DAY EFFECT IN RETURN AND VOLATILITY OF THE SELECTED SECTOR INDICES IN COLOMBO STOCK EXCHANGE

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Declaration of the Candidate and Supervisor

The work submitted in this thesis is the results of my own investigation, except where otherwise stated.

It has not already been accepted for any degree, and is also not been concurrently submitted for any other degree.

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24/07/2017
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I endorse the declaration by the candidate,

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Abstract

One of the significant anomalies of Efficient Market Hypothesis (EMH) is the seasonal effect. The existence of the seasonal effect implies market inefficiency. Most of the investors, especially international investors are more concerned with the market efficiency. The most common seasonal anomalies are *the Day of the week effect, Day of the month effect, week of the month* and *the month of the year effect.* According to past empirical studies Day of the week is the most talked anomaly among those. When the day of the week effect exists, investors can earn abnormal profit by buying the stock in low return day of the week and selling them at a higher return day of the week.

In Sri Lankan context, all the studies on finding the existence of day of the week effects in stock return and volatility in Colombo Stock Exchange (CSE) are conducted for the whole market using All Share Price Index (ASPI). As all those studies mainly focused on ASPI and no studies focused on sector wise, this study examines the same problem focusing two sectors: Hotels and Travels (H&T), Investment Trusts (INV) in CSE. The daily returns for each sector over a period of two years from 2014 to 2016 are tested using three types of conditional time varying models, namely GARCH, EGARCH, and GJR-GARCH. The study finds strong evidence for the presence of day of the week effect in stock returns and in volatility of the two sectors. Among the five days of the week Thursday returns are negative in H&T and it is significantly higher than that of other days of the week. Only Monday returns are significant in INV and it is negative. While Monday volatility is significantly positive and higher than that of other days of the week in H&T, Thursdays and Fridays volatility are significantly different from zero and negative in INV.

Key Words: Volatility, Stock Return, All share price index, GARCH, EGARCH, Colombo Stock Exchange, Day of the week effect.

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LIST OF ABBREVIATIONS

Abbreviation	Description
ASPI	All Share Price Index
CSE	Colombo Stock Exchange
EMH	Efficient Market Hypothesis
NYSE	New York Stock Exchange
BSE	Bombay Stock Exchange
SAARC	South Asian Association for Regional Cooperation
BET-C	Bucharest Exchange Trading -Composite Index
DWG	Dow Jones Global Total Stock Market Index
OLS	Ordinary Least Square
GARCH	Generalized Auto Regressive Conditional Heteroscedasticity
ARCH	Auto Regressive Conditional Heteroscedasticity
QMLE	Quasi Maximum Likelihood Estimation
KLCI	Kuala Lumpur Composite Index
EGARCH	Exponential Generalized Auto RegressiveConditional Heteroscedasticity
TGARCH	Threshold Generalized Auto Regressive Conditional Heteroscedasticity
DF	Dickey-Fuller
ADF	Augmented Dickey-Fuller
AIC	Akaike's Information Criterion
BIC	Bayesian Information Criterion
GJR GARCH	Glosten Jagannathan Runkle Generalized Auto Regressive Conditional Heteroscedasticity

H&T	Hotels and Travels
INV	Investment Trusts
SBA	Share Brokers' Association
CSBA	Colombo Share Brokers' Association
WTC	World Trade Centre

CHAPTER 1

INTRODUCTION

1.1 Colombo Stock Exchange

Share trading is an important aspect of the economy of a country from both the industry's and investor's point of view. Stock market is the place where the secondary shares are issued to fulfill the capital requirements of public companies ensuring the continuity of the economic expansion and making opportunities for people to earn higher returns for their investments.

The establishment of the current Stock Market of Sri Lanka has a long history and it goes back to 19th century. Share trading in Sri Lanka was initiated in 1896 under *Share Brokers Association* (SBA) by British planters in order to find the financial requirements for setting up the tea plantation in Sri Lanka. In 1904 SBA was renamed as *Colombo Share Brokers' Association* (CSBA). The establishment of a formal stock exchange took place in 1985 with the incorporation of the Colombo Securities Exchange, which took over the Stock Market from the Colombo Share Brokers Association. In 1990, the business was renamed as Colombo Stock Exchange (CSE). It currently has a membership of 15 institutions, all of which are licensed to operate as stockbrokers. CSE introduced Central Depository System and clearing was automated by that. In 1995 CSE headquarters was opened at World Trade Centre (WTC), Colombo.

1.2 Stock Market Index

A stock index or stock market index is a mathematical construction which is used to measure the value of a section of the stock market or all of the market. It is computed from the prices of selected stocks (typically a weighted average). It is a tool used by investors and financial managers to describe the market, and to compare the return on specific investments.

In Sri Lanka there are three stock market indexes to measure the performance of the CSE:

1. All share price index (ASPI)
2. S&P Sri Lanka 20 (S&P SL20)
3. Colombo Stock Exchange Sector indices (CSE Sectors)

1.2.1 All Share Price Index (ASPI)

The All Share Price Index is one of the principal stock indices of the Colombo Stock Exchange in Sri Lanka. ASPI measures the movement of share prices of all listed companies. It is based on market capitalization. Weighting of shares is conducted in proportion to the issued ordinary capital of the listed companies, valued at current market price (i.e. market capitalization). The base year is 1985, and the base value of the index is 100. This is the longest and the broadest measure of the Sri Lankan Stock market. The ASPI indicates the price fluctuations of shares of all the listed companies and covers all the traded shares of companies during the market day.

The ASPI is calculated using the formula;

$$\text{All share price index} = \left(\frac{\text{Market Capitalization All Listed Companies}}{\text{Base Market Capitalization}}\right) \times 100$$

Where,

$$\text{Market Capitalization} = \sum (\text{Current No of Listed Shares of Compan } y_i)\ (\text{Market Price}_i)$$

$$\text{Base Market Capitalization} = \sum (\text{ No of Listed Shares of Compan } y_i)\ (\text{Market Price}_i)$$

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

$$\text{Opening Base Market Capitalization} = \frac{\text{Total Market Capitalization in 1985}}{\text{No of Trading Days in 1985}}$$

1.2.2 S&P SL20 Index

The S&P SL20 Index was initiated on 18 June 2012 and was launched in Colombo on 26 June 2012. The S&P Sri Lanka 20 seeks to be comprised of liquid and tradable stocks for easy and cost effective replication as trading instruments, with possible application as index funds and Exchange-Traded Funds (ETFs). Index constituents are the 20 largest blue chip companies chosen from the universe of all stocks listed on Colombo Stock Exchange. The indices are calculated using a capped market capitalization-weighting scheme (capped at 15%). The S&P Sri Lanka 20 is calculated in Sri Lankan Rupee. The base period of the S&P Sri Lanka 20 is December 17, 2004 and the base value is 1000.

1.2.3 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, which is used to calculate 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)

1.3 Background of the study

Whenever a company wants to raise funds for further expansion or settling up a new business venture, instead of taking loans, it can issue shares of the company. On the other hand, an investor can get part ownership of the company by buying shares. This gives him/her a vote at annual shareholder meetings, and a right to a share of future profits. Investors have the ability to quickly and easily sell shares. This is an attractive feature of investing in stocks, compared to other less liquid investments such as real estate. Most of the investors, especially international investors are more concerned with the market efficiency.

The term 'Efficient Market' which was first introduced by Fama (1970), refers to a market that adjusts rapidly to new information. After his introduction of this term, there has been number of attempts to seek the consistency of the Efficient Market Hypothesis (EMH) which asserts that the current stock prices fully reflect all available information about the value of the firm, and there is no way to earn excess profits, (more than the market overall), by adopting a certain trading strategy. The term "all available information" gives three versions of the EMH as weak form efficiency, semi strong form efficiency and strong form efficiency.

The EMH holds since the investors react instantaneously to any informational advantages they have thereby eliminating profit opportunities. Thus, prices always fully reflect the information available and no profit can be made from information based trading (Lo and MacKinley, 1999). This leads to a random walk where the more efficient the market, the more random the sequence of price changes.

However, it should be noted that the EMH and random walks do not denote the same thing. A random walk of stock prices does not imply that the stock market is efficient with rational investors. That is, existence of the random walk of stock prices is a necessary condition to have an efficient market. The contrapositive of this statement gives a method to check the efficiency of the market. That is, if there does not exist a random walk of stock prices, then market is not efficient.

Predictability of asset returns plays a vital role in a stock market as it makes investment decisions easy and much profitable. Fundamental Analysis and Technical Analysis are the two main strands of investment decisions. Fundamental Analysis involves analyzing the economic factors or characteristics of a company, namely, company value, company earnings, etc. in order to estimate the intrinsic value of a company while Technical Analysis focuses on price movements and trading volume in the market.

One of the significant anomalies of EMH is the seasonal effect. The existence of the seasonal effect implies market inefficiency. Seasonal anomalies are reported by researches for developed as well as emerging stock markets. But, most of the studies were conducted on developed countries. The most common seasonal anomalies are *the Day of the week effect, Day of the month effect* and *the month of the year effect.* If the seasonal effects are well-known and systematic in the stock markets, then investors can have useful clues regarding their investment decisions. Therefore, if investors have this knowledge they can adjust their portfolios by considering these variations in the stock returns.

According to past empirical studies, Day of the week is the frequently studied anomaly among the seasonal anomalies. This study seeks to test whether the day of the week effect exists in selected sector of the Colombo Stock Exchange. When the day of the week effect exists, investors can earn abnormal profit by buying the stock in low return day of the week and selling them at a higher return day of the week.

1.4 Research Problem

Stock market is a very important section in a country. The more the stock market developed, the more the economy of the country developed. Stock market will be developed when investors invest much in the stock market. The more the investors invest in the stock market the more they gain the profit for their investments. Thus, to earn much profit investors have to use different strategies and methods. Since the Colombo Stock Exchange is not even touch the weak form efficiency as a share market, share prices are not reflect all available information through their prices. Hence, if investors know which day of the week has low return and which day has the higher return then investors have an opportunity to earn abnormal gains through close-fitting the historical share prices. Consequently this research will investigate whether there is a relationship between historical prices and the Day of the week effect in selected sector of CSE.

1.5 Objective of the study

Main objective:

Examine each sector of Colombo stock Exchange in Sri Lanka for the existence of Day of the Week Effect in daily return and volatility.

To achieve the main objective, the study focuses on the

Sub objectives:

- Examine the existence of Heteroscedasticity in each sector;
- Find the best fitted model for each sector.

1.6 Significance of the study

In Sri Lankan context all the studies on finding the existence of day of the week effects in CSE are conducted for the whole market using All Share Price Index (ASPI). This study examines the same problem focusing the sectors of the CSE. The major contributions of this study to the literature will be two fold. First, it will be the first study that focuses on sectors of CSE to examine the existence of Day of the

Week Effect. Second, it will be an extension of the existing methods to find the existence of day of the week effect which can be used in future studies.

1.7 Data Collection

The study relied on secondary data, which was obtained from the records at Colombo Stock Exchange. Data for the ten year period from 6th November 2006 to 4th November 2016 are collected. The data series is comprised of daily stock market closing prices (All share price index for sectors) of all the sectors which are listed at the CSE as at 4th November 2016.

1.8 Outline of the rest of the Chapters

The detailed literature review related to this study is given in chapter 2.The details of the analytical framework are provided in chapter 3. All theories which are related to each method that will be used to analyse data are given in this chapter. The results obtained from employing the fitted model for the data for each sector are illustrated in chapter 4. The overall outcome of the data analysis is explained in the last part of the chapter. The major findings of the study are distilled in the final chapter (Chapter 5) of the thesis. The results are compared with previous studies and any differences and similarities are explained. The limitations of the study are also discussed and suggestions are provided for further research as well.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Both the theoretical framework and the empirical literature on day-of-the-week effect of stock return and volatility are presented in this chapter. Theoretical framework focusing on the Efficient Market Hypothesis, Random Walk Theory, Trading Time Hypothesis and the Calendar Time Hypothesis are covered. Review of empirical literature is also covered in this chapter.

2.2 Theoretical Frame Work

This section examines theoretical foundation where the following theories are discussed: Efficient Market Hypothesis of Fama (1970), Random Walk Theory of Samuelson (1965), Trading Time and the Calendar Time Hypothesis of French (1980).

2.2.1 Efficient Market Hypothesis

Efficient Market Hypothesis (EMH) which asserts that the current stock prices fully reflect all available information about the value of the firm and there is no way to earn excess profits, (more than the market overall), by adopting a certain trading strategy. All available information includes not only past stock prices but also every publicly announced information of the company and evenly private information about the company. The efficient market hypothesis is associated with the idea of a random walk which characterizes price series where all subsequent price changes represent random departures from previous prices (Malkiel, 2003). The logic behind the random walk idea is that if the flow of information is unhindered and information is immediately reflected in stock prices, then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today. Fama (1970) categorized market efficiency into three forms: weak form, semi-strong form and strong form of market efficiency according to the term "all available information".

Weak Form Efficiency

The weak form of the efficient markets hypothesis asserts that the current stock price fully reflect information which are related to the past sequence of stock prices only. That is, nobody can detect mis-priced securities and outperform the market by analyzing past prices. The weak form of the hypothesis got its name as stock prices are the most public as well as the most easily available pieces of information. Thus, nobody should be able to profit from using something that "everybody else knows". On the other hand, many financial analysts attempt to generate profits by studying exactly past stock price series and trading volume data, ingrowing the validity of this this hypothesis. This technique is called technical analysis.

Semi-strong Form Efficiency

The semi-strong-form of efficient market hypothesis suggests that the current price fully reflects *all publicly available* information. Public information includes not only past stock prices, but also data reported in a company's financial statements (annual reports, income statements, etc.), earnings and dividend announcements, announced merger plans, the financial situation of company's competitors, expectations regarding macroeconomic factors (such as inflation, unemployment), etc. In fact, the public information does not even have to be of a strictly financial nature. For example, for the analysis of pharmaceutical companies, the relevant public information may include the current (published) state of research in pain-relieving drugs.

Strong Form Efficiency

The strong form of efficient market hypothesis states that the current price fully reflects all existing information, both public and private (inside information). The main difference between the semi-strong and strong efficiency hypotheses is that in the latter case, nobody should be able to systematically generate profits even if trading on information *not* publicly known at the time. In other words, the strong form of EMH states that a company's management (insiders) should not be able to systematically gain from inside information by buying company's shares ten minutes after they decided (but did not publicly announce) to pursue what they perceive to be a profitable acquisition. Similarly, the members of the company's research department should not be able to profit from the information about the new revolutionary discovery they completed half an hour ago. The rationale for strong-form market efficiency is that the market anticipates, in an unbiased manner, future developments and therefore the stock price may have incorporated the information and evaluated in a much more objective and informative way than the insiders. Not surprisingly, though, empirical research in finance has found evidence, that is inconsistent with the strong form of the EMH.

2.2.2 Random Walk Theory

Samuelson (1965) proposed the random walk theory by arguing that in competitive markets there is a buyer for every seller and if one could be sure that a price will rise, it would have already risen. He concluded that competitive prices must display changes overtime that follow a random walk with no predictable bias.

Dupernex (2007) pointed out that the idea of stock prices following a random walk is connected to that of the EMH, where the more efficient the market, the more random the sequence of price changes which leads to a random walk. Further he pointed out that the EMH and random walks do not amount to the same thing and random walk of stock prices does not imply that the stock market is efficient with rational investors.

Poshakwale (1996) stated that random walk is used to refer to successive price changes which are independent of each other. In other words, tomorrow's price changes as well as tomorrow's price cannot be predicted by looking at today's price change. That is $P_{t+1} - P_t$ is independent of $P_t - P_{t-1}$. Thus there should be no trends in price changes. Poshakwale (1996) further states that random walk theory for share prices reflects a securities market where new information is rapidly incorporated into prices and where abnormal returns or excess returns cannot be made by spotting trends or trading on new information.

2.2.3 The Trading Time and Calendar Time Hypothesis

French (1980) proposed both the trading time and calendar time hypothesis where the former asserts that returns are generated only during active trading and the daily returns should be same for every trading day of the week; and the later asserts that returns are generated continuously and since the time between the close of trading on Friday and the close of trading on Monday is three days, Monday returns should reflect returns for three days and should be three times higher than other week day returns.

Ball, Torous and Tschoegl (1982) noted that the trading time hypothesis implies an identical return distribution across all trading days and calendar time hypothesis takes into account the presence of the weekends and implies that the mean and variance of the return following these periods should be significantly higher.

Lakonishok and Levi (1982) noted that the trading time hypothesis asserts that the stock returns are equal on different days while Calendar time hypothesis asserts that higher expected returns on Monday to compensate for the longer holding period.

2.3 Empirical Review

2.3.1 International Studies on Day of the Week Effect

Cross (1973) examined the relationship between price changes on Fridays and Mondays as well as the distribution of the price changes. The study aimed to determine non-random movements in stock prices. The population of the study is the Standard & Poor's Composite Stock Index where a sample of 844 sets of Fridays and following Mondays from January 2, 1953 through December 21, 1970 for which the NYSE was open on both days is drawn. The study observed that the index performed better on Fridays than on Mondays.

Poshakwale (1996) examined the weak form efficiency and the day of the week effect on the Bombay Stock Exchange using daily BSE national index data for the period 1987 to 1994. The study utilized descriptive statistics to tests the hypotheses: the prices on Indian Stock market follow a random walk, the Indian stock market is efficient in weak form and that there is no difference in the returns between the days of the week. Findings showed that the prices of BSE do not follow a random walk. Further the findings indicated that the average returns are different on each day of the week.

Muhammad and Rahman (2010) empirically investigated the presence of weekend effect in stock market return for the period of January 1999 to December 2006 for Kuala Lumpur Composite Index. The study was both descriptive in nature and a longitudinal study as it focused on more than one point in time. Log different was used to compute daily returns and ordinary least square method to estimate the day of the week effect. Findings indicated that the day of the week effect was present in the Malaysian market.

Abbas and Javid (2015) aimed to test the existence of Day of the week anomaly in market return volume and volatility in SAARC countries. The study measured the existence of market anomalies with respect to daily closing market index value from 1999 to 2014 for Pakistan, India, and Sri Lanka and from 2006 to 2012 for Bangladesh. Results reported day-of-the-week effect in return and volumes for all markets except India. In Pakistan, there are observed positive volatilities on Monday while negative volatilities on Wednesday, Thursday and Friday. In case of India, interestingly, although no day of week effects is found but there are seen positive volatilities on Monday while negative volatilities on all other days of week except Friday. In Bangladesh there are seen positive volatility effects on Monday and Sunday and on all other day negative volatility. In Sri Lanka there are found positive Monday effect while negative on Tuesday and Thursday. One common effect is positive Monday and negative Friday volatilities in all markets.

Valentina and Oprea (2014) studied the evolution of stock indices: Bucharest Exchange Trading - Composite Index (BET-C) and the Dow Jones Global Total Stock Market Index (DWG) between 2005 and 2011. They found that the seasonality of day return is present on the Romanian stock market due to the existence of seasonality in the risk-return relationship by applying OLS and GARCH(1,1) models.

Octavio Maroto Santana and Alejandro Rodriguez Caro (2006) studied the evolution of stock indices from the European markets: Germany, Austria, Belgium, Denmark, Spain, France, The Netherlands, Italy,Portugal, The United Kingdom, The Czech Republic, Sweden and Switzerland between 1997 and 2004. They found days with higher and lower returns on every market.

Berument and Kiymaz (2003) have conducted a research on the day of the week effect on stock market volatility and volume for the period of 1998-2002. Data consisted on daily prices of different stock returns. They used ARCH & GARCH and QMLE models in their study their results show that highest volatility occurs on Monday for Germany and Japan, on Fridays for Canada and United States and Thursday for United Kingdom. The results also shows that market with high volatility have lowest trading volume.

Daw Tin Hla, Chandana Gunathilaka and Abu Hssan Md Isa (2015) examine the presence of day-of-the-week effect in returns on four indices: Kuala Lumpur Composite Index (KLCI), Mid70 Index, Top100 Index and EMAS index of Bursa Malasia. The daily returns over a period of 18 years from 1996 to 2014 are tested using both parametric and non-parametric statistics and found strong evidence for the existence of day-of-the-week effect on returns. Monday returns are negative; Friday returns are positive and significantly higher than that of other week days. Also found no evidence for random walk hypothesis.

2.3.2 Local Studies on Day of the Week Effect

In the Sri Lankan context, day-of-the-week effect is performed in few studies on the Colombo Stock Exchange.

Deysappriya (2014) used OLS regression and GARCH(1,1) models to investigate the day of the week effect on stock return of the Colombo Stock Exchange(CSE) using ASPI index between 2004 and 2013. In his study he found that the average stock return on Friday is significantly higher than the other days of the week and also revealed that the negative Monday effect. Athambawa (2015) made a similar conclusion in line with Deysappriya by employing OLS regression to ASPI index from 2004 to 2015.

Thushara (2013) tested day of the week effect in CSE using both OLS model and GARCH (1,1) model and found that there is a Thursday, Wednesday and Friday effect in the stock returns for the period of 2002 to 2011.

Narasinghe and Perera (2015) examine the day of the week effect anomaly within the Sri Lankan stock market for the period from 2004 to 2013 using the All Share Price Index (ASPI). The results demonstrate that, Day of the week effect exists by applying one sample t- test in the CSE and positive Friday and negative Monday.

2.4 Chapter Summary

Day of the week effect on stock returns have been extensively documented for different stock markets around the world and have yielded different results for different countries depending on the specific time-period chosen as well as the choice of model with which the effect was examined hence more studies in these area to study these anomalies.

The study conducted by Poshakwale (1996) provides empirical evidence on weak form efficiency and the day of the week effect in Bombay Stock Exchange. Muhammad and Rahman (2010) indicated that the day of the week effect was present in the Malaysian market. Abbas and Javid (2015) examine the existence of Day of the week anomaly in market return, volume and volatility in SAARC countries and reported day-of-the-week effect exists in return and volumes for all markets except India. Valentina and Oprea (2014) studied the indices: Bucharest Exchange Trading - Composite Index (BET-C) and the Dow Jones Global Total Stock Market Index (DWG) and found that the seasonality of day return is present on the Romanian stock market. Octavio Maroto Santana and Alejandro Rodriguez Caro (2006) studied the evolution of stock indices from the European markets and found days with higher and lower returns on every market. Kiymaz and Berument (2003) have conducted a research on the day of the week effect on stock market volatility and volume and results show that highest volatility occurs on Monday for Germany and Japan, on Fridays for Canada and United States and Thursday for United Kingdom. Daw Tin Hla, Chandana Gunathilaka and Abu Hssan Md Isa (2015) examine the presence of day-of-the-week effect in returns on four indices in Malaysian stock market and found that Monday returns are negative; Friday returns are positive and significantly higher than that of other week days. Also found no evidence for random walk hypothesis.

Deysappriya (2014) investigate the day of the week effect on stock return of the Colombo Stock Exchange and found that the average stock return on Friday is significantly higher than the other days of the week and also revealed that the negative Monday effect while Athambawa (2015) made a similar conclusion in line with Deysappriya. Thushara (2013) tested day of the week effect in CSE reported that there is a Thursday, Wednesday and Friday effect in the stock returns, Narasinghe and Perera (2015) examine the same thing in the Sri Lankan stock market and reported that, day of the week effect exists.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The steps and approaches which are followed in the proposed study are presented in this chapter. Specifically the research design, statistical models, tests and statistical techniques which are used to analyze the data are discussed. In addition, descriptive statistic terms are also introduced in this section to provide a general understanding about the data sets.

3.2 Research Design

In this study first, basic OLS model is fitted by taking dummy variables for each day of the week as independent variables and return as the dependent variable. Then the fitted model is tested for ARCH effect. (See figure 3.1) If the ARCH effect is not present in the data set then the fitted model is tested for auto correlation of the residuals and if residuals are not auto correlated then the fitted model is tested for normality of the residuals. If the residuals are normally distributed then accept the model as the best model that describes the data set.

If the residuals are auto correlated then the model will be modified until the residuals are not auto correlated by introducing lag values of the dependent variable into the regression model and then the fitted model is tested for normality of the residuals. If the residuals are normally distributed then accept the modified model as the best model that describes the data set.

If the ARCH effect is present in the data set then a model from GARCH, EGARCH or GJR-GARCH family are fitted until there is no ARCH effect and no auto correlation of the residuals and the residuals are normally distributed.

3.3 Descriptive Statistics

3.3.1 Skewness

Skewness measures the symmetric/asymmetric dispersion of data around the mean level of a given data set. When skewness index is zero then data set dispersed around the mean symmetrically. Positive and negative skewness can be identified by analysing the tail of correlogram as if it is right tail; distribution is positively skewed in contrast if it is left tailed distribution is negative skewness.

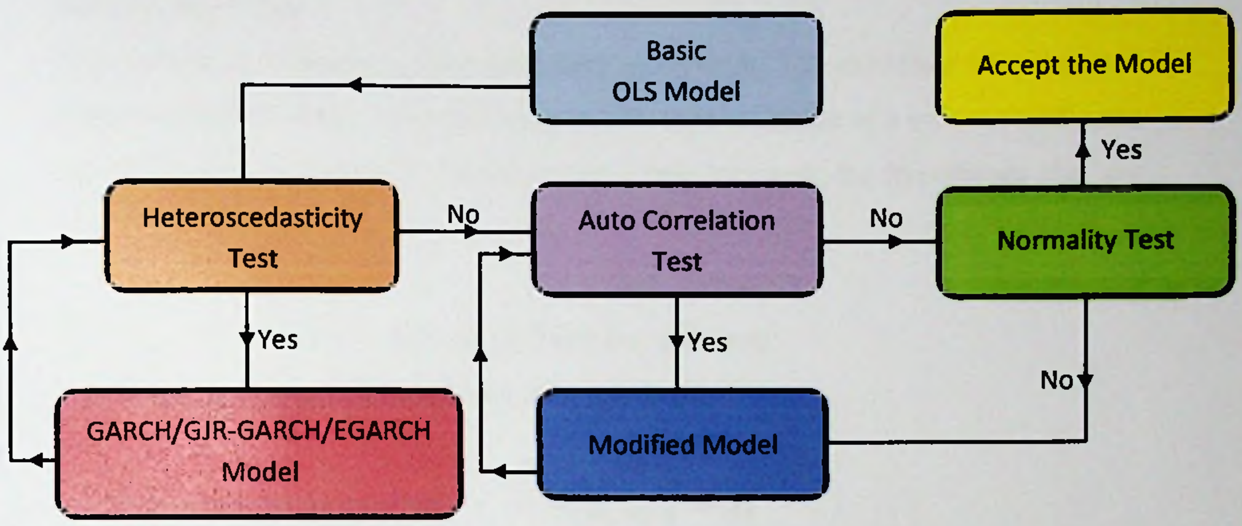

Figure 3.1: Algorithm of fitting the models

3.3.2 Kurtosis

This measures the peak of the data set. If the kurtosis is higher, then the distribution tends to have a peak within the limits of mean, conversely low kurtosis signifies spread of data over wider area. Theoretically, if the kurtosis is greater than 3, it implies deviation of data set from normality conditions. This means data set tends to have more extreme values.

3.3.3 Time Series Analysis

Time series analysis is a collection of data which is collected in sequential points in time. It can be continuous or discrete depending on the sequence of data collected. In time series the distance between two data points is same.

A significant feature in time series analysis is that the stationary condition. Therefore, before further analysis on time series models stationary conditions should be examined. There are three main properties in stationary process,

- Mean constant over the time
- Variance constant over the time

- Covariance between two time periods is only depending on lag between two periods of time

3.4 Unit Root Test

Unit root is an indication of the stationary of a series. The existence of a unit root indicates that the series is not stationary while none existence of a unit root indicates that the series is stationary. Therefore, in a unit root test, the hypotheses that are tested is as below,

H_0: Time series is non – stationary (There is a unit root)

H_1: Time series is stationary (There is no unit root)

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + \varepsilon_t$$

Above mentioned stochastic process $\{y_t\}$ is called as an autoregressive process of order p. It can be also denoted as $AR(p)$ and ε_t represents the white noise.

$$y_t - \alpha_1 y_{t-1} - \alpha_2 y_{t-2} - \cdots - \alpha_p y_{t-p} = c + \varepsilon_t$$

Alternatively, it can be represented with lag operator B, as below,

$$(1 - \alpha_1 B - \alpha_2 B^2 - \cdots - \alpha_p B^p) y_t = c + \varepsilon_t ;$$

$$where\ B^k(y_{t-k}) = y_{t-k}\ for\ k = 1,2, \ldots k$$

Let $\Phi_p(B) = 1 - \alpha_1 B - \alpha_2 B^2 - \cdots - \alpha_p B^p$

The AR (p) process is said to be stationary if the roots of $\Phi_p(B)$ lie strictly outside the unit circle. Then $\{y_t\}$ is said to be stationary. $\Phi_p(B)$ is also known as the characteristic polynomial of AR (p) process.

3.4.1 Dickey-Fuller (DF) test

Dickey Fuller test is used to test whether there exists a unit root in the autoregressive model. This test was found by Dickey and Fuller in 1979.

$$y_t = \alpha_1 y_{t-1} + \varepsilon_t$$

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t$$

Test Statistic:

t ratio of the least-squares (LS) estimate of α_1 under the null hypothesis.

$$i.e. DF \equiv t\,ratio = \frac{\hat{\alpha}_1 - 1}{std(\hat{\alpha}_1)} = \frac{\sum_{t=1}^{n} y_{t-1}\varepsilon_t}{\hat{\sigma}_e \sqrt{\sum_{t=1}^{n} y_{t-1}^2}}$$

where $\hat{\alpha}_1 = \frac{\sum_{t=1}^{n} y_{t-1}y_t}{\sum_{t=1}^{n} y_{t-1}^2}$, $\hat{\sigma}_e = \frac{\sum_{t=1}^{n}(y_t - \hat{\alpha}_1 y_{t-1})^2}{n-1}$, $y_0 = 0$ and n is the sample size.

Hypothesis:

$H_0: \alpha_1 = 1$

$H_1: \alpha_1 < 1$

Conclusion:

If $DF_{estimated} < DF_{critical}$ reject the null hypothesis at α level of significance.

As an extension of the Dickey-Fuller test, Augmented Dickey-Fuller (ADF) test was introduced which removes the structural effects in the series.

3.4.2 Augmented Dickey-Fuller (ADF) test

As clear from the name, this test is an augmented version of the Dickey-Fuller test for larger and more complex time series models. This test is useful if the series is correlated at higher order lags and the assumption of the white noise disturbance ε_t is violated.

A parametric correction for higher order correlation has been done by the ADF test in these situations by assuming that y series follows a AR (p) process. In this test p lagged difference terms of the dependent variable is added to the right hand side of the

$$\Delta y_t = c_t + \beta y_{t-1} + \sum_{i=1}^{p} \rho_i \Delta y_{t-i} + \varepsilon_t$$

where c_t is a deterministic function of the time index t and $\Delta y_t = y_t - y_{t-1}$ is the differenced series of y_t . In practice, c_t can be zero or a constant or $c_t = \omega_0 + \omega_1 t$.

Test Statistic:

t ratio of the least-squares (LS) estimate of β under the null hypothesis.

$i.e. ADF \equiv t\ ratio = \frac{\hat{\beta}-1}{std(\hat{\beta})}$

Hypothesis:

$H_0: \beta = 1$

$H_1: \beta < 1$

Conclusion:

If $ADF_{estimated} < ADF_{critical}$ reject the null hypothesis at α level of significance.

3.5 Testing the existence of Volatility Clusters

Volatility clustering is one of the main characteristics exist in volatility. This implies that the existence of the strong autocorrelation of the squared returns. Therefore, first order autocorrelation of the squared returns can be used to test the volatility clustering. Box-Pierce LM test is used for this purpose.

In this test,

1st order autocorrelation in squared returns is given by,

$$\hat{\gamma}_1 = \frac{\sum_{t=2}^{n} r_t{}^2 r_{t-1}^2}{\sum_{t=2}^{n} r_t{}^4}$$

Then the Box-Pierce test statistic is given by

$$Q(1) = n\hat{\gamma}_1$$

Where n is the number of observations.

Test Statistic:

$Q(1) \sim \chi_1^2$ (Chi-squared with 1 degrees of freedom)

Hypothesis:

H_0: There's no autocorrelation in squared returns (no volatility clusters)

H_1: There exist an autocorrelation in squared returns. (There exist volatility clusters)

Conclusion:

If $\chi^2_{estimated} > \chi^2_{critical}$ reject the null hypothesis at α level of significance.

This is not a very robust test. But the results of the above test can be enhanced through some adjustments to the series. If the above test suggests that there exist no volatility clustering, then it needs to be checked whether the low volatility clustering is due to the large negative returns. This is because the above test checked for the chi-squared distribution (more suitable for large positive returns). This can be analysed using the skewness and kurtosis as well.

3.6 Testing the presence of asymmetry in volatility clusters

In some situations, some equity markets tend to show an asymmetry in volatility clustering. As mentioned above this will be happened due to the increase of volatility more, when stock prices are falling than the stock price decrease by the same amount. Therefore, depending on the symmetry/ asymmetry of the volatility clusters, an appropriate GARCH model (volatility model) needs to be selected in order to obtain the correct results. If a symmetric GARCH model is used in a place where there is asymmetric volatility clusters present, then it will lead to unreliable results. Therefore, testing asymmetric nature in volatility is very important.

The asymmetry of the volatility can be detected by the autocorrelation between the yesterday's return and the today's squared return. This is because when asymmetry present, the volatility will be higher following a negative return than following a positive return.

$$v = \frac{\sum_{t=2}^{n} r_t^2 r_{t-1}}{\sqrt{\sum_{t=2}^{n} {r_t}^4 * \sum_{t=2}^{n} r_{t-1}^2}}$$

If the above mentioned autocorrelation (v) is negative in value or the Box-Pierce test statistic corresponds to the above function is significantly different from zero, then it implies the existence of the asymmetry in volatility.

3.7 Basic OLS Model

Most of the previous studies (French 1980, Berument 2003, Khanthavit 2016) are extensively employed the standard OLS methodology by regressing returns on five daily dummy variables to investigate the day of the week effect in returns as follows:

$$r_t = \mu_1 D_1 + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \mu_5 D_5 + \varepsilon_t ; \ \varepsilon_t \sim N(0, \sigma^2) --- (1)$$

Where,

$r_t -$ log return of the sector index (ASPI) of the day;

$D_1 -$ dummy variable for Monday ;

$D_2 -$ dummy variable for Tuesday ;

$D_3 -$ dummy variable for Wednesday;

$D_4 -$ dummy variable for Thursday ;

$D_5 -$ dummy variable for Friday ;

$$D_i = \begin{cases} 1 \text{ ; if the obsevation is on } i^{th} \text{ trading day of the week} \\ 0 \text{ ; otherwise} \end{cases}$$

This methodology assumes the following assumptions on the residuals:

1) Residuals are not auto correlated
2) Residuals are homoscedastic
3) Residuals are normally distributed

If the above assumptions are not fulfilled then results obtained using this model may be invalid.

3.8 Modified OLS Model

Fail to meet the first assumption can be solved by introducing lagged values of the return variable in the regression equation as used in the studies conducted by Berument and Kiymaz (2003) and Rodriguez (2012).

Then the model is expressed as:

$$r_t = \mu_1 D_1 + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \mu_5 D_5 + \sum_{i=1}^{n} \theta_i r_{t-i} + \varepsilon_t \,;\; \varepsilon_t \sim N(0, \sigma^2)$$

3.9 AR(p) Model

$$r_t = \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots + \phi_p r_{t-p} + \varepsilon_t \,;\; \varepsilon_t \sim N(0, \sigma^2)$$

3.10 MA(q) Model

$$r_t = \phi_0 - \phi_1 \varepsilon_{t-1} - \phi_2 \varepsilon_{t-2} - \cdots - \phi_p \varepsilon_{t-q} \;;\; \varepsilon_t \sim N(0, \sigma^2)$$

3.11 ARMA(p,q) Model

$$r_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \,;\; \varepsilon_t \sim N(0, \sigma^2)$$

3.12 ARCH/GARCH Model

If the second assumption is not fulfilled, variance of the residuals is heteroscedastic. As a solution to that, Autoregressive Conditional Heterosecdasticity (ARCH) models are proposed by Engle (1982) and these models are built by expressing the conditional variance as a function of past squared errors in order to address the variability in the variance of the residuals. The generalized version of these models (GARCH) is introduced by Bollerslev (1986) and modeled the conditional variance as a linear function of past squared errors and lagged value of the variance itself. Then the model is expressed as:

$$r_t = \mu_1 D_1 + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \mu_5 D_5 + \sum_{i=1}^{n} \theta_i r_{t-i} + \varepsilon_t$$

where $\varepsilon_t = \sigma_t e_t; e_t \sim N(0,1)$

and $\sigma_t^2 = \lambda_0 + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{k=1}^{p} \beta_k \sigma_{t-k}^2$

3.13 EGARCH Model

The exponential GARCH or EGARCH model was first developed by Nelson (1991) and the model is given by:

$$r_t = \mu_1 D_1 + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \mu_5 D_5 + \sum_{i=1}^{n} \theta_i r_{t-i} + \varepsilon_t$$

where $\varepsilon_t = \sigma_t e_t; e_t \sim N(0,1)$

$$\text{and} \ln \sigma_t^2 = \lambda_0 + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \sum_{j=1}^{p} \alpha_j \frac{|\varepsilon_{t-j}|}{|\sigma_{t-j}|} + \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}}$$

$$+ \sum_{k=1}^{q} \beta_k \ln \sigma_{t-k}^2$$

3.14 GJR-GARCH Model

The GJR-GARCH model was introduced by, Glosten, Jagannathan and Runkle (1993). It extends the standard GARCH (p,q) and it is similar to EGARCH model. Main GJR- GARCH model is also capable of capturing asymmetric volatility clusters in the conditional variance equation.

GJR- GARCH (p,q) model is defined as:

$$r_t = \mu_1 D_1 + \mu_2 D_2 + \mu_3 D_3 + \mu_4 D_4 + \mu_5 D_5 + \textstyle\sum_{i=1}^{n} \theta_i r_{t-i} + \varepsilon_t$$

where $\varepsilon_t = \sigma_t e_t; e_t \sim N(0,1)$

$$\text{and } \sigma_t^2 = \lambda_0 + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \gamma_j I_{t-j} \varepsilon_{t-j}^2$$

$$+ \sum_{k=1}^{p} \beta_k \sigma_{t-k}^2 +$$

$$where\ I_{t-i} = \begin{cases} 1 \ ; \ \varepsilon_{t-i} < 0 \\ 0 \ ; \ \varepsilon_{t-i} \geq 0 \end{cases}$$

3.15 Residual Analysis

3.15.1 Tests for Auto Correlation

Residuals obtained from OLS regression model is used to test the autocorrelation of the residuals. There are two tests which are widely used to test the autocorrelation. Fist is Durbin-Watson test and second is Ljung-Box Test. When the explanatory variables include a lagged dependent variable the Durbin-Watson test statistic is biased towards 2 and therefore it is not a valid test for autocorrelation. Therefore in this study Ljung-Box Test is used to test the autocorrelation.

Ljung-Box Test

This test is based on the autocorrelation coefficients proposed by Ljung-Box (1978) and test statistic is computed as:

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

where $\hat{\gamma}_k = \frac{\sum_{t=k+1}^{n}\varepsilon_t\varepsilon_{t-k}}{\sum_{t=k+1}^{n}{\varepsilon_t}^2}$ and n is the number of observations.

Test Statistic:

$Q(m) \sim \chi^2_{m-(p+q)}$ (Chi-squared with $m-(p+q)$ degrees of freedom)

Hypothesis:

H_0: There is no autocorrelation between residuals

H_1: There is autocorrelation between residuals

Conclusion:

If $\chi^2_{estimated} > \chi^2_{critical}$ reject the null hypothesis at α level of significance.

3.15.2 Tests for Heteroscedasticity

Two tests are available to check for Conditional heteroscedasticity, which is also known as the *ARCH* effects. The first test is to apply White's test to the residuals.

The second test for conditional heteroscedasticity is the Lagrange multiplier test of Engle (1984).

White Test

Regression Model:

Following regression will be employed using the residuals obtained from the initial regression.

$$\varepsilon_t^2 = \sum_{i=1}^{5} \delta_i D_i + \sum_{j=1}^{5} \gamma_i r_{t-i} + \sum_{i=1}^{5} \rho_i r_{t-i}^2 + v_t$$

Compute R_{aux}^2 from the above auxiliary regression.

Test Statistic:

$nR_{aux}^2 \sim \chi_p^2$ (Chi-squared with p degrees of freedom)

Hypothesis:

H_0: Variance of the residuals is homoscedastic.

H_1: Variance of the residuals is heteroscedastic.

Conclusion:

If $\chi_{estimated}^2 > \chi_{critical}^2$ reject the null hypothesis at α level of significance.

ARCH - LM Test

Regression Model:

Following regression is employed using the residuals obtained from the initial regression.

$$\varepsilon_t^2 = \gamma_0 + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2$$

R_{aux}^2 is computed from the above auxiliary regression.

Test Statistic:

$(n-p)R_{aux}^2 \sim \chi_p^2$ (Chi-squared with p degrees of freedom)

Hypothesis:

H_0: Variance of the residuals is homoscedastic.

H_1: Variance of the residuals is heteroscedastic.

Conclusion:

If $\chi^2_{estimated} > \chi^2_{critical}$ reject the null hypothesis at α level of significance.

3.15.3 Test for Normality

The normality of the residuals is tested using the Jarque-Bera test for normality. This test measures the skewness and kurtosis of the residuals compared to the normal distribution.

Jarque-Bera test

Test statistic is: $L = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$

Where S: Skewness

K: Kurtosis

N: Number of observations

Test Statistic:

Under the null hypothesis $L \sim \chi^2_2$ (Chi-squared with 2 degrees of freedom)

Hypothesis:

H_0: Residuals are normally distributed

H_1: Residuals are not normally distributed

Conclusion:

If $\chi^2_{estimated} > \chi^2_{critical}$ reject the null hypothesis at α level of significance.

3.16 Information Criteria

Akaike's Information Criterion (AIC) and Schwarz Information Criterion (SIC) are used in order to compare two GARCH family models with same parameters. The models with the lowest AIC and SIC are typically preferred.

3.16.1 Akaike,s Information Criterion (AIC)

Akaike (1973, 1974) introduced an information criterion which is known as Akaike's information criterion:

$$\text{AIC} = -2\ \ln\left(L(\hat{\theta})\right) + 2K,$$

where $L(\hat{\theta})$ is likelihood function and k is the number of parameters.

In the special case of least squares (LS) estimation with normally distributed errors, AIC can be expressed as:

$$\text{AIC} = n\ln(\hat{\sigma}^2) + 2K,$$

where $\hat{\sigma}^2 = \frac{\sum_{i=1}^{n}(\hat{\varepsilon}_t)^2}{n}$, k is the number of parameters and n is the number of observations.

3.16.2 Schwarz Information Criterion (SIC)

Schwarz (1978) derived the Schwarz information criterion as

$$\text{SIC} = -2\ \ln\left(L(\hat{\theta})\right) + K\ln(n).$$

where $L(\hat{\theta})$ is likelihood function, k is the number of parameters and n is the number of observations.

3.17 Day of the week effect

Best fitted model for each sector is used to test the following hypothesis in order to find the existence of day of the week effect in selected sectors of CSE which is the main objective of this study.

For the mean equation

$\text{H}_0: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$(Average returns of all days of the week are equal)

$\text{H}_1: \mu_1, \mu_2, \mu_3, \mu_4, \mu_5$ are different each other

For the variance equation

$\text{H}_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$

$\text{H}_1: \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ are different each other

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Introduction

This chapter depicts the results obtain from employing the models for the data set of selected sectors based on the algorithm given in section 3.2 of chapter 3. As represented in that algorithm, first basic OLS model is fitted by taking dummy variables for each day of the week as independent variables and return as the dependent variable. Then the fitted model is tested for ARCH effect. If the ARCH effect is not present in the data set then the fitted model is tested for auto correlation of the residuals and if residuals are not auto correlated then the fitted model is tested for normality of the residuals. If the residuals are normally distributed then accept the model as the best model that describes the data set.

If the residuals are auto correlated then the model will be modified until the residuals are not auto correlated by introducing lag values of the dependent variable into the regression model and then the fitted model is tested for normality of the residuals. If the residuals are normally distributed then accept the modified model as the best model that describes the data set.

If the ARCH effect is present in the data set then a model from GARCH, EGARCH or GJR-GARCH family are fitted until there is no ARCH effect and no auto correlation of the residuals and the residuals are normally distributed. If more than one model is fitted for a sector, the best fitted model that describes the data set is determine by using Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC).

In this study following two sectors are tested for the existence of day of the week effect among twenty sectors of the Colombo stock exchange.

1) Hotels and Travels – (H&T)
2) Investment Trusts – (INV)

The daily returns are calculated using the log difference of the ASPI index for each sector, as follows:

$$r_t = 100 * \log\left(\frac{P_t}{P_{t-1}}\right)$$

Where r_t is the daily return on day t, P_t is the closing value of ASPI on day t, and P_{t-1} is the previous day closing value of ASPI.

4.2 Hotel and Travels Sector

Under this sector there are 37 companies from the 296 companies registered at Colombo stock exchange.

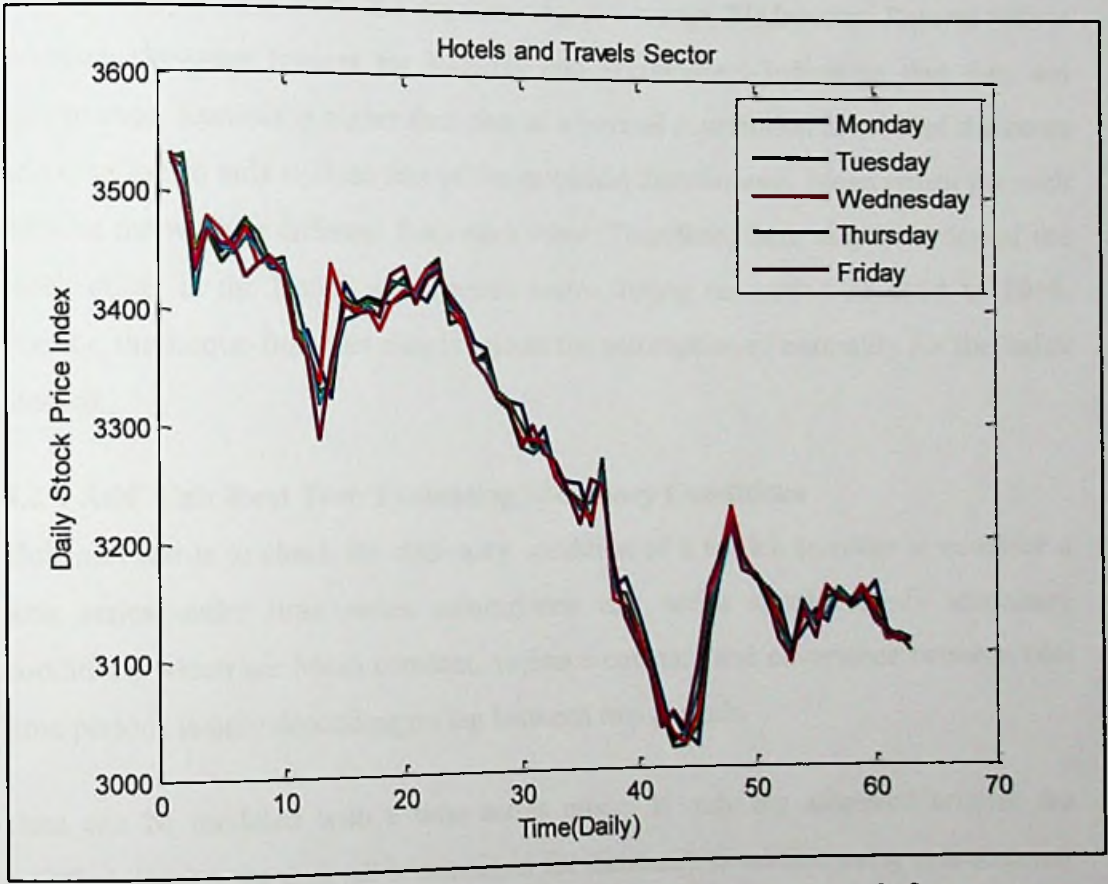

Figure 4.1: Plot of Daily stock price index of Hotels and Travels Sector

As depicted in figure 4.1 there are some equalities and differences of daily stock prices on each day of the week. Further analysis of the stock prices is needed to capture these differences and equalities.

Table 4.1 : Descriptive Statistics of Returns for each day of the week of H&T

Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	-0.0874	-0.0567	0.0003	-0.0530	-0.0055
Median	-0.1017	-0.1072	-0.0935	-0.0456	-0.0567
Standard Deviation	0.6865	0.3339	0.4716	0.4684	0.3706
Kurtosis	4.5336	0.0482	25.6291	16.0406	0.8665
Skewness	-0.6114	0.4665	4.1878	-2.6700	-0.2790
Jarque-Bera	9.9386	25.1561	1528.3521	521.2548	12.7662

Table 4.1 reports descriptive statistics of returns for each day of the week of Hotels and Travels sector of Colombo stock exchange for the period 2014 to 2016. The average daily returns of all the days are negative except Wednesday. Returns reflect negative skewness (except for Tuesday and Wednesday) indicating that they are asymmetric. Kurtosis is higher than that of a normal distribution in most of the cases showing the fat tails stylized fact of the empirical distributions. Mean return for each days of the week is different from each other. Therefore, there may be a day of the week effect in the Hotels and Travels sector during the period of 2014 to 2016. Finally, the Jarque-Bera test clearly rejects the assumption of normality for the index studied.

4.2.1 ADF Unit Root Test: Evaluating Stationary Conditions

Unit root test is to check the stationary condition of a model. In order to consider a data series under time series assumptions that series should satisfy stationary conditions which are Mean constant, variance constant and covariance between two time periods is only depending on lag between two periods.

Data can be modeled with a time series model if only the aforesaid criteria are satisfied. Hence, the data set is examined for stationary condition using unit root test with below hypothesis,

H_0: Data set has a unit root

H_1: Data set doesn't have a unit root

First, ADF test is applied on level series including both intercept and trend parameters as the data set shows the existence of trend and intercept, Respective results for the data set is as follow,

Table 4.2: ADF Unit Root Test - H&T sector index level series

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.2655	0.4512
Test critical values:	1% level	-3.9876	
	5% level	-3.4242	
	10% level	-3.1351	

As per the above results P value of the test is 0.4512 which is greater than 0.05. Hence null hypothesis should be accepted and conclude that level series of ASPI has a unit root. Therefore, ASPI level data series is non-stationary.

Further P value of the intercept is 0.0270, which is significant at 0.05 level. However, level series is not significant, therefore ADF test was carried out on first log differenced series of ASPI and results are depicted below,

Table 4.3: ADF Unit Root Test – H&T sector index first differenced series

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.9408	0.0000
Test critical values:	1% level	-3.9876	
	5% level	-3.4242	
	10% level	-3.1352	

P value of the first log differenced series is 0 (P value is < 0.05), therefore it can be concluded that null hypothesis is rejected and series doesn't have a unit root. Therefore, 1st differenced series is stationary.

After applying ADF test on the dependent variable it was shown that the 1st difference series of the data set is stationary. Therefore, differenced series of the dependent variable is used to build a time series model in order to capture the existence of day of the week effect of this sector. Generally, return series is commonly considered in analyzing the volatility of the stocks as it provides a better view of volatility. Therefore, log returns of daily ASPI were taken in to consideration to model conditional returns and volatility.

4.2.2 Testing Volatility Clusters

Below graph depicts daily returns of ASPI over considered time period and it can be easily seen the fluctuations/volatility of returns based on factors, which prevailed during the same period. The impact on volatility due to bad and good news can be explained by analyzing the patterns of the graph. High stabilities may be due to unexpected bad news, while lower volatilities represent expected good news. Similar scenario can be led to asymmetric scenario in volatility clusters,

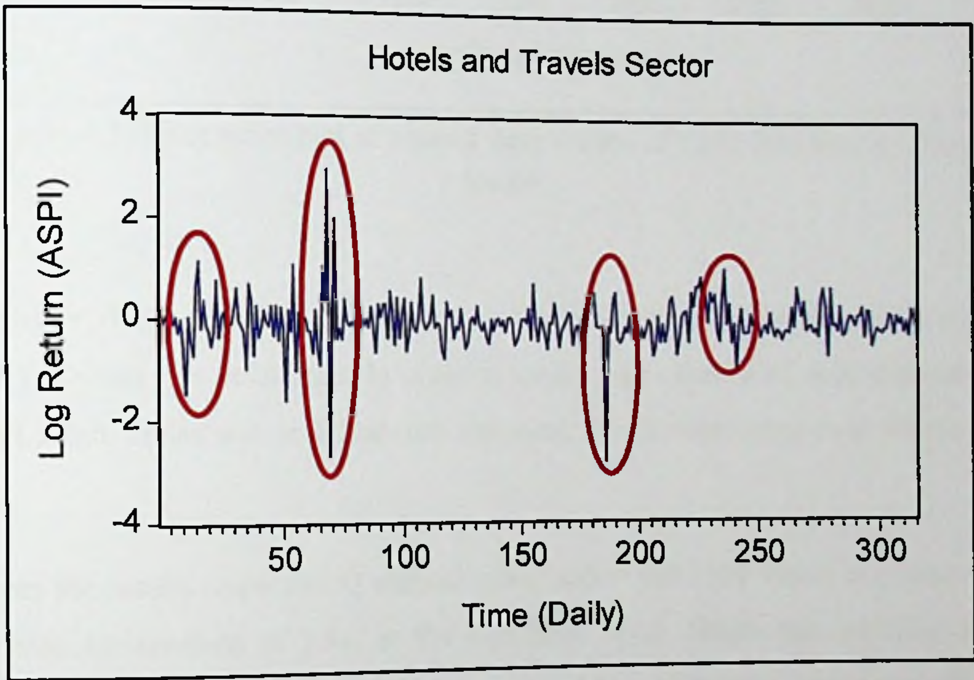

Figure 4.2 Time series plot of daily returns of ASPI for Hotels & Travels Sector

As volatility clustering depicts a strong autocorrelation in squared returns, the same series of ASPI was obtained as below to get a clear view of the volatility clusters,

It is completely clear that there are multiple volatility clusters in the above diagrams. Moreover, high volatility is followed by another period high volatility and low volatility is followed by another period of low volatility and this pattern prolonged over a considerable amount of time. Clusters, which depict aforesaid properties, were highlighted in the above figures.

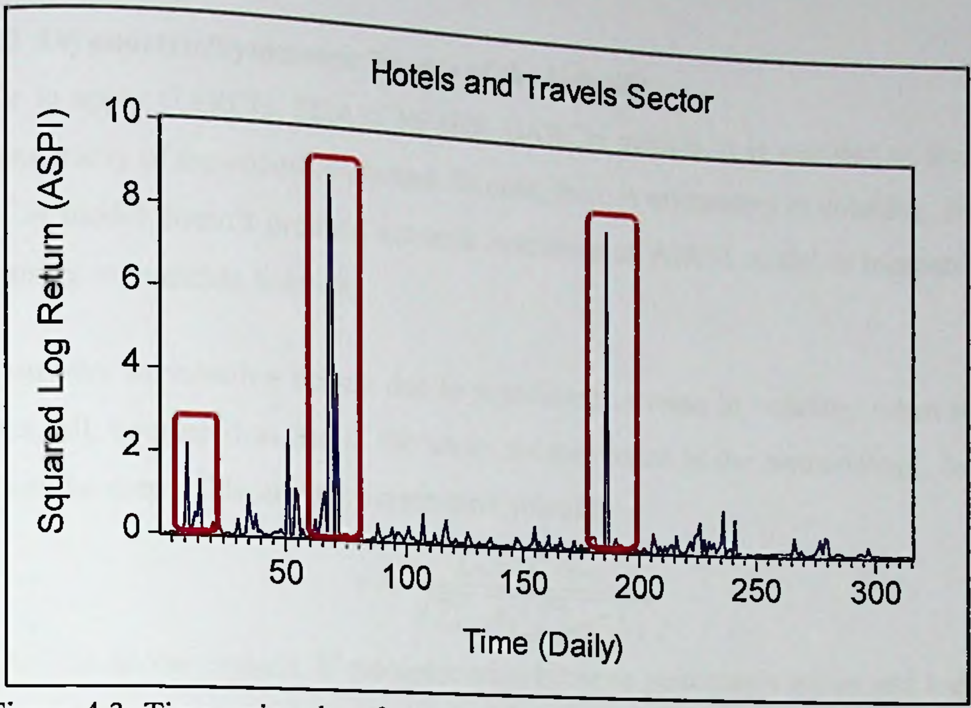

Figure 4.3: Time series plot of squared daily returns of ASPI for Hotel & Travels Sector

Therefore, it can be considered that daily values of ASPI comprise volatility clusters with high and low volatilities. In order to assure the existence of volatility clusters ASPI return series was tested against statistical significance using Box- Pierce LM test.

As per the results respective Q statistic value is Q = 100.1354 which is greater than test statistic criterion of 3.84, at 5% significant level. Hence this provided clear evidence to reject null hypothesis and it reassured non-existence of autocorrelation in squared return at 5% significance level. Similarly, this provided a sufficient evidence to prove that there exists a conditional heteroscedasticity in daily returns of ASPI. Now it is clear that the existence of significant volatility clusters in ASPI log return series, therefore it is safe to conclude that there is an ARCH effect in the data set during the considered time period. Hence, this can be considered as the entry criteria to use ARCH model in order to capture the existence of day of the week effect of this sector.

4.2.3 Asymmetric/Symmetric Nature of the Volatility

Prior to apply GARCH/ EGARCH/ GJR GARCH models, it is required to analyze symmetricity of the volatility clusters. In case, there is asymmetry in volatility, fitting ARCH model doesn't produce accurate outcomes as ARCH model is incapable of capturing asymmetric volatility.

Asymmetry in volatility occurs due to significant increase in volatility when stock prices fall, compared to rise of the same. As mentioned in the methodology, below test can be used to identify the asymmetric volatility.

$$v = \frac{\sum_{t=2}^{n} r_t^{\,2} r_{t-1}}{\sqrt{\sum_{t=2}^{n} r_t^{\,4} \sum_{t=2}^{n} r_{t-1}^2}}$$

As per the above formula, if autocorrelation between yesterday's return and today's square returns are negative, it can be concluded the existence of asymmetric volatility. In order to calculate the above V value, test was carried out on Microsoft excel and the result is as below,

$$\sum_{t=2}^{n} r_t^{\,2} r_{t-1} = -21.9712$$

$$\sqrt{\sum_{t=2}^{n} r_t^{\,4} \sum_{t=2}^{n} r_{t-1}^2} = 132.4110$$

$$v = \frac{\sum_{t=2}^{n} r_t^{\,2} r_{t-1}}{\sqrt{\sum_{t=2}^{n} r_t^{\,4} \sum_{t=2}^{n} r_{t-1}^2}} = -0.1659$$

Result of the above test is negative hence, it provides sufficient grounds to conclude that volatility in ASPI returns is asymmetric. Therefore, EGARCH and GJR GARCH models can be used to derive a model which is used to identify the existence of day of the week effect.

Subsequent to the above test corresponding Box Pierce LM statistic is calculated to reassure the asymmetric nature of the volatility.

Box Pierce LM statistic,

$$Q = (-0.1659)^2 \times 314$$
$$= 8.6455$$

Since Q statistics corresponding to v value is greater than $\chi^2_1, 5\%$ (= 3.84), implies that it is significantly different from zero. Therefore, it rejects null hypothesis and safe to conclude that there exists asymmetric nature in volatility. Hence, it is more suitable to use EGARCH and GJR GARCH model in order to capture day of the week effect of this sector.

Secondary data is used to examine the existence of day of the week effect in stock return and volatility in this sector. Although, data for the ten year period from 6th November 2006 to 4th November 2016 are collected, H&T sector index from 11th November 2014 to 4th November 2016 is only used to derive the models that are used to examine the existence of day of the week effect, in order to keep the normality of the residuals. Aforesaid period contains 315 data points.

Model fitting was carried out on EViews, as the first step log returns of ASPI, modeled using GARCH method taking dummy variables for each day of the week as independent variables. Error distribution is modeled using normal distribution.

Table 4.4: Mean and variance equation of GARCH(2,1) model - H&T sector

Variable	Coefficient	Std. Error	Z-Statistic	Prob.
Conditional Mean Equation				
D_1	-0.1707	0.0584	-2.9224	0.0035
D_2	-0.0953	0.0381	-2.5006	0.0124
D_3	-0.0467	0.0430	-1.0867	0.2772
D_4	0.0297	0.0337	0.8807	0.3785
D_5	-0.0353	0.0283	-1.2496	0.2115
Conditional Variance Equation				
C	0.0187	0.0080	2.3293	0.0198
ε_{t-1}	0.2473	0.0866	2.8553	0.0043
ε_{t-2}	0.1688	0.0614	2.7490	0.0060
σ_{t-1}	0.2870	0.0774	3.7073	0.0002
D_1	0.3122	0.0405	7.7094	0.0000
D_2	-0.0518	0.0162	-3.1959	0.0014

Using the coefficients depicted in the above table mean and variance equations of GARCH (2,1) model can be written as below,

Mean Equation:

$$r_t = -0.1707\, D_1 - 0.0953 D_2 - 0.0467 D_3 + 0.0297\, D_4 - 0.0353 D_5 + \varepsilon_t$$

Variance Equation:

$$\sigma_t^2 = 0.0187 + 0.3122 D_1 - 0.0518 D_2 + 0.2473 \varepsilon_{t-1} + 0.1688 \varepsilon_{t-2} + 0.2870 \sigma_{t-1}^2$$

Moreover, another model was built using higher order EGARCH terms.

Table 4.5: Mean and variance equation of EGARCH(3,2) model-H&T sector

Variable	Coefficient	Std. Error	Z-Statistic	Prob.
Conditional Mean Equation				
D_1	-0.1149	0.0499	-2.3036	0.0212
D_2	-0.0906	0.0065	-13.8858	0.0000
D_3	-0.0336	0.0249	-1.3483	0.1776
D_4	-0.0513	0.0161	-3.1925	0.0014
D_5	-0.0075	0.0225	-0.3328	0.7393
Conditional Variance Equation				
C	-0.4379	0.1165	-3.7599	0.0002
$\frac{\lvert\varepsilon_{t-1}\rvert}{\lvert\sigma_{t-1}\rvert}$	0.4136	0.1324	3.1234	0.0018
$\frac{\lvert\varepsilon_{t-2}\rvert}{\lvert\sigma_{t-2}\rvert}$	-0.6568	0.2370	-2.7717	0.0056
$\frac{\lvert\varepsilon_{t-3}\rvert}{\lvert\sigma_{t-3}\rvert}$	0.5579	0.1507	3.7025	0.0002
$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-0.0324	0.0096	-3.3822	0.0007
$\ln \sigma_{t-1}^2$	1.7388	0.0216	80.5908	0.0000
$\ln \sigma_{t-2}^2$	-0.9121	0.0192	-47.4928	0.0000
D_1	0.6826	0.2406	2.8373	0.0045
D_2	-1.6452	0.2947	-5.5820	0.0000

Using the coefficients depicted in the above table mean and variance equations of EGARCH (3,2) model can be written as below, Mean Equation:

$$r_t = -0.1149\,D_1 - 0.0906D_2 - 0.0336D_3 - 0.0513D_4 - 0.0075D_5 + \varepsilon_t$$

Variance Equation:

$$\ln\sigma_t^2 = -0.4379 + 0.6826D_1 - 1.6452D_2 + 0.4136\frac{|\varepsilon_{t-1}|}{|\sigma_{t-1}|} - 0.6568\frac{|\varepsilon_{t-2}|}{|\sigma_{t-2}|} + 0.5579\frac{|\varepsilon_{t-3}|}{|\sigma_{t-3}|} - 0.0324\frac{\varepsilon_{t-j}}{\sigma_{t-j}} + 1.7388\ln\sigma_{t-1}^2 - 0.9121\ln\sigma_{t-2}^2$$

The results obtained on both models are depicted below,

Table 4.6: Mean and variance equation of GARCH(2,1) and EGARCH(3,2) model – H&T sector

Model I – GARCH(2,1)			**Model II – EGARCH(3,2)**		
Variable	**Coefficient**	**Probability**	**Variable**	**Coefficient**	**Probability**
Conditional Mean Equation					
D_1	-0.1707	0.0035	D_1	-0.1149	0.0212
D_2	-0.0953	0.0124	D_2	-0.0906	0.0000
D_3	-0.0467	0.2772	D_3	-0.0336	0.1776
D_4	0.0297	0.3785	D_4	-0.0513	0.0014
D_5	-0.0353	0.2115	D_5	-0.0075	0.7393
Conditional Variance Equation					
C	0.0187	0.0198	C	-0.4379	0.0002
ε_{t-1}	0.2473	0.0043	$\frac{\lvert\varepsilon_{t-1}\rvert}{\lvert\sigma_{t-1}\rvert}$	0.4136	0.0018
ε_{t-2}	0.1688	0.0060	$\frac{\lvert\varepsilon_{t-2}\rvert}{\lvert\sigma_{t-2}\rvert}$	-0.6568	0.0056
σ_{t-1}	0.2870	0.0002	$\frac{\lvert\varepsilon_{t-3}\rvert}{\lvert\sigma_{t-3}\rvert}$	0.5579	0.0002
D_1	0.3122	0.0000	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	-0.0324	0.0007
D_2	-0.0518	0.0014	$\ln\sigma_{t-1}^2$	1.7388	0.0000
			$\ln\sigma_{t-2}^2$	-0.9121	0.0000
			D_1	0.6826	0.0045
			D_2	-1.6452	0.0000

Model I : GARCH(2,1)

Mean Equation:

$$r_t = -0.1707\,D_1 - 0.0953D_2 - 0.0467D_3 + 0.0297\,D_4 - 0.0353D_5 + \varepsilon_t$$

Variance Equation:

$$\sigma_t^2 = 0.0187 + 0.3122D_1 - 0.0518D_2 + 0.2473\varepsilon_{t-1} + 0.1688\varepsilon_{t-2} + 0.2870\sigma_{t-1}^2$$

Model II : EGARCH(3,2)

Mean Equation:

$$r_t = -0.1149\,D_1 - 0.0906D_2 - 0.0336D_3 - 0.0513D_4 - 0.0075D_5 + \varepsilon_t$$

Variance Equation:

$$\ln\sigma_t^2 = -0.4379 + 0.6826D_1 - 1.6452D_2 + 0.4136\frac{|\varepsilon_{t-1}|}{|\sigma_{t-1}|} - 0.6568\frac{|\varepsilon_{t-2}|}{|\sigma_{t-2}|} + 0.5579\frac{|\varepsilon_{t-3}|}{|\sigma_{t-3}|} - 0.0324\frac{\varepsilon_{t-j}}{\sigma_{t-j}} + 1.7388\ln\sigma_{t-1}^2 - 0.9121\ln\sigma_{t-2}^2$$

4.2.4 Model I and Model II diagnostic testing

Both models finalized under the above section depicted a sufficient capability in capturing the existence of day of the week effect of the sector. Therefore, it was decided to run below diagnostic test on each model to check their adequacy of the finalized model,

1. Ljung-Box Q-statistics for squared standardized residuals
2. Ljung-Box Q-statistics for squared standardized returns
3. ARCH LM test

Ljung-Box Q-statistics for standardized residuals

Ljung-Box Q-statistics test is carried out on standardized residual series in order to measure the adequacy of both models and results are as follow,

Table 4.7: Q-statistics and P value of Ljung-Box test on standard residuals of Model I and Model II

Lag	Model I – GARCH(2,1)		Model II – EGARCH(3,2)	
	Q statistic	Probability	Q statistic	Probability
1	0.145	0.703	0.190	0.663
2	0.739	0.691	0.238	0.888
3	1.021	0.796	0.451	0.929
4	2.684	0.612	1.384	0.847
5	2.732	0.741	2.677	0.750
6	4.914	0.555	5.289	0.507
7	4.914	0.670	5.364	0.616
8	4.953	0.763	5.376	0.717
9	5.728	0.767	5.459	0.793
10	5.775	0.834	5.621	0.846

Main objective of the test is to analyze whether there is a pattern in the residual terms. If there is a pattern in the error terms, the fitted model is not adequate as model hasn't been captured the trend in the data set. However, in the above table, all other P values in subsequent lags are insignificant because respective P values are higher than 0.05 at 5% significant level. Therefore, it depicts adequate evidence to conclude that that there is no serial autocorrelation in squared standard residuals. Hence, it provides sufficient evidence on adequacy of the finalized two models accordingly to the test statistics of Ljung-Box Q-statistics.

Ljung-Box Q-statistics for standardized returns squared

Similar to the above test, main objective of the standardized return squared test is to ensure whether fitted model captures the trend in the data set. However, it has a different approach as it uses return series instead of residuals which were used in the first test. To create a squared return series, firstly GARCH variance series should be created, thereafter ASPI log return series is divided by GARCH variance series. Finally calculated the squares of the results which were obtained by dividing ASPI log returns by GARCH series. Below table depicts the correlogram results of the squared returns,

Table 4.8: Q-statistics and P value of Ljung-Box test on standard squared residuals of Model I and Model II

Lag	Model I – GARCH(2,1)		Model II– EGARCH(3,2)	
	Q statistic	Probability	Q statistic	Probability
1	0.409	0.522	0.190	0.663
2	1.337	0.513	0.238	0.888
3	1.674	0.643	0.451	0.929
4	1.691	0.792	1.384	0.847
5	1.693	0.890	2.677	0.750
6	2.954	0.815	5.289	0.507
7	3.130	0.873	5.364	0.616
8	4.943	0.764	5.376	0.717
9	5.194	0.817	5.459	0.793
10	5.337	0.868	5.621	0.846

ARCH LM test

In order to test the presence of additional autoregressive conditional heteroscedasticity, ARCH-LM test is used.

Table 4.9: ARCH LM test statistic values and P values of Model I and Model II

	Model I – GARCH(2,1)		Model II – EGARCH(3,2)	
	Test statistic	Probability	Test statistic	Probability
F – Statistic	0.1904	0.663	0.0012	0.9719
Obs*R - squared	0.2384	0.888	0.0013	0.9718

According to the above table, it is clear that two test statistics do not reject the null hypothesis, of non-existence of autoregressive conditional heteroscedasticity (ARCH) in the residuals at 5% significant level. This means residuals of both models do not contain autoregressive conditional heteroscedasticity. Thus, these tests provide further assurance on adequacy of the models.

4.2.5 Comparison of Fitted Models

The above three test examine sufficiency of the models. Therefore, the following table depicts the two information criteria's related to the Model I and Model II.

Table 4.10: Information criteria of Model I and Model II

	Model I – GARCH(2,1)	Model II – EGARCH(3,2)
Akaike Information Criterion (AIC)	0.9505	0.8044
Schwarz Information Criterion (SIC)	1.0819	0.9716

It is clear that Model II has the lowest positive values of information criterion. Thus it implies there is less information loss in Model II-EGARCH (3,2) compared to Model I-GARCH (2,1). Therefore, Model II-EGARCH (3,2) can be considered as the best model from two models.

If these models are well specified, error distribution should behave in random manner, in other words Skewness and Kurtosis of residuals tend to depict properties of normality by depicting values 0 and 3 Skewness and Kurtosis respectively. Hence, the normality of errors is checked for the two models as below.

Table 4.11: Normality test (on residuals) results of two models

Description	Model I – GARCH(2,1)	Model II – EGARCH(3,2)
Skewness	0.0136	0.1752
Kurtosis	4.9327	3.2784
Jarque-Bera	48.3254	2.6123
Probability	0.0000	0.2709

It is clear that error distributions of model-II depict properties of normality conditions and kurtosis and skewness of errors in model-I almost satisfy normality condition. Hence, it is safe to consider that errors are normally distributed.

4.2.6 Results

From the outcomes of the conditional mean equation of the all models employed, it can be concluded that Monday and Tuesday effects is present on stock returns. Thursday effects is present only on EGARCH (3,2) Model. Returns on Monday are negative and statistically significant at 1% level in Model I. Returns on Tuesday and Thursday are negative and statistically significant at 1% level in Model II.

In terms of volatility, Mondays and Tuesdays coefficients are significantly positive at 1% level in all the models employed. These results imply that there exists day of the week effect on stock returns in terms of volatility in the Hotel and Travels sector.

Based on the information criteria measures, the EGARCH (3,2) models with normal distribution outperform the GARCH (2,1) indicating that asymmetry plays a role when investigating the day of the week effect. The Ljung-Box and ARCH-LM tests which indicate no evidence of neither autocorrelation nor heteroscedasticity in all models employed implies that these two models best describe the data set for the Hotel and Travels sector. EGARCH (3,2) model is preferred based on AIC and SIC criterion. Consequently, the EGARCH (3,2) model seems to be the best capture for the day of the week effect on both the stock returns and volatility for Hotels and Travels sector.

4.3 Investment Trusts Sector

Under this sector there are 9 companies from the 296 companies registered at Colombo stock exchange.

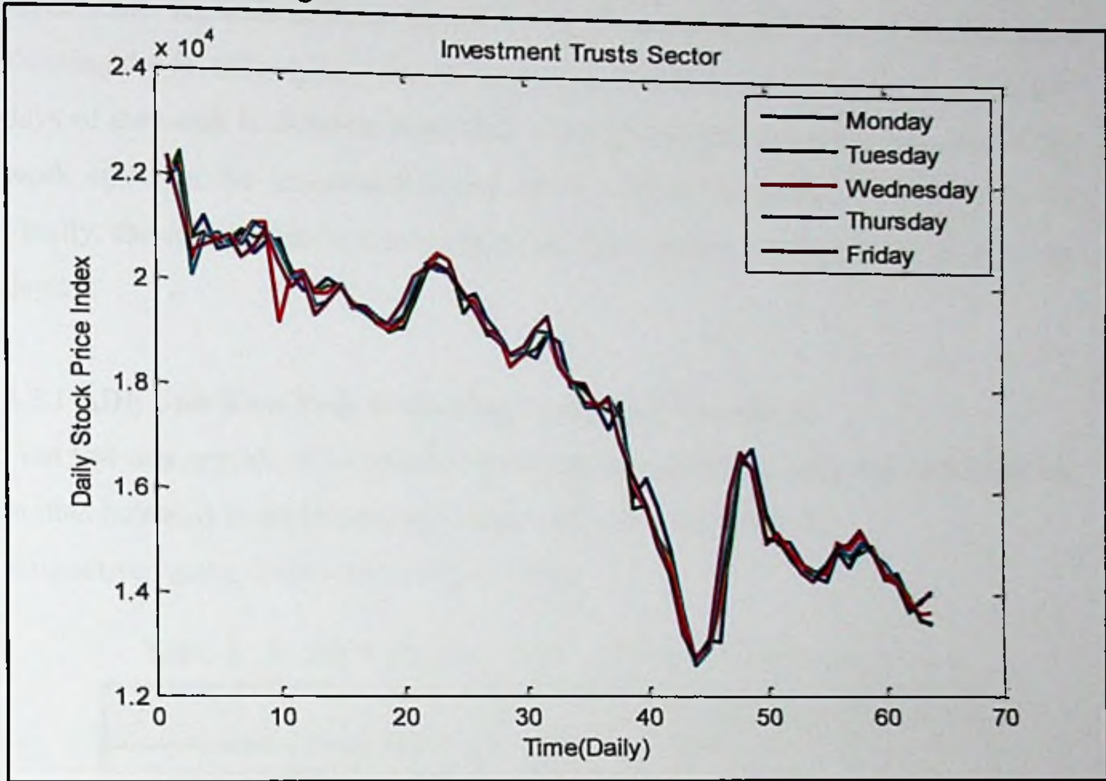

Figure 4.4: Plot of Daily stock price index of Investment Trusts Sector

As depicted in the figure 4.4 there are some equalities and differences of daily stock prices on each day of the week. Further analysis of the stock prices is needed to capture these differences and equalities.

Table 4.12 : Descriptive Statistics of Returns for each day of the week of INV

Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	-0.7045	-0.1655	0.0263	0.0197	0.1289
Median	-0.5222	-0.1032	-0.0293	-0.0842	0.0138
Standard Deviation	2.0692	1.2713	1.4298	1.2574	1.1009
Kurtosis	1.8159	4.5695	10.8424	13.2801	2.3307
Skewness	0.0543	0.5287	-2.0426	2.8031	0.4182
Jarque-Bera	3.7111	9.5501	208.5139	365.6236	3.0600

Table 4.12 reports descriptive statistics of returns for each day of the week of Investment Trusts sector of Colombo stock exchange for the period 2014 to 2016.

The average daily returns of all the days are positive except Monday and Tuesday. Returns reflect positive skewness (except Wednesday) indicating that they are asymmetric. Kurtosis is higher than that of a normal distribution in most of the cases showing the fat tails stylized fact of the empirical distributions. Mean return for each days of the week is different from each other. Therefore, there may be a day of the week effect in the Investment Trusts sector during the period of 2014 to 2016. Finally, the Jarque-Bera test also rejects the assumption of normality in most of the days.

4.3.1 ADF Unit Root Test: Evaluating Stationary Conditions

First test was applied on level series including both intercept and trend parameters as plotted below, data set shows the existence of trend and intercept,

Respective results for the data set is as follow,

Table 4.13: ADF Unit Root Test - INV sector index level series

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.1686	0.5050
Test critical values:	1% level	-3.9871	
	5% level	-3.4240	
	10% level	-3.1350	

As per the above results P value of the test is 0.5050 which is greater than 0.05. Hence null hypothesis should be accepted and conclude that level series of ASPI has a unit root. Therefore, ASPI level data series is non stationary.

Further P value of the intercept is 0.0402, which is significant at 0.05 level. However, level series is not significant, therefore ADF test was carried out on first log differenced series of ASPI and results are depicted below,

Table 4.14: ADF Unit Root Test – INV sector index first differenced series

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-17.9395	0.0000
Test critical values:	1% level	-3.9872	
	5% level	-3.4240	
	10% level	-3.1350	

P value of the first log differenced series is 0 (P value is < 0.05), therefore it can be concluded that null hypothesis is rejected and series doesn't have a unit root. Therefore, 1st differenced series is stationary.

After applying ADF test on all the independent and dependent variables it was shown that the 1st difference series of all three data sets are stationary. Therefore, differenced series of each variable was used to build a time series model in order to predict future stock values. Generally, return series is commonly considered in analysing the volatility of the stocks as it provides a better view of volatility. Therefore, log returns of daily ASPI were taken in to consideration to model conditional returns and volatility.

4.3.2 Testing Volatility Clusters

Below graph depicts daily returns of ASPI over considered time period and it can be easily seen the fluctuations/volatility of returns based on factors, which prevailed during the same period. The impact on volatility due to bad and good news can be explained by analyzing the patterns of the graph. High stabilities may be due to unexpected bad news, while lower volatilities represent expected good news. Similar scenario can be led to asymmetric scenario in volatility clusters,

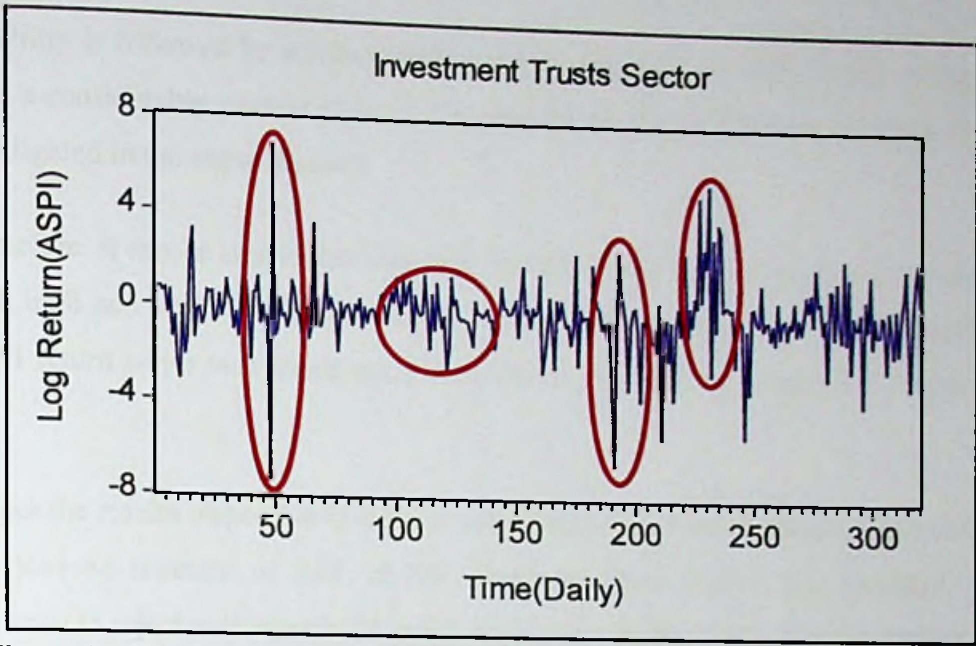

Figure 4.5 Time series plot of daily returns of ASPI for Investment Trusts Sector

As volatility clustering depicts a strong autocorrelation in squared returns, the same series of ASPI was obtained as below to get a clear view of the volatility clusters,

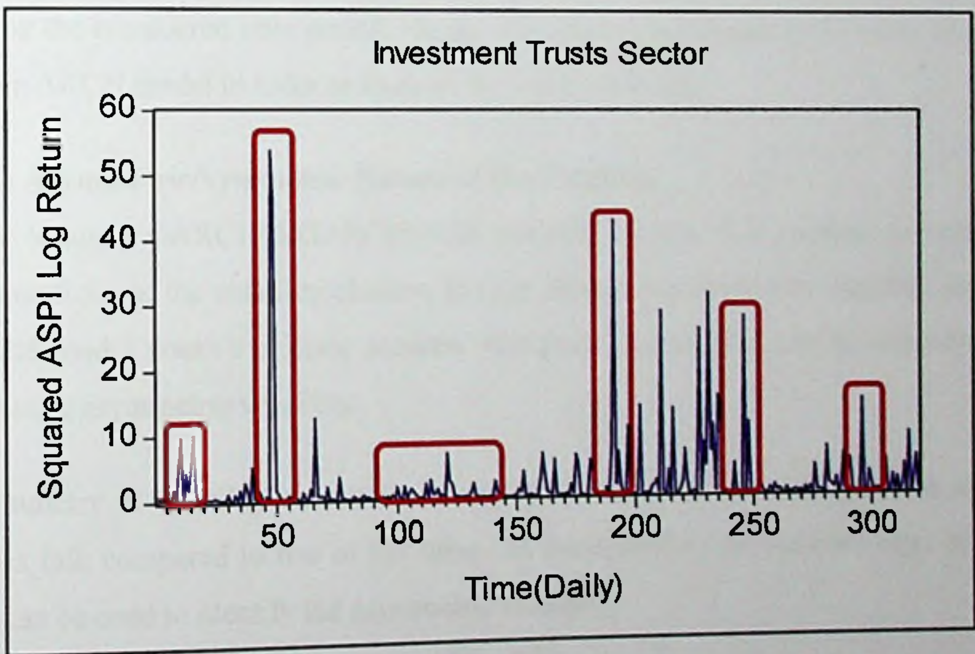

Figure 4.6: Time series plot of squared daily returns of ASPI for Investment Trusts Sector

It is completely clear that there are multiple volatility clusters in the above diagrams. Moreover, high volatility is followed by another period high volatility and low volatility is followed by another period of low volatility and this pattern prolonged over a considerable amount of time. Clusters, which depict aforesaid properties were highlighted in the above figures.

Therefore, it can be considered that daily values of ASPI comprise volatility clusters with high and low volatilities. In order to assure the existence of volatility clusters ASPI return series was tested against statistical significance using Box- Pierce LM test.

As per the results respective Q statistic value was Q = 106.6662 which is greater than test statistic criterion of 3.84, at 5% significant level. Hence this provided clear evidence to reject null hypothesis and it reassured non-existence of autocorrelation in squared return at 5% significance level. Similarly, this provided a sufficient evidence to prove that there exists a conditional heteroscedasticity in daily returns of ASPI. Now it is clear that the existence of significant volatility clusters in ASPI log return series, therefore it is safe to conclude that there is an ARCH effect in the data set during the considered time period. Hence, this can be considered as the entry criteria to use ARCH model in order to forecast the stock behavior.

4.3.3 Asymmetric/Symmetric Nature of the Volatility

Prior to apply GARCH/ EGARCH/ GJR GARCH models, it is required to analyze symmetricity of the volatility clusters. In case, there is asymmetry in volatility, fitting ARCH model doesn't produce accurate outcomes as ARCH model is incapable of capturing asymmetric volatility.

Asymmetry in volatility occurs due to significant increase in volatility when stock prices fall, compared to rise of the same. As mentioned in the methodology, below test can be used to identify the asymmetric volatility.

$$v = \frac{\sum_{t=2}^{n} {r_t}^2 r_{t-1}}{\sqrt{\sum_{t=2}^{n} {r_t}^4 \sum_{t=2}^{n} {r_{t-1}}^2}}$$

As per the above formula, if autocorrelation between yesterday's return and today's square returns are negative, it can be concluded the existence of asymmetric volatility. In order to calculate the above V value, test was carried out on Microsoft excel and the result is as below,

$$\sum_{t=2}^{n} r_t^2 r_{t-1} = -386.4970$$

$$\sqrt{\sum_{t=2}^{n} r_t^4 \sum_{t=2}^{n} r_{t-1}^2} = 3047.043$$

$$v = \frac{\sum_{t=2}^{n} r_t^2 r_{t-1}}{\sqrt{\sum_{t=2}^{n} r_t^4 \sum_{t=2}^{n} r_{t-1}^2}} = -0.1268$$

Result of the above test is negative hence, it provides sufficient grounds to conclude that volatility in ASPI returns is asymmetric. Therefore, EGARCH and GJR GARCH models can be used to derive a models.

Subsequent to the above test corresponding Box Pierce LM statistic was calculated to reassure the asymmetric nature of the volatility.
Box Pierce LM statistic,

$$Q = (-0.1268)^2 \times 319$$
$$= 5.1325$$

Since Q statistics corresponding to v value is greater than $\chi_1^2, 5\%$ (= 3.84), implies that it is significantly different from zero. Therefore, it rejects null hypothesis and safe to conclude that there exists asymmetric nature in volatility. Hence, it is more suitable to use EGARCH and GJR GARCH model in order to capture day of the week effect of this sector.

Secondary data is used to examine the existence of day of the week effect in stock return and volatility in this sector. Although, data for the ten year period from 6th November 2006 to 4th November 2016 are collected, INV sector index from 10th

November 2014 to 4th November 2016 is only used to derive the models that are used to examine the existence of day of the week effect, in order to keep the normality of the residuals. Aforesaid period contains 320 data points.

Model fitting was carried out on EViews, as the first step log returns of ASPI, modelled using GARCH method taking dummy variables for each day of the week as independent variables. Error distribution is modelled using normal distribution.

Table 4.15: Mean and variance equation of GARCH(2,2) model - INV sector

Variable	Coefficient	Std. Error	Z-Statistic	Prob.
Conditional Mean Equation				
D_1	-0.8078	0.1632	-4.9486	0.0000
D_2	-0.1509	0.1843	-0.8187	0.4129
D_3	0.0073	0.2134	0.0344	0.9726
D_4	-0.1349	0.1061	-1.2707	0.2038
D_5	0.1112	0.1234	0.9012	0.3675
Conditional Variance Equation				
C	2.3322	0.2292	10.1774	0.0000
ε_{t-1}	0.2093	0.0480	4.3565	0.0000
ε_{t-2}	0.2054	0.0460	4.4649	0.0000
σ_{t-1}	-0.6074	0.0224	-27.0577	0.0000
σ_{t-2}	0.3619	0.0162	22.3636	0.0000
D_4	-1.1219	0.1820	-6.1643	0.0000
D_5	-1.9961	0.2547	-7.8377	0.0000

Using the coefficients depicted in the above table mean and variance equations of GARCH (2,2) model can be written as below,

Mean Equation:

$$r_t = -0.8078\, D_1 - 0.1509 D_2 + 0.0073 D_3 - 0.1349 D_4 + 0.1112 D_5 + \varepsilon_t$$

Variance Equation:

$$\sigma_t^2 = 2.3322 - -1.1219 D_4 - 1.9961 D_5 + 0.2093 \varepsilon_{t-1} + 0.2054 \varepsilon_{t-2} - 0.6074 \sigma_{t-1}^2 + 0.3619 \sigma_{t-2}^2$$

Moreover, another model was built using higher order EGARCH terms.

Table 4.16: Mean and variance equation of EGARCH(2,3) model - INV sector

Variable	Coefficient	Std. Error	Z-Statistic	Prob.
Conditional Mean Equation				
GARCH	-0.1121	0.0389	-2.8817	0.0040
D_1	-0.4643	0.1459	-3.1811	0.0015
D_2	-0.0067	0.1069	-0.0626	0.9501
D_3	0.2367	0.1250	1.8938	0.0582
D_4	0.0097	0.0875	0.1103	0.9122
D_5	0.1054	0.0991	1.0636	0.2875
Conditional Variance Equation				
C	-0.1565	0.1389	-1.1266	0.2599
$\frac{\lvert\varepsilon_{t-1}\rvert}{\lvert\sigma_{t-1}\rvert}$	0.2283	0.0641	3.5612	0.0004
$\frac{\lvert\varepsilon_{t-2}\rvert}{\lvert\sigma_{t-2}\rvert}$	0.4808	0.0534	8.9969	0.0000
$\ln\sigma_{t-1}^2$	0.2895	0.0167	17.2939	0.0000
$\ln\sigma_{t-2}^2$	-0.2956	0.0184	-16.0353	0.0000
$\ln\sigma_{t-3}^2$	0.9006	0.0183	49.1298	0.0000
D_4	-1.1636	0.3007	-3.8704	0.0001
D_5	-0.6412	0.2711	-2.3653	0.0180

Using the coefficients depicted in the above table mean and variance equations of EGARCH (2,3) model can be written as below,

Mean Equation:

$$r_t = -0.4643\,D_1 - 0.0067D_2 + 0.2367D_3 + 0.0097D_4 + 0.1054D_5 + \varepsilon_t$$

Variance Equation:

$$\ln\sigma_t^2 = -0.1565 - 1.1636D_4 - 0.6412D_5 + 0.2283\frac{|\varepsilon_{t-1}|}{|\sigma_{t-1}|} + 0.4808\frac{|\varepsilon_{t-2}|}{|\sigma_{t-2}|} + 0.2895\ln\sigma_{t-1}^2 - 0.2956\ln\sigma_{t-2}^2 + 0.9006\ln\sigma_{t-3}^2$$

The results obtained on both models are depicted below,

Table 4.17: Mean and variance equation of GARCH(2,2) & EGARCH(2,3) model - INV sector

Model I – GARCH(2,2)			Model II – EGARCH(2,3)		
Variable	**Coefficient**	**Probability**	**Variable**	**Coefficient**	**Probability**
Conditional Mean Equation					
			GARCH	-0.1121	0.0040
D_1	-0.8078	0.0000	D_1	-0.4643	0.0015
D_2	-0.1509	0.4129	D_2	-0.0067	0.9501
D_3	0.0073	0.9726	D_3	0.2367	0.0582
D_4	-0.1349	0.2038	D_4	0.0097	0.9122
D_5	0.1112	0.3675	D_5	0.1054	0.2875
Conditional Variance Equation					
C	2.3322	0.0000	C	-0.1565	0.2599
ε_{t-1}	0.2093	0.0000	$\frac{\lvert\varepsilon_{t-1}\rvert}{\lvert\sigma_{t-1}\rvert}$	0.2283	0.0004
ε_{t-2}	0.2054	0.0000	$\frac{\lvert\varepsilon_{t-2}\rvert}{\lvert\sigma_{t-2}\rvert}$	0.4808	0.0000
σ_{t-1}	-0.6074	0.0000	$\ln \sigma_{t-1}^2$	0.2895	0.0000
σ_{t-2}	0.3619	0.0000	$\ln \sigma_{t-2}^2$	-0.2956	0.0000
D_4	-1.1219	0.0000	$\ln \sigma_{t-3}^2$	0.9006	0.0000
D_5	-1.9961	0.0000	D_4	-1.1636	0.0001
			D_5	-0.6412	0.0180

Model I : GARCH(2,2)

Mean Equation:

$$r_t = -0.8078\,D_1 - 0.1509D_2 + 0.0073D_3 - 0.1349D_4 + 0.1112D_5 + \varepsilon_t$$

Variance Equation:

$$\sigma_t^2 = 2.3322 - -1.1219D_4 - 1.9961D_5 + 0.2093\varepsilon_{t-1} + 0.2054\varepsilon_{t-2} - 0.6074\sigma_{t-1}^2 + 0.3619\sigma_{t-2}^2$$

Model II : EGARCH(2,3)

Mean Equation:

$$r_t = -0.4643\,D_1 - 0.0067D_2 + 0.2367D_3 + 0.0097D_4 + 0.1054D_5 + \varepsilon_t$$

Variance Equation:

$$\ln \sigma_t^2 = -0.1565 - 1.1636D_4 - 0.6412D_5 + 0.2283\frac{|\varepsilon_{t-1}|}{|\sigma_{t-1}|} + 0.4808\frac{|\varepsilon_{t-2}|}{|\sigma_{t-2}|} + 0.2895\ln \sigma_{t-1}^2 - 0.2956\ln \sigma_{t-2}^2 + 0.9006\ln \sigma_{t-3}^2$$

4.3.4 Model I and Model II diagnostic testing

Both models finalized under the above section depicted a sufficient capability in deriving future log return values of ASPI. Therefore, it was decided to run below diagnostic test on each model to check their adequacy of the finalized model,

1. Ljung-Box Q-statistics for squared standardized residuals
2. Ljung-Box Q-statistics for squared standardized returns
3. ARCH LM test

Ljung-Box Q-statistics for standardized residuals

Ljung-Box Q-statistics test is carried out on squared residual series in order to measure the adequacy of both models and results are as follow,

Table 4.18: Q-statistics and P value of Ljung-Box test on standard residuals of Model I and Model II

Lag	Model I – GARCH(2,1)		Model II – EGARCH(3,2)	
	Q statistic	Probability	Q statistic	Probability
1	1.284	0.257	1.612	0.204
2	4.308	0.116	3.014	0.222
3	4.316	0.229	3.626	0.305
4	4.952	0.292	4.092	0.394
5	5.627	0.344	4.312	0.505
6	6.567	0.363	6.407	0.379
7	7.709	0.359	7.410	0.387
8	9.105	0.334	8.017	0.432
9	9.315	0.409	9.012	0.436
10	9.384	0.496	9.126	0.520

P values of first two lags are adjusted for two autoregressive terms, thus Q statistics and probabilities are available from the third lag. Main objective of the test is to analyse whether there is a pattern in the squared residual terms. If there is a pattern in the error terms, the fitted model is not adequate as model hasn't been captured the trend in the data set. However, in the above table, all other P values in subsequent lags are insignificant because respective P values are higher than 0.05 at 5% significant level. Therefore, it depicts adequate evidence to conclude that that there is no serial autocorrelation in squared standard residuals. Hence, it provides sufficient evidence on adequacy of the finalized two models accordingly to the test statistics of Ljung-Box Q-statistics.

Ljung-Box Q-statistics for standardized returns squared

Similar to the above test, main objective of the standardized return squared test is to ensure whether fitted model captures the trend in the data set. However, it has a different approach as it uses return series instead of residuals which were used in the first test. To create a squared return series, firstly GARCH variance series should be created, thereafter ASPI log return series is divided by GARCH variance series. Finally calculated the squares of the results which were obtained by dividing ASPI log returns by GARCH series. Below table depicts the correlogram results of the squared returns,

Table 4.19: Q-statistics and P value of Ljung-Box test on standard squared residuals of Model I and Model II

Lag	Model I – EGARCH(3,2)		Model II– EGARCH(3,2)	
	Q statistic	Probability	Q statistic	Probability
1	0.210	0.647	0.567	0.451
2	0.380	0.827	1.298	0.523
3	1.680	0.641	1.342	0.719
4	2.306	0.680	1.343	0.854
5	3.032	0.695	2.247	0.814
6	3.376	0.760	2.499	0.869

7	3.404	0.845	2.921	0.892
8	3.794	0.875	5.747	0.676
9	4.767	0.854	7.498	0.585
10	4.771	0.906	8.556	0.575

ARCH LM test

In order to test the presence of additional autoregressive conditional heteroscedasticity, ARCH-LM test is used.

Table 4.20: ARCH LM test statistic values and P values of Model I and Model II

	Model I – EGARCH(2,1)		Model II – EGARCH(3,2)	
	Test statistic	Probability	Test statistic	Probability
F – Statistic	0.1654	0.6845	0.4894	0.4847
Obs*R - squared	0.1664	0.6833	0.4917	0.4832

According to the above table, it is clear that two test statistics do not reject the null hypothesis, of non-existence of autoregressive conditional heteroscedasticity (ARCH) in the residuals at 5% significant level. This means residuals of both models do not contain autoregressive conditional heteroscedasticity. Thus, these tests provide further assurance on adequacy of the models.

4.3.5 Comparison of Fitted Models

The above three test examine sufficiency of the models. Therefore, the following table depicts the two information criteria's related to the Model I and Model II.

Table 4.21: Information criteria of Model I and Model II

	Model I – GARCH(2,2)	Model II – EGARCH(2,3)
Akaike Information Criterion (AIC)	3.4245	3.2315
Schwarz Information Criterion (SIC)	3.5661	3.3967

It is clear that model two has the lowest positive values of information criterion. Thus it implies there is less information loss in Model II- EGARCH (2,3) compared to Model I-GARCH (2,2). Therefore, Model II-EGARCH (2,3) can be considered as the best model from two models.

If these models are well specified, error distribution should behave in random manner, in other words Skewness and Kurtosis of residuals tend to depict properties of normality by depicting values 0 and 3 Skewness and Kurtosis respectively. Hence, the normality of errors is checked for the two models as below.

Table 4.22: Normality test (on residuals) results of two models

Description	Model I – GARCH(2,2)	Model II – EGARCH(2,3)
Skewness	-0.2032	-0.0116
Kurtosis	5.8283	3.9000
Jarque-Bera	108.5211	10.7746
Probability	0.0000	0.0046

Although error distributions of the two models not satisfy the Jarque-Bera test for normality condition, kurtosis and skewness of errors in model-II almost satisfy required values for normality condition. Hence, model-II can be considered as the best model compared to model-I.

4.3.6 Results

From the outcomes of the conditional mean equation of the all models employed, it can be concluded that Monday effects is present on stock returns. Returns on Monday are negative and statistically significant at 1%level in both Models.

In terms of volatility, Thursdays and Fridays coefficients are statistically significant at 1% level in Model I, whereas only Thursday coefficient is statistically significant at 1% level in Model II and Friday coefficient is statistically significant at 5% level.

These results imply that there exists day of the week effect on stock returns in terms of volatility in the Investment Trusts sector.

Based on the information criteria measures, the EGARCH (2,3) models with normal distribution outperform the GARCH (2,2) indicating that asymmetry plays a role when investigating the day of the week effect. The Ljung-Box and ARCH-LM tests which indicate no evidence of neither autocorrelation nor heteroscedasticity in all models employed implies that these two models best describe the data set for the Investment Trusts sector. EGARCH (2,3) model is preferred based on AIC and SIC criterion. Consequently, the EGARCH (2,3) model seems to be the best capture for the day of the week effect on both the stock returns and volatility for Investment Trusts sector.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter displays the conclusions from the empirical studies concerning day of the week effect. The results are compared with previous studies and any differences and similarities are explained. The limitations of the study are also discussed and suggestions are provided for further research as well.

5.2 Summary of findings

This study examined persistence of day of the week effect on returns and volatility of two sectors in Colombo Stock Exchange, namely Hotels and Travels sector, Investment Trusts sector for the period from November 11, 2014 to November 04, 2016. The empirical analysis using two different models of time-varying conditional volatility with normal distributions found that the *day-of-the-week* effect is present in all sectors examined.

Hotels and Travels sector and Investment Trusts sector of Colombo Stock Exchange show clear evidence for day of the week effect on both the stock returns and volatility.

5.2.1 Results on Return

In the Hotels and Travels sector, returns on Thursdays are higher than returns on other days of the week and also return on Monday and Tuesday are significant at 1% level but all are negative, whereas in the Investment Trusts sector only Monday return is significant at 1% level and it is negative. This is not in line with the results obtained by Athambawa Jahfer (2015) who studied the All Share Price Index of the Colombo stock market from January 2004 through June 2015 and found lowest returns on Monday and highest on Friday.

5.2.2 Results on Volatility

In terms of volatility, only Monday and Tuesday coefficients are significant and Monday shows significantly higher positive effect than other days of the week in Hotel and Travels sector. This may be occur because investors would have had no chance to react to financial information that occurred from Friday closing to opening of trading on Monday. In Investment Trusts sector, only Thursday and Friday coefficients are significant and negative.

5.3 Conclusion of the study

In conclusion, the day of the week effect is present in both return and volatility of Hotels and Travels sector and Investment Trusts sector in Colombo Stock Exchange. Due to this day of the week effect, investors can earn an abnormal return by buying stocks on Mondays, Tuesdays and Thursdays and selling stocks on Wednesdays and Fridays. Further it can be concluded that Colombo Stock Exchange is not weak form efficient as investors can earn abnormal returns by trading on strategy based on past information. The study strongly recommends investors to follow stock market anomalies appropriately in order to make advantage investment decisions.

5.4 Limitations of the study

Daily return calculated using the ASPI daily closing prices for each sector. One of the limitations of the study is to eliminate the data of the weeks, where data are not available for all days of the week.

5.5 Discussion and Recommendations for Further Research

Although data for the ten year period from 2006 to 2016 are collected, this study used only two years data from 2014 to 2016. The reason behind this reduction is that when the ten year period data are considered, normality of the residuals of any models could not be observed. Therefore, two year data are considered, tested and successfully fitted the model for which the residuals are homoscedastic, normal and not auto correlated. According to the referred previous research papers (Thushara & Perera, 2013). (Deyshappriya, 2014), (Jahfer, 2015), (Narasinghe & Perera, 2015) on stock market anomalies (Day of the week effect, Month of the year effect, etc.) in

CSE, none of the research papers reported that normality of the residuals is considered or not in the fitted models. Therefore, in this study every fitted model is tested for heteroscedasticity, auto correlation and residuals' normality which was not considered by the pioneers.

Also none of the studies used advanced ARCH/GARCH family models such as EGARCH and GJR – GARCH which are used in this study to get more accurate results. Therefore this study is an extension of the methods that are used to capture the day of the week effect in CSE.

This study focused only on two sectors of the Colombo stock exchange. There is an opportunity for future researchers to analyze other sectors of the Colombo Stock Exchange not only for Day of the week effect but also for other trading strategies like week end effect, Month of the year effect and week of the month effect, etc. Also future researchers can do further research on this area company wise to obtain better results than this.

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