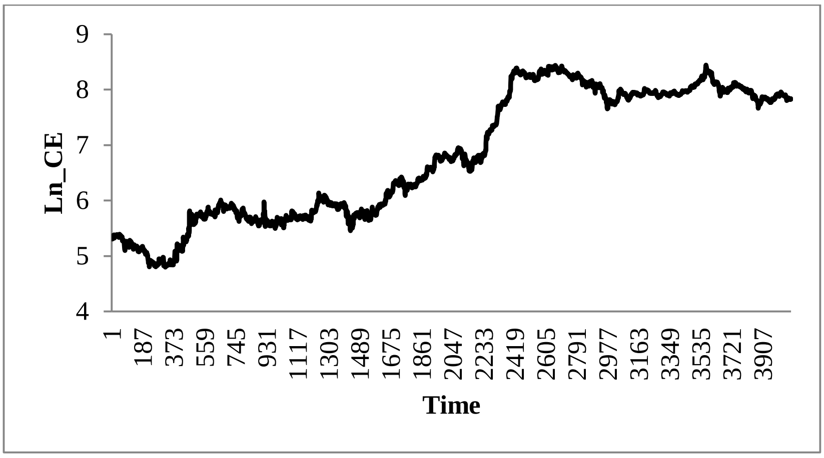

Figure 5.15 : Log Transformed series of the CE

According to the Figure 5.15, log transformed series of the CE index also depicts little fluctuation patterns. Severe fluctuations patterns had observed in original series have been removed. However, very slight fluctuation patterns can be seen. 1st difference series of the CE index series is obtained for more assessment.

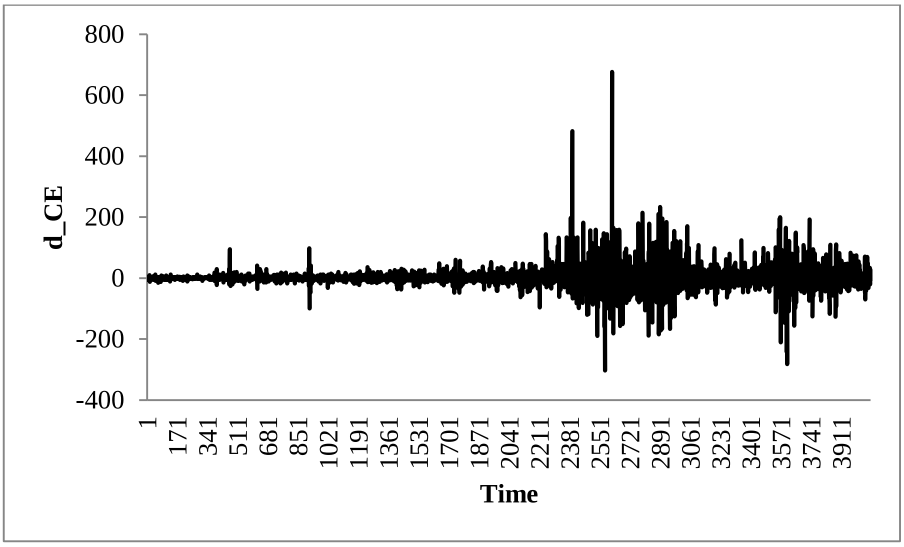

Figure 5.16 : Returns series of the CE

According to the Figure 5.16, it can be seen that variance of the returns of CE index has been changed over the time. In first half of the plot, returns of CE seems to be remain constant while in last part of the considered period returns values has been fluctuated noticeably. Thus it can be supposed that returns series of the CE exist volatility clusters.

Existence of the volatility clusters and the symmetricity of the volatility clusters were examined using appropriate statistical tests.

Test for existing of volatility clusters in returns series of the BFI

Box-pierce LM Test:

The value of the formula 3.7 is calculated.

$\sum_{t=2}^{T} r_t^2 r_{t-1}^2$ = 34629136717.14

$\sum_{t=2}^{T} r_t^4$ = 345855727354.48

1st order autocorrelation coefficient of squared return series= $\frac{\sum_{t=2}^{T} r_t^2 r_{t-1}^2}{\sum_{t=2}^{T} r_t^4}$ = 0.100126

T=4075, χ^2 = 3.871

Test statistic= Q =0.100126×4075=408.01

Since Q = 408.01 > χ^2 = 3.871 we reject H_0 and conclude that there exist volatility clustering in the return series of the CE price index at 5% level.

Since this test is not very robust one, Test for an ARCH effect method is also performed.

Test for an ARCH effect

Step1: The regression of the returns series is run with intercept using Ordinary Least Squares (OLS) and residuals are obtained.

Step2: Squared residuals are calculated. The following regression is run for the residuals series.

$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + v_t$

Where u is the residual from the initial regression and lag 1 term is included in this secondary regression.

Table 5.13 : Results of the secondary regression run for the squared residuals

Method: Least Squares				
Included observations: 4074 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Squared Residuals	0.081066	0.015619	5.190075	0.0000
C	1213.273	143.6860	8.443916	0.0000
R-squared	0.006572	Mean dependent var		1320.289
Adjusted R-squared	0.006328	S.D. dependent var		9105.106
S.E. of regression	9076.253	Akaike info criterion		21.06520

Step 3 :T*R^2 is calculated.

H_0: There is no ARCH effect present

H_1: There exists an ARCH effect.

T= 4074 $R^2 = 0.006572$

T*$R^2 = 26.77 \sim x^2(1)$

$x^2(1) = 3.871$ at 5% level of significance.

Since T*$R^2 = 26.77 \gg 3.871$ H_0 is rejected at 5 % level. Therefore the returns series of the CE exists an ARCH effect.

Test for asymmetry in volatility clustering:

The value of the denominator of the formula 3.9 is calculated.

1st order autocorrelation coefficient between lag returns and current squared returns,

ν = $\sum_{t=2}^{T} r_t^2 r_{t-1}$ = 69387170.07

Since ν = $\sum_{t=2}^{T} r_t^2 r_{t-1}$ has taken positive value, formula 3.9 is a positive quantity.

Also corresponding Box-Pierce LM test is significant at 5% level. Thus as the test described in Chapter 3, there is no asymmetric volatility clusters in the return series of the CE.

GARCH model for the CE

According to the Chapter 4, returns series of the CE is not normally distributed. In addition Skewness and Kurtosis values also indicates that the deviation of the returns from the normal distribution. Hence error distribution of the model requires to be assumed away from the normal distribution.

GARCH (1, 2) Model

Table 5.14 : Parameter Estimation of the GARCH(1,2) Model

	Coefficient	Std. Error	z-Statistic	Prob.
Mean equation				
c	0.230413	0.104299	2.209152	0.0272
Variance Equation				
α_0	0.979106	0.109862	8.912133	0.0000
α	0.220424	0.009442	23.34481	0.0000
β_1	0.439019	0.047024	9.336059	0.0000
β_2	0.388682	0.041251	9.422279	0.0000

As depicts in Table 5.14, all the coefficients of the GARCH(1,2) model significant at 5 % level. The mean and variance equations of the fitted model are represented as follows.

The Mean Equation

$$r_t = C + \theta r_{t-1} + \varepsilon_t$$

$$r_t = 0.23$$

The Variance Equation

$$\sigma_t^2 = a_0 + \alpha\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \beta_2\sigma_{t-2}^2$$

$$\sigma_t^2 = 0.98 + 0.22\varepsilon_{t-1}^2 + 0.44\sigma_{t-1}^2 + 0.39\sigma_{t-2}^2$$

$$a_0 > 0 \ \ and \alpha, \beta_1, \beta_2 > 0$$

Diagnostic checking

Heteroskedasticity Test (ARCH-LM test)

Table 5.15 : Heteroskedasticity Test for GARCH (1,2) model

F-statistic	0.012459	Prob. F(1,4071)	0.9111
Observed R-squared	0.012466	Prob. Chi-Square(1)	0.9111

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Standard ε_{t-1}^2	-0.001749	0.015671	-0.111622	0.9111

According to the results of the Table 5.15, coefficient of the lag value of the squared standard error is insignificant. Thus errors do not depend on the lag values of the errors. Both test statistics (F statistic & observed R-squared) do not reject the null hypothesis that standardized residuals exhibit additional ARCH effect. Hence there is no heteroscedasticity in the standardized residuals.

The correlogram of the squared residuals

Table 5.16: The correlogram of standardized residuals

Lag	AC	PAC	Q-Stat	Prob*
1	-0.002	-0.002	0.0125	0.911
2	0.005	0.005	0.1274	0.938
3	-0.002	-0.002	0.1520	0.985
4	0.035	0.035	5.0675	0.280
5	-0.006	-0.006	5.2394	0.387
6	-0.011	-0.011	5.6975	0.458
7	-0.004	-0.004	5.7721	0.567
8	-0.004	-0.005	5.8267	0.667
9	-0.010	-0.010	6.2630	0.713
10	-0.016	-0.016	7.3519	0.692
11	-0.012	-0.012	7.9905	0.714
12	-0.016	-0.016	9.0119	0.702
13	-0.005	-0.005	9.1348	0.763
14	-0.015	-0.014	10.057	0.758
15	-0.021	-0.020	11.811	0.693
16	-0.012	-0.011	12.385	0.717
17	-0.025	-0.025	14.972	0.598
18	-0.007	-0.007	15.199	0.648
19	-0.025	-0.024	17.698	0.543
20	-0.014	-0.015	18.469	0.557
21	-0.015	-0.015	19.388	0.560
22	-0.015	-0.017	20.321	0.563

23	-0.018	-0.018	21.585	0.545
24	0.016	0.015	22.690	0.538
25	-0.021	-0.023	24.558	0.487
26	-0.006	-0.008	24.710	0.535
27	-0.018	-0.020	26.089	0.514
28	0.001	-0.004	26.091	0.568
29	0.002	-0.000	26.103	0.620
30	-0.019	-0.022	27.646	0.589
31	-0.003	-0.006	27.684	0.637
32	-0.002	-0.006	27.707	0.684
33	-0.012	-0.016	28.298	0.700
34	-0.012	-0.014	28.857	0.718
35	0.072	0.069	50.053	0.058
36	-0.006	-0.010	50.203	0.058

The correlogram of standardized residuals of the GARCH(1,2) model are shown in Table 5.16. Q-statistics values of the correlogram of the squared residuals are insignificance up to lag 36 at 5% level. These results prove that the chosen variance equation is highly accepted to describe the error variance of the mean equation.

Q-Q plot:

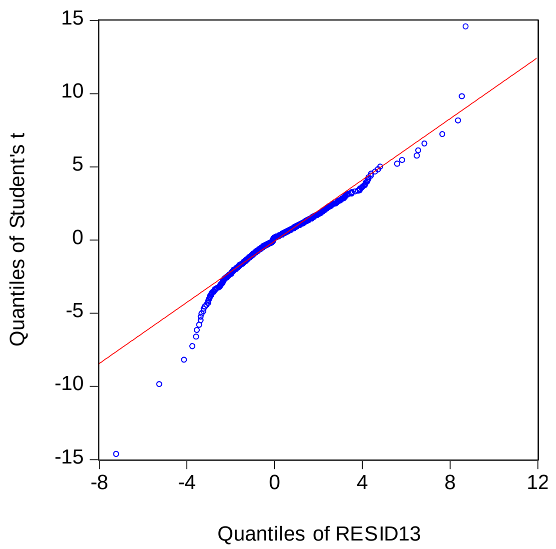

Figure 5.17 : Q-Q plot of the GARCH (1, 2) model

The Figure 5.17 depicts the Q-Q plot which has drawn with the assumption of the residuals follows t-distribution. Since the Q-Q plot form a straight line, error distribution has correctly specified.

Actual and fitted volatility

Since the actual volatility is unobservable, the squared return series will be used as a proxy for the realized volatility. A plot of the proxy against the fitted volatility provides an indication of the models ability to track variations in CE price index.

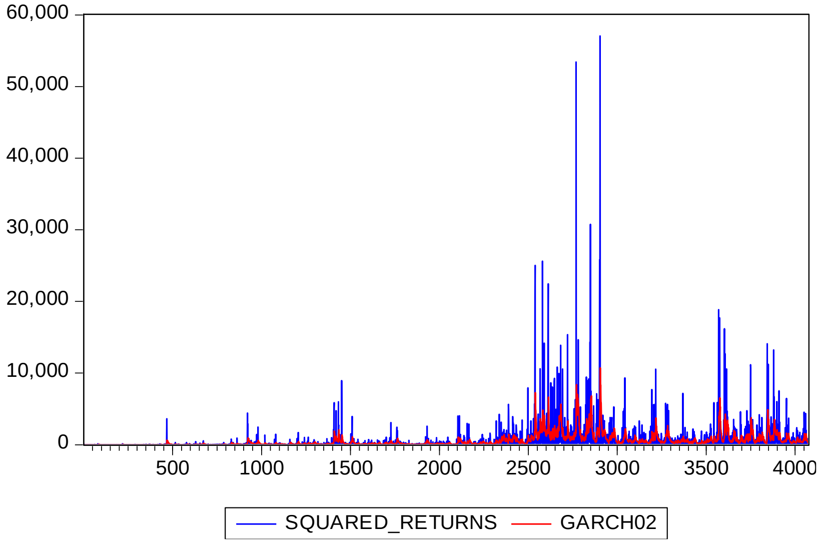

Figure 5.18 : Actual & fitted volatility in return series of the CE

As shown in Figure 5.18, fitted volatilities have captured the patterns of the squared return series. Thus this model can be used to forecast the volatilities of the MFU price index.

5.3.3 Manufacturing (MFU) Sector Price Index (2000-2016)

Identifying the stationarity of the MFU Series

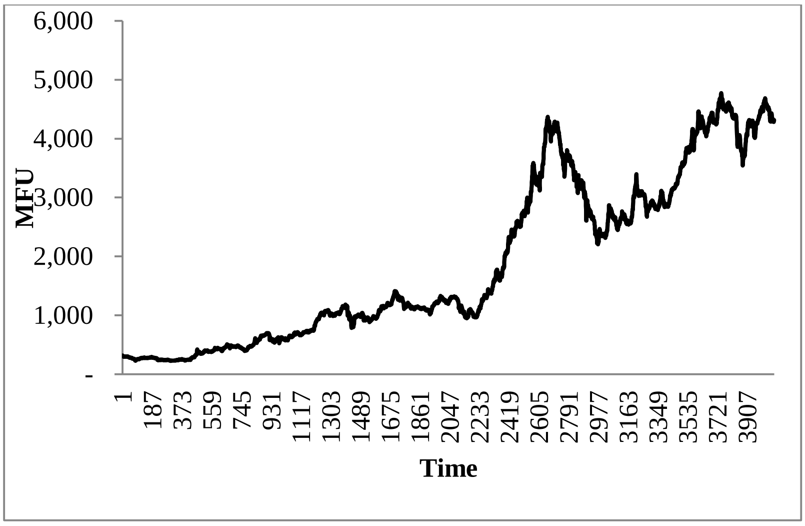

Figure 5.19 : Time Series plot of the daily MFU

The Figure 5.19 depicts the time series plot of the daily price index of the Manufacturing (MFU) sector over the period (2000-2016). According to this plot, it can be seen a clear trend with slight variation patterns over the first half time period (2000-2008), while noticeable up and down fluctuations thereafter.

Log transformed series of the MFU sector index has been obtained to inspect the variance stability.

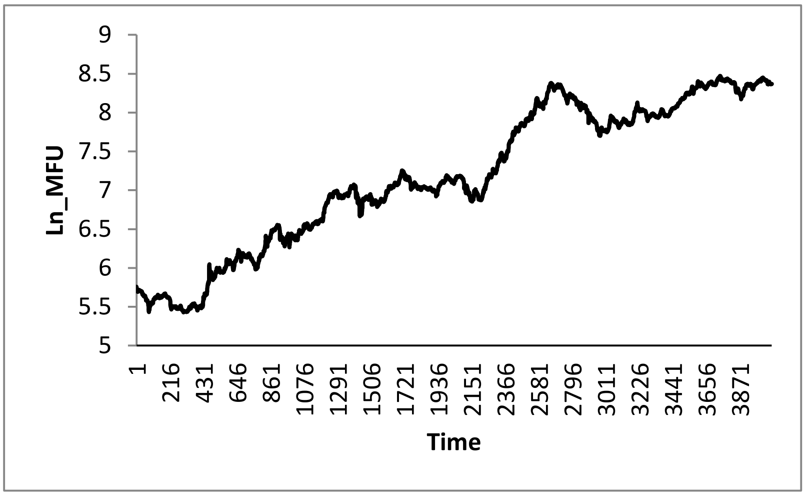

Figure 5.20 : Log Transformed series of the MFU

As shown in the Figure 5.20, log transformed series of the MFU index consists many variation patterns. However, huge fluctuation patterns had observed in original series has been removed. 1st difference series of the MFU index series obtained for more evaluation.

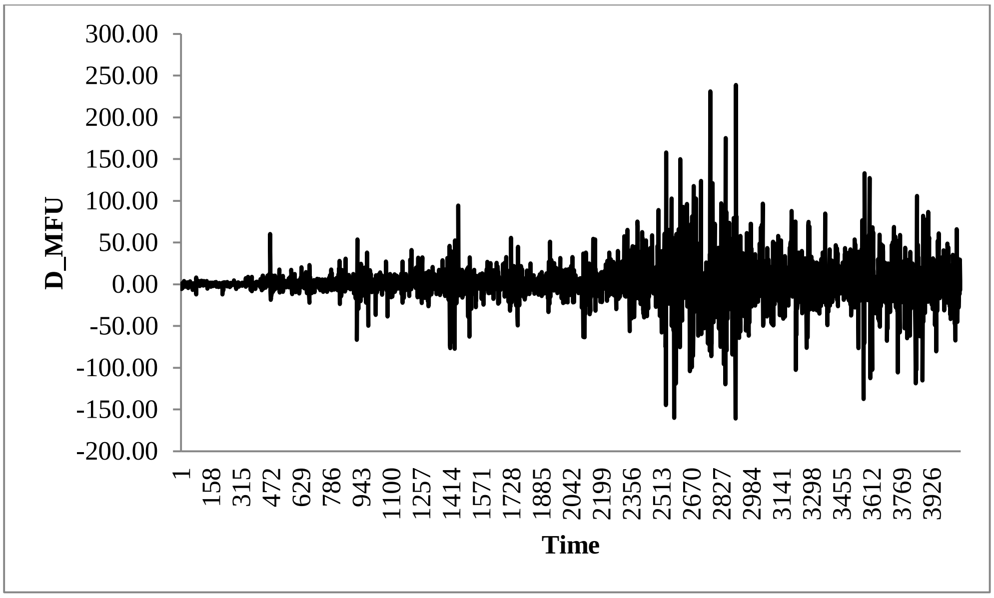

Figure 5.21 : Returns series of the MFU

Time series plot of the returns of the MFU index has visibly depicted that variance of the series change over the time. In first half time period, returns of MFU series seems to be vary in small range (between -100 and 100) while in last part of the considered period returns values fluctuated extremely with higher variation. Thus it can be supposed that returns series of the MFU index exists volatility clusters.

Existence of the volatility clusters and nature of the volatility (Symmetric or Asymmetric) were examined using appropriate statistical tests.

Test for existing of volatility clusters in returns series of the MFU

Box-pierce LM Test:

The value of the formula 3.7 is calculated.

$\sum_{t=2}^{T} r_t^2 r_{t-1}^2$ = 4762149296.80

$\sum_{t=2}^{T} r_t^4$ =19030729690.64

1st order autocorrelation coefficient of squared return series= $\frac{\sum_{t=2}^{T} r_t^2 r_{t-1}^2}{\sum_{t=2}^{T} r_t^4}$ = 0.250235

T=4075, χ^2 = 3.871

Test statistic= Q =0.250235×4075=1019.71

Since Q=1019.71 > χ^2 = 3.871 we reject H_0 and conclude that there exist volatility clustering in the return series of the CE price index at 5% level.

Since this test is not very robust one, Test for an ARCH effect method is also performed.

Test for an ARCH effect

Step1: The regression of the returns series is run with intercept using Ordinary Least Squares (OLS) and residuals are obtained.

Step2: Squared residuals are calculated. The following regression is run for the residuals series.

$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + v_t$

Where u is the residual from the initial regression and lag 1 term is included in this secondary regression.

Table 5.17 : Results of the secondary regression run for the squared residuals

Method: Least Squares				
Included observations: 4074 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Squared Residuals	0.199386	0.015356	12.98400	0.0000
C	441.6462	33.07571	13.35258	0.0000
R-squared	0.039755	Mean dependent var		551.6324
Adjusted R-squared	0.039519	S.D. dependent var		2082.303
S.E. of regression	2040.743	Akaike info criterion		18.08051

Step3:T*R^2 is calculated.

H_0: There is no ARCH effect in returns of the MFU

H_1: There exists an ARCH effect in returns of the MFU

T=4074 R^2 =0.039755

T*$R^2 = 161.96 \sim x^2(1)$

$x^2(1) = 3.871$ at 5% level of significance.

Since T*$R^2 = 161.96 \gg 3.871$ H_0 is rejected at 5 % level. Therefore the returns series of the MFU exists an ARCH effect.

Test for asymmetry in volatility clustering:

The value of the denominator of the formula 3.9 is calculated.

1st order autocorrelation coefficient between lag returns and current squared returns,

$\nu = \sum_{t=2}^{T} r_t^2 r_{t-1}$ = -1692527

Since $\nu = \sum_{t=2}^{T} r_t^2 r_{t-1}$ has taken negative value, formula 3.9 is a negative quantity.

As explained in earlier, corresponding Box-Pierce LM test is significant at 5% level. Accordingly, there exist asymmetric volatility clusters in the return series of the MFU index.

The Asymmetric of the volatility is happened when volatility increases more when the stock prices were falling than when it was rising by the same amount. Asymmetric Volatility series can be modeled using asymmetric GARCH models such as EGARCH.

GARCH model for the MFU

As described in Chapter 4, returns series of the MFU is not normally distributed. Skewness and Kurtosis values also indicates that the deviation of the returns from the normal distribution. Therefore Error Distribution is require to be assumed away from the Normal Distribution.

EGARCH (2, 2) Model

Table 5.18 : Parameter Estimation of the EGARCH(2,2) Model

	Coefficient	Std. Error	z-Statistic	Prob.
Mean equation				
θ	0.150268	0.001696	88.58649	0.0000
Variance Equation				
ω	-0.415210	0.018435	-22.52261	0.0000
α_1	0.358674	0.010001	35.86218	0.0000
α_2	0.336556	0.011852	28.39706	0.0000
β_1	-0.008586	0.001898	-4.523691	0.0000
β_2	0.986896	0.001398	705.7737	0.0000
γ	-0.005913	0.000788	-7.500764	0.0000

As depicts in Table 5.18, all the coefficients of the EGARCH(2,2) model significant at 5 % level. The mean and variance equations of the fitted model are represented as follows.

The Mean Equation

$$r_t = C + \theta r_{t-1} + \varepsilon_t$$

$$r_t = 0.15 r_{t-1}$$

The Variance Equation

$$\log(\sigma_t^2) = \omega + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha_2 \left|\frac{\varepsilon_{t-2}}{\sigma_{t-2}}\right| + \beta_1 log(\sigma_{t-1}^2) + +\beta_2 log(\sigma_{t-2}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

$$\log(\sigma_t^2) = -0.41 + 0.36 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.34 \left|\frac{\varepsilon_{t-2}}{\sigma_{t-2}}\right| - 0.001 log(\sigma_{t-1}^2) + 0.99 log(\sigma_{t-2}^2) - 0.006 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

$\alpha_1, \beta_1 > 0$

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative.

Diagnostic checking

Heteroskedasticity Test (ARCH-LM test)

Table 5.19 : Heteroskedasticity Test for EGARCH (2,2) model

F-statistic	0.993561	Prob. F(1,4071)		0.3189
Observed R-squared	0.993806	Prob. Chi-Square(1)		0.3188
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Standard ε_{t-1}^2	0.015621	0.015671	0.996775	0.3189

According to the results of the Table 5.19, coefficient of the lag value of the squared standard error is insignificant. Thus errors do not depend on the lag values of the errors. Both test statistics (F statistic & observed R-squared) do not reject the null hypothesis that standardized residuals exhibit additional ARCH effect. Hence there is no heteroscedasticity in the standardized residuals.

The correlogram of the squared residuals

Table 5.20: The correlogram of standardized residuals

Lag	AC	PAC	Q-Stat	Prob*
1	0.016	0.016	0.9948	0.319
2	-0.025	-0.025	3.5077	0.173

3	-0.026	-0.025	6.3175	0.097
4	-0.014	-0.013	7.0651	0.132
5	0.007	0.006	7.2520	0.203
6	-0.018	-0.020	8.6309	0.195
7	0.018	0.018	9.9359	0.192
8	-0.023	-0.025	12.165	0.144
9	-0.011	-0.011	12.701	0.177
10	-0.019	-0.019	14.124	0.167
11	-0.001	-0.002	14.129	0.226
12	0.007	0.004	14.316	0.281
13	-0.003	-0.003	14.350	0.350
14	-0.021	-0.022	16.146	0.305
15	-0.008	-0.006	16.399	0.356
16	-0.020	-0.021	17.963	0.326
17	-0.017	-0.018	19.164	0.319
18	-0.020	-0.022	20.795	0.290
19	-0.016	-0.018	21.828	0.293
20	-0.003	-0.006	21.860	0.348
21	-0.020	-0.022	23.565	0.315
22	-0.018	-0.021	24.906	0.302
23	-0.012	-0.014	25.517	0.324
24	-0.024	-0.028	27.846	0.267
25	-0.006	-0.010	28.000	0.308
26	-0.008	-0.012	28.235	0.347
27	-0.001	-0.006	28.238	0.399
28	-0.022	-0.026	30.210	0.353
29	-0.025	-0.028	32.763	0.287
30	-0.004	-0.008	32.821	0.330
31	0.006	0.000	32.946	0.372
32	0.001	-0.007	32.947	0.421
33	-0.008	-0.013	33.244	0.455
34	-0.002	-0.006	33.257	0.504
35	-0.016	-0.021	34.347	0.499
36	-0.003	-0.008	34.391	0.545

The correlogram of standardized residuals of the EGARCH(2,2) model are shown in Table 5.20. Q-statistics values of the correlogram of the squared residuals are insignificance up to lag 36 at 5% level, implies that chosen variance equation can be accepted to describe the error variance of the mean equation.

Q-Q plot:

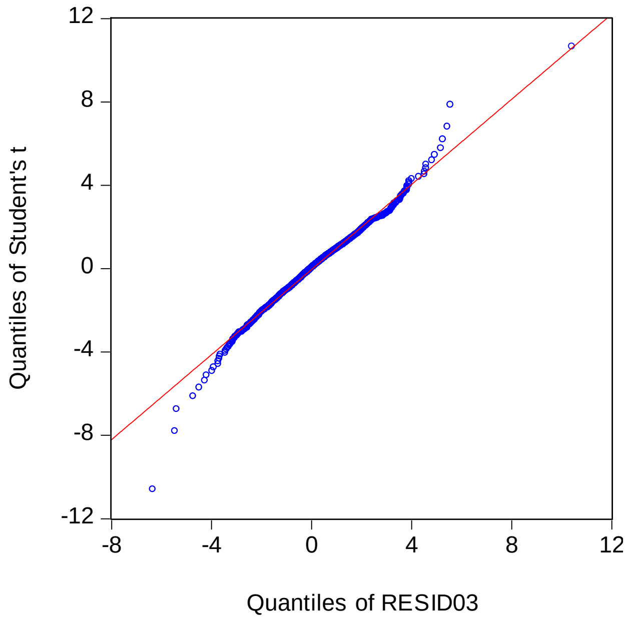

Figure 5.22 : Q-Q plot of the EGARCH (2, 2) model

The Figure 5.22 illustrates the Q-Q plot which has drawn with the assumption of the residuals follows t-distribution. As above plot, it can be seen that the residuals are much closed to the straight line. Thus the assumption made for the error distribution as t-distribution can be accepted.

Actual and fitted volatility

Since the actual volatility is unobservable, the squared return series will be used as a proxy for the realized volatility. A plot of the proxy against the fitted volatility provides an indication of the models ability to track variations in MFU price index.

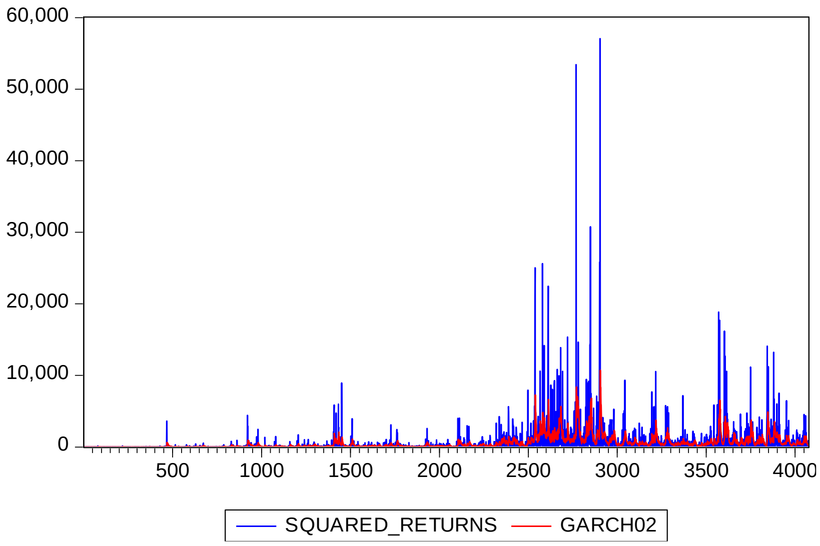

Figure 5.23 : Actual & fitted volatility in return series of the MFU

As shown in Figure 5.23, fitted volatilities have captured the patterns of the squared return series. Thus this model can be used to forecast the volatilities of the MFU price index.

CHAPTER 6: GENERAL DISCUSSION & CONCLUSION

This chapter explains on the whole discussion of the thesis, findings, limitation and the future suggestions and the conclusions to be taken.

6.1 General Discussion

6.1.1 Overview of the Study

This research is based on a statistical analysis of ASPI and sector wise stock price indices in Colombo Stock Exchange (CSE) during the period of 2000 to 2016. The main objective of this research was to build an appropriate model to estimate market volatility of All Share Price Index (ASPI). Under this main objective, volatility pattern of the stock indices investigated using symmetric and asymmetric models. Since there was a significant fall in the ASPI during the period of ending the war the data set was divided in to two main parts such as 2000-2009 May and 2009 May 2016. Two distinct models were built for that time periods, in order to identify the changers in the ASPI before and after the ending of the war. Apart from that, appropriate Generalized Autoregressive Conditional Heteroscedastic (GARCH) family models were built for three selected sector price indices.

In order to gain a fundamental idea of the monthly and daily stock market indices and other variables which can be affected on stock market indices, preliminary analysis was carried out in chapter 4. The preliminary analysis was based on monthly variation of three main market price indices, daily variation of All Share Total Returns Index (ASTRI), descriptive statistics of returns of the ASPI, monthly variation of market price indices of selected sectors and descriptive statistics of market price indices of selected sectors.

When considering ASPI, It can be clearly identify a positive trend over the time. However, it can be seen a significant fall in price indices corresponding to the 2008 and 2009 years. This decreasing pattern is corresponded to to the critical time period of the war had occurred in Sri Lanka. Further, ASPI has been improved considerably in 2009-2011 periods and the highest ASPI value had been recorded in February 2011. According to the time series plot of S&P SL 20 index, there cannot be clearly identified negative or positive trend over time. It can be seen a rapid growth during 2014. However S&P SL 20 index has been declined to 3200 in 2016 which was the lowest price had recorded yet 2016.

Analysis on Daily variation of All Share Total Returns Index (ASTRI) has shown that ASTRI has been increased steadily over the period 2004-2016. But It can be clearly identified a huge rise occurred suddenly, in 6th July 2010 apart from the regular increment. When comparing total market returns by ASPI and ASTRI, there is no difference in total market returns calculated for ASPI and ASTRI. Hence, for the rest of the study, the analysis was continued by using total market returns calculated by ASPI.

In view of descriptive statistics of returns of the ASPI, indicates that negative Skewness (-0.057585) implies series consist of more decrements than the increments. The Jarque-berra statistics of the return series are highly significance (Probability=0.00). It rejects the null hypothesis that returns series is normally distributed. Thus returns series of the ASPI is not normally distributed. Further Skewness and Kurtosis values also indicates that the deviation of the returns from the normal distribution. Therefore, when developing a GARCH model it is required to assume the error distribution away from the normal distribution. Moreover Q-Q Plot of the returns of the ASPI evidently violates the normality.

When considering monthly variation of market price indices of three sectors, Bank Finance and Insurance sector recorded higher price indices at all times when compared with other two sectors. According to the descriptive statistics of the returns of the three sector price indices, mean value and the standard deviation value of the returns of the BFI sector is noticeably high when compared with returns of the other two sectors. All the three return series indicate the positive skewness implies that all the three series consist of more growth than fall. According to the Q-Q plots of return series of the three price indices, it can be clearly identified that three series are deviated from the normal distribution.

6.1.2 Discussion on GARCH family models

Two models were finalized for ASPI, for before and after the 2009, May and three models were built for sector price indices named BFI, CE & MFU consecutively.

GARCH Models for ASPI

Time series plot of the daily ASPI series has clearly showed a positive trend and a non-constant variance over the periods 2000-2016. However, ASPI has declined significantly, during the critical time period of the war which was ended in 18th May 2018. Thus two distinct models were developed for ASPI before and after the ending of the war.

EGARCH (1,1) Model for ASPI (2000-2009 May)

Time series plot of the daily ASPI series of (2000-2009 May) illustrated a positive trend till 2007. Thereafter a significant decrement can be observed. Returns series indicated the existence of volatility clusters of ASPI(2000-2009 May).

Results of the Box-pierce LM Test and Test for an ARCH effect proved that returns series of the ASPI(2000-2009 May) consist an ARCH effect. Test for asymmetry in volatility clustering has resulted that asymmetric volatility clusters exist in the return series of the ASPI(2000-2009 May).

EGARCH (1,1) model is developed to estimate the volatility of ASPI for 2000-2009 May time period. ARCH-LM test resulted that there is no heteroscedasticity in the standardized residuals of the EGARCH model. The correlogram of the squared residuals consists of insignificance Q-Statistics values up to lag 36 for developed model for the returns of the ASPI of 2000 -2009 May. These results indicate that the selected variance equation is highly accepted to describe the error variance of the mean equation. Q-Q plots which have drawn with the assumption of the residuals follows t-distribution depicted an straight line apart from few large and small data points , evidently supported for the made assumption on the error distribution.

Since the actual volatility is unobservable, the squared return series can be used as a substitute for the realized volatility. A plot of squared returns against the fitted volatility provides an indication of the model ability to track variance in the returns of the ASPI of 2000-2009 May time period.

EGARCH (2,2) Model for ASPI (2009 May-2016)

Time series plot of the daily ASPI series of (2009 May-2016) showed a positive trend over the period. Returns series indicated the existence of volatility clusters of ASPI(2000-2009 May).

Results of the Box-pierce LM Test and Test for an ARCH effect resulted that returns series of the ASPI (2009 May-2016) consist an ARCH effect. Test for asymmetry in volatility clustering has showed that asymmetric volatility clusters exist in the return series of the ASPI (2009 May-2016) also.

EGARCH (2,2) model is appropriated to estimate the volatility of ASPI for 2009 May-2016 time period. According to the ARCH-LM test, is no heteroscedasticity in the standardized residuals of the EGARCH model. The correlogram of the squared residuals consists of insignificance Q-Statistics values up to lag 36 for the model built up for ASPI of 2009 May - 2016. Thus the selected variance equation can be accepted to describe the error variance of the mean equation. Q-Q plots which have drawn with the assumption of the residuals follows t-distribution depicted an straight line apart from few large and small data points , evidently supported for the made assumption on the error distribution.

Since the actual volatility is unobservable, the squared return series can be used as a substitute for the realized volatility. A plot of squared returns against the fitted volatility provides an indication of the model ability to track variance in the returns of the ASPI of 2009 May-2016 period.

Comparison for pre and post war performance of the ASPI of the CSE

The behavior of the ASPI before and after the war has been observed through distinct GARCH models. Both series consist asymmetric volatility, and developed EGARCH models. But EGARCH (1,1) model is appropriated to capture the volatility of the ASPI ,before the war while EGARCH(2,2) model is fitted well for capture the volatility of the ASPI after the ending of the war. Thus more terms are required to capture the variance of the ASPI after the ending of the war implies that variance of the price has been fluctuated highly in post war period. Those highly fluctuated variance patterns can be observed also through the graphs of the actual versus estimated volatilities.

GARCH Model for BFI sector price index

Time series plot of the BFI has been illustrated a positive trend over the period 2000-2016. But BFI sector price index has been dropped noticeably in several time intervals of the considered period. Log transformed series of the BFI sector price index depicted a very little fluctuation pattern when compare with the original series. Returns series of the BFI price index has indicated the existence of volatility patterns of the series. As discussed in Chapter 5, Statistical Tests have performed for verify the suitability of developing GARCH family model for BFI series, have indicated that series exist symmetric volatilities. GARCH(1,2) were recognized for estimate the volatility of BFI sector price index. Diagnostic tests were supported to this model and error distribution was correctly specified as the t-distribution.

GARCH Model for CE sector price index

Time series plot of the CE sector price index consist a positive trend when considering initial and final data points. However there were many sudden increments and decrements of the price index during the considered period (2000-2016). Hence variance of the CE price index was identified as non-constant. When considering returns series of the CE sector price index, in first half time period returns seems to be remaining constant while in last part of the considered period returns values have fluctuated highly with higher variance. Appropriate Tests were performed for verify the suitability of developing GARCH family model for returns of the CE sector price index.

GARCH(1,2) Model was recognized for estimate the variance due to the symmetricity of the returns series of the CE sector price index. Diagnostics tests were used for check the suitability of the model and the error distribution was distributed as t-distribution according to the drawn Q-Q plot.

GARCH Model for MFU sector price index

According to the time series plot of the Manufacturing (MFU) sector during 2000-2016, there were slight trend during first half time period (2000-2008), while considerable up and down fluctuations thereafter. Log transformed series of the MFU index also showed numerous deviation patterns, but huge fluctuation patterns had observed in original series has been removed. According to the time series plot of the returns of MFU, returns of fist half period had fluctuated in small range (between -100 and 100) while returns of second half period had been changed extremely with higher variation. Box-pierce LM Test and ARCH effect test statistically proved the existence of volatility in the returns series of the MFU. Existence of asymmetric volatility of the returns of MFU was indicated by the results of the test for Asymmetric volatility.

EGARCH(2,2) model was developed to estimate the variance of the returns series of the MFU sector price index. ARCH LM test had resulted that there was no heteroscedasticity in the standardized residuals of the model. Q-statistics values of the correlogram of the squared residuals of the model were highly insignificance from lag

1 to 36 at 5% level. Thus error distribution of EGARCH(2,2) model has been correctly specified as t- distribution.

6.2 Conclusions

ASPI of the both pre and post war periods consist asymmetric volatilities indicated that existence of leverage effect in the series. Therefore returns and the conditional returns volatility of the ASPI are negatively correlated. The presence of the asymmetric volatility is most apparent during stock market crashes when a large decline in stock price is associated with a significant increase in market volatility. Thus it can be concluded that the drop of the ASPI during the critical period of the war associated with asymmetric behavior of the series. Further, significant increment of the stock price after the ending of the war has been observed also due to the stock market crash occurred during the 2009.

As the comparison made for the EGARCH models pre and post period of the war, more terms are required to estimate the volatility of the ASPI for the post war period. According to the Figures of actual versus estimated volatilities it can be concluded that the estimated variance has fluctuated in a wide range for the post-war (2000-2009 May) period when compared with pre-war period (2009 May-2016).

When considering the sector price indices, asymmetric behavior of the price can be observed only in the MFU sector. The estimated volatility of the BFI sector has been fluctuated in a wide range when compared with other two sectors CE and MFU as indicated by the plots of actual versus estimated volatilities.

6.3 Recommendations and Limitations

- When developing a GARCH model for ASPI and all other sector price indices of Colombo Stock Exchange, it is required to assume the error distribution away from the normal distribution.
- All GARCH model were fitted using Eviews software and it doesn’t has an option to forecast just for next few data points without considering all data

points of the fitted model. As future work GARCH models can be improved with new software.

- Arithmetic returns were used for all analysis of price indices, as a future work geometric return can be used to reconstruct volatility models for Colombo Stock Exchange price indices.

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