REPERCUSSIONS OF TERRORIST ATTACKS, POLITICAL EVENTS AND FINANCIAL CRISIS ON PAKISTAN STOCK EXCHANGE

SUPERVISEE:

Bilal Ahmed

30/MPhil-EAF/2013/PIDE

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A dissertation submitted to the Pakistan institute of Development Economics, Islamabad in partial fulfillment of the requirement of the degree of Master of Philosophy in Economics and Finance.

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Dedication

I dedicate this thesis to my parents, teachers, family and friends for their support, encouragement and endless love.

I am also dedicating my research work to those who have been victimized by the act of terrorism; specifically Aitzaz Hassan who has given his life in saving other lives and martyrs of International Islamic University Islamabad, Army Public School Peshawar and Bacha Khan University Charsadda. Moreover, I am also dedicating this thesis to those who are reason of proud for us especially our younger sister Arfa Karim who has died on 14th January, 2012 fighting against Cardiac Arrest.

Corroboration

You can only warn one who follows the message and fears the Most Merciful unseen. So give him good tidings of forgiveness and noble reward. (Surah Yasin – 11)

All praise is to Allah, Lord of the Worlds, and may the peace and blessings be on the most noble of Prophets and Messengers, our Holy Prophet Muhammad (PBUH), and on his family and all of his Companions. I offer to Him all praise and gratitude, and seek His assistance and forgiveness. I seek refuge in Allah from the evils of our souls and the wickedness of our deeds. Whomsoever Allah guides, none can misguide, and whomsoever Allah misguides, none can guide. I thank Allah, the Exalted, for the completion of this MPhil thesis. Alhamdulillah, Allah gave me the enough strengths and patience to tackle every problem with calm and ease. I would like to express my deepest gratitude to my Supervisor **Dr. Attiya Yasmin Javid**, *Internal Reviewer* **Dr. Saud Ahmed Khan**, *External Reviewer* **Dr. Hashim Khan** *and all my teachers especially Dr. Fazal Hussain, Dr. Sajid Amin, Dr. Shujat Farooq, Dr. Arshad Hassan, Dr. Muhammad Aslam Chaudhary, Dr. Zulfiqar Ali Shah, Ma'am Azma Batool,* **Dr. Fahim Aslam**, *Dr. Ahsan ul Haq Satti and Sir Khizer Jawad, for their guidance and individual advice. I would also like to express my deepest gratitude to my family especially Ghulam Fareed, Akhtar Ali,* **Khalid Farooq Anjum**, **Amjad Ali**, **Qummer Awais**, **Zain ul Abdin**, *Amir Farooq, Sajid Hussain, M. Azhar, M. Attique, M. Zafar, Sohaib Azhar and many other special ones, all of my friends especially* **Khizer Rehman**, **Ghulam Ghouse Raza**, **Tahir Nawaz**, **Waqar Ahmed**, **Rizwan Ali**, **Waqar Ali**, **Muhammad Junaid Nasrullah**, *Sajid Iqbal Sukhera, Ali Raza, Syed Ali Abbas Shah, Syed Ali Arslan Shah, Nazim Farooq, Hassam Shahid, Gulraiz Alsam, Kashif Ali, Muhammad Sultan, Zubair Khalid, Ahmed Rafique, Waqas Yousaf, Maaz Javed, Saad Baloch, Adeel Khaliq, Sardar Ahmed Watto, Sardar Yasir Dogar, Naqash Haider, Rai Abdul Salam, Khawar Fayyaz, Muhammad Muzammil, Ahsan Tariq, Ahsan Latif, Faiz ur Rehman, Shoaib Khan, Mohaiman Khan, Sardar Hassan, Habib ur Rehman, Karar Mayo, Umer Ayub, Samraiz Hafeez, Usman Tariq and many many others who were always there for my every kind of support and they were with me in ups and downs of life. Moreover, special thanks to our very own* **Shehzad Bhai** *and* **Shahid Bhai**. *I just want to say thanks to all of you. I really love you all.*

CONSPECTUS

The research work illustrates that impact of terrorist attacks, political events and financial crises on eight divergent sectors of *PSX* for daily sample data set from *2004* to *2014*. There are two different methodologies that *Event Study Methodology* and *Impulse Indicator Saturation*, being employed to check the significance of the events on returns and volatility series. Results indicate that each sector reacts differently in response to different type of news. Almost all the sectors react on the occurrence of *Political Events*, few sectors reacts in response to the *Terrorist Attacks* where all the sectors significantly react in response to the *Global Financial Crises* except chemical sector. However, the results under two different methodologies are almost similar though *Impulse Indicator Saturation* able to provide better results in comparison to the *Event Study Methodology* because as it captures all *Breaks* and *Co-Breaks* within a sample period, moreover it clearly helps in defining rebounding period of the market.

***Key Words**:* Pakistan Stock Exchange (*PSX*), Terrorist Attacks, Political Event, Financial Crises, Event Study Methodology, Impulse Indicator Saturation, Breaks, Co-Breaks

Table of Contents

CHAPTER I

INTRODUCTION

Background of the Study

"*No News is Good News*" is a prevailing remark by most of the fact finders of different fields including financial researchers. It is well-known fact that stock markets react over some factors even if they are not directly related to the firm's performance. These factors might be a social, economic or political disturbance and may increase or decrease the value of the stock. News reveals information on these disturbances and leaves momentous and historic chain reaction which creates disturbance in the stock markets and leads to structural breaks. These disturbance's payoffs may let someone to put you in other's shoes. Cropping up of news always leaves some structural breaks and Information revealed through news is the occurrence of an event. These events can be good or a bad in nature, however, both in nature novelties the historic aspects and become a reason to create seesaws in the market. Moreover, in response to the news, structural breaks occur which can alter a historic trend called alpha shift, which is the depiction of an efficient market. This concept of the efficient market hypothesis was given by (*Fama and French, 1970)* that can be further categorized into weak, semi-strong and strong forms of market efficiency. If the past information don't let the investors beget abnormal returns than it is weak form of market efficiency, if the investors beget abnormal returns from the past information and publicly available news than it is semi-strong market efficiency, while the strong form of market efficiency depicts the begetting of the abnormal returns against past, publicly available information and private news.

Stock markets seesaws are aped by sundry events that may be domestic or distant and could be of any category in character. A number diversified event creates vacillates in the stock market and the market may under or over react to these financial and non-financial events. These events might be anticipated or unanticipated and the reaction might be different in both cases. The effect of a nuclear detonation on the *Karachi Stock Exchange (KSE)* has also been delved into (*Javed and Ahmed, 1999)*. Further, natural underground eruption's impact on the *KSE* has also been explored (*Javid, 2007)*. Numerous researchers found that political and terrorist activities are the main source to better stock market as their impact imposed on the country as a whole. The impact of political and economic events impact on the *Philippine Stock Exchange* has also been investigated (*Bautista, 2003), Tel Aviv Stock Exchange* are more volatile on the day of the occurrence of a political event as compared a day when there is no political event (*Zach, 2003)*. The impact of terrorism activities on the emerging markets has also been scouted out (*Arin et al., 2007)*. In *Asia*, ten emerging stock market's reaction to the financial crisis has also investigated *(Yang et al., 2003)*.

Trading in stock market is a very unpredictable activity, someone with sound returns at the opening of a market on a new day, may have the end of his wealth at the end of the day. Returns could be very high, high, low or very low or might be negative. Greater the difference in the returns depicts greater the volatility *(Sweeney 1998)*. In the case of a market crash or against the occurrence of an event, *Jumps* might be generated in returns and volatility. These *Jumps* are not long lasting, that might become ineffective on the next trading day but the effects of *Jumps* in volatility may persist, however, the volatility may reverts back to its long run mean *(Eraker et al. 2003).* In response to certain events causing

Jumps in returns and volatility, effects can be observed through *Co-Breaks*. A thread of literature illustrated the significant impact of the terrorism, political and financial crisis stock returns and volatility of the stock returns.

Events History in Pakistan

Since the Pakistan came into being a number of political instabilities are occurring. After the 4 years of independence first Prime Minister of Pakistan was assassinated in 1951. The history of dictatorship started after the 11 years of the independence of the Pakistan. In 1958 first martial imposed in Pakistan and Constitution of 1956 was abrogated. The dictatorship regime continued for next 12 years. In 1970 first ever general election took place to lead to a civil war ends at the breakaway of East Pakistan to become Bangladesh in 1971. A democratic regime started in 1973 which ends after two years when once again martial law being imposed and dictatorial regime continued for 11 years in 1988. After the general election of 1988 a democratic regime started that was also dismissed in 1990 and a period of autocratic regime started which ends at the 1990 general elections, 1993 lead to another general election with resignations of democratic government, 1996 start of an autocratic regime lead to the 1997 general election in which a new democratic regime started. In 1999, dismissal of a democratic government leads to an autocratic regime which ended in 2008 after the general election. The political history of the country shows a number of instabilities.

Political decision makings, stabilities, and instabilities also play a major role in the economic structure of a country. In the same manners stock market also behaves in a different way under different political situations. Different governing structure depicts the different stock behavior. In *Pakistan* case, there is a number of major changes have taken place past 15 years regarding regime shifting between autocratic and democratic regime. A trend has been observed in the country that new government hardly continues with the previous government policies *(Express Tribune 2014)*[1]; democratic and autocratic governments adopts different policies in terms economic, foreign and internal affairs. *KSE* depicts the behavior of the people when a new government came in power *(Geo News 2013)*[2].

Political Events can be categorized into anticipated and unanticipated political events. Most of the times political are anticipated political events. There are a number of political events like privatization decisions, the arrest of the political leaders, calls for a strike, long marches, general and local body elections and foreign affairs against which the stock markets react.

Pakistan holds a great importance due to its geographical boundaries as it stretched between the *Arabian Sea* to the range of *Karakoram Mountains* with 6th largest population among 196 countries of the world and land fully enriched by a number of natural resources. Pakistan is surrounded by the *Iran, Afghanistan, China,* and *India. Pakistan* shares it's 2250 km and 2900 km of borders in length with *Afghanistan* and *India* respectively. *Indo-Pakistan* border named *Line of Control* found to be the 2nd most sensitive border in the world due to the *Occupied Kashmir Issue* and both of the countries have fought three wars over this issue that’s why there are a number of instabilities in both countries on the account of *Occupied Kashmir Issue*. Moreover, civil wars in *Afghanistan* since 1989 directly or indirectly also affect the stability of the adjacent countries especially the *Pakistan*. Due to the tightness on *Line of Control* and civil wars in neighboring

1 http://tribune.com.pk/ October 2, 2014
2 http://geo.tv/ 13 May, 2013

country, a number of challenges like terrorism have risen in *Pakistan* in past as the external forces also pay a major role in creating instabilities in the country *(Ahmar, 1996)*.

Terrorism has become a serious problem in *Pakistan* since the incident of *9/11* as reluctantly *Pakistan* has become the front line of *NATO Alliance*. Therefore, the cost that it has to pay was the severe terrorist attacks, which were increased in 2004 when the *United States of America* declared it as a *Major Non-NATO Ally*. Although, *Pakistan* is facing the issue of terrorism since it has come into being, but the intensity of the terrorist attacks has risen by 5.1 times in comparison to last 14 years and last 44 years. According to the *Global Terrorism Database,*[3] 9659 number of a terrorist incident have taken place in *Pakistan* from 2004 to 2014 with at least 16554 casualties and more than 29083 injuries, whereas from 1970 to 2000, only the number of terrorist events was 1863 with 3391 causalities. Every time a terrorist attack takes place it leaves a long lasting psychologically disturbing situation and left some bad memories to raise a number of terrorists.

According to the *Express Tribune (2014),* [4] *the* economic cost of *War on Terror* was $102.5 billion. Moreover, sectarian and ethnic conflicts are also playing a major role in terrorism. Terrorist events have always left an impact not only in terms of the loss of lives and in monetary terms, but it also has a psychological impact by creating fear and uncertainty which prevails for a long time. The terrorist attack on an educational institute leaves a situation of uncertainty for the other educational institution. While, terrorism attack on a business activity drags another investor to shut down the business activity. Terrorism events are taking place in *Pakistan* almost on daily basis. In the presence of ethnic and sectarian groups, one external disturbance creates more disturbances originated

3 http://www.start.umd.edu/gtd/ (accessed in December 2015)
4 http://tribune.com.pk/ (accessed in December, 2015)

by some inside factors. One terrorist attack on a religious place gives birth to other sectarian attacks. These types of events are responsible for closing institutional and business activities which will resultingly have a harsh impact on the stock market. Stock markets backlash in response to a terrorist attack depending on its intensity. This intensity can be depicted by the number of casualties, injuries, responsible group and target group and through the weapon that is used in a terrorist attack.

Situations in which financial institution lose a huge part of their value is known as *Financial Crises*. *Federal Reserve System (FED)* started decreasing interest rate from 6 to 1.5% in 2001 to save the market crash and unemployment. Generally, interest rate decreased to enhance the investment however, behavior of investor have a tendency to invest in real estate business, as the *FED* could not sustain lower level of interest rate anymore where more borrowings could not be entertained to pay back previous borrowings which become one major reason among others of the crash down of *Lehman Brothers* and *Frennie May and Freddie Mac* and overall situation lead to the *Global Financial Crisis* in 2008. Shortly, it was due to the series of wrong decisions regarding mortgage which leads to crash in financial markets. From this example we can understand the impact of a decision (event) on the financial market. It can crash the financial system nationally and internationally. In this era of *Globalization*, effects of these crises transferred to all those countries linked with *International Market.*

As *Pakistan* is linked with *International Market*; therefore, effects of this *Global Financial Crisis* observed in Pakistan, however they are minute in nature. Therefore, this study is mainly concerned with the *KSE* and the internal events taken place in Pakistan. *KSE* did not reflect any strong pieces of evidence on any prominent under or overreaction during and after the *Global Financial Crisis (Sohail 2014).* This could be explained by the fact that as *Pakistan* has a very small share in the *International Market*. *Sohail (2009)* ensure the presence of three intense financial crises in *KSE* and *LSE-25* in March 2005, May 2006 and May 2008 to Jan 2009 respectively due to the market crashes. This can be stated that *Financial Crises* in Pakistan might be reasoned by some other factors.

Karachi Stock Exchange (KSE) established on September 18th, 1948 and among of the most matured stock exchanges in South Asia. According to the *Javid (2007),* it is a leading stock market in *Pakistan* as the 75 to 80% of the current trading takes place in *Karachi Stock Exchange, and it* consists of 38 different sectors. *Islamabad, Lahore,* and *Karachi Stock Exchange* are combinedly named as *Pakistan Stock Exchange (PSX)*[5]. *PSX (2014)* [6] cited that there are 557 numbers of companies that are listed with the rupees in million, with total market capitalizations as 7,380,531.74.

In the light of all above discussion *Pakistan* has been chosen as a vehicle of empirical research work because it is one of the ideal places in the present context of this study. As there are a number of political fluctuations in the governing system and regime shifting have taken place last decade. Moreover, *Pakistan* is also the *Major Non- NATO Ally* since 2004 that's a major reason behind number of terrorist attacks taking place in *Pakistan*. *PSX* is unified stock market in the country that's why companies of different sectors listed with *PSX* were chosen as the sample.

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5 http://www.dawn.com/news/1232253
6 http://www.kse.com.pk/ (accessed on June 23, 2015)

Research Questions

1. *How the returns and volatility of the returns of the different sectors of PSX react over the Political, Terrorism and Financial Crises Events?*
2. *Are the employed methodologies depicting the some comparable results for both returns and volatility of the returns?*

Objectives of the Study

The core objective of this study is to examine the effect of the different events on the returns and volatility of the different sectors. This study also examines the reaction of the 8 different sectors over the occurrence of Political Events, Terrorism Events and Financial Crisis under the different methodologies. The reaction of returns and volatility; over the political events, terrorist attacks, and financial crises events examined in this study. As expected returns of investors are dependent on the volatile, hence it is important to calculate volatility. One of the most astonishing attributes of the stock market is the volatility of the returns that can be varying time to time in seconds.

CHAPTER II

REVIEW OF THE LITERATURE

This chapter reviews the relevant literature. Particularly, literature relevant to the impact of terrorism events, political events and financial crisis on series of return and volatility discussed along with the modeling and methodology. Moreover, an attempt is made to explore the literature relevant to the variables considered and in the context of Pakistan. In the first quarter of this literature impact of different events on *Karachi Stock Exchange* discussed, while in the second quarter compatibility of considered events checked in the light of literature, in third quarter methodologies that can be adapted has been discussed, while in the last and final quarter of this chapter gap for this discussed.

Javed et al. (1999) examined the effect of nuclear experiments in India and Pakistan, on the average returns, volume and the volatility of *Karachi Stock Exchange*. *ARCH* model is being used for the analysis of daily data of *KSE*. Study results reveal that nuclear experiments in India significantly and negatively affected the returns and trading volume when volatility also increased. However, *Pakistan's* nuclear experiments did not significant impact on the returns, in times when volatility and trading volume has increased.

Javid (2007) have studied that impact of a natural disaster, 8th October, 2005's earth quake on volume and capitalization of the sixty firms of *Karachi Stock Exchange*. For this purpose *GARCH* modeling is being used to check the impact of catastrophic changes on average return, trading volume and volatility. The results depict a rise in returns of cement, steel, food and banking as an individual can predict a rise in the demand of the goods of the relevant sectors. However, no significant volatility observed.

Jhonston et al. (2005) elucidated the significant impact of *9/11 World Trade Centre* terrorist attack on 14 different stock exchanges. Study illustrates that the markets are efficient to absorb the impact of this attack, different stock exchanges rebounds in different number of days. Such as *Hong Kong* stock exchange rebounds in 6 days which is earlier than any other market, whereas the *Johannesburg* rebounds in 162 days which is later than all other markets.

Yamin et al. (2014) stated that in past ten years number of violence have significantly increased in *Pakistan*. Since the last ten years, areas located near the *Afghan* border and *Khyber Pakhtunkhwa*, *Balochistan* and *Urban Sindh* were the most concentrated, whereas Punjab faced the least numbers of violence in Pakistan. However, sectarian's violence and terrorism observed all over the country.

Irshad (2011) theoretically investigated that *Pakistan* has squeezed in war on terror between the *Afghan Jihadi Militants* and *United States of America*. Pakistan's war on terrorism is deteriorating economy by decreasing investment and increasing inflation. Moreover, it is also creating a situation of uncertainty for the investors and for general public.

Erb et al. (1996) constructed a study to find out the relation between the five different measures of country risk and expected future returns for 117 countries. These countries were categorized based on equity markets. The study reveals that these country's' risk measures are correlated with equity returns and are highly correlated with the equity valuation measures.

Sesay (2004) investigated impact of conflicts in the neighboring countries on the economic growth of country, for this purpose 72 developing counties considered for investigation. Results of the panel data concludes that conflicts in the neighboring country do not the affect the economic growth of a country alone, however it also an influence on the growth in the neighboring countries.

Nguyen et al. (2009) find out the effect of terrorism on the two different stock exchanges located in *Pakistan* and *Iran*, for both returns and volatility, *GARCH (1,1)* is being employed for the analysis. The results state that *Karachi Stock Exchange* is more reactive to the terrorist attacks taken place in different countries other than *Pakistan* and *Iran*. However, the terrorist attacks relevant to *World Trade Centre* and *Madrid* have a significant impact on returns for both counties, while terrorist attack in *London* has significant impact on the volatility series of both the counties.

Ahmed et al. (2008) ascertained the significant impact of 9/11 terrorist attacks on *Karachi Stock Exchange*. The study illustrates that the behavior of stock volatility was different from the pre attack period whereas volatility of the stock shows a significant reaction in post attack period.

Aslam et al. (2014) have examined the impact of terrorism activities on the volatility and returns of the *Karachi Stock Exchange*. For this study 330 terrorism events has selected and empirically significance of terrorism events on volatility measured in the categories of Event Day Analysis, Location Wise Impact of Terrorism Events Analysis, Event Type and Target Type by Events Analysis through *EGARCH* Modeling. Result depicts a significant impact of terrorism activities on the volatility of the *KSE-100 Index* and market recovers to the normal point one day.

Hassan et al. (2014) have studied the impact of most severe terrorism events for the decade of 2000 on *KSE-100* companies by differentiating the firms of into different sectors. Three events, fist one is the assassination of *Chairman of Pakistan People Party*, second *Darra Adam Khel Attack* and third is *Marriot Hotel Attack* were considered in the analysis. Events study methodology concluded that all three events have significant impact on the sectors of the *KSE-100 Index*.

Aslam et al. (2013) examined the impact of 300 major terrorism events on the *KSE-100* index daily data. Researchers have concluded through event study methodology that terrorist attacks have negative impact on *KSE-100* daily data. However the market recovers to its normal point in one day time. Study based on the Event Day, Location, Casualties and Attack Type analysis.

Zach (2003) has examined that effect of political events, can be categorized as foreign affair on *Israel Stock Market TAD-100 (Tel Aviv)* and *ISRIX (Israel Stock in US).* The results have shown that the reaction of *TAD-100* and *ISRIX* is different for the companies that are not cross listed over the Political Events, for those that are peace talks between Arab Nations and Israel where the results for cross listed companies behaves in a same way. Study shows that the returns are more extreme on the event days compare to a normal day.

Beaulieu et al. (2005) developed a study to find out the impact of different political events in *Canada* on the volatility of the returns of 102 numbers of firms listed in *Montreal Stock Exchange* and *Toronto Stock Exchange*. The results of the study illustrates that political news do have a significant impact on the volatility of the stock returns.

Dangol (2008) investigated the impact of anticipated and un-anticipated political events on *Nepalese Stock Exchange,* the study illustrates that by using event study methodology, good political events and bad political events is a reason to generate positive and negative abnormal returns respectively. The rebounding period of the market against the new information related to the political events is 2 to 3 days.

Clark et al. (2008) made analysis of stock market reaction for political events from 1947 to 2001. Primary data is used, collected from different politicians, economists and stock markets analysts. Under the *Bayesian Modeling* and *Monte Carlo* techniques it is being observed that political risk lies between 10.725% and 16.725% which has affected the *Karachi Stock Exchange*.

Mahmood et al. (2014) investigated the impact of different political events on *KSE-100* index from 1998 to 2013. For this purpose 60 days event window designed, that consists of abnormal returns and commutative abnormal returns. The results of the event study shows that market fluctuates over the occurrence of the events. Moreover, the selected events have significant negative relation with the political instabilities.

Khalid et al. (2010) analyzed the impact of political events categorized into domestic (regime shifting etc.) and international events on financial market from 1999 to 2006. Three financial indicators used to check the impact of the political events. The results illustrates that the volatility of the indicators significantly reacts over the occurrence of the political events, however there is no long terms linkages.

Mei et al. (2004) investigated that relationship between the financial crises and political events *i.e.*, elections and transition periods for 22 emerging markets. The results state that there is a significant relation between political events and financial crises. Moreover the volatility also increased during the elections and transitions periods. However, out of nine, eight financial crises have taken place during political elections and transition periods.

Jin and An (2016) analyzed the behavior of *US* stock markets to *BRICS* stock markets during global financial crises. The results stats that markets are interrelated with each other, therefore the volatility in stock markets of *BRICS* countries increased. A positive significant impact on the volatility of stock returns of the *BRICS* is being observed during the financial crises events. However, the volatility in response to large shock and persistence has also been observed.

Sohail & Javid (2014) developed a study for investor's behavior in *Karachi Stock Exchange* during global financial crises events. The study further divided into financial and non-financial sectors. The results explains that during global financial crises, financial sector shows highly significant results in 12^{th} and 24^{th} week, where the non-financial sectors shows undervaluation throughout the period except the first week but results remains insignificant.

For the residual analysis, *ARCH/GARCH* modeling has become much successful in financial modeling. A number of researcher use univariate and multivariate *ARCH/GARCH* family models for volatility clustering and residual analysis. *Tse (1990)* used *ARCH/GARCH* modeling for the volatility in *Tokyo Stock Exchange.* In purpose to investigate the persistence of a shock, *GARCH* models are being employed *(Chou, 1988).* Financial decisions depend on returns and risk, for capturing the *ARCH* and *GARCH* models are being employed *(Engle, 2001). Campbell and Hentschel (1991)* employed *Quadratic GARCH* model to asymmetries, to find positive and negative skewness and excess kurtosis. *Karolyi (1995)* employed multivariate *GARCH* model for international transmission of volatility and stock returns.

Event study methodology is among one of the oldest and widely used techniques all over the world. *Jong et al. (1992)* discussed a number of event study situations to find out the weekend and option expiring effect. *Binder (1998)* discussed a number of event study methodologies. Most of the time a nonparametric event study methodologies are employed in which abnormal returns are calculated *(Crowan, 1992)*. Both, *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM)* can be employed for the calculation of the abnormal returns *(Cable and Holland, 1999)* and *(Strong, 1992)*.

Impulse Indicator Saturation is used to capture out the breaks in series and co-breaks in two series. *Hendry (2001)* used this general to specific technique for modeling inflation UK. *Russell et al. (2010)* used this technique to capture the structural breaks. *Doornik et al. (2013)* used this methodology to capture the level shifts or multiple breaks. *Reade and Volz (2011)* employed this methodology to model inflation for *China* along some other macroeconomic variables including stock market growth.

Although, there a lot of literature related to this study however it is comparatively different from the others as it specifically differentiates that how different sectors of *Pakistan Stock Exchange* reacts in the presence of numbers of instabilities, it is important to know the behavior of investor. Therefore, three different types of events are being taken into account and the effect of these different events is considered for the analysis under different employed methodologies.

CHAPTER III
MODEL SPECIFICATIONS AND DATA DESCRIPTION

In this chapter, model specifications acquainted in the first section. In the second section, the data description, in which criterions for selection of the variables are elucidated. Moreover, definitions specifically for terrorism and political events are delineated; sources of data are furnished at the end of the second section.

3.1 Model Specifications

Modeling holds a significant importance, as it has adeptness to provide the evidences to support the theories, avoiding the uncertainties and provides us with some directions to deal with the problems. Therefore, the specifications of the models of which to be used to support this study are discussed in this section.

3.1.1 Calculation of the Returns

Since the study examine the impact of events on equity investments, so the first step is to calculate the returns. Financial data series may hold some trends most of the times therefore the issues of non-stationary and non-normal distribution can be arise. Hence, the returns for each sector will be calculated to avoid the issues of non-stationary and non-normal distribution. Logarithmic returns are calculated followed by the given formulas:

Logarithmic Returns $$\boldsymbol{R_{i,t} = In\left(\frac{P_{i,t}}{P_{i,t-1}}\right)}$$

Where:

$\boldsymbol{R_{i,t}}$	:	*Returns of sector* ***i*** *time* ***t***
$\boldsymbol{P_{i,t}}$	:	*Closing price of sector* ***i*** *on time* ***t***
$\boldsymbol{P_{i,t-1}}$	:	*Closing price of sector* ***i*** *on time* ***t-1***

Strong (1992) stated that theoretical and empirical evidence turns one's choice rational towards choosing the logarithmic returns, as they are close to the normally distribution. Therefore, the logarithmic returns being chosen to obtain the returns series. Moreover, the dividend paid will not be included for the calculation of the returns as the *Nelson (1991)* concluded that, for the calculation of the index returns, interest rate and dividend paid do not cause a significant effect.

3.1.2 Modeling for Volatility Gauging

Volatility modeling is widely used in financial econometrics and its building blocks are time varying volatility anticipation. Since the financial times series, such stock prices has the characteristics of hetroscedastic and autocorrelation, therefore for capturing the volatility *Autoregressive Conditional Hetroscedastic (ARCH)* family models are more suitable:

ARCH GARCH Model Specifications

Engle (1982) contributed with *(ARCH)* model for the description of the time varying volatility or the conditional variance. Nevertheless, *ARCH* model is a solid endeavor in econometric gizmo; along with its strengths, immense lag length and non-negativity restriction on parameters it has some imperfections too. *Bollerslev (1986)* has come up with *Generalized Autoregressive Conditional Hetroskedastic (GARCH)* model that has enhanced the exclusive property with an addition of smooth lag value of conditional variance; as the *GARCH* model cannot capture leverage effect there *Glosten et al. (1993)* suggested *Glosten Jagannathan Runkle - Generalized Autoregressive Conditional Hetroskedastic (GJR-GARCH)* model. *GJR* is an extension of *GARCH* Model which has overcome the problem of asymmetric term.

Univariate *GARCH* type model such as *GARCH (p,q)* and *GJR-GARCH (p,q)* being employed to handle the problems of non-convergence to estimate volatility models and to attain a series of volatility. The *GARCH (p,q)* and *GJR-GARCH (p,q)* univariate models are capable of exploring volatility.

ARCH (q) Model

Autoregressive Conditional Hetroscedastic (*ARCH*) model was introduced by (*Engle, 1982)*. This model overcomes all weakness which exists in previous models. Conditional mean and conditional variance equations are being used in this model. *ARMA (p,q)* process is followed by conditional mean equation while square of past values of error process ε_t is used in the conditional variance.

The general description of *ARCH* model is

Conditional Mean Equation

$$\boldsymbol{R_t = \alpha_0 + \sum_{t=1}^{p} \beta R_{t-i} + \sum_{t=1}^{q} \gamma \varepsilon_{t-1} + \varepsilon_t} \quad \textbf{(1)}$$

Where $\boldsymbol{\varepsilon_t \sim N(0, \sigma_t^2)}$

Conditional Variance Equation

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

Where $\boldsymbol{\theta_0} > 0, \boldsymbol{\theta_i \geq 0} \quad \boldsymbol{i = 1, 2, \ldots, q}$

R_t represents the returns in conditional mean equation and a linear function of *ARMA* in equation 1, where β represents the vector of *AR* term and $\boldsymbol{\gamma}$ is the vector of *MA*. Empirically its illustrate *ARMA (m,n)* process with different specifications. In some cases it may be *ARMA (0,0)* which represents that series is significant at level, there is no inclusion of any autoregressive and residual term lag. R_t represents mean reversion behavior and it is unpredictable according to the "*Efficient Market Hypothesis (EMH)*". Coefficients of conditional variance equation must be non-negative. Conditional variance is represented by $\boldsymbol{h_t}$ in equation 2 and depends upon lags of squared past value of $\boldsymbol{\varepsilon_t}$ process.

GARCH (p, q) Model

Linear *ARCH (q)* model has some problems first, sometime takes long lag length '*q*' due to this number of parameters are going to increase as result loss of degree of freedom. Second is non-negativity condition of parameters. *Bollerslev (1986)* proposed generalized extension of *ARCH (q)* model *Generalized Autoregressive Conditional Hetroscedastic (GARCH)* model.

The general *GARCH* model can be given as:

Conditional Mean Equation

$$\boldsymbol{R_t = \alpha_0 + \sum_{t=1}^{p} \beta R_{t-i} + \sum_{t=1}^{q} \gamma \varepsilon_{t-1} + \varepsilon_t} \quad \textit{(3)}$$

Where $\boldsymbol{\varepsilon_t \sim N(0, \sigma_t^2)}$

Conditional Variance Equation

$$\boldsymbol{h_t = \theta_0 + \sum_{i=1}^{q} \theta_i\, \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \varphi_j\, h_{t-1}} \quad \textit{(4)}$$

Where $\boldsymbol{\theta_0} > 0, \boldsymbol{\theta_i \geq 0, \varphi_j \geq 0}$

In *GARCH (p,q)* model the conditional variance depends upon square of past values of process $\boldsymbol{\varepsilon_t}$ and lag of conditional variance$\boldsymbol{h_{t-1}}$. The condition of non-negativity of parameter also applied in this model.

GARCH (1,1)

GARCH (1,1) is frequently used in financial econometric literature for volatility modeling. *Sajid et al. (2012)* employed *ARMA-GARCH* for measurement of inflation and inflation uncertainty. The *GARCH (1,1)* is the modest form in dispersion models family. The *GARCH (1,1)* provide most robust estimations than other volatility models. *GARCH (p,q)* mostly use when data is very large and require higher lags.

The general representation of *ARMA (1,1)* with *GARCH (1,1)* is

Conditional Mean Equation

$$\boldsymbol{R_t = \alpha_0 + \sum_{t=1}^{p} \beta R_{t-i} + \sum_{t=1}^{q} \gamma \varepsilon_{t-1} + \varepsilon_t} \tag{5}$$

Where $\boldsymbol{\varepsilon_t \sim N(0, \sigma_t^2)}$

Conditional Variance Equation

$$\boldsymbol{h_t = \theta_0 + \theta_1 \varepsilon_{t-1}^2 + \varphi_1 h_{t-1}} \tag{6}$$

Where $\boldsymbol{\theta_0} > 0, \boldsymbol{\theta_1 \geq 0, \varphi_1 \geq 0}$

These are the restrictions $\theta_0 > 0$, $\theta_1 \geq 0$, $\varphi_1 \geq 0$ of non-negativity on coefficients of conditional variance equation. Here $\boldsymbol{R_t}$ represents the return series of stock market index. Equation (13) the conditional mean equation follow *ARMA (p,q)* process. ε_t is Error series with normal distribution of zero mean and σ_t^2 conditional variance. *Bollerslev (1986)* established *GARCH (1,1)* model statistical properties for unconditional moment of residual (ε_t). *($\theta_i + \varphi_j$< 1)* is sufficient and necessary condition represents the persistence of shock to volatility, it satisfies the wide sense stationary condition. The unconditional variance is *Var (ε_t) = E (σ_t^2) = (θ_0/ 1-θ_1-φ_1)*. The fourth moment of error ***($\boldsymbol{\varepsilon_t}$)*** is ***($\boldsymbol{3\theta_1^2 + 2\theta_1\varphi_1 + \varphi_1^2}$).*** It is sufficient and necessary condition and the kurtosis is more than 3.

Asymmetric GARCH Models

In the light of this study Asymmetric *GARCH* type model is used as it captures the asymmetries in responsiveness to the news. Further, these models take leverage effect into the account, this effect gives the negative correlation among the assets returns and the volatility of the assets return *(Black 1976),* and simply the magnitude of news is not same. Unlike the Simple *GARCH* models is that only capture the symmetric effect of news (good or bad) on the volatility but do not incorporate the asymmetries (associated with the distribution).

As we concerned with asymmetries the *EGARCH* model confine the asymmetries but by using this, standard deviation become higher unlike *GJR* model so the *GJR* model is best to use *Engle and Victor (1993).* Further a brief discussion is conducted on how univariate *GARCH* type model capture the asymmetric effect.

GJR-GARCH (p, q) Model

GJR model is introduced by *Glosten et al. (1993)* that is a significant extension of simple *GARCH* model also it take asymmetries in *ARCH* process into account and importantly it capture the leverage effect in a financial series. Generally the model can be expressed as:

Conditional Mean Equation

$$\boldsymbol{R_t = \alpha_0 + \sum_{t=1}^{p} \beta R_{t-i} + \sum_{t=1}^{q} \gamma \varepsilon_{t-1} + \varepsilon_t} \qquad \textit{(7)}$$

Where $\boldsymbol{\varepsilon_t \sim N(0, \sigma_t^2)}$

Conditional Variance Equation

$$\boldsymbol{h_t = \theta_0 + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \delta_i \, \varepsilon_{t-i}^2 M_t + \sum_{i=1}^{p} \varphi_j \, h_{t-j}} \qquad \textit{(8)}$$

Where $\boldsymbol{\theta_0} > 0$, $\boldsymbol{\theta_i \geq 0}$, $\boldsymbol{\varphi_i \geq 0}$

$\boldsymbol{0 \leq \delta_i} < 1$ is the range of leverage effect parameter.

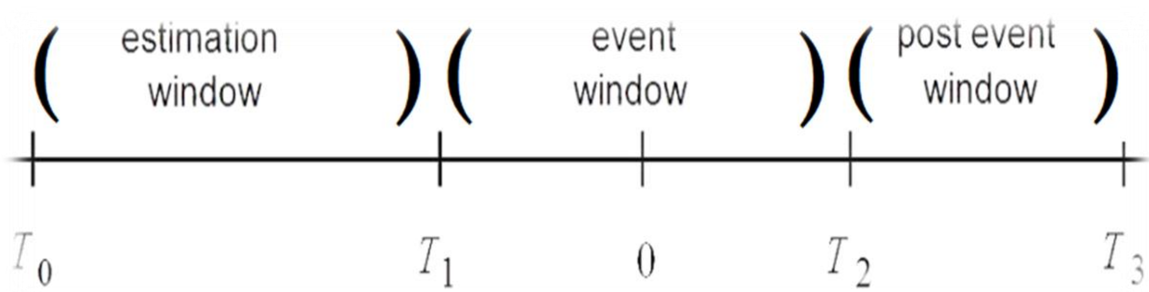
$D_t = 1$ when $\boldsymbol{\varepsilon_{t-1}} < 0$ and *$D_t = 0$* when $\boldsymbol{\varepsilon_{t-1} \geq 0}$

$G_t = 1$ when $\boldsymbol{\varepsilon_{t-1}} < 0$ indicates the bad news or the negative shock and *$M_t = 0$* when $\boldsymbol{\varepsilon_{t-1} \geq 0}$ indicates asymmetric information. *GJR* model also illustrate that bad news has stronger impact $\boldsymbol{(\theta_i + \delta_i)}$ as compared to news $\boldsymbol{(\theta_i)}$**.** If the $\boldsymbol{\delta_i > 0}$ then there is leverage effect and response to shock is distinct. If the $\boldsymbol{\delta_i = 0}$ means symmetric response to distinct

shock (In other words both news have same impact). Condition ***(θ_i+φ_i+$\frac{\delta_i}{2}$ <1)*** shows the persistence of shock.

3.1.3 Event Study

Event Study is among one of the oldest and widely used technique to check out the significance of the events on the stock returns. *Dollley (1933)* used this technique for the stock splitting. Event is being used to check the impact of different Events on the prices of the underlying assets, therefore event study can be use for almost all kind of the events that are may be firm specific, social, economic event or political events. This method helps us to check the significance of an event individually and also used as to check the significance of a group of similar events. Event window which basically defines that within that period an event has occurred, and compare its results with estimation window which basically provide us with the information of the pre event window, after that we calculate the abnormal returns which actually depicts a difference between expected returns and actual returns within the event window for an underlying firm, sector or index than go for the significance of the abnormal returns. Following diagram is depicting the methodology framework of event window study:



(Figure 3.1: Event Window Study)

Calculation of the Abnormal Returns

The abnormal return exhibits the reaction over one specific event at a particular point of time. The daily abnormal returns are calculated as difference between actual returns and expected returns for an individual security.

$$\boldsymbol{AR_{i,t} = R_t - E\left(R_{i,t}\right)} \qquad \textbf{\textit{(9)}}$$

Before getting into the abnormal return, used the economic model *CAPM* for the estimation of expected return $E(R_t)$.

Capital Asset Pricing Model

MacKinlay (1997) asserted that expected returns economic obtained by the *CAPM* are more precise, because assumptions of *CAPM* based on economic factors that are why *CAPM* has adopted for the calculation of abnormal returns:

$$\boldsymbol{E(R_t) = R_{ft} + \beta\left(R_{m,t} - R_{ft}\right)} \qquad \textbf{\textit{(10)}}$$

Where

$\boldsymbol{E(R_t)}$	:	*Expected return of sector i on time t,*
$\boldsymbol{R_{ft}}$	:	*Risk free rate*
$\boldsymbol{\beta}$	:	*Sensitivity of sector to market returns*
$\boldsymbol{R_{m,t}}$ - $\boldsymbol{R_{ft}}$	:	*Market risk premium*

Mean Adjusted Return Model

Mean adjusted model has derived from the *CAPM*, where the sector specific risk assumed to be zero and market risk is assumed to be equal to 1. *Cable (1999)* and *Strong (1992)* adjusted the *CAPM* to *Mean Adjusted Return Model* by lifting restrictions on *CAPM*. It is also known as *General Unrestricted Capital Asset Pricing Model*. This model is used to check how the events impact when the sector is independent of the market. For the calculation of the abnormal returns equation of mean adjusted model can be given as:

$$\boldsymbol{R_{i,t} = E(\bar{R}_{i,t}) + \varepsilon_{i,t}} \qquad (11)$$

Equation (5) depicts that abnormal returns are the difference between $\boldsymbol{R_{i,t}}$ and $\boldsymbol{E(\bar{R}_{i,t})}$. In this equation expected returns calculated by taking the average of returns in the estimation window.

Average Abnormal Returns (AAR)

Average Abnormal Returns (AAR) calculated because it gives overall impact of one type of events in the model, AAR obtained by taking the average of all the abnormal returns related to a specific event, can be given as in equation:

$$\boldsymbol{AAR_{i,t} = \sum_{i=1}^{N} AR_{i,t} \times n^{-1}} \qquad (12)$$

Where;

$\boldsymbol{AAR_{i,t}}$	:	*Average Abnormal Returns of sector* $\boldsymbol{i}$ *on time* $\boldsymbol{t}$
$\boldsymbol{AR_{i,t}}$	:	*Abnormal Return of a sector* $\boldsymbol{i}$ *on time* $\boldsymbol{t}$*,*
$\boldsymbol{N}$	:	*Number of events*

3.1.4 Event Day Analysis

Binder (1998) used this methodology to check impact of the events on stock returns. In the modeling of this both the *Market Return Model* i.e., also *CAPM Model* and *Mean Adjusted Model* both can be used. *Aslam et al. (2014), Aslam et al. (2013)* and *Aslam et al (2015)* used the *Mean Adjusted Model* to check significance of terrorism events on returns and volatility both for *Pakistan* and *South Asian Countries*. In this methodology a multiple intercept day's dummy variables are being used to find the significance of the events. The basic equation for the returns behavior over the occurrence of an event becomes:

$$\boldsymbol{R_{i,t} = \alpha + \sum_{d=-n}^{n} \beta_i D_{i,t} + \varepsilon_i} \qquad (13)$$

Where $\boldsymbol{R_{i,t}}$ is the return of the sector's $\boldsymbol{i}$ at time of $\boldsymbol{t}$ $\boldsymbol{D_{i,t}}$ is the dummy variable depicts occurrence of the event against firm $\boldsymbol{i}$ at time $\boldsymbol{t}$. If the event occurs than $D = 1$ and 0 otherwise. Where n depicts the number of day's dummy including in the regression.

$$\boldsymbol{v_{i,t} = \alpha + \sum_{d=-n}^{n} \beta_i D_{i,t} + \varepsilon_i} \qquad \textbf{\textit{(14)}}$$

Where $\boldsymbol{v_{i,t}}$ is the volatility of the sector's $\boldsymbol{i}$ at time of $\boldsymbol{t}$ $\boldsymbol{D_{i,t}}$ is the dummy variable depicts occurrence of the event against firm $\boldsymbol{i}$ at time $\boldsymbol{t}$. If the event occurs than D = 1 and 0 otherwise. Where n depicts the number of day's dummy including in the regression.

3.1.5 Impulse Indicator Saturation Modeling

Hendry at al. (2008), Jhansen (2009), Ericsson (2011) and *Castle et al. (2012)* proposed a methodology in which a *General Unrestricted Model (GUM)* in which presence of multiple structural breaks or level shifts are being captured. Basically, in this methodology one dummy variable generated against one observation, so in this way each observation holds its own dummy variable. In this way lift up one assumption of Classical Linear Regression Model that number of observations should be greater than number of parameters, but in Impulse Indicator Saturation number of observations becomes equal or greater than the number of parameters. Dealing with this we spilt our data sample in two or more than two parts, so in that case number of observations becomes greater than number of parameters. Only the significant dummies at 5% level of significance captured. In the case our study we have split our data sample in eleven parts and we check the significance of our events by comparing the results of multiple structural breaks or level shifts obtained by combining dummies. Impact of our selected events checked on the series of return and volatility. Given equations are explaining the methodology of Impulse Indicator Saturation for returns and volatility both:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \sum_{s=1}^{250} \beta_2 D_{i,t} + \varepsilon_{i,t} \ ; \ \varepsilon_{i,t} \sim IIN[0, \sigma_t^2] \ t = 1, 2, \dots, 250 \qquad (15a)$$

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \sum_{s=251}^{500} \beta_2 D_{i,t} + \varepsilon_{i,t} \ ; \ \varepsilon_{i,t} \sim IIN[0, \sigma_t^2] \ t = 251, 252, \dots, 500 \qquad (15b)$$

………

………

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \sum_{s=2501}^{2705} \beta_2 D_{i,t} + \varepsilon_{i,t} \ ; \ \varepsilon_{i,t} \sim IIN[0, \sigma_t^2] \ t = 2501, \dots, 2705 \qquad (15k)$$

Equation (7) is acquainting that $R_{i,t}$ is the return of index series of sector i at time t depends its own lag and the dummies against each observation. Where the Equations from (7a) to (7k) are depicting that our sample divided into 11 splits.

$$h_{i,t} = \beta_0 + \beta_1 v_{i,t-1} + \sum_{s=1}^{250} \beta_2 D_{i,t} + \varepsilon_{i,t} \ ; \ \varepsilon_{i,t} \sim IIN[0, \sigma_t^2] \ t = 1, 2, \dots, 250 \qquad (16a)$$

$$h_{i,t} = \beta_0 + \beta_1 v_{i,t-1} + \sum_{s=251}^{500} \beta_2 D_{i,t} + \varepsilon_{i,t} \ ; \ \varepsilon_{i,t} \sim IIN[0, \sigma_t^2] \ t = 251, 252, \dots, 500 \qquad (16b)$$

………

………

$$h_{i,t} = \beta_0 + \beta_1 v_{i,t-1} + \sum_{s=2501}^{2705} \beta_2 D_{i,t} + \varepsilon_{i,t} \ ; \ \varepsilon_{i,t} \sim IIN[0, \sigma_t^2] \ t = 2501, \dots, 2705 \qquad (16k)$$

Equation (8) is acquainting that $h_{i,t}$ is the volatility of index series of sector i at time t depends its own lag and the dummies against each observation. Where the Equations from (7a) to (7k) are depicting that our sample divided into 11 splits for the volatility series.

3.2 Data Description and Sources

This research work hinged on branched datasets of 8 divergent sectors of *Pakistan Stock Exchange* and peculiar number of events pigeonholed, in three groups, can be categorized as Political, Terrorism and Financial Events. Corresponding sectors subsists of a disparate number of companies, selected according to the availability of the daily frequency data of Capital Paid-Up and Closing Prices from January 1st, 2004 to December 31st, 2014. We have brought 8 sectors in consideration out of 38 currently operating sectors in *Pakistan Stock Exchange*, where out of 38 different sectors 3 are non-operational sectors. *Pakistan Stock Exchange* sectors can be categorized into Financial Services Sectors and Non-Financial Services Sector, Financial Services Sectors covers 44.25% of the total Market Capitalization, According to *KSE (2014)*[7] where Non-Financial Service Sectors covers 55.74% of the total Market Capitalization, where the 8 divergent sectors we have selected covers around 82.66% of the Market Capitalization among Non-Financial Services Sector. The reason behind selection of the firms depends on availability of the daily data for time period of this study. According to *MacKinlay (1997)* securities data should be chosen on the basis of the event data, as our events data was daily discontinuous data therefore firm and firm's data has also selected accordingly. Terrorism, Political and Financial Crisis data has also been selected from 2004 to 2014 from different sources that will also be discussed later on. All the data has compiled in context of the Pakistan. In generic, all the sectors encompass a total of 100 companies in number. The following table acquainting the number of companies in definitive sector:

7 http://kse.org.pk/kse_list_of_sectors.shtml (accessed on June 23, 2015)

Table 3.1 Number of Companies in Each Sector Frequency Distribution

1	*Automobile Assembler & Parts*	*14*
2	*Cement Sector*	*12*
3	*Chemical and Fertilizers Sector*	*14*
4	*Food Producer & Brewery Sector*	*09*
5	*Oil & Gas-Marketing & Refinery Sector*	*13*
6	*Sugar Sector*	*19*
7	*Telecommunication & Technology Sector*	*04*
8	*Textile Composite-Spinning & Weaving Sector*	*15*
	Total	***100***

It is problematic to present each firm's stock returns solely, therefore all the companies in one sector being turned into a series of Index of each sector. In order to achieve the objective of the study, we compiled data of the following variables which are Sector Indices and Events further categorized into terrorism, political and financial crisis events.

Indices

Index is a single series that is the representation of the overall sector, as it was difficult to discuss all the companies individually, that's why one index for each sector developed of cognate companies. First market capitalization for each company obtained from the given formula:

$$\boldsymbol{Market\ Capitalization_{i,t} = Capital\ Paid\ Up_{i,t} \times Closing\ Price_{i,t}}$$

[8]*Gufran (2006)* rooted that Market Capitalization Index being used for the *KSE-100 Index*. *Jones (2014)* gave that Market Capitalization Weighted Index are the most commonly and widely used indices. Therefore the Market Capitalization Weighted Indices being calculated under the given formula:

$$\boldsymbol{Index\ Level} = \frac{\sum(\boldsymbol{P_{i,t}} \times \boldsymbol{Q_{i,t}})}{\boldsymbol{Divisor}}$$

Where:

$\boldsymbol{P_{i,t}} \times \boldsymbol{Q_{i,t}}$ **:** *Market Capitalization*

$\boldsymbol{P_{i,\,t}}$**:** *Closing Price of the Share of firm* ***i*** *at time* ***t***

$\boldsymbol{Q_{i,\,t}}$**:** *Capital Paid-Up or number of shares outstanding of the firm* ***i*** *at time* ***t***

Divisor: *Base Value of total Market Capitalization of all the companies in relevant sector at January 1st, 2004 in this data*

Subsequently, we have come up with the series of indices and each series consists of 2705 number of observations in each sector.

Events

The events data categorized into three different parts those are Financial, Political and Terrorism. Terrorism events selected according to definition of the terrorism in the International Laws.

According to UN Document, *Walter (2009)* defined terrorism as:

"Criminal acts intended or calculated to provoke a state of terror in the general public, a group of persons or particular, persons for political purposes are in any circumstance unjustifiable, whatever the considerations of a political, philosophical,

8 www.sbp.org.pk/stats/2006/Wrkshp_Present/.../share-Price-Gufran.ppt (accessed on July 3rd, 2015) *ideological, racial, ethnic, religious or any other nature that may be invoked to justify them."*

Political events also selected according to the definition of the political events. *Tassiopoulos (2005)* defines political events as:

"We can define a political event as a carefully planned, organized, managed and implemented event by political office bearers in either government, civil society members or outsourced to event managers. Furthermore this event has a political or a public nature with a political purpose and message, with the intention to reach as many people as possible a variety of mean such as hosting an event and the intentions to reach a specific objective or number of objectives."

After analyzing the data, we came to know there are 379 number of events categorized in the table 3.2:

Table 3.2 Events Frequency Distribution

Financial	*Political*	*Terrorism*	***Total***
02	*160*	*217*	***379***

In general we have compiled 379 events data, out of which 2 are financial events which includes financial crisis, 160 political events and 217 terrorism events. All the events selected according to the definition of the events. For the selection of the terrorism events [9]*Global Terrorism Database* criterions are being used:

*"**Criterion I:** The act must be meant to attain a political, economic, religious, or social goal."*

9 http://www.start.umd.edu/gtd/

*"**Criterion II:** There must be evidence of an intention to pressurize, frighten, or express some other message to a larger audience than the immediate victims."*

*"**Criterion III:** If there is any kind of ambiguity in any of the event will be excluded and after filtration, events with equal to or more than 10 causalities will be considered in our sample."*

Table 3.3 Terrorism Events Frequency Distribution

Location		***Target Group***	
Capital	*20*	*Civilians*	*89*
Provincial Capital (PNJ)	*13*	*Security Forces*	*48*
Provincial Capital (SIN)	*14*	*Others*	*80*
Provincial Capital (KPK)	*21*	***Attack Type***	
Provincial Capital (BLCH)	*19*	*Armed Assault*	*32*
Others	*130*	*Bombing*	*168*
Responsible Group		*Assassination*	*4*
Al-Qa`ida	*2*	*Others*	*13*
BLA	*7*	***Target***	
TTP	*112*	*Business*	*20*
Others	*96*	*Educational Institution*	*5*
Loss		*Government Property*	*26*
Casualties	*5731*	*Political or Religious Figures/Institutions*	*27*
Injuries	*10013*	*Private Property*	*76*
Total	***217***	*Transportation*	*9*

Table 3.3 is acquainting the frequency distribution of our considered terrorism events for this study. In total 217 in number terrorism event has selected. Further, terrorism events are categorized into Location, Target Type, Responsible Group, Attack Type, Loss and Target. Location is further categorized into 6 sub groups; according to the information

20 terrorism events have taken place in Federal Capital, 13 in Provincial Capital of *Punjab*, 14 in Provincial Capital of *Sindh*, 21 in Provincial Capital of *KPK*, 19 in Provincial Capital of *Balochistan* and 130 terrorism events have taken place in other cities of the Pakistan. *Al-Qa`ida* has taken the responsibility of 2 terrorism events, *BLA* has taken the responsibility of 7 terrorism events, *TTP* has taken the responsibility of 112 terrorism events where 96 terrorism events have done by some other groups. According to the sample that we have selected for our study 5731 number of people have lost their lives, 10013 numbers of people have injured in response o these attacks. According to the *Sandler et al. (2011)* number of injuries taken in that period can be turn into 5707 number of lost of lives. Out of 217 terrorism events 89 times target was civilians; 48 times target was security forces and 80 times target was other that is actually a category of a mix group of religious and political figures, government officials, civilians and security forces together.

Table 3.4 acquaints the frequency distribution of the political events that have taken place from 2004 to 2014 in Pakistan:

Table 3.4 Political Events Frequency Distribution

Categorization	
Elections	*005*
Foreign Affair	*027*
Internal Affair	*121*
Long March/Political Gathering	*007*

Political events are very important because the number of political changes have taken place during 2004 to 2014. There is also a shift of regime from *Autocratic Regime* to

Democratic Regime. There a number political disabilities. According to the definition we have categorized our events in diversified bunches like foreign affairs, internal affairs, long marches and sit-ins, general and local body elections political gatherings riots and rallies. Foreign affair includes the talks and foreign policy announcements with *SAARC*, *NATO* and Neighboring countries, where the internal affairs includes political decisions related to privatization of the institutions, strikes by the political parties and against government, lawyers movement, arrest and house arrest of Religio-Political parties, resignations and appointments on the top posts etc. *Local Body* and *General Election* also includes *2 General Elections* in *Azad Kashmir*. Only those political gatherings and rallies being selected which was lead by a political party having at least 25 seats in the *National Assembly*. In general 160 political events have selected out of which 5 are the Elections, 27 are the foreign affairs, 121 are the internal affairs and 7 political events are relevant to the long marches and political gatherings.

Under considered events have exactly traced out on the same dates and being compiled against the event date. However, some limitations being made for those events which do occur on other than working day. *Muntermann (2007)* elucidate that if the event occur on any other day, on which the market is not functioning, we take that event to the next date when market is functioning. Moreover, another limitation also added to incorporate terrorism event data, *Aslam (2014)* absolved that occurrence of an terrorist activity after the Karachi Stock Exchange office timing *i.e., 3:30 PM*, that kind of event will be considerable to the next market functioning day. Therefore, the events occurring on weekends or vacations will be added to next market functioning day. Where, the events occurring after *3:30 PM* from Monday to Thursday and *4:30 PM* on Friday will also be shifted to the next day.

Data Sources

Entire data of Closing Prices and Capital Paid-Up has collected from [10]*Business Recorder*, where the data of *Terrorism, Political* and Financial Events has compiled from [11]*South Asian Terrorism Portal*, [12]*DAWN Newspaper*, [13]*Express Newspaper* and [14]*Global Terrorism Database*.

10 www.brecorder.com/ (accessed from February 2015 to November 2015)
11 www.satp.org/ (accessed from August 2015 to September 2015)
12 epaper.dawn.com/ (accessed from August 2015 to September 2015)
13 www.express.com.pk/epaper (accessed from August 2015 to September 2015)
14 http://www.start.umd.edu/gtd/ (accessed from August 2015 to December 2015)

CHAPTER IV

RESULTS AND DISCUSSION

This chapter reveals the evidence and across meditation on the basis of the data under differently employed methodologies and model specifications in an organized manner with examination of each exclusive sector. Beforehand, statistical analysis on returns and volatility gauging, graphical and descriptive stats also made. Subsequently, the results obtained under distinct methodologies discussed along with the renderings. The analysis begins with the calculation of returns by taking into account the logarithmic first difference of the closing prices. Then *Argumented Dicky Fuller (ADF)* is applied to check stationarity of the data. Results reveal that closing prices of stocks are non-stationary but the first difference that is stock returns is stationary.

The main objective of this study is to analyze the impact of different events on stock returns of the sectors and their volatility. For this purpose, three types of events considered: terrorist attacks, political and financial crises events. To obtain the volatility series *GARCH* and *GJR* models are being employed after checking the *ARCH* affect by *ARCH LM* test. *GARCH* type models have advantage that they take account of hetroscedasty and autocorrelation presence in the stock returns. In the following discussion the analysis of each sector performed individually to understand the response of these sectors to different events. The analysis begins with the descriptive stats.

4. 1 Automobile Sector

4.1.1 Exploratory Analysis

Returns Gauging

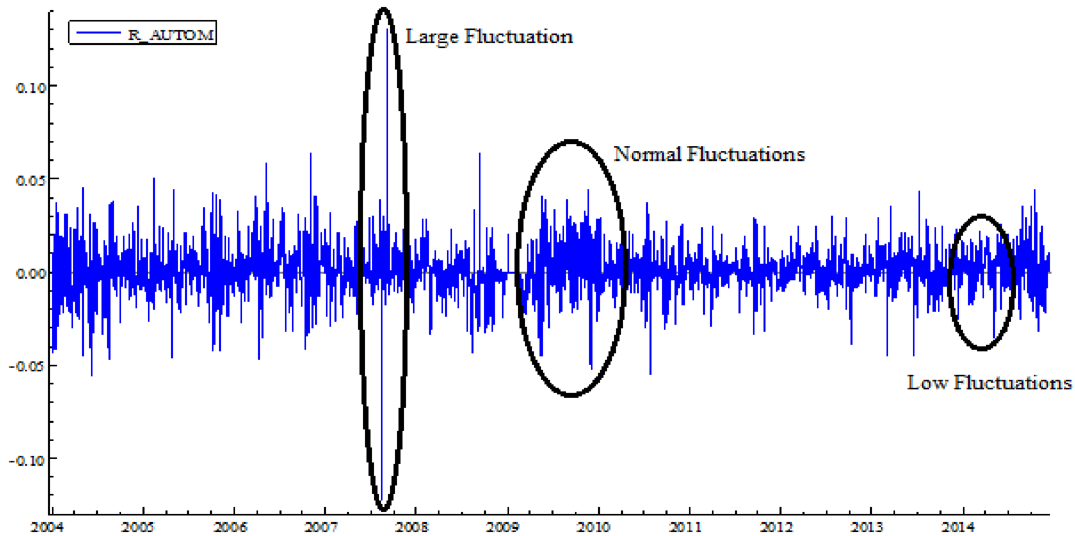
Prices Index of *Automobile Sector* dwells into 2706 number of observations. While, after calculation of logarithmic returns series of returns left with 2705 observations. Descriptive statistics of returns from *Automobile Sector* are provided below in table 4.1

Table 4.1 Returns of Automobile Sector

Mean	*0.00077*
Median	*0.00040*
Maximum	*0.13061*
Minimum	*-0.12252*
Std. Dev.	*0.01358*
Skewness	*0.03853*
Kurtosis	*9.87014*
Jarque-Bera	*5320.372*
Probability	*0.000*
Sum	*2.080937*
Sum Sq. Dev.	*0.498776*
Observations	*2705*

The mean value of the returns for the price index of *Automobile Sector* is 0.077%, mid value appears to be 0.04% and maximum value 13.06%, maximum fall in the value of the returns is up to 12.25%, deviation from the mean value is 1.35%, data series is positively skewed, the distribution of return series is leptokurtic and significance of

Jarque-Bera is stating that null hypothesis of the normal distribution has been rejected. Graph*4.1* is acquainting the behavior of the daily returns series from 2004 to 2014:



The graph 4.1 is explaining the spreading behavior of the returns series over the time. The spread of the returns lies between the range of -12% to +13%. Normal and small fluctuations can be observed throughout the period from 2004 to 2014 except for the third quarter of 2007.

Modeling of Volatility Gauging

In *Automobile Sector*, volatility in the returns series has been observed. Conditional mean equation illustrates that the returns depend on its own 2 lags and 1 lag of the disturbance term. While the conditional variance equation illustrates that it depends on 1 lag of the square of the disturbance term and 1 lag of the square of the variance as the data series is showing symmetric effects under the t-distribution followed by the given equations:

$$\boldsymbol{R_t = 0.0011 + 1.17R_{t-1} - 0.19R_{t-2} - 0.97\varepsilon_{t-1} + \varepsilon_t} \qquad \textit{(Conditional Mean Equation)}$$

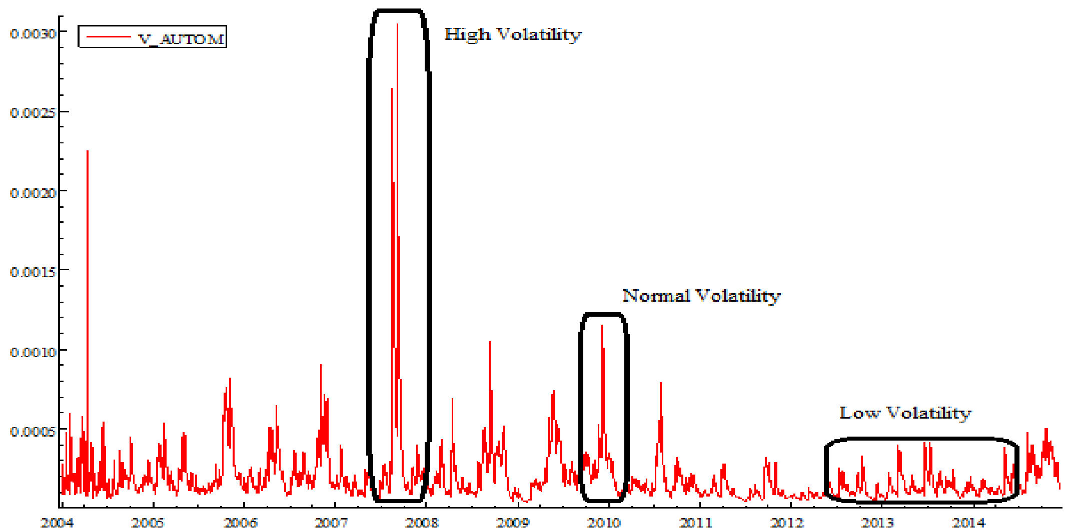
$$\boldsymbol{h_t = 0.07 + 0.15\,\varepsilon_{t-1}^2 + 0.82h_{t-1}} \qquad \textit{(Conditional Variance Equation)}$$

The value of persistence is 0.98, depicting that persistence of a shock takes a long time to decay. *Table 4.2* is acquainting the descriptive statistics analysis for the volatility:

Table 4.1.1.2 Volatility of Automobile Sector

Mean	*0.000197*
Median	*0.000149*
Maximum	*0.003046*
Minimum	*4.16E-05*
Std. Dev.	*0.000185*
Skewness	*6.338814*
Kurtosis	*70.34061*
Jarque-Bera	*529219.7*
Probability	*0*
Sum	*0.532758*
Sum Sq. Dev.	*9.24E-05*
Observations	*2705*

The mean value of volatility of the returns in *Automobile Sector* is 0.0197%, mid value 0.0149%, the maximum value 0.304%, and maximum fall in the value of the returns is 0.00416%, while the spread of the data from the mean value is 0.018%. Data series is positively skewed, and the distribution of return series is leptokurtic. However, significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. *Graph 4.2* is explaining the behavior of the volatility series from 2004 to 2014:



The graph 4.2 is explaining the spread of the volatility series over the time that the spread of the volatility lies between the range of -0.004% to +0.3%. Normal and small fluctuations in the volatility observed throughout the period of 2004 to 2014, except for the second quarter of 2004 and third quarter of 2007.

4.1.2 Event Study

This section discusses the response of daily returns against events. For this purpose data divided into two splits, the estimation window or the control period consists of 60 days and event window consists of 11 days; event window[15] from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days before the event. *Table 4.3* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.3 Event Window Automobile Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
Day	*AAR*	*t-test*	*AAR*	*t-test*
-5	*0.0002*	*0.1795*	*0.0003*	*0.3512*
-4	*0.0008*	*0.9394*	*0.0009*	*1.0131*
-3	*0.0003*	*0.3290*	*0.0005*	*0.5947*
-2	*0.0006*	*0.6366*	*0.0007*	*0.7491*
-1	*-0.0001*	*-0.0885*	*0.0001*	*0.1201*
0	*-0.0004*	*-0.4110*	*-0.0002*	*-0.2106*
1	*0.0006*	*0.6456*	*0.0005*	*0.5736*
2	*-0.0004*	*-0.4628*	*-0.0001*	*-0.1224*
3	*-0.0009*	*-0.9985*	*-0.0009*	*-0.9810*
4	*0.0002*	*0.2509*	*0.0002*	*0.1936*
5	*0.0004*	*0.4081*	*0.0002*	*0.1754*

Significance Level: *10% **5% ***1%

15 The Event window has extended to 21 days (Eger, 2009) but terrorist event for some sectors remain insignificant.

The above table is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM)*. Results are depicting those terrorist events that are not significant in 11 days event window at any level of significance for the *Automobile Sector* under both *CAPM* and *MAR model*.

Table 4.4 is explains the AAR against political events:

Table 4.4 Event Window Automobile Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.0007*	*-0.5060*	*-0.0007*	*-0.4450*
-4	*-0.0011*	*-0.7167*	*-0.0012*	*-0.8049*
-3	*0.0014*	*0.9379*	*0.0014*	*0.9617*
-2	*0.0007*	*0.4719*	*0.0006*	*0.3870*
-1	*0.0003*	*0.1772*	*0.0003*	*0.2277*
0	*-0.0031*	*-2.0947***	*-0.0030*	*-1.9929***
1	*-0.0001*	*-0.0709*	*-0.0002*	*-0.1255*
2	*-0.0013*	*-0.9021*	*-0.0014*	*-0.9229*
3	*-0.0021*	*-1.4220*	*-0.0022*	*-1.4973*
4	*0.0017*	*1.1612*	*0.0017*	*1.1331*
5	*0.0005*	*0.3653*	*0.0008*	*0.5116*

Significance Level: *10% **5% ***1%

The above table portrayed *AAR* and *t-stats* around the political events under *CAMP* and *MARM* for *Automobile Sector*. The above table is depicting that overall political events are significant at 5% level of significance on the event day for both *CAMP* and *MAR models*. However after the event day, the impact of the political events turns insignificant.

Table 4.5 is acquainting the *AAR* against financial crises events:

Table 4.5 Event Window Automobile Sector: Financial Crises

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.0087*	*-1.8186**	*-0.0070*	*-1.5099*
-4	*-0.0073*	*-1.5353*	*-0.0063*	*-1.3534*
-3	*-0.0070*	*-1.4727*	*-0.0067*	*-1.4476*
-2	*-0.0028*	*-0.5861*	*-0.0017*	*-0.3777*
-1	*-0.0018*	*-0.3726*	*-0.0006*	*-0.1369*
0	*-0.0064*	*-1.3321*	*-0.0063*	*-1.3565*
1	*-0.0003*	*-0.0672*	*0.0002*	*0.0423*
2	*0.0015*	*0.3130*	*0.0026*	*0.5547*
3	*0.0013*	*0.2738*	*0.0019*	*0.4070*
4	*-0.0071*	*-1.4836*	*-0.0061*	*-1.3189*
5	*-0.0139*	*-2.9221***	*-0.0125*	*-2.6936***

Significance Level: *10% **5% ***1%

The table 4.5 is acquainting the behavior of the *Automobile Sector* around the financial crises events. The results indicate that returns series have significant reaction over the financial crises events. As financial crises events turns significant at 5% level of significance on the 5th day[16] under both *CAMP* and *MAR models*.

16 The significant impact of the financial crises events on the returns of Automobile Sector starts at 5th day and lasts for 33 days.

4.1.3 Event Day Analysis

In this methodology day dummies has been introduced to observe the impact of two different kinds of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate $\boldsymbol{D_i}$ **=** 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.6 & 7* are acquitting the response of returns and volatility against the terrorist events for *Automobile Sector:*

Table 4.6 Event Day Analysis of Automobile Sector: Terrorist Attacks[17]

Number of Observations *2705*

Date *1/1/2004* *12/31/2014*

RETURN

	C	T_B_5	T_B_4	T_B_3	T_B_2	T_B_1	T_0	T_1	T_2	T_3	T_4	T_5	AR(1)
Coefficient	0.00076	-0.00117	-0.00093	-0.00147	0.00065	0.00092	0.00091	-0.00062	-0.00136	0.00110	0.00178	0.00037	0.20835
Std. Error	0.00042	0.00095	0.00097	0.00097	0.00097	0.00097	0.00097	0.00097	0.00097	0.00097	0.00097	0.00095	0.01886
t-Statistic	1.78295*	-1.23584	-0.96119	-1.52298	0.67421	0.95402	0.93741	-0.64646	-1.40963	1.14380	1.83595*	0.39573	11.04925***
VOLATILITY													
Coefficient	0.00019	-0.00001	-0.00001	0.00000	-0.00001	0.00002	0.00001	0.00002	0.00001	0.00000	0.00001	0.00000	0.82954
Std. Error	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001	0.01077
t-Statistic	14.69920***	-0.68776	-0.88267	-0.22663	-1.16607	1.31936	0.99934	1.27847	0.80219	-0.06438	0.78806	0.58314	76.99553***

WALD TEST	RETURNS			VOLATILITY		
Test Statistic	F-statistic	Chi-square	DW	F-statistic	Chi-square	DW
Value	10.82078	140.6701	1.99	480.2866	6243.726	2.23
Df	(13, 2691)	13		(13, 2691)	13	
Probability	0.000	0.000		0.000	0.000	

17 Significance Level: *10% **5% ***1%

Table 4.6 Event Day Analysis of Automobile Sector: Political Events[18]

Number of Observations		*2705*					
Date	*1/1/2004*			*12/31/2014*			
RETURN							
	C	***P_B_2***	***P_B_1***	***P_0***	***P_1***	***P_2***	***AR(1)***
Coefficient	*0.001118*	*-0.000635*	*-0.002463*	*-0.002958*	*0.000316*	*-0.000135*	*0.207140*
Std. Error	*0.000360*	*0.001085*	*0.001101*	*0.001100*	*0.001101*	*0.001084*	*0.018844*
t-Statistic	*3.10456***	*-0.58575*	*-2.23618***	*-2.68779***	*0.28737*	*-0.12462*	*10.99260****
VOLATILITY							
Coefficient	*0.0001960*	*0.0000082*	*0.0000025*	*-0.0000050*	*0.0000088*	*0.0000002*	*0.8288350*
Std. Error	*0.0000118*	*0.0000083*	*0.0000103*	*0.0000109*	*0.0000103*	*0.0000083*	*0.0107760*
t-Statistic	*16.577610*	*0.985533*	*0.238610*	*-0.454717*	*0.851965*	*0.020031*	*76.917400****
WALD TEST	***RETURNS***			***VOLATILITY***			
Test Statistic	***F-statistic***	***Chi-square***	***DW***	***F-statistic***	***Chi-square***	***DW***	
Value	*19.59455*	*137.1618*	*1.99*	*886.9875*	*6208.912*	*2.23*	
Df	*(7, 2697)*	*7*		*(7, 2697)*	*7*		
Probability	*0.000*	*0.000*		*0.000*	*0.000*		

18 *Significance Level: *10% **5% ***1%*

In tables 4.6 and 4.7, the table 4.6 is explaining the impact of terrorist events on the returns and volatility of the *Automobile Sector*, *T_B_5* represents the 5^{th} day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5^{th} day after the events day. The returns and volatility series are depending on their own 1^{st} lags. For the returns series, *T_0, T_1, T_3,* and *T_5* are insignificant, whereas the *T_4* is significant at 10% level of significance, indicating that a significant impact of terrorist attacks on the returns of 4^{th} day while this impact turns insignificant right after a day. Moreover, volatility remains insignificant for all 5 days for the terrorist attacks, as no day dummy turns significant at any level of significance.

The table 4.7 is acquainting the impact of political events on the returns and volatility of the *Automobile Sector*, *P_B_2* represents the 2^{nd} day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2^{nd} day after the occurrence of a political event. Returns and volatility series are depending on their own 1^{st} lag. Results show that political events are significant on the event day at 5% level of significance however they turn insignificant after the event day. Moreover, as the political events are anticipated and so they are significant on the event day and 1 day before the event in the volatility of the returns for *Automobile Sector,* at 5% level of significance.

4.1.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.8* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.8 Impulse Indicator Saturation: Automobile Sector [19]

	Co-Breaks		*Significance*[0]	*Significance*[1]	*Significance*[2]	*Significance*[3]	*Persistence*
Terrorist Attacks	*73*	*Returns*	*73*	*37*	*16*	*10*	*1 day 71 minutes*
		Volatility	*142*	*35*	*14*	*7*	*2 day 36 minutes*
Political Events	*79*	*Returns*	*99*	*11*	*3*	*7*	*1 day 199 minutes*
		Volatility	*100*	*45*	*3*	*4*	*2 days 157 minutes*

[0]on day significant [1] after 1 day significant 2after 2 days significant 3after 3 days significant, at 5% level of significance, Persistence is average time during working hours.

The table 4.8 above explains the results obtained through Impulse Indicator Saturation. It depicts that out of total 217 terrorist attacks 73 attacks found to be significant in returns series on the event day, of these events 37, 16 and 10 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average, the persistence of terrorist attacks remains significant for 1 day and 71 minutes of a working day. There are 142 significant terrorist attacks in the volatility of the returns

19 *Detailed Results for each individual event are being tabled in Appendix.*

series of which 35, 14 and 7 number of events are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average persistence of terrorist attacks remains significant for 2 days and 36 minutes of a working day. Moreover, 73 numbers of co-breaks captured against the terrorist events. In political events, out of 160, there are 99 events that are significant on the event day under return series, of which 11, 3 and 7 are significant after the event day on 1^{st}, 2^{nd} and 3^{rd} day respectively in return series. There are 100 political events that are significant in volatility on the event day whereas 45, 3 and 4 are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average, the significance persistence of political events is 1 day and 199 minutes in returns, and 2 days and 157 minutes in volatility of a working day. Moreover, 79 co-breaks captured for political events.

4. 2 *Cement Sector*

4.2.1 Exploratory Analysis

Returns Gauging

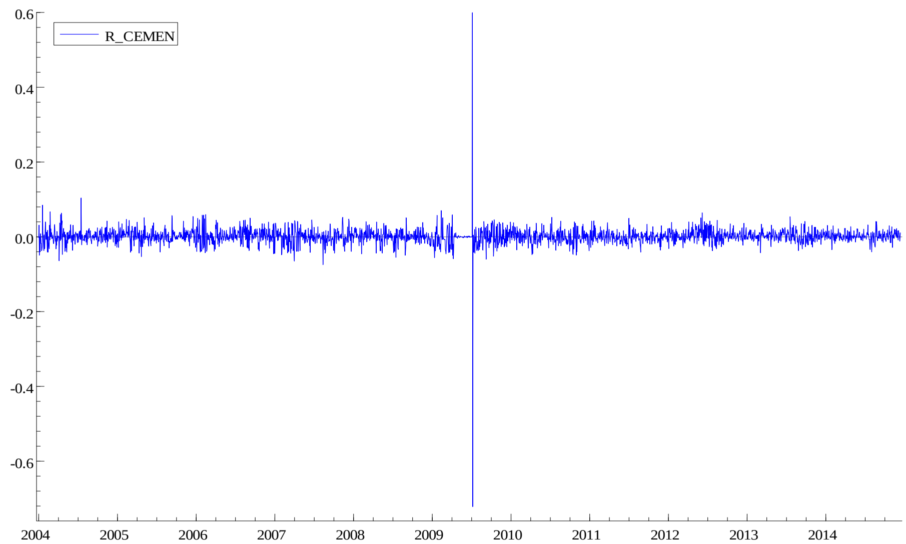
Prices Index of *Cement Sector* consists of 2706 number of observations. When calculation of logarithmic returns was made series of returns left with 2705 observations. Descriptive statistics the returns from *Cement Sector* are provided below in table 4.9.

Table 4.9 Returns of Cement Sector

Mean	*0.00089*
Median	*0.00030*
Maximum	*0.59969*
Minimum	*-0.72175*
Std. Dev.	*0.02541*
Skewness	*-3.63093*
Kurtosis	*357.29550*
Jarque-Bera	*14153692.000*
Probability	*0.000*
Sum	*2.416226*
Sum Sq. Dev.	*1.745674*
Observations	*2705*

The mean value of the returns for the prices index of *Cement Sector* is 0.089%, mid value appears to be 0.03% and maximum value 59.96%, maximum fall in the value of the returns is up to 72.17%, deviation from the mean value is 2.54%, data series is negatively skewed, the distribution of return series is leptokurtic and significance of

Jarque-Bera is stating that null hypothesis of the normal distribution has been rejected. Graph*4.1* is acquainting the behavior of the daily returns series from 2004 to 2014:



The graph 4.9 is explaining the spreading behavior of the returns series over the time. The spread of the returns lies between -72 to +60%. Small fluctuations can be observed throughout the period from 2004 to 2014 except in the second quarter of 2009.

Modeling of Volatility Gauging

In *Cement Sector*, volatility against the returns series has been observed. Conditional mean equation illustrates that the returns depend on its own first lag and the conditional variance equation illustrate that it depends on 1 lag of the square of the disturbance term and 1 lag of the square of the variance as the data series is showing symmetric effects under the t-distribution followed by the given equations:

$\boldsymbol{R_t = 0.001 + 0.123R_{t-1} + \varepsilon_t}$ *(Conditional Mean Equation)*

$\boldsymbol{h_t = 0.099 + 0.17\,\varepsilon_{t-1}^2 + 0.82h_{t-1}}$ *(Conditional Variance Equation)*

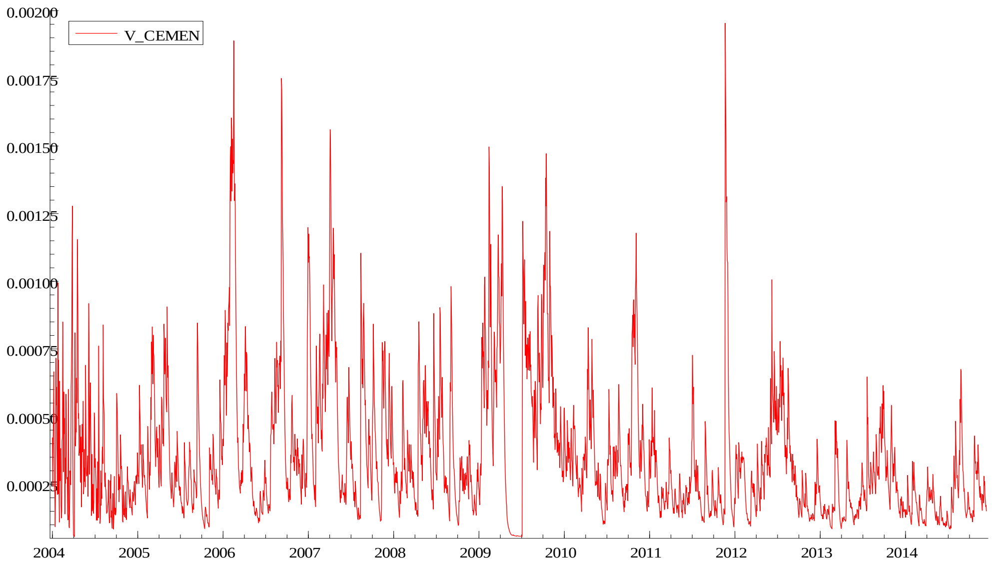
The value of persistence is 0.99, depicting that persistence of a shock takes a long time to decay. *Table 4.10* is acquainting the descriptive statistics analysis for the volatility:

Table 4.10 Volatility of Cement Sector

Mean	*0.000358*
Median	*0.00028*
Maximum	*0.001954*
Minimum	*5.69E-05*
Std. Dev.	*0.000257*
Skewness	*1.907503*
Kurtosis	*7.75101*
Jarque-Bera	*4184.45*
Probability	*0*
Sum	*0.968148*
Sum Sq. Dev.	*0.000178*
Observations	*2705*

The mean value of volatility of the returns in *Cement Sector* is 0.036%, mid value 0.028%, the maximum value 0.1954%, and maximum fall in the value of the volatility is 0.0057% the spread of the data from the mean value is 0.026%, data series is positively skewed, and the distribution of return series is leptokurtic while significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected.

Graph 4.10 is explaining the behavior of the volatility series from 2004 to 2014:



The graph 4.10 is explaining the spread of the volatility series over the time and the spread of the volatility lies between -0.0057% to +0.195%. Large and normal fluctuations in the volatility observed throughout the period from 2004 to 2014.

4.2.2 Event Study

This section discusses the response of daily returns against events. For this purpose data has divided into two splits, the estimation window or the control period consists of 60 days, and event window consist of 11 days; event window begins from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days before the event. *Table 4.11* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.11 Event Window Cement Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*0.0001*	*0.0211*	*0.0018*	*0.8119*
-4	*-0.0021*	*-0.8124*	*0.0008*	*0.3495*
-3	*-0.0019*	*-0.7402*	*0.0006*	*0.2525*
-2	*-0.0014*	*-0.5414*	*0.0012*	*0.5201*
-1	*-0.0020*	*-0.7762*	*0.0008*	*0.3401*
0	*-0.0026*	*-0.9989*	*-0.0007*	*-0.2938*
1	*0.0008*	*0.2970*	*0.0029*	*1.2589*
2	*-0.0058*	*-2.2361***	*-0.0030*	*-1.3173*
3	*-0.0001*	*-0.0295*	*0.0019*	*0.8493*
4	*-0.0051*	*-1.9758***	*-0.0040*	*-1.7380**
5	*0.0003*	*0.1281*	*-0.0006*	*-0.2826*

Significance Level: *10% **5% ***1%

The table 4.11 is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM).* Results are depicting those terrorist events are significant at 5% level of significance only 2^{nd} and 4^{th} day in 11 days event window under the employed model *CAPM,* where terrorists attacks are showing significant impact at 10% level of significance at 4^{th} day under employed model *MARM* for the *Cement Sector*. After a day impact of the terrorist attacks turns insignificant.

Table 4.12 is explains the *AAR* against political events:

Table 4.12 Event Window Cement Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.001275*	*-0.652726*	*-0.001031*	*-0.551399*
-4	*-0.000551*	*-0.281838*	*-0.000329*	*-0.175925*
-3	*-0.000465*	*-0.237901*	*-0.000058*	*-0.031125*
-2	*-0.000364*	*-0.186321*	*-0.000013*	*-0.006724*
-1	*-0.001656*	*-0.847578*	*-0.001038*	*-0.555299*
0	*-0.005469*	*-2.799840***	*-0.004805*	*-2.570699***
1	*0.000601*	*0.307726*	*0.001257*	*0.672406*
2	*-0.003157*	*-1.616039**	*-0.002517*	*-1.346308*
3	*0.000333*	*0.170305*	*0.000205*	*0.109777*
4	*0.001509*	*0.772651*	*0.001890*	*1.011375*
5	*0.000245*	*0.125178*	*0.000917*	*0.490448*

Significance Level: *10% **5% ***1%

The table 4.12 portrayed *AAR* and *t-stats* around the political events under *CAPM* and *MARM* for *Cement Sector*. The above table is depicting that overall political events are significant at 5% level of significance on the event day for both *CAPM* and *MARM*. However after the event day, the impact of the political events turns insignificant.

Table 4.13 is acquainting the *AAR* against financial crises events:

Table 4.13 Event Window Cement Sector: Financial Crises

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.009605*	*-1.838264*	*-0.008090*	*-1.493125*
-4	*-0.008762*	*-1.677041*	*-0.008470*	*-1.563377*
-3	*-0.007798*	*-1.492474*	*-0.006974*	*-1.287267*
-2	*-0.003594*	*-0.687823*	*-0.002364*	*-0.436273*
-1	*-0.005556*	*-1.063461*	*-0.004030*	*-0.743839*
0	*-0.007539*	*-1.442843*	*-0.007930*	*-1.463726*
1	*-0.003699*	*-0.708059*	*-0.003041*	*-0.561284*
2	*0.001679*	*0.321273*	*0.003053*	*0.563567*
3	*0.003715*	*0.710967*	*0.004730*	*0.873087*
4	*-0.010994*	*-2.104114***	*-0.009286*	*-1.713947**
5	*-0.013564*	*-2.596153***	*-0.013360*	*-2.465826***

*Significance Level: *10% **5% ***1%*

The table 4.13 is acquainting the behavior of the *Cement Sector* around the financial crises events. The results indicate that returns series have significant reaction over the financial crises events. Financial crises events turn significant at 5% level of significance on the 4^{th} and 5^{th} day under *CAMP model*, however, under *MARM* turn significant at 10% level of significance on 4^{th} day whereas on 5^{th} day turns significant[20] at 5% level of significance.

20 Impact of financial crises events persists for 24 days.

4.2.3 Event Day Analysis

In this methodology day dummies has been introduced to observe the impact of two different kinds of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate D_i = 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.14 & 15* are acquitting the response of returns and volatility against the terrorist events for *Cement Sector:*

Table 4.14 Event Day Analysis of Cement Sector: Terrorist Attacks[21]

Number of Observations	*2705*												
Date	*1/1/2004*		*12/31/2014*										
RETURN													
	C	***T_B_5***	***T_B_4***	***T_B_3***	***T_B_2***	***T_B_1***	***T_0***	***T_1***	***T_2***	***T_3***	***T_4***	***T_5***	***AR(1)***
Coefficient	*0.00061*	*-0.00064*	*-0.00072*	*0.00488*	*-0.00106*	*0.00159*	*0.00143*	*0.00143*	*-0.00070*	*-0.00165*	*0.00042*	*-0.00151*	*-0.18318*
Std. Error	*0.00054*	*0.00178*	*0.00181*	*0.00181*	*0.00180*	*0.00181*	*0.00181*	*0.00181*	*0.00180*	*0.00181*	*0.00181*	*0.00178*	*0.01895*
t-Statistic	*1.13525*	*-0.35661*	*-0.39722*	*2.70330*	*-0.58645*	*0.87884*	*0.79346*	*0.79231*	*-0.38526*	*-0.91125*	*0.23056*	*-0.84738*	*-9.66440****
VOLATILITY													
Coefficient	*0.00036*	*-0.00001*	*-0.00001*	*0.00000*	*0.00001*	*0.00000*	*-0.00001*	*0.00000*	*0.00000*	*0.00000*	*0.00001*	*0.00001*	*0.89842*
Std. Error	*0.00002*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00848*
t-Statistic	*15.75972*	*-1.09433*	*-1.05331*	*0.19389*	*0.41525*	*-0.16668*	*-0.68990*	*-0.05282*	*-0.26165*	*-0.35311*	*0.59109*	*0.73110*	*105.9809****
WALD TEST		***RETURNS***			***VOLATILITY***								
Test Statistic	***F-statistic***	***Chi-square***	***DW***	***F-statistic***	***Chi-square***	***DW***							
Value	*8.446122*	*109.7996*	*2.01*	*888.2719*	*11547.53*	*2.07*							
Df	*(13, 2691)*	*13*		*(13, 2691)*	*13*								
Probability	*0.0000*	*0.0000*		*0.0000*	*0.0000*								

*21 Significance Level: *10% **5% ***1%*

Table 4.15 Event Day Analysis of Cement Sector: Political Events[22]

Number of Observations		2705					
Date		1/1/2004		12/31/2014			
RETURN							
	C	**P_B_2**	**P_B_1**	**P_0**	**P_1**	**P_2**	**AR(1)**
Coefficient	0.00100	0.00043	-0.00056	-0.00248	-0.00032	0.00113	-0.18396
Std. Error	0.00046	0.00204	0.00209	0.00209	0.00209	0.00204	0.01893
t-Statistic	2.16506	0.21265	-0.26929	-1.87077*	-0.15174	0.55305	-9.71915
VOLATILITY							
Coefficient	0.0003580	-0.0000172	0.0000101	0.0000058	-0.0000007	-0.0000126	0.8986290
Std. Error	0.0000215	0.0000089	0.0000112	0.0000119	0.0000112	0.0000089	0.0084520
t-Statistic	16.60992	-1.93556**	0.89934	0.48954	-0.06509	-1.42285	106.31520
WALD TEST		**RETURNS**			**VOLATILITY**		
Test Statistic	**F-statistic**	**Chi-square**	**DW**	**F-statistic**	**Chi-square**	**DW**	
Value	14.48177	101.3724	2.01	1658.426	11608.98	2.06	
df	(7, 2697)	7		(7, 2697)	7		
Probability	0.000	0.000		0.000	0.000		

22 Significance Level: *10% **5% ***1%

In tables 4.14 and 4.15, the table 4.14 is explaining the impact of terrorist events on the returns and volatility of the *Cement Sector*, *T_B_5* represents the 5^{th} day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5^{th} day after the events day. The returns and volatility series are depending on their own 1^{st} lags. For the returns series, all the day dummy variables are insignificant at any level of significance. Moreover, volatility also remains insignificant for all 5 days against the terrorist attacks, as no day dummy turns significant at any level of significance.

The table 4.15 is acquainting the impact of political events on the returns and volatility of the *Cement Sector*, *P_B_2* represents the 2^{nd} day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2^{nd} day after the occurrence of a political event. Returns and volatility series are depending on their own 1^{st} lag. Results show that political events are significant on the event day at 10% level of significance however they turn insignificant after the event day. Moreover, as the political events are anticipated that's why political events are also significant at 5% level of significance on the day before the event for *Cement Sector*, where the political events are insignificant on and after the event day.

4.2.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.16* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.16 Impulse Indicator Saturation: Cement Sector

	Co-Breaks		*Significance⁰*	*Significance¹*	*Significance²*	*Significance³*	*Persistence*
Terrorist Attacks	*82*	*Returns*	*91*	*37*	*17*	*9*	*1day 79 mins*
		Volatility	*133*	*40*	*16*	*7*	*2days 59 mins*
Political Events	*74*	*Returns*	*118*	*10*	*1*	*4*	*1 day 153mins*
		Volatility	*89*	*55*	*3*	*1*	*2 days 153 mins*

⁰ on day significant ¹ after 1 day significant ²after 2 days significant ³after 3 days significant, at 5% level of significance

The table 4.16 above, explains the results obtained through Impulse Indicator Saturation, depicts that out of total 217 terrorist attacks 91 attacks found to be significant in returns series on the event day, of these events 37, 17 and 9 number of events are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average, the persistence of terrorist attacks remains significant for 1 day and 79 minutes of a working day. There are 133 significant terrorist attacks in the volatility of the returns series of which 40, 16 and 7 number of events are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average, the persistence of terrorist attacks remains significant for 2 days and 59 minutes of a working day. Moreover, 82 numbers of co-breaks captured against the terrorist events.

In political events, out of 160, there are 118 events that are significant on the event day under return series, of which 10, 1 and 4 are significant after the event day on 1^{st}, 2^{nd} and 3^{rd} day respectively in return series. There are 89 political events that are significant in volatility on the event day, of which 55, 3 and 1 are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average, the persistence of political events is significant for 1 day and 153 minutes of a working day, for volatility 2 days and 153 minutes. Moreover, 74 co-breaks captured against political events.

4.3 Chemical Sector

4.3.1 Exploratory Analysis

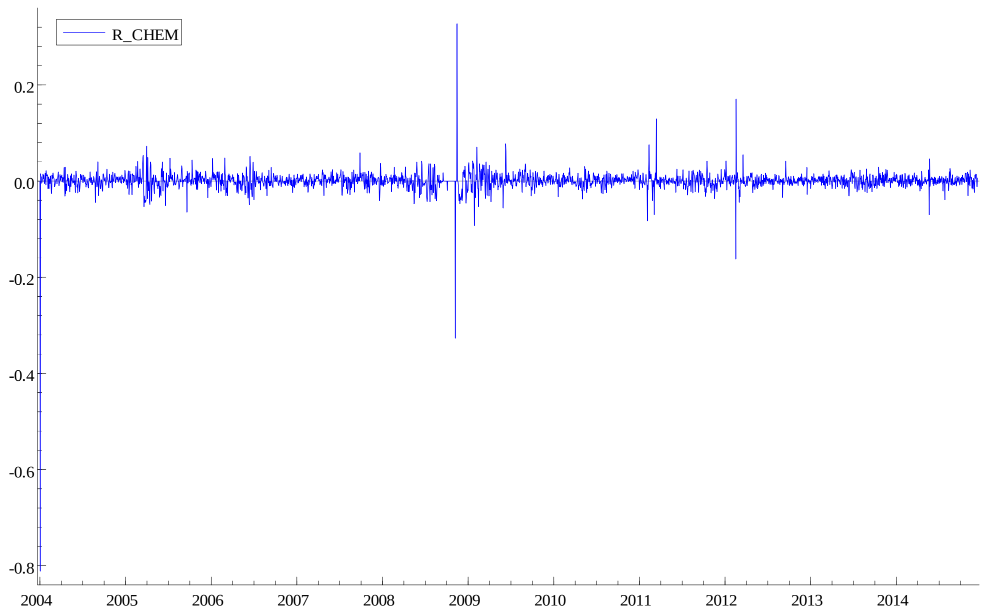
Returns Gauging

Prices Index of *Chemical Sector* dwells into 2706 number of observations. While, after calculation of logarithmic returns series of returns left with 2705 observations. Descriptive statistics the returns from *Chemical Sector* are provided below in table 4.17

Table 4.17 Returns of Chemical Sector

Mean	*0.00027*
Median	*0.00055*
Maximum	*0.32704*
Minimum	*-0.81135*
Std. Dev.	*0.02317*
Skewness	*-15.87569*
Kurtosis	*590.16880*
Jarque-Bera	*38971760.000*
Probability	*0.000*
Sum	*0.735513*
Sum Sq. Dev.	*1.451011*
Observations	*2705*

The mean value of the returns for the prices index of *Chemical Sector* is 0.027%, mid value appears to be 0.055% and maximum value 32.70%, maximum fall in the value of the returns is up to 81.13%, aberration value is 2.3%, data series is negatively skewed, the distribution of return series is leptokurtic and significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. Graph*4.1* is explaining the behavior of the daily returns series from 2004 to 2014:



The graph 4.17 is explaining the spread behavior of the returns series over the time. The spread lies between -81.13% to +32.70%. Small and few normal fluctuations can be seen through the whole period from 2004 to 2014.

Modeling of Volatility Gauging

In *Chemical Sector*, volatility against the returns series has been observed. Conditional mean equation illustrates that the returns depend on 1 lag of the disturbance term and the illustrate the presence of asymmetric effect in the return series and that's why *GJR-GARCH* has taken into account for volatility gauging therefore the conditional variance equation depends on 1 lag of the square of the disturbance term and 1 lag of the square of the variance under the t-distribution followed by the given equations:

$\boldsymbol{R_t = 0.0008 + 0.25\varepsilon_{t-1} + \varepsilon_t}$ *(Conditional Mean Equation)*

$\boldsymbol{h_t = 0.07 + 0.15\,\varepsilon^2_{t-1} + 0.20\,\varepsilon^2_{t-1}M_t + 0.65h_{t-1}}$ *(Conditional Variance Equation)*

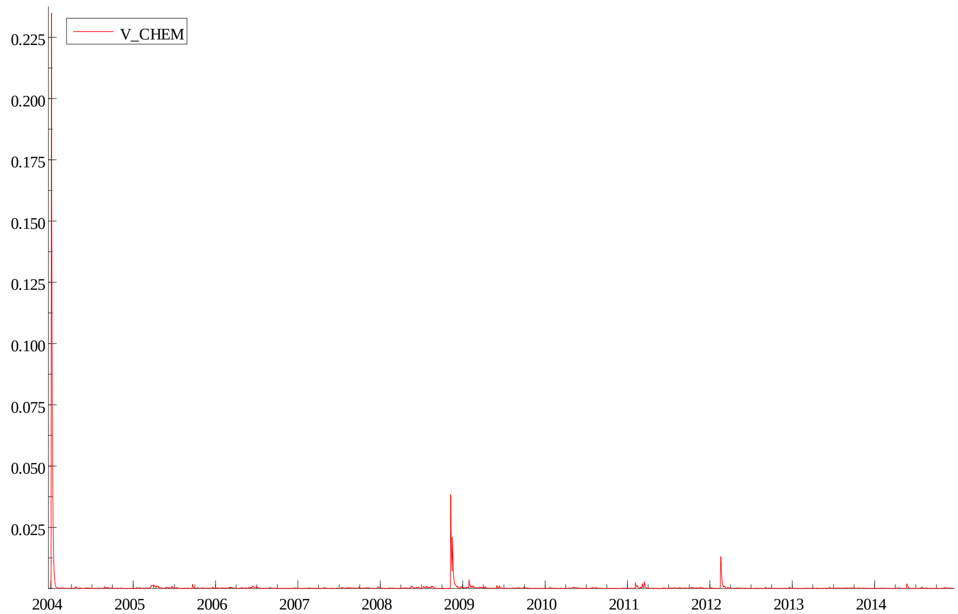
The value of persistence is 0.90, depicting that persistence of a shock takes a long time to decay.

Table 4.18 is acquainting the descriptive statistics analysis for the volatility:

Table 4.18 Volatility of Chemical Sector

Mean	*0.000541*
Median	*0.000139*
Maximum	*0.234918*
Minimum	*7.85E-05*
Std. Dev.	*0.006165*
Skewness	*29.24047*
Kurtosis	*973.6819*
Jarque-Bera	*1.07E+08*
Probability	*0*
Sum	*1.464341*
Sum Sq. Dev.	*0.102755*
Observations	*2705*

The volatility returns mean value in *Chemical Sector* is 0.0541%, median value 0.0139%, the maximum value 23.49%, and minimum value of the volatility is 0.00785%, the deviation from the mean value is 0.62%, data series is positively skewed, and the distribution of return series is leptokurtic while significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. *Graph 4.18* is showing the behavior of the volatility series from 2004 to 2014:



The graph 4.18 is explaining the spread of the volatility series over the time and the spread of the volatility lies between +0.00785% to +23.49%. In the first quarter of 2004, it shows large fluctuations, while in the rest of period under consideration, small and few normal fluctuations can be seen.

4.3.2 Event Study

This section discusses the response of daily returns against events. For this purpose data has separated into two splits, the estimation window or control period consists of 60 days, the event window consists of 11 days; event window from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days. *Table 4.19* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.19 Event Window Chemical Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*0.002195*	*1.789502*	*0.002575*	*2.026511*
-4	*0.000141*	*0.114627*	*0.000425*	*0.334326*
-3	*0.001367*	*1.114277*	*0.001635*	*1.286334*
-2	*0.000269*	*0.218957*	*0.000311*	*0.245023*
-1	*0.000540*	*0.440204*	*0.001136*	*0.893782*
0	*-0.000515*	*-0.420270*	*-0.000119*	*-0.093303*
1	*-0.000543*	*-0.443025*	*-0.000577*	*-0.454031*
2	*-0.001014*	*-0.826854*	*-0.000387*	*-0.304240*
3	*0.000114*	*0.093275*	*0.000212*	*0.166941*
4	*-0.000879*	*-0.716982*	*-0.001184*	*-0.931264*
5	*-0.000038*	*-0.031303*	*0.000016*	*0.012339*

*Significance Level: *10% **5% ***1%*

The table 4.19 is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM).*

Results are depicting that terrorist attacks are not significant in 11 days event window at any level of significance for the *Chemical Sector* under both *CAPM* and *MAR model*.

Table 4.20 is explains the AAR against political events:

Table 4.20 Event Window Chemical Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.008798*	*0.619380*	*0.000898*	*0.529955*
-4	*-0.008836*	*-0.349840*	*-0.000389*	*-0.229497*
-3	*-0.010241*	*-0.109747*	*-0.000179*	*-0.105687*
-2	*-0.008092*	*0.258460*	*0.000373*	*0.219831*
-1	*-0.003029*	*-0.893648*	*-0.001453*	*-0.857196*
0	*-0.000933*	*-2.389431*****	*-0.003490*	*-2.058816*****
1	*-0.003538*	*-0.9897474*	*-0.001679*	*-0.990759*
2	*0.000123*	*-0.6582901*	*-0.001239*	*-0.731081*
3	*0.002185*	*-0.8792746*	*-0.001548*	*-0.913068*
4	*-0.004912*	*1.5398431*	*0.002094*	*1.235324*
5	*-0.012022*	*1.2084694*	*0.002023*	*1.193377*

*Significance Level: *10% **5% ***1%*

The table 4.20 portrayed *AAR* and *t-stats* around the political events under *CAMP* and *MARM* for *Chemical Sector*. The above table is depicting that overall political events are significant at 5% level of significance on the event day for *MARM model.* As the political events are anticipated events, therefore in *CAPM*, political events are significant on 5^{th} and 2^{nd} day before the event day at 10% level of significance, also significant at 4^{th} and 3^{rd} day before and at 5^{th} day after the event day at 5% level of significance.

Table 4.21 is acquainting the *AAR* against financial crises events:

Table 4.21 Event Window Chemical Sector: Financial Crises

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.008798*	*-1.897199***	*-0.007616*	*-1.557421*
-4	*-0.008836*	*-1.905450***	*-0.010809*	*-2.210361***
-3	*-0.010241*	*-2.208360***	*-0.011662*	*-2.384798***
-2	*-0.008092*	*-1.745003**	*-0.008709*	*-1.781056**
-1	*-0.003029*	*-0.653144*	*-0.002908*	*-0.594694*
0	*-0.000933*	*-0.201188*	*-0.004153*	*-0.849263*
1	*-0.003538*	*-0.762993*	*-0.006212*	*-1.270340*
2	*0.000123*	*0.026465*	*-0.001421*	*-0.290665*
3	*0.002185*	*0.471216*	*0.001554*	*0.317853*
4	*-0.004912*	*-1.059114*	*-0.003700*	*-0.756600*
5	*-0.012022*	*-2.592446***	*-0.014918*	*-3.050795***

*Significance Level: *10% **5% ***1%*

The table 4.21 is acquainting the behavior of the *Chemical Sector* around the financial crises events. The results indicate that returns series have significant reaction on 5th, 4th and 3rd day before and 5th day after the event day at 5% level of significance and significant on 2nd day before day event day at 10% level of significance over the financial crises events under *CAPM*. Moreover, financial events are significant on 4th and 3rd day before and 5th day after the event day at 5% level of significance and significant[23] on 2nd day before the event day at 10% level of significance.

23 The impact of financial crises events persists for 10 days. Moreover, Pre-Event will not be considered in case of terrorist events.

4.3.3 Event Day Analysis

In this methodology, day dummies have been introduced to observe the impact of two different kind of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate $\boldsymbol{D_i}$ **=** 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.22 & 23* are acquitting the response of returns and volatility against the terrorist events for *Chemical Sector:*

Table 4.22 Event Day Analysis of Chemical Sector: Terrorism Events[24]

Number of Observations *2705*

Date *1/1/2004* *12/31/2014*

	C	T_B_5	T_B_4	T_B_3	T_B_2	T_B_1	T_0	T_1	T_2	T_3	T_4	T_5	AR(1)	MA(1)
RETURN														
Coefficient	-0.00016	0.00262	0.00089	0.00213	0.00081	0.00150	0.00022	-0.00063	-0.00034	-0.00021	-0.00118	-0.00013	-0.51258	0.71385
Std. Error	0.00058	0.00144	0.00147	0.00148	0.00148	0.00149	0.00149	0.00149	0.00148	0.00148	0.00147	0.00144	0.02492	0.02192
t-Statistic	-0.28	1.81666	0.60462	1.43419	0.54525	1.01149	0.14454	-0.42593	-0.23014	-0.14142	-0.79760	-0.08695	-20.57***	32.567***
VOLATILITY														
Coefficient	0.00069	-0.000081	-0.00007	-0.0001	-0.00012	-0.0002	-0.0002	-0.00024	-0.00025	-0.0002	-0.00015	-0.00013	0.6674560	
Std. Error	0.0003	0.0003270	0.0003940	0.0004170	0.0004270	0.0004290	0.0004290	0.0004290	0.00043	0.00048	0.0003940	0.0003280	0.0143550	
t-Statistic	2.090**	-0.2415	-0.1780	-0.34944	-0.3139	-0.4498	-0.5262	-0.553	-0.578	-0.4606	-0.3788	-0.390	46.499***	

WALD TEST	RETURNS			VOLATILITY		
Test Statistic	F-statistic	Chi-square	DW	F-statistic	Chi-square	DW
Value	86.82724	1215.581	1.85	166.6883	2166.948	1.97
df	(14, 2690)	14		(13, 2691)	13	
Probability	0.0000	0.0000		0.0000	0.0000	

24 Significance Level: *10% **5% ***1%

Table 4.23 Event Day Analysis of Cement Sector: Political Events[25]

Number of Observations		2705						
Date	1/1/2004		12/31/2014					
RETURN								
	C	P_B_2	P_B_1	P_0	P_1	P_2	AR(1)	MA(1)
Coefficient	0.000647	0.000600	-0.000857	-0.003891	-0.001096	-0.000738	-0.512764	0.713582
Std. Error	0.000497	0.001655	0.001677	0.001693	0.001677	0.001655	0.024910	0.021916
t-Statistic	1.30107	0.36239	-0.51099	-2.29794**	-0.65347	-0.44621	-20.58468***	32.56039***
VOLATILITY								
Coefficient	0.00057	-0.00006	-0.00013	-0.00017	-0.00009	-0.00007	0.66767	
Std. Error	0.00028	0.00038	0.00044	0.00046	0.00044	0.00038	0.01434	
t-Statistic	2.04352**	-0.16483	-0.30324	-0.37001	-0.20691	-0.18205	46.57144***	

WALD TEST	RETURNS			VOLATILITY		
Test Statistic	F-statistic	Chi-square	DW	F-statistic	Chi-square	DW
Value	151.686	1213.488	1.82	310.5735	2174.015	1.97
Df	(8, 2696)	8		(7, 2697)	7	
Probability	0	0		0	0	

25 Significance Level: *10% **5% ***1%

In tables 4.22 and 4.23, the first table is explaining the impact of terrorist events on the returns and volatility of the *Chemical Sector*, *T_B_5* represents the 5th day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5th day after the events day. The returns and volatility series are depending on their own 1st lag and 1st lag of the error term. For the returns series, all the terrorist day dummies are insignificant at any level of significance. Moreover, volatility remains insignificant for all 5 days against the terrorist attacks, as no day dummy turns significant at any level of significance.

The table 4.23 is explaining the impact of political events on the returns and volatility of the *Chemical Sector, P_B_2* represents the 2nd day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2nd day after the occurrence of a political event. Returns and volatility series are depending on their own 1st lag and 1st lag of their error term. Results show that political events are significant on the event day at 5% level of significance however they are insignificant before and after the event day. Moreover, the volatility of the returns shows no evidence of significance of political events in volatility.

4.3.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.24* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.24 Impulse Indicator Saturation: Chemical Sector

	Co-Breaks		*Significance^{0}*	*Significance^{1}*	*Significance^{2}*	*Significance^{3}*	*Persistence*
Terrorist Attacks	*61*	*Returns*	*64*	*31*	*15*	*13*	*0 d 312 mins*
		Volatility	*110*	*51*	*21*	*4*	*1 d 286 mins*
Political Events	*67*	*Returns*	*101*	*10*	*8*	*7*	*1 d 81 mins*
		Volatility	*87*	*58*	*5*	*3*	*2 d 103mins*

^{0}on day significant ^{1} after 1 day significant ^{2}after 2 days significant ^{3}after 3 days significant, at 5% level of significance

The table 4.24 above explains the results obtained through Impulse Indicator Saturation, depicts that out of total 217 terrorist attacks, 64 attacks found to be significant in returns series on the event day, of these events 31, 15 and 13 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of the significant terrorist attacks is 312 minutes of a working day. There are 113 significant terrorist attacks in the volatility of the returns series of which 51, 21 and 4 number of events are significant on 1st, 2nd and 3rd day respectively after the event day.

On average, persistence of significant terrorist attacks is 1 day and 186 minutes of a working day. Moreover, 61 numbers of co-breaks captured against the terrorist events. In political events, out of 160, there are 101 events that are significant on the event day under return series, of which 10, 8 and 7 are significant after the event day on 1^{st}, 2^{nd} and 3^{rd} day respectively in return series. There are 87 political events that are significant in volatility on the event day, of which 58, 5 and 3 are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average, persistence time of significant political events is 1 day and 81 minutes in returns, and 2 days and 103 minutes in volatility of a working day. Moreover, 67 co-breaks captured against political events.

4.4 *Food Sector*

4.4.1 *Exploratory Analysis*

Returns Gauging

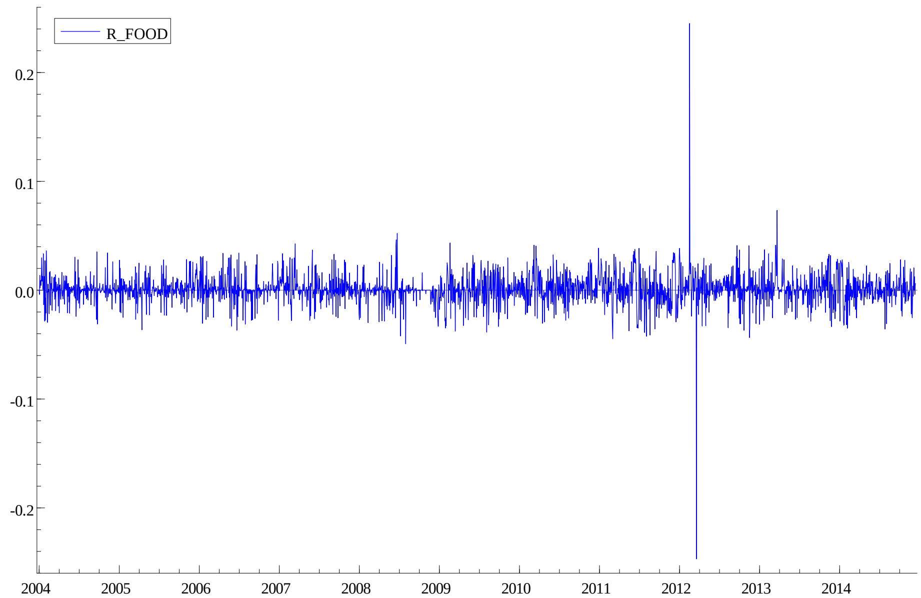
Prices Index of *Food Sector* dwells into 2706 number of observations. While, after calculation of logarithmic returns series of returns left with 2705 observations. Descriptive statistics the returns from *Food Sector* are provided below in table 4.25

Table 4.25 Returns of Food Sector

Mean	*0.00107*
Median	*0.00023*
Maximum	*0.24507*
Minimum	*-0.24688*
Std. Dev.	*0.01444*
Skewness	*-0.03617*
Kurtosis	*65.10236*
Jarque-Bera	*434683.100*
Probability	*0.000*
Sum	*2.895113*
Sum Sq. Dev.	*0.564102*
Observations	*2705*

The mean value of the returns for the price index of *Food Sector* is 0.107%, mid value appears to be 0.023% and maximum value 24.507%, maximum fall in the value of the returns is up to 24.688%, deviation from the mean value is 1.444%, data series is negatively skewed, the distribution of return series is leptokurtic and significance of

Jarque-Bera shows that non-normal distribution exist. Graph *4.25* is acquainting the behavior of the daily returns series from 2004 to 2014:



The graph 4.25 is explaining the spreading behavior of the returns series over the time. The spread of the returns lies between -24.688 to +24.507%. Normal and small fluctuations can be observed throughout the period from 2004 to 2014 except for the first quarter of 2012.

Modeling of Volatility Gauging

In *Food Sector*, volatility against the returns series followed by the given equation has been observed:

$$\boldsymbol{R_t = 0.005 + 0.96R_{t-1} - 0.95\varepsilon_{t-1} + \varepsilon_t} \qquad \textit{(Conditional Mean Equation)}$$

$$\boldsymbol{h_t = 0.0023 + 0.00\, \varepsilon^2_{t-1} + 1.00h_{t-1}} \qquad \textit{(Conditional Variance Equation)}$$

Conditional mean equation illustrates that the returns depend on its own 1 lags and 1 lag of the disturbance term and the conditional variance equation illustrate that it depends on

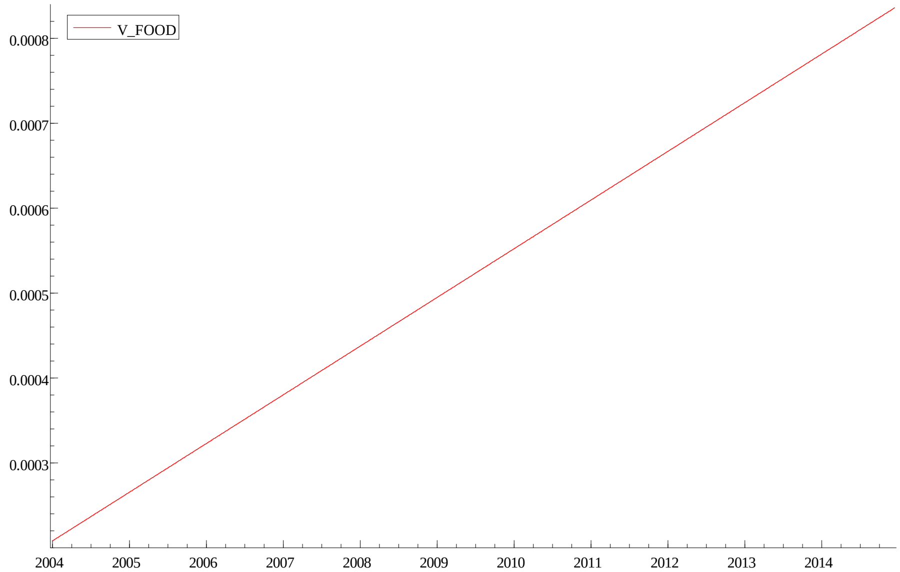
1 lag of the square of the disturbance term and no *GARCH* effect is being observed this means series holds a constant variance effects under the t-distribution. The value of persistence is 1, depicting that persistence of a shock takes a long time to decay.

Table 4.26 is acquainting the descriptive statistics analysis for the volatility:

Table 4.26 Volatility of Food Sector

Mean	*0.000522*
Median	*0.000522*
Maximum	*0.000836*
Minimum	*0.000208*
Std. Dev.	*0.000181*
Skewness	*-3.90E-16*
Kurtosis	*1.8*
Jarque-Bera	*162.3001*
Probability	*0*
Sum	*1.412315*
Sum Sq. Dev.	*8.89E-05*
Observations	*2705*

The mean value of volatility of the returns in *Food Sector* is 0.0522%, mid value is also 0.0522%, the maximum value 0.0836%, and maximum fall in the value of the volatility is 0.0208% the spread of the data from the mean value is 0.0181%, data series is negatively skewed, and the distribution of return series is mesokurtic while significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. *Graph 4.26* is explaining the behavior of the volatility series from 2004 to 2014:



The graph 4.26 is explaining the spread of the volatility series over the time that the spread of the volatility lies between +0.0208 to +0.0836%. The graph 4.26 is showing constantly increasing trend of variance over time. The volatility observed throughout the period from 2004 to 2014. Constant variance depicts the absence of any *ARCH* effect.

4.4.2 Event Study

This section discusses the response of daily returns against events. For this purpose data has broken split into two splits, the estimation window or control period consists of 60 days, the event window consists of 11 days; event window from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days. *Table 4.27* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.27 Event Window Food Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.0016*	*-1.4331*	*-0.0010*	*-0.9523*
-4	*-0.0017*	*-1.4935*	*-0.0017*	*-1.5197*
-3	*0.0002*	*0.1422*	*0.0001*	*0.1233*
-2	*-0.0008*	*-0.6982*	*-0.0006*	*-0.5466*
-1	*0.0001*	*0.0792*	*0.0001*	*0.0844*
0	*-0.0004*	*-0.3916*	*-0.0003*	*-0.2599*
1	*-0.0012*	*-1.0721*	*-0.0013*	*-1.1433*
2	*0.0018*	*1.6164**	*0.0019*	*1.7739**
3	*-0.0007*	*-0.6653*	*-0.0004*	*-0.3320*
4	*0.0000*	*-0.0311*	*0.0004*	*0.3626*
5	*0.0000*	*-0.0401*	*0.0002*	*0.2130*

*Significance Level: *10% **5% ***1%*

The table 4.27 is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM)*. Results are depicting that terrorist attacks are significant on second day in 11 days event window at 10% level of significance for the *Food Sector* under both *CAPM* and *MAR model*.

Table 4.28 is explains the AAR against political events:

Table 4.28 Event Window Food Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*0.000740*	*0.557144*	*0.000945*	*0.711234*
-4	*-0.000351*	*-0.264235*	*-0.000418*	*-0.314717*
-3	*0.002621*	*1.972640**	*0.002775*	*2.087813***
-2	*0.000152*	*0.114647*	*0.000296*	*0.222699*
-1	*0.001992*	*1.498613*	*0.002163*	*1.627722**
0	*-0.000901*	*-0.677907*	*-0.000640*	*-0.481357*
1	*-0.000654*	*-0.492481*	*-0.000034*	*-0.025333*
2	*-0.000206*	*-0.154778*	*0.000091*	*0.068642*
3	*0.000250*	*0.188138*	*0.000199*	*0.149501*
4	*-0.002022*	*-1.521885*	*-0.001933*	*-1.454529*
5	*-0.000863*	*-0.649230*	*-0.000765*	*-0.575723*

*Significance Level: *10% **5% ***1%*

The table 4.28 portrayed *AAR* and *t-stats* around the political events under *CAMP* and *MARM* for *Food Sector.* The above table is depicting that overall political events are insignificant in 11 days window at any level of significance in *CAPM* except 3rd day before the event at 5% level of significance. Where, the political are significant on 3rd day before the event occurrence day at 5% level significance and significant 1 day before the event occurrence day at 10% level of significance under the *MAR model*.

Table 4.29 is acquainting the *AAR* against financial crises events:

Table 4.29 Event Window Food Sector: Financial Crises

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.002060*	*-0.797977*	*-0.001630*	*-0.605234*
-4	*-0.001064*	*-0.412175*	*-0.000632*	*-0.234477*
-3	*-0.003228*	*-1.250657*	*-0.002760*	*-1.024539*
-2	*-0.002287*	*-0.886014*	*-0.001720*	*-0.638661*
-1	*-0.005641*	*-2.185358***	*-0.005273*	*-1.957531**
0	*-0.007983*	*-3.092750***	*-0.007913*	*-2.937631**
1	*-0.003726*	*-1.443430*	*-0.002905*	*-1.078622*
2	*0.001622*	*0.628439*	*0.002298*	*0.853063*
3	*-0.000287*	*-0.111225*	*0.000101*	*0.037598*
4	*-0.001767*	*-0.684449*	*-0.001185*	*-0.439971*
5	*-0.003032*	*-1.174684*	*-0.002509*	*-0.931424*

*Significance Level: *10% **5% ***1%*

The table 4.29 is acquainting the behavior of the *Food Sector* around the financial crises events. The results indicate that returns series have significant[26] reaction at 5% level of signifance on event day and 1 day before the news revelation day over the financial crises events under both *CAMP* and *MAR models*.

26 The shock of financial crises persists for more than 30 days.

4.1.3 Event Day Analysis

In this methodology, day dummies have been introduced to observe the impact of two different kinds of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate $\boldsymbol{D_i} =$ 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.30 & 31* are acquitting the response of returns and volatility against the terrorist events for *Food Sector:*

Table 4.30 Event Day Analysis of Food Sector: Terrorist Attacks[27]

Number of Observations		2705										
Date	1/1/2004		12/31/2014									
RETURN												
	C	T_B_5	T_B_4	T_B_3	T_B_2	T_B_1	T_0	T_1	T_2	T_3	T_4	T_5
		-	-		-		-	-		-		
Coefficient	0.0010620	0.0008270	0.0014530	0.0003400	0.0003830	0.0003430	0.0001110	0.0010280	0.0021540	0.0001430	0.0006450	0.0005620
Std. Error	0.0003680	0.0010290	0.0010290	0.0010270	0.0010270	0.0010280	0.0010290	0.0010280	0.0010270	0.0010270	0.0010290	0.0010290
		-	-		-		-	-		-		
t-Statistic	2.8888020	0.8033540	1.4120530	0.3313700	0.3733830	0.3341620	0.1082090	1.0004990	2.0977430**	0.1387500	0.6272430	0.5458520
VOLATILITY												
		-	-	-	-	-	-	-		-	-	-
Coefficient	0.0006860	0.0000791	0.0000702	0.0001460	0.0001340	0.0001930	0.0002260	0.0002380	-0.0002470	0.0001920	0.0001490	0.0001280
Std. Error	0.0003300	0.0003270	0.0003940	0.0004170	0.0004270	0.0004290	0.0004290	0.0004290	0.0004270	0.0004170	0.0003940	0.0003280
		-	-	-	-	-	-	-		-	-	-
t-Statistic	2.0783880	0.2415240	0.1780710	0.3494420	0.3139070	0.4498290	0.5262200	0.5535740	-0.5785000	0.4606390	0.3788730	0.3903690
WALD TEST		RETURNS			VOLATILITY							
		Chi-			Chi-							
Test Statistic	F-statistic	square	DW	F-statistic	square	DW						
Value	1.992539	23.91046	1.81	166.6883	2166.948	1.32						
Df	(12, 2693)	12		(13, 2691)	13							
Probability	0.0213	0.0209		0.0000	0.0000							

27 Significance Level: *10% **5% ***1%

Table 4.31 Event Day Analysis of Food Sector: Political Events[28]

Number of Observations		*2705*					
Date		*1/1/2004*		*12/31/2014*			
RETURN							
	C	***P_B_2***	***P_B_1***	***P_0***	***P_1***	***P_2***	***AR(1)***
Coefficient	*0.001023*	*0.000598*	*0.00203*	*-0.000651*	*-0.000556*	*-0.000625*	
Std. Error	*0.000314*	*0.00118*	*0.00118*	*0.00118*	*0.00118*	*0.00118*	
t-Statistic	*3.261017*	*0.506624*	*1.720154**	*-0.551409*	*-0.47112*	*-0.529603*	
VOLATILITY							
Coefficient	*0.0001960*	*0.0000082*	*0.0000025*	*-0.0000050*	*0.0000088*	*0.0000002*	*0.8288350*
Std. Error	*0.0000118*	*0.0000083*	*0.0000103*	*0.0000109*	*0.0000103*	*0.0000083*	*0.0107760*
t-Statistic	*16.577610*	*0.985533*	*0.238610*	*-0.454717*	*0.851965*	*0.020031*	*76.917400*

WALD TEST		***RETURNS***			***VOLATILITY***	
Test Statistic	***F-statistic***	***Chi-square***	***DW***	***F-statistic***	***Chi-square***	***DW***
Value	*3.123013*	*18.73808*	*1.81*	*886.9875*	*6208.912*	*2.23*
Df	*(6, 2699)*	*6*		*(7, 2697)*	*7*	
Probability	*0.0047*	*0.0046*		*0.000*	*0.000*	

*28 Significance Level: *10% **5% ***1%*

In tables 4.30 and 4.31, the table 4.30 is explaining the impact of terrorist events on the returns and volatility of the *Food Sector*, *T_B_5* represents the 5^{th} day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5^{th} day after the events day. For the returns series, *t_2* is significant at 5% level of significance, indicating that a significant impact of terrorist attacks on the returns of 2nd day is significant, while this impact turns insignificant right after a day. Moreover, volatility remains insignificant for all 5 days against the terrorist attacks, as no day dummy turns significant at any level of significance.

The table 4.31 is acquainting the impact of political events on the returns and volatility of the *Food Sector, P_B_2* represents the 2^{nd} day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2^{nd} day after the occurrence of a political event. Returns have no lag whereas volatility series are depending on their own 1^{st} lag. In case of returns series results show that political events are significant on the day before event day at 10% level of significance however they turn insignificant at the event day for *Food Sector*. Moreover, as the political events are anticipated that’s why political events are significant on the day before the event for *Food Sector,* whereas the political events are insignificant over the volatility of the returns.

4.1.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.32* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.32 Impulse Indicator Saturation: Food Sector

	Co-Breaks		*Significance⁰*	*Significance¹*	*Significance²*	*Significance³*	*Persistence*
Terrorist Attacks	*55*	*Returns*	*116*	*37*	*20*	*5*	*1 d 311 mins*
		Volatility	*62*	*44*	*33*	*38*	*1 d 1 min*
Political Events	*39*	*Returns*	*114*	*15*	*9*	*1*	*1 d 310 mins*
		Volatility	*44*	*33*	*32*	*25*	*1 d 20 mins*

[0] on day significant [1] after 1 day significant [2] after 2 days significant [3] after 3 days significant, at 5% level of significance

The table 4.32 above explains the results obtained through Impulse Indicator Saturation, depicts that out of total 217 terrorist attacks 116 attacks found to be significant in returns series on the event day, of these events 37, 20 and 5 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of the significant terrorist attacks is 1 day and 311 minutes of a working day. There are 62 significant terrorist attacks in the volatility of the returns series of which 44, 33 and 38 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of significant terrorist attacks is 1 day and 1 minutes of a working day. Moreover, 55 numbers of co-breaks captured against the terrorist events. In political events, out of 160, there are 114 events that are significant on the event day under return series, of which 15, 9 and 1 are significant after the event day on 1st, 2nd and 3rd day respectively in return series. There are 44 political events that are significant in volatility on the event day, of which 33, 32 and 25 are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of significance political events is 1 day and 310 minutes in returns, and 1 days and 20 minutes in volatility of a working day. Moreover, 39 co-breaks captured against political events.

4.5 Oil and Gas Sector

4.5.1 Exploratory Analysis

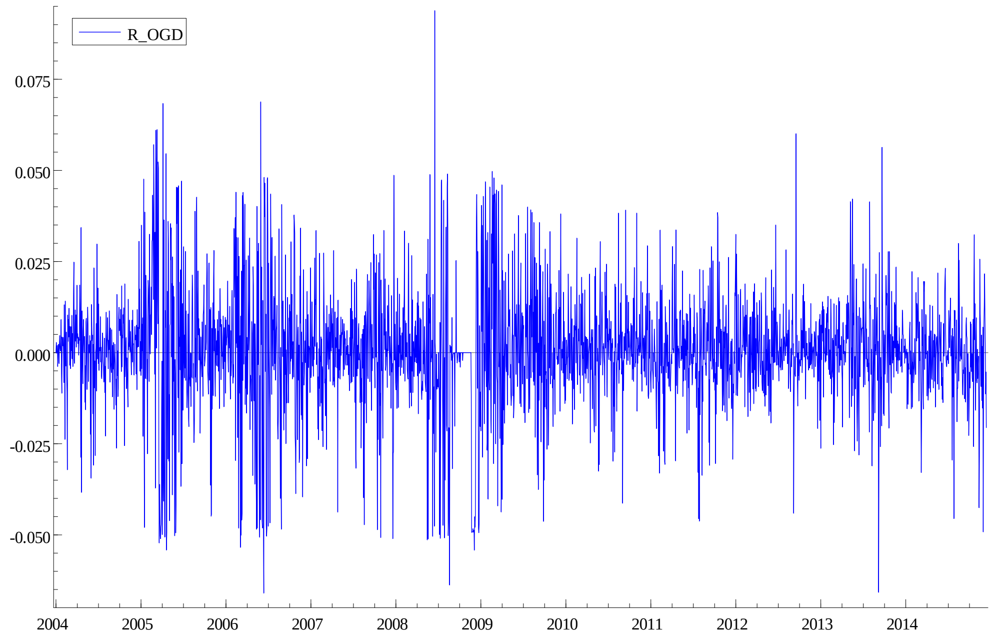
Returns Gauging

Prices Index of *Oil and gas Sector* dwells into 2706 number of observations. While, after calculation of logarithmic returns series of returns left with 2705 observations. Descriptive statistics the returns from *Oil and gas Sector* are provided below in table 4.33

Table 4.33 Returns of Oil and Gas Sector

Mean	*0.00044*
Median	*0.00000*
Maximum	*0.09384*
Minimum	*-0.06599*
Std. Dev.	*0.01672*
Skewness	*-0.14031*
Kurtosis	*5.44487*
Jarque-Bera	*682.576*
Probability	*0.000*
Sum	*1.191001*
Sum Sq. Dev.	*0.755842*
Observations	*2705*

The mean value of the returns for the prices index of *Oil and gas Sector* is 0.044%, mid value appears to be 0.0% and maximum value 9.38%, maximum fall in the value of the returns is up to 6.60%, variation from the mean value is 1.67%, data series is negatively skewed, the distribution of return series is mesokurtic and significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. Graph*4.33* is acquainting the behavior of the daily returns series from 2004 to 2014:



The graph 4.33 is explaining the spreading behavior of the returns series over the time. The spread of the returns lie between -6.60% to +9.38%. Large and normal fluctuations can be observed throughout the period from 2004 to 2014.

Modeling of Volatility Gauging

In *Oil and gas Sector*, volatility against the returns series has been observed followed by the given equation:

$\boldsymbol{R_t = 0.0009 + 0.069R_{t-1} + \varepsilon_t}$ *(Conditional Mean Equation)*

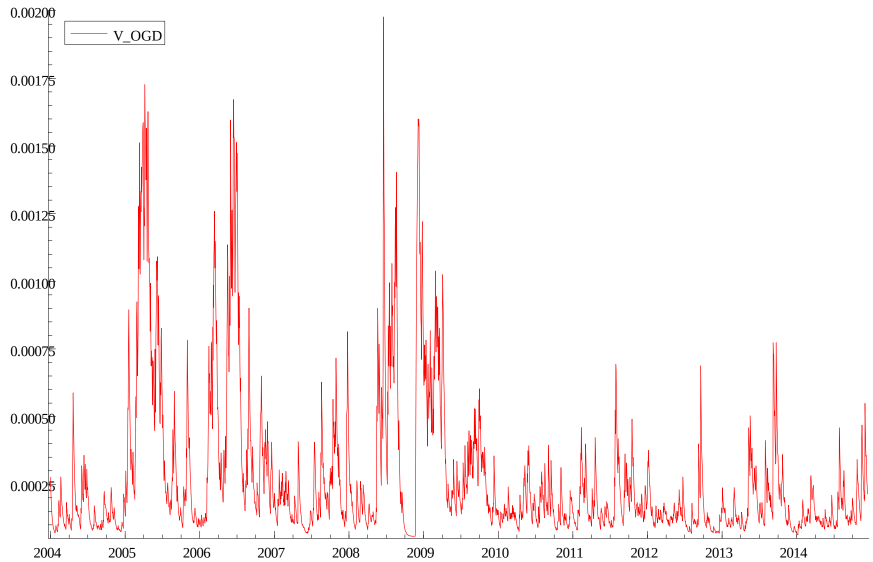
$\boldsymbol{h_t = 0.109 + 0.1512\ \varepsilon_{t-1}^2 + 0.809h_{t-1}}$ *(Conditional Variance Equation)*

Conditional mean equation illustrates that the returns depend on its own 1 lag and the conditional variance equation illustrate that it depends on 1 lag of the square of the disturbance term and 1 lag of the square of the variance as the data series is showing symmetric effects under the t-distribution. The value of persistence is 0.92, depicting that persistence of a shock takes a long time to decay. *Table 4.34* is acquainting the descriptive statistics analysis for the volatility:

Table 4.34 Volatility of Oil and Gas Sector

Mean	*0.000276*
Median	*0.00017*
Maximum	*0.001977*
Minimum	*5.81E-05*
Std. Dev.	*0.000275*
Skewness	*2.541708*
Kurtosis	*10.0293*
Jarque-Bera	*8481.541*
Probability	*0*
Sum	*0.747884*
Sum Sq. Dev.	*0.000205*
Observations	*2705*

The mean value of volatility of the returns in *Oil and gas Sector* is 0.028%, mid value 0.017%, the maximum value 0.20%, and maximum fall in the value of the volatility is 0.0058%, the spread of the data from the mean value is 0.028%, data series is positively skewed, and the distribution of return series is leptokurtic while significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. *Graph 4.34* is explaining the behavior of the volatility series from 2004 to 2014:



The graph 4.34 is explaining the spread of the volatility series over the time and the spread of the volatility lies between -0.0058% to +0.20%. High fluctuations in the volatility observed in the first quarter of 2005, mid of 2006 and also in the last quarter of 2008, whereas normal fluctuations in the volatility were observed in rest of the period.

4.5.2 Event Study

This section discusses the response of daily returns against events. For this purpose data has carved into two splits, the estimation window or control period consists of 60 days, the event window consist of 11 days; event window from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days. *Table 4.35* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.35 Event Window Oil and Gas Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.000089*	*-0.080356*	*0.000418*	*0.392748*
-4	*-0.000273*	*-0.246751*	*0.000216*	*0.203251*
-3	*0.000013*	*0.011585*	*-0.000002*	*-0.002064*
-2	*0.001564*	*1.411757*	*0.001449*	*1.360375*
-1	*0.001042*	*0.940985*	*0.001419*	*1.332306*
0	*-0.002142*	*-1.933450***	*-0.001472*	*-1.381874*
1	*0.000666*	*0.601503*	*0.001288*	*1.209669*
2	*0.000123*	*0.111096*	*0.000489*	*0.459542*
3	*-0.000459*	*-0.414208*	*-0.000460*	*-0.431423*
4	*-0.000325*	*-0.293543*	*-0.000345*	*-0.323771*
5	*-0.000384*	*-0.346420*	*0.000063*	*0.059214*

*Significance Level: *10% **5% ***1%*

The table 4.35 is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM)*. Results are depicting that terrorist attacks are significant only on the event day at the 5% level of significance under the *CAPM* model in 11 days event window and remain insignificant in rest of the days. While under the *MARM* model the terrorist attack are not significant at any level of significance for the *Oil and gas Sector*.

Table 4.36 is explains the AAR against political events:

Table 4.36 Event Window Oil and Gas Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.000498*	*-0.189685*	*0.000356*	*0.138767*
-4	*-0.000039*	*-0.014815*	*0.000137*	*0.053183*
-3	*0.001983*	*0.754789*	*0.002748*	*1.070168*
-2	*-0.001151*	*-0.438229*	*-0.000328*	*-0.127784*
-1	*0.001121*	*0.426767*	*0.001818*	*0.707823*
0	*-0.006382*	*-2.429373***	*-0.005271*	*-2.052585***
1	*0.001546*	*0.588463*	*0.001958*	*0.762388*
2	*-0.002387*	*-0.908647*	*-0.001609*	*-0.626397*
3	*0.000954*	*0.363183*	*0.000755*	*0.293834*
4	*0.002450*	*0.932733*	*0.003666*	*1.427684*
5	*0.002553*	*0.971876*	*0.003464*	*1.349104*

*Significance Level: *10% **5% ***1%*

The table 4.36 portrayed *AAR* and *t-stats* around the political events under *CAMP* and *MARM* for *Oil and gas Sector*. The above table is depicting that political events are significant only on the event day at the 5% level of significance under the *CAPM* model in 11 days event window and remain insignificant in rest of the days. While under the *MARM* model the political events are significant only on the event day at 5% level of significance and remain insignificant in rest of the days at any level of significance for the *Oil and gas Sector*.

Table 4.37 is acquainting the *AAR* against financial crises events:

Table 4.37 Event Window Oil and Gas Sector: Financial Crises

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.013545*	*-3.258963***	*-0.012817*	*-2.964667***
-4	*-0.014470*	*-3.481728***	*-0.016641*	*-3.849176***
-3	*-0.018984*	*-4.567663***	*-0.018938*	*-4.380469***
-2	*-0.020726*	*-4.987014***	*-0.017978*	*-4.158532***
-1	*-0.016585*	*-3.990550***	*-0.012624*	*-2.920090***
0	*-0.013374*	*-3.217928***	*-0.017308*	*-4.003419***
1	*-0.021591*	*-5.195005***	*-0.022972*	*-5.313577***
2	*-0.018084*	*-4.351279***	*-0.015872*	*-3.671277***
3	*-0.014202*	*-3.417056***	*-0.011481*	*-2.655570***
4	*-0.023995*	*-5.773506***	*-0.019046*	*-4.405452***
5	*-0.024770*	*-5.960025***	*-0.025687*	*-5.941684***

*Significance Level: *10% **5% ***1%*

The table 4.37 is acquainting the behavior of the *Oil and gas Sector* around the financial crises events. The results indicate that returns series have significant[29] reaction throughout the financial crises events at 5% level of significance under both *CAMP* and *MARM models*.

29 The shock of financial crises persists for more than 100 days.

4.5.3 Event Day Analysis

In this methodology, day dummies have been introduced to observe the impact of two different kinds of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate $\boldsymbol{D_i}$ **=** 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.38 & 39* are acquitting the response of returns and volatility against the terrorist events for *Oil and gas Sector:*

Table 4.38 Event Day Analysis of Oil and Gas Sector: Terrorist Attacks[30]

Number of Observations	*2705*		
Date	*1/1/2004*	*12/31/2014*	

RETURN

	C	***T_B_5***	***T_B_4***	***T_B_3***	***T_B_2***	***T_B_1***	***T_0***	***T_1***	***T_2***	***T_3***	***T_4***	***T_5***	***AR(1)***
Coefficient	*0.00027*	*0.00045*	*0.00025*	*0.00010*	*0.00159*	*0.00154*	*-0.00167*	*0.00115*	*0.00021*	*-0.00114*	*-0.00037*	*0.00006*	*0.12401*
Std. Error	*0.00048*	*0.00118*	*0.00119*	*0.00119*	*0.00119*	*0.00119*	*0.00119*	*0.00119*	*0.00119*	*0.00119*	*0.00119*	*0.00118*	*0.01913*
t-Statistic	*0.55027*	*0.38352*	*0.21184*	*0.08465*	*1.33919*	*1.29475*	*-1.40163*	*0.96455*	*0.17463*	*-0.95999*	*-0.30752*	*0.05303*	*6.48112*

VOLATILITY

Coefficient	*0.000284*	*-0.000008*	*-0.000012*	*-0.000007*	*-0.000016*	*-0.000021*	*-0.000025*	*-0.000011*	*0.000002*	*0.000003*	*-0.000006*	*-0.000001*	*0.959522*
Std. Error	*0.000037*	*0.000005*	*0.000007*	*0.000009*	*0.000010*	*0.000010*	*0.000010*	*0.000010*	*0.000010*	*0.000009*	*0.000007*	*0.000005*	*0.005432*
t-Statistic	*7.6279*	*-1.5440*	*-1.6537*	*-0.8609*	*-1.6433*	*-2.0867*	*-2.4790***	*-1.0601*	*0.2366*	*0.3058*	*-0.8343*	*-0.1705*	*176.6313*

WALD TEST	***RETURNS***			***VOLATILITY***		
Test Statistic	***F-statistic***	***Chi-square***	***DW***	***F-statistic***	***Chi-square***	***DW***
Value	*3.943521*	*51.26577*	*2.01*	*2409.768*	*31326.98*	*1.93*
Df	*(13, 2691)*	*13*		*(13, 2691)*	*13*	
Probability	*0.000*	*0.000*		*0.000*	*0.000*	

*30 Significance Level: *10% **5% ***1%*

Table 4.39 Event Day Analysis of Oil and Gas Sector: Political Events[31]

Number of Observations		*2705*					
Date		*1/1/2004*		*12/31/2014*			
RETURN							
	C	***P_B_2***	***P_B_1***	***P_0***	***P_1***	***P_2***	***AR(1)***
Coefficient	*0.00060*	*-0.00092*	*0.00217*	*-0.00572*	*0.00306*	*-0.00132*	*0.13183*
Std. Error	*0.00041*	*0.00135*	*0.00136*	*0.00136*	*0.00136*	*0.00135*	*0.01910*
t-Statistic	*1.46216*	*-0.68466*	*1.60320*	*-4.21754***	*2.25369***	*-0.97861*	*6.90156*
VOLATILITY							
Coefficient	*0.00028*	*-0.00001*	*-0.00002*	*-0.00002*	*0.00003*	*0.00002*	*0.96056*
Std. Error	*0.00004*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00536*
t-Statistic	*7.38913*	*-1.72745**	*-2.21813***	*-3.08873***	*4.11209***	*3.70296***	*179.368*

WALD TEST		***RETURNS***			***VOLATILITY***	
Test Statistic	***F-statistic***	***Chi-square***	***DW***	***F-statistic***	***Chi-square***	***DW***
Value	*11.57184*	*81.00287*	*2.01*	*4617.635*	*32323.44*	*1.91*
Df	*(7, 2697)*	*7*		*(7, 2697)*	*7*	
Probability	*0.000*	*0.000*		*0.000*	*0.000*	

*31 Significance Level: *10% **5% ***1%*

In tables 4.38 and 4.39, the table 4.38 is explaining the impact of terrorist events on the returns and volatility of the *Oil and gas Sector*, *T_B_5* represents the 5^{th} day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5^{th} day after the events day. The returns and volatility series are depending on their own 1^{st} lag. For the returns series, all the terrorist day dummies are insignificant at any level of significance. Moreover, volatility remains insignificant for all days against the terrorist attacks except the event day at 5% level of significance.

The table 4.39 is acquainting the impact of political events on the returns and volatility of the *Oil and gas Sector*, *P_B_2* represents the 2^{nd} day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2^{nd} day after the occurrence of a political event. Returns and volatility series are depending on their own 1^{st} lag. Results show that political events are significant on the event day and very next day of the event day at 5% level of significance however they remain insignificant in rest of the days at any level of significance in return series. Whereas the political events are significant over the volatility of the returns at 5% level of significance except the 2^{nd} day before the event day, which is significant at 10% level of significance.

4.5.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.40* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.40 Impulse Indicator Saturation: Oil and Gas Sector

	Co-Breaks		Significance⁰	Significance¹	Significance²	Significance³	Persistence
Terrorist Attacks	*89*	*Returns*	*91*	*30*	*13*	*8*	*1 d 61 mins*
		Volatility	*113*	*54*	*17*	*9*	*2 d 66 mins*
Political Events	*86*	*Returns*	*114*	*12*	*5*	*2*	*1 d 1 min*
		Volatility	*112*	*34*	*4*	*1*	*2 d 220 mins*

[0]on day significant [1] after 1 day significant [2]after 2 days significant [3]after 3 days significant, at 5% level of significance

The table 4.40 above explains the results obtained through Impulse Indicator Saturation, depicts that out of total 217 terrorist attacks 91 attacks found to be significant in returns series on the event day, of these events 30, 13 and 8 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of the significant terrorist attacks is 1 day and 61 minutes of a working day. There are 113 significant terrorist attacks in the volatility of the returns series of which 54, 17 and 9 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of significant terrorist attacks is 2 day and 66 minutes of a working day. Moreover, 89 numbers of co-breaks captured against the terrorist events. In political events, out of 160, there are 114 events that are significant on the event day under return series, of which 12, 5 and 2 are significant after the event day on 1st, 2nd and 3rd day respectively in return series. There are 112 political events that are significant in volatility on the event day, of which 34, 4 and 1 are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of significant political events is 1 day and 1 minute in returns, and 2 days and 220 minutes in volatility of a working day. Moreover, 86 co-breaks captured against political events.

4.6 Sugar Sector

4.6.1 Exploratory Analysis

Returns Gauging

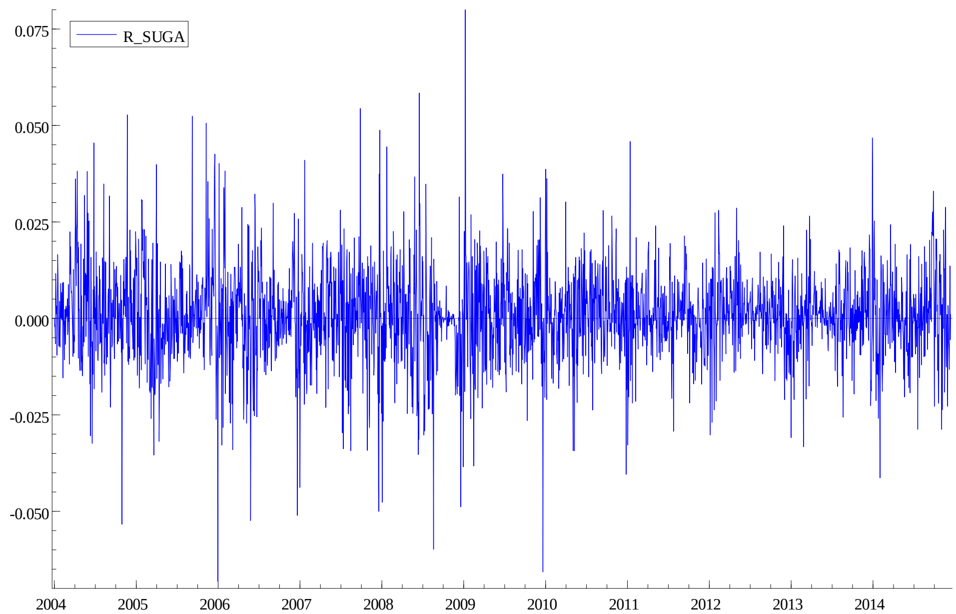
Prices Index of *Sugar Sector* resides of 2706 number of observations. While, after gauging the logarithmic returns series of returns left with 2705 observations. Descriptive statistics the returns from *Sugar Sector* are given below in table 4.41

Table 4.41 Returns of Sugar Sector

Mean	*0.00070*
Median	*0.00037*
Maximum	*0.07999*
Minimum	*-0.06815*
Std. Dev.	*0.01206*
Skewness	*0.00976*
Kurtosis	*6.54617*
Jarque-Bera	*1417.383*
Probability	*0.000*
Sum	*1.887007*
Sum Sq. Dev.	*0.393450*
Observations	*2705*

The mean value of the returns for the price index of *Sugar Sector* is 0.070%, in an arrayed data central value appears to be 0.037% and maximum value 7.99%, maximum fall in the value of the returns is up to 6.81%, transition from the mean value is 1.206%, data series is positively skewed, the distribution of return series is leptokurtic and significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected.

Graph *4.41* is acquainting the behavior of the daily returns series from 2004 to 2014:



The graph 4.41 is explaining the spreading behavior of the returns series over the time. The spread of the returns lies between -6.81 to +7.99%. Small and normal fluctuations can be observed throughout the period from 2004 to 2014. However, large fluctuations are being observed 2006, 2009 and 2010.

Modeling of Volatility Gauging

In *Sugar Sector*, volatility against the returns series has been observed followed by the given equation:

$\boldsymbol{R_t = 0.007 + 0.51R_{t-1} - 0.37\varepsilon_{t-1} + \varepsilon_t}$ *(Conditional Mean Equation)*

$\boldsymbol{h_t = 0.027 + 0.14\ \varepsilon_{t-1}^2 + 0.86\ h_{t-1}}$ *(Conditional Variance Equation)*

Conditional mean equation illustrates that the returns depend on its own 1 lags and 1 lag of the disturbance term and the conditional variance equation illustrate that it depends on

1 lag of the square of the disturbance term and 1 lag of the square of the variance as the data series is showing symmetric effects under the t-distribution. The value of persistence is 0.99, depicting that persistence of a shock takes a long time to decay.

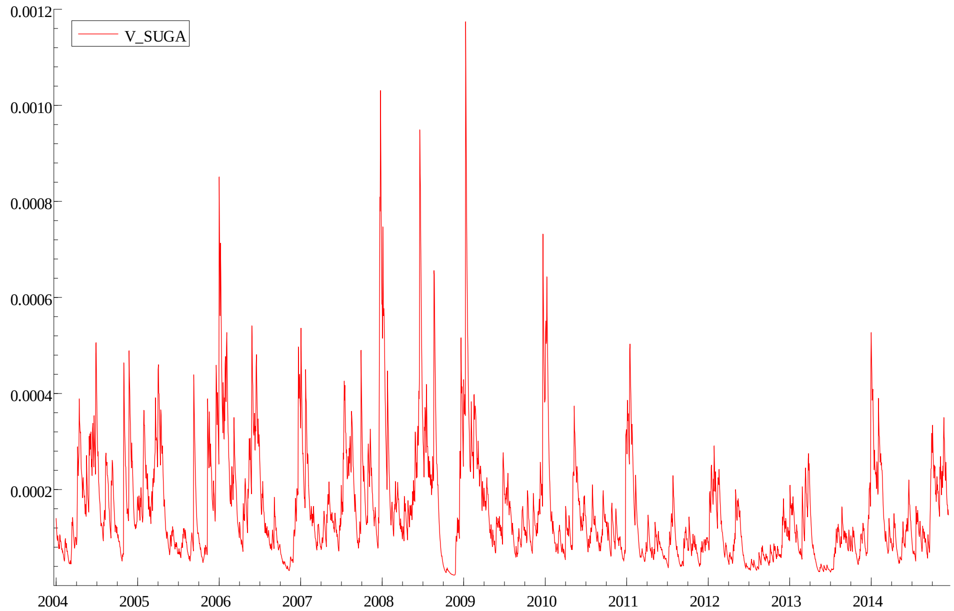
Table 4.42 is acquainting the descriptive statistics analysis for the volatility:

Table 4.42 Volatility of Sugar Sector

Mean	*0.00016*
Median	*0.000123*
Maximum	*0.001174*
Minimum	*2.16E-05*
Std. Dev.	*0.000122*
Skewness	*2.322483*
Kurtosis	*11.67367*
Jarque-Bera	*10911.09*
Probability	*0*
Sum	*0.433601*
Sum Sq. Dev.	*4.02E-05*
Observations	*2705*

The mean value of volatility of the returns in *Sugar Sector* is 0.016%, mid value is 0.0123%, the maximum value 1.174%, and maximum fall in the value of volatility is 0.00216% the spread of the data from the mean value is 0.012%, data series is positively skewed, and the distribution of return series is leptokurtic while significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected.

Graph 4.42 is explaining the behavior of the volatility series from 2004 to 2014:



The graph 4.42 is explaining the spread of the volatility series over the time from 2004 to 2014 and the spread of the volatility lies between -0.00216% to +1.174%. Series is highly volatile is last quarter 2005, 2008 and in the 2nd quarter of 2010, in the rest of the years series normally volatile.

4.6.2 Event Study

This section discusses the response of daily returns against events. For this purpose data has divided into two splits, the estimation window or control period consists of 60 days, the event window consists of 11 days; event window from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days. *Table 4.43* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.43 Event Window Sugar Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*0.000459*	*0.507121*	*0.000661*	*0.695760*
-4	*0.001458*	*1.610073*	*0.001696*	*1.784733*
-3	*0.002017*	*2.227412*	*0.002228*	*2.343873*
-2	*-0.000682*	*-0.753328*	*-0.000564*	*-0.593833*
-1	*-0.001261*	*-1.392168*	*-0.001021*	*-1.074411*
0	*0.000044*	*0.048100*	*0.000362*	*0.380972*
1	*-0.000832*	*-0.918127*	*-0.000663*	*-0.697877*
2	*0.000336*	*0.371147*	*0.000561*	*0.590171*
3	*-0.000889*	*-0.981211*	*-0.000860*	*-0.904919*
4	*0.000513*	*0.566314*	*0.000495*	*0.521313*
5	*-0.000370*	*-0.408163*	*-0.000526*	*-0.553690*

*Significance Level: *10% **5% ***1%*

The table 4.43 is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM)*. Results are depicting that terrorist event not significant in 11 days event window at any level of significance for the *Sugar Sector* under both *CAPM* and *MAR model*.

Table 4.44 is explains the AAR against political events:

Table 4.44 Event Window Sugar Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.000659*	*-0.492919*	*-0.000204*	*-0.157852*
-4	*0.001106*	*0.826883*	*0.001294*	*1.001515*
-3	*0.000306*	*0.229119*	*0.000561*	*0.434281*
-2	*-0.000696*	*-0.520791*	*-0.000590*	*-0.456594*
-1	*0.000416*	*0.311385*	*0.000680*	*0.526492*
0	*-0.003411*	*-2.551168**	*-0.002922*	*-2.260953**
1	*-0.000836*	*-0.625189*	*-0.000854*	*-0.661198*
2	*-0.001296*	*-0.968845*	*-0.000751*	*-0.580857*
3	*-0.000424*	*-0.317121*	*-0.000541*	*-0.418425*
4	*0.001620*	*1.211126*	*0.001973*	*1.526759*
5	*-0.000801*	*-0.598762*	*-0.000300*	*-0.232291*

*Significance Level: *10% **5% ***1%*

The table 4.44 portrayed *AAR* and *t-stats* around the political events under *CAMP* and *MARM* for *Sugar Sector.* The above table is depicting that overall political events are significant at 5% level of significance on the event day for both *CAMP* and *MARM models* However after the event day, the impact of the political events turns insignificant.

Table 4.45 is acquainting the *AAR* against financial crises events:

Table 4.45 Event Window Sugar Sector: Financial Crises Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.010385*	*-5.298585***	*-0.008381*	*-4.455436***
-4	*-0.010009*	*-5.107163***	*-0.008166*	*-4.340923***
-3	*-0.011155*	*-5.691597***	*-0.009836*	*-5.228885***
-2	*-0.010162*	*-5.185065***	*-0.008081*	*-4.295741***
-1	*-0.007386*	*-3.768836***	*-0.005417*	*-2.879904***
0	*-0.007973*	*-4.067963***	*-0.007237*	*-3.847132***
1	*-0.010237*	*-5.223473***	*-0.008191*	*-4.354284***
2	*-0.007744*	*-3.951350***	*-0.005187*	*-2.757445***
3	*-0.004809*	*-2.453566***	*-0.003357*	*-1.784676**
4	*-0.007761*	*-3.960115***	*-0.006049*	*-3.215704***
5	*-0.010906*	*-5.564698***	*-0.008261*	*-4.391653***

*Significance Level: *10% **5% ***1%*

The table 4.45 is acquainting the behavior of the *Sugar Sector* around the financial crises events. The results indicate that returns series have significant[32] reaction over the financial crises events in 11 days window at 5% level of significance except for the 3rd day which is significant 10% level of significance under both *CAMP* and *MAR models*.

32 The impact of financial crises events persists for more than 100 days.

4.6.3 Event Day Analysis

In this methodology, day dummies have been introduced to observe the impact of two different kinds of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate $\boldsymbol{D_i}$ **=** 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.46 & 47* are acquitting the response of returns and volatility against the terrorist events for *Sugar Sector:*

Table 4.46 Event Day Analysis of Sugar Sector: Terrorist Attacks[33]

Number of Observations		*2705*											
Date	*1/1/2004*			*12/31/2014*									
RETURN													
	C	*T_B_5*	*T_B_4*	*T_B_3*	*T_B_2*	*T_B_1*	*T_0*	*T_1*	*T_2*	*T_3*	*T_4*	*T_5*	*AR(1)*
Coefficient	*0.0006080*	*0.0007490*	*0.0020350*	*0.0025240*	*-0.0006700*	*-0.0011730*	*-0.0000241*	*-0.0011130*	*0.0003330*	*-0.0012830*	*0.0008220*	*-0.0010820*	*0.1839270*
Std. Error	*0.0003670*	*0.0008430*	*0.0008580*	*0.0008560*	*0.0008550*	*0.0008560*	*0.0008580*	*0.0008560*	*0.0008550*	*0.0008560*	*0.0008580*	*0.0008430*	*0.0189480*
t-Statistic	*1.6580410*	*0.8890320*	*2.3720680*	*2.9490320*	*-0.7827120*	*-1.3699840*	*-0.0281530*	*-1.3002700*	*0.3895870*	*-1.4992640*	*0.9584360*	*-1.2838550*	*9.7067420*
VOLATILITY													
Coefficient	*0.0001630*	*-0.0000022*	*-0.0000003*	*-0.0000012*	*-0.0000011*	*-0.0000043*	*-0.0000064*	*-0.0000032*	*-0.0000003*	*-0.0000020*	*-0.0000046*	*-0.0000019*	*0.9279850*
Std. Error	*0.0000126*	*0.0000032*	*0.0000044*	*0.0000051*	*0.0000055*	*0.0000058*	*0.0000058*	*0.0000058*	*0.0000055*	*0.0000051*	*0.0000044*	*0.0000032*	*0.0071830*
t-Statistic	*12.92460*	*-0.67311*	*-0.06198*	*-0.24436*	*-0.19872*	*-0.73645*	*-1.09253*	*-0.55984*	*-0.06197*	*-0.38376*	*-1.05120*	*-0.57648*	*129.19220*
WALD TEST		*RETURNS*			*VOLATILITY*								
Test Statistic	*F-statistic*	*Chi-square*	*DW*	*F-statistic*	*Chi-square*	*DW*							
Value	*9.577039*	*124.5015*	*2.02*	*1297.591*	*16868.68*	*2.01*							
Df	*(13, 2691)*	*13*		*(13, 2691)*	*13*								
Probability	*0.000*	*0.000*		*0.000*	*0.000*								

33 Significance Level: *10% **5% ***1%

Table 4.47 Event Day Analysis of Sugar Sector: Political Events[34]

Number of Observations		*2705*					
Date		*1/1/2004*			*12/31/2014*		
RETURN							
	C	*P_B_2*	*P_B_1*	*P_0*	*P_1*	*P_2*	*AR(1)*
Coefficient	*0.00100*	*-0.00070*	*-0.00020*	*-0.00321*	*-0.00054*	*-0.00045*	*0.18218*
Std. Error	*0.00031*	*0.00097*	*0.00098*	*0.00098*	*0.00098*	*0.00097*	*0.01893*
t-Statistic	*3.20235*	*-0.71930*	*-0.19998*	*-3.28343***	*-0.55452*	*-0.46270*	*9.62158*
VOLATILITY							
Coefficient	*0.0001590*	*0.0000035*	*0.0000006*	*-0.0000059*	*0.0000096*	*0.0000072*	*0.9282780*
Std. Error	*0.0000122*	*0.0000035*	*0.0000045*	*0.0000047*	*0.0000045*	*0.0000035*	*0.0071610*
t-Statistic	*13.07642*	*0.99150*	*0.12537*	*-1.25268*	*2.15328***	*2.02905***	*129.63060*

WALD TEST		*RETURNS*			*VOLATILITY*	
Test Statistic	*F-statistic*	*Chi-square*	*DW*	*F-statistic*	*Chi-square*	*DW*
Value	*15.77695*	*110.4386*	*2.02*	*2429.05*	*17003.35*	*2*
Df	*(7, 2697)*	*7*		*(7, 2697)*	*7*	
Probability	*0*	*0*		*0*	*0*	

*34 Significance Level: *10% **5% ***1%*

In tables 4.46 and 4.47, the table 4.46 is explaining the impact of terrorist events on the returns and volatility of the *Sugar Sector*, *T_B_5* represents the 5^{th} day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5^{th} day after the events day. The returns and volatility series are depending on their own 1^{st} lag. For the returns series, all terrorist day dummies are insignificant at any level of significance. Moreover, volatility remains insignificant for all 5 days against the terrorist attacks, as no day dummy turns significant at any level of significance.

The table 4.47 is acquainting the impact of political events on the returns and volatility of the *Sugar Sector*, *P_B_2* represents the 2^{nd} day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2^{nd} day after the occurrence of a political event. Returns and volatility series are depending on their own 1^{st} lag. Results show that political events shows significant impact on returns on event day at 5% level of significance however they turn insignificant after the event day. Moreover, as the political events are anticipated that's why political events are also significant on the day before the event for *Sugar Sector,* where the political events are significant on 2^{nd} and 3^{rd} day after the event day on the volatility of the returns.

4.6.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.48* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.48 Impulse Indicator Saturation: Sugar Sector

	Co-Breaks		Significance⁰	Significance¹	Significance²	Significance³	Persistence
Terrorist Attacks	*83*	*Returns*	*75*	*29*	*14*	*13*	*0 d 354 mins*
		Volatility	*113*	*49*	*13*	*7*	*1 d 276 mins*
Political Events	*63*	*Returns*	*80*	*11*	*8*	*5*	*1 d 22 mins*
		Volatility	*82*	*47*	*8*	*5*	*1 d 351 mins*

[0]on day significant [1] after 1 day significant [2]after 2 days significant [3]after 3 days significant, at 5% level of significance

The table 4.48 above explains the results obtained through Impulse Indicator Saturation, depicts that out of total 217 terrorist attacks 75 attacks found to be significant in returns series on the event day, of these events 37, 16 and 10 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average, persistence time of the significant terrorist attacks is 354 minutes of a working day. There are 113 significant terrorist attacks in the volatility of the returns series of which 49, 13 and 7 number of events are significant on 1st, 2nd and 3rd day respectively after the event day.

On average, persistence time of significant terrorist attacks is 1 day and 276 minutes of a working day. Moreover, 83 numbers of co-breaks captured against the terrorist events. In political events, out of 160, there are 80 events that are significant on the event day under return series, of which 11, 8 and 5 are significant after the event day on 1^{st}, 2^{nd} and 3^{rd} day respectively in return series. There are 82 political events that are significant in volatility on the event day, of which 47, 8 and 5 are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average persistence time of significant political events is 1 day and 22 minutes in returns, and 1 days and 351 minutes in volatility of a working day. Moreover, 63 co-breaks captured against political events.

4.7 Telecommunication Sector

4.7.1 Exploratory Analysis

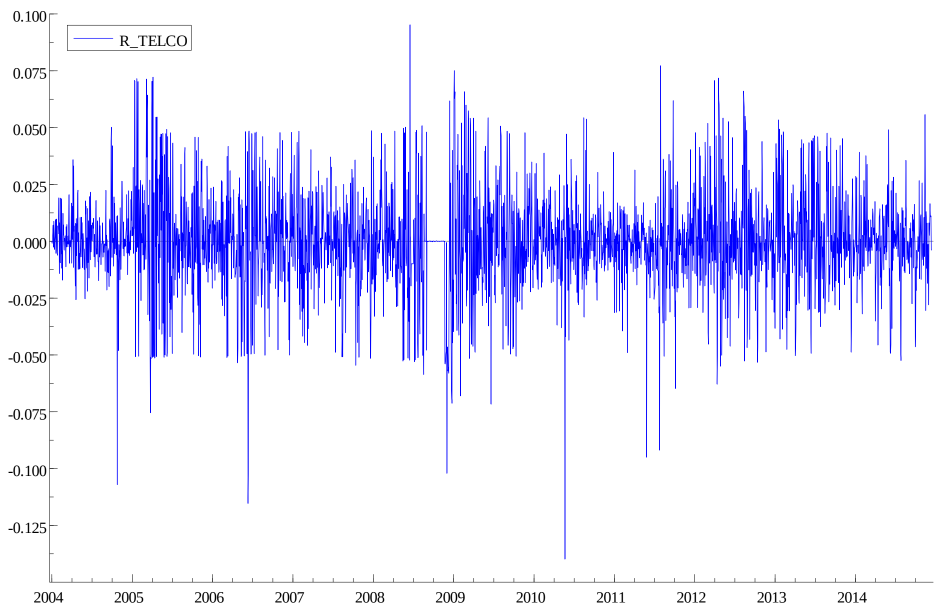
Returns Gauging

Prices Index of *Telecommunication Sector* dwells into 2706 number of observations. While, after calculation of logarithmic returns series of returns left with 2705 observations. Descriptive statistics the returns from *Telecommunication Sector* are provided below in table 4.49;

Table 4.49 Returns of Telecommunication Sector

Mean	*-0.00015*
Median	*-0.00007*
Maximum	*0.09522*
Minimum	*-0.13983*
Std. Dev.	*0.02245*
Skewness	*-0.16372*
Kurtosis	*5.22497*
Jarque-Bera	*570.047*
Probability	*0.000*
Sum	*-0.415767*
Sum Sq. Dev.	*1.362409*
Observations	*2705*

The mean value of the returns for the price index of *Telecommunication Sector* is 0.015%, median value appears to be 0.007% and maximum value 9.5%, maximum fall in the value of the returns is up to 14%, deviation from the mean value is 2.2%, data series is negatively skewed, the distribution of return series is meso-kurtic and significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. Graph *4.49* is acquainting the behavior of the daily returns series from 2004 to 2014:



The graph 4.49 is explaining the spreading behavior of the returns series over the time. The spread of the returns lies between -14 to +9.5%. Normal and Large fluctuations can be observed throughout the period from 2004 to 2014.

Modeling of Volatility Gauging

In *Telecommunication Sector*, volatility against the returns series has been observed followed by the given equations:

$$\boldsymbol{R_t = 0.00003 + 0.078R_{t-1} + \varepsilon_t} \qquad \textit{(Conditional Mean Equation)}$$

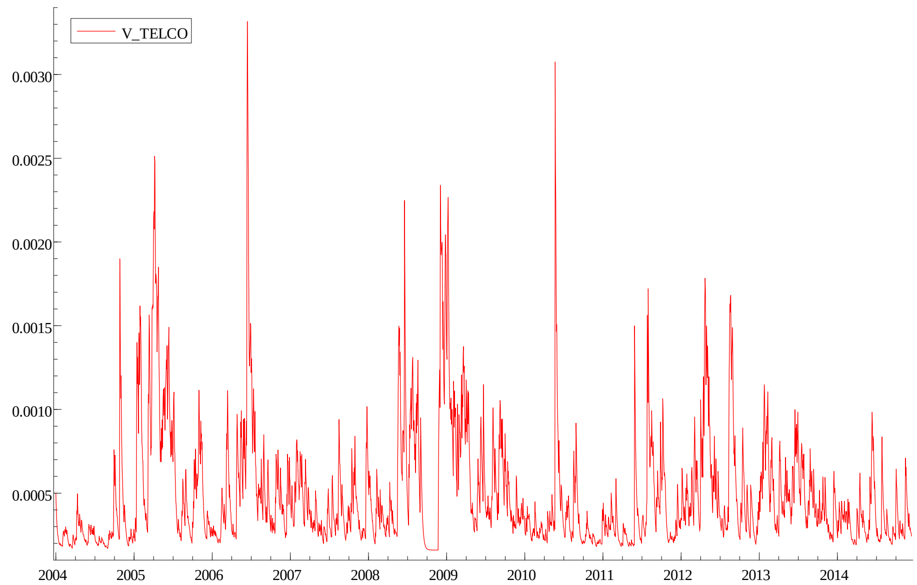
$$\boldsymbol{h_t = 0.338 + 0.144\, \varepsilon_{t-1}^2 + 0.778\, h_{t-1}} \qquad \textit{(Conditional Variance Equation)}$$

Conditional mean equation illustrates that the returns depend on its own 1 lag only and the conditional variance equation illustrate that it depends on 1 lag of the square of the disturbance term and 1 lag of the square of the variance as the data series is showing symmetric effects under the t-distribution. The value of persistence is 0.93, depicting that persistence of a shock takes a long time to decay. *Table 4.50* is acquainting the descriptive statistics analysis for the volatility:

Table 4.50 Volatility of Telecommunication Sector

Mean	*0.000501*
Median	*0.000374*
Maximum	*0.003317*
Minimum	*0.00016*
Std. Dev.	*0.000362*
Skewness	*2.442769*
Kurtosis	*11.41435*
Jarque-Bera	*10670.07*
Probability	*0*
Sum	*1.356175*
Sum Sq. Dev.	*0.000354*
Observations	*2705*

The mean value of volatility of the returns in *Telecommunication Sector* is 0.0501%, median value 0.0374%, the maximum value 0.3317%, and maximum fall in the value of the returns is 0.016% the spread of the data from the mean value is 0.0362%, data series is positively skewed, and the distribution of return series is leptokurtic while significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. *Graph 4.50* is explaining the behavior of the volatility series from 2004 to 2014:



The graph 4.50 is explaining the spread of the volatility series over the time that the spread of the volatility lies between 0.016% to +0.33%. Large and normal fluctuations in the volatility observed throughout the period from 2004 to 2014.

4.7.2 Event Study

This section discusses the response of daily returns against events. For this purpose data has divided split into two splits, the control period consists of 60 days, while estimation window and event period consist of 11 days; event window from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days. *Table 4.51* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.51 Event Window Telecommunication Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*0.000441*	*0.265982*	*0.001003*	*0.607405*
-4	*-0.000248*	*-0.149298*	*-0.000001*	*-0.000581*
-3	*0.000487*	*0.293944*	*0.000485*	*0.293600*
-2	*0.003265*	*1.969368*	*0.002705*	*1.638713*
-1	*0.001542*	*0.930050*	*0.001428*	*0.865382*
0	*0.000102*	*0.061641*	*0.000668*	*0.404635*
1	*-0.000009*	*-0.005612*	*0.000415*	*0.251662*
2	*0.000782*	*0.471753*	*0.000915*	*0.554301*
3	*-0.001740*	*-1.049359*	*-0.001747*	*-1.058388*
4	*0.000092*	*0.055258*	*-0.000062*	*-0.037571*
5	*0.002496*	*1.505625*	*0.003010*	*1.823341**

*Significance Level: *10% **5% ***1%*

The table 4.51 is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM)*. Results are depicting those terrorist events not significant in 11 days event window at any level of significance for the *Telecommunication Sector* under both *CAPM* and *MAR model*, except at 5th day at 10% level of significance under *MAR model*.

Table 4.52 is explains the AAR against political events:

Table 4.52 Event Window Telecommunication Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*0.000738*	*0.254969*	*0.001425*	*0.509847*
-4	*0.001023*	*0.353466*	*0.000580*	*0.207398*
-3	*0.002384*	*0.823638*	*0.003180*	*1.137574*
-2	*-0.001314*	*-0.453806*	*-0.000479*	*-0.171498*
-1	*-0.000956*	*-0.330371*	*0.000059*	*0.021035*
0	*-0.006752*	*-2.332559***	*-0.005965*	*-2.133466***
1	*0.000469*	*0.162179*	*0.000549*	*0.196476*
2	*-0.005200*	*-1.796226**	*-0.004254*	*-1.521740*
3	*0.000971*	*0.335528*	*0.000920*	*0.329111*
4	*0.000904*	*0.312304*	*0.002222*	*0.794758*
5	*0.001629*	*0.562913*	*0.002392*	*0.855445*

*Significance Level: *10% **5% ***1%*

The table 4.52 portrayed *AAR* and *t-stats* around the political events under *CAMP* and *MARM* for *Telecommunication Sector*. The above table is depicting that overall political events are significant at 5% level of significance on the event day for both *CAMP* and *MARM models* and also significant on 2nd day at 10% level of significance under *CAMP*. However after the event day, the impact of the political events turns insignificant.

Table 4.53 is acquainting the *AAR* against financial crises events:

Table 4.53 Event Window Telecommunication Sector: Financial Crises Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.018505*	*-3.164799***	*-0.018329*	*-3.445502***
-4	*-0.009994*	*-1.709256**	*-0.011946*	*-2.245583***
-3	*-0.023907*	*-4.088545***	*-0.021445*	*-4.031261***
-2	*-0.027158*	*-4.644656***	*-0.023109*	*-4.344131***
-1	*-0.020972*	*-3.586717***	*-0.016217*	*-3.048484***
0	*-0.017127*	*-2.929097***	*-0.019673*	*-3.698232***
1	*-0.014867*	*-2.542517***	*-0.016399*	*-3.082815***
2	*-0.009979*	*-1.706644**	*-0.009110*	*-1.712509**
3	*-0.008935*	*-1.528005*	*-0.007475*	*-1.405189*
4	*-0.019022*	*-3.253164***	*-0.015694*	*-2.950164***
5	*-0.018045*	*-3.086020***	*-0.023132*	*-4.348516***

*Significance Level: *10% **5% ***1%*

The table 4.53 is acquainting the behavior of the *Telecommunication Sector* around the financial crises events. The results indicate that returns series have significant[35] reaction over the financial crises events. As financial crises events turns significant on all days in 11 days event window except the 3rd day in *CAPM* and 4th day in *MAR model.*

35 The impact of financial crises events also persists for more than 100 days.

4.7.3 Event Day Analysis

In this methodology day dummies has been introduced to observe the impact of two different kinds of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate $\boldsymbol{D_i}$ **=** 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.54 & 55* are acquitting the response of returns and volatility against the terrorist events for *Telecommunication Sector:*

Table 4.55 Event Day Analysis of Telecommunication Sector: Terrorist Attacks [36]

Number of Observations	*2705*												
Date	*1/1/2004*		*12/31/2014*										
RETURN													
	C	*T_B_5*	*T_B_4*	*T_B_3*	*T_B_2*	*T_B_1*	*T_0*	*T_1*	*T_2*	*T_3*	*T_4*	*T_5*	*AR(1)*
Coefficient	*-0.0005440*	*0.0008140*	*-0.0000573*	*0.0004580*	*0.0027130*	*0.0014310*	*0.0000276*	*-0.0000322*	*0.0001280*	*-0.0029180*	*-0.0004330*	*0.0027300*	*0.1231380*
Std. Error	*0.0006440*	*0.0015870*	*0.0016000*	*0.0015970*	*0.0015960*	*0.0015970*	*0.0016000*	*0.0015970*	*0.0015960*	*0.0015970*	*0.0016000*	*0.0015870*	*0.0191310*
t-Statistic	*-0.8444700*	*0.5128320*	*-0.0358240*	*0.2865570*	*1.7002000*	*0.8962960*	*0.0172780*	*-0.0201660*	*0.0801770*	*-1.827784**	*-0.2707000*	*1.719913**	*6.4366600*
VOLATILITY													
Coefficient	*0.0005140*	*0.0000023*	*-0.0000115*	*-0.0000193*	*-0.0000178*	*-0.0000231*	*-0.0000175*	*-0.0000211*	*-0.0000177*	*-0.0000269*	*-0.0000288*	*0.0000081*	*0.9252400*
Std. Error	*0.0000367*	*0.0000098*	*0.0000132*	*0.0000153*	*0.0000167*	*0.0000175*	*0.0000176*	*0.0000175*	*0.0000167*	*0.0000153*	*0.0000132*	*0.0000098*	*0.0073210*
t-Statistic	*13.99115*	*0.24044*	*-0.86834*	*-1.26072*	*-1.06386*	*-1.32331*	*-0.99104*	*-1.20951*	*-1.06076*	*-1.7527**	*-2.182***	*0.82790*	*126.37520*
WALD TEST		*RETURNS*			*VOLATILITY*								
Test Statistic	*F-statistic*	*Chi-square*	*DW*	*F-statistic*	*Chi-square*	*DW*							
Value	*3.948451*	*51.32987*	*2.01*	*1247.637*	*16219.28*	*1.88*							
df	*(13, 2691)*	*13*		*(13, 2691)*	*13*								
Probability	*0.000*	*0.000*		*0.000*	*0.000*								

*36 Significance Level: *10% **5% ***1%*

Table 4.55 Event Day Analysis of Telecommunication Sector: Political Events[37]

Number of Observations		2705					
Date		1/1/2004		12/31/2014			
RETURN							
	C	***P_B_2***	***P_B_1***	***P_0***	***P_1***	***P_2***	***AR(1)***
Coefficient	0.00051	-0.00100	-0.00033	-0.00599	0.00034	-0.00421	0.12630
Std. Error	0.00055	0.00182	0.00182	0.00182	0.00182	0.00182	0.01910
t-Statistic	0.92513	-0.54893	-0.18258	-3.28792**	0.18648	-2.32039**	6.61100
VOLATILITY							
Coefficient	0.00050	-0.00002	-0.00003	-0.00002	0.00004	0.00002	0.92555
Std. Error	0.00004	0.00001	0.00001	0.00001	0.00001	0.00001	0.00730
t-Statistic	14.09521	-1.92890**	-2.37355**	-1.48518	3.08546**	1.96246**	126.860
WALD TEST		***RETURNS***			***VOLATILITY***		
Test Statistic	***F-statistic***	***Chi-square***	***DW***	***F-statistic***	***Chi-square***	***DW***	
Value	8.748955	61.24268	1.99	2335.44	16348.08	1.88	
Df	(7, 2697)	7		(7, 2697)	7		
Probability	0	0		0	0		

*37 Significance Level: *10% **5% ***1%*

In tables 4.54 and 4.55, the table 4.54 is explaining the impact of terrorist events on the returns and volatility of the *Telecommunication Sector*, *T_B_5* represents the 5^{th} day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5^{th} day after the events day. Significant impact of terrorist attacks on the returns 3^{rd} and 5^{th} day is being observed at 10% level of significance while this impact turns insignificant right after a day. Moreover, terrorist attacks are showing significant impact on volatility on 3^{rd} day at 10% level of significance and on 4^{th} day at 5% level of significance. However, events turn insignificant right after that day.

The table 4.55 is acquainting the impact of political events on the returns and volatility of the *Telecommunication Sector, P_B_2* represents the 2^{nd} day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2^{nd} day after the occurrence of a political event. Returns and volatility series are depending on their own 1^{st} lag. In returns series, results show that political events are significant on the event day and 2^{nd} day after the event at 5% level of significance however they turn insignificant after the event day. Moreover, as the political events are anticipated that's why political events are also significant on all the days before and after the event day for *Telecommunication Sector,* where the political events are insignificant on event day.

4.7.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.56* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.56 Impulse Indicator Saturation: Telecommunication Sector

	Co-Breaks		*Significance^{0}*	*Significance^{1}*	*Significance^{2}*	*Significance^{3}*	*Persistence*
Terrorist Attacks	*3*	*Returns*	*85*	*32*	*18*	*10*	*1 d 91 mins*
		Volatility	*4*	*1*	*0*	*1*	*0 day 16 mins*
Political Events	*0*	*Returns*	*103*	*12*	*9*	*5*	*1 day 229 mins*
		Volatility	*0*	*0*	*0*	*0*	*0 days 0 min*

*^ on day significant * after 1 day significant **after 2 days significant ***after 3 days significant, at 5% level of significance*

The table 4.56 above explains the results obtained through Impulse Indicator Saturation, depicts that out of total 217 terrorist attacks 85 attacks found to be significant in returns series on the event day, of these events 32, 18 and 10 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average persistence of the significanct of terrorist attacks is 1 day and 91 minutes of a working day. There are 4 significant terrorist attacks in the volatility of the returns series of which 1, 0 and 1 number of events are significant on 1st, 2nd and 3rd day respectively after the event day.

On the average persistence of significant terrorist attacks is 2 day and 36 minutes of a working day. Moreover, 3 co-breaks captured against the terrorist events. In political events, out of 160, there are 103 events that are significant on the event day under return series, of which 12, 9 and 5 are significant after the event day on 1^{st}, 2^{nd} and 3^{rd} day respectively in return series. There are no political events that are significant in volatility on the event day or any other day. On the average persistence of significance political events is 1 day and 229 minutes in returns, and 0 days and 0 minute in volatility of a working day. Moreover, 0 co-breaks captured against political events.

4.8 *Textile Sector*

4.8.1 Exploratory Analysis

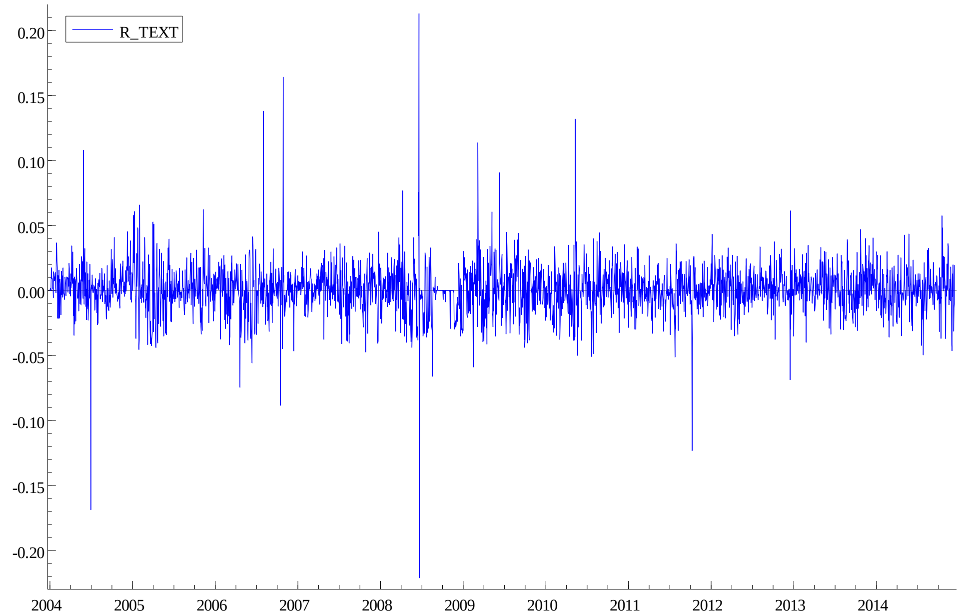
Returns Gauging

Prices Index of *Textile Sector* consists of 2706 number of observations. While, after calculating the logarithmic returns series of returns left with 2705 observations. Descriptive statistics the returns from *Textile Sector* are provided below in table 4.57

Table 4.57 Returns of Textile Sector

Mean	*0.00069*
Median	*0.00048*
Maximum	*0.21311*
Minimum	*-0.22127*
Std. Dev.	*0.01933*
Skewness	*0.12170*
Kurtosis	*21.77507*
Jarque-Bera	*39736.730*
Probability	*0.000*
Sum	*1.860688*
Sum Sq. Dev.	*1.010584*
Observations	*2705*

The mean value of the returns for the price index of *Textile Sector* is 0.069%, median is 0.048% and maximum value 21.31%, minimum value is -22.12%, abberation from the average value is 1.35%, data series is positively skewed, the distribution of return series is leptokurtic and significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. Graph *4.57* is acquainting the behavior of the daily returns series from 2004 to 2014:



The graph 4.57 is explaining the spread of the returns series over the time. The spread of the returns lies between -22 to +21%. Normal and small fluctuations can be observed throughout the period from 2004 to 2014 except for the second quarter of 2008.

Modeling of Volatility Gauging

In *Textile Sector*, volatility against the returns series has been observed followed by the given equations:

$\boldsymbol{R_t = 0.0011 + 0.16R_{t-1} + \varepsilon_t}$ *(Conditional Mean Equation)*

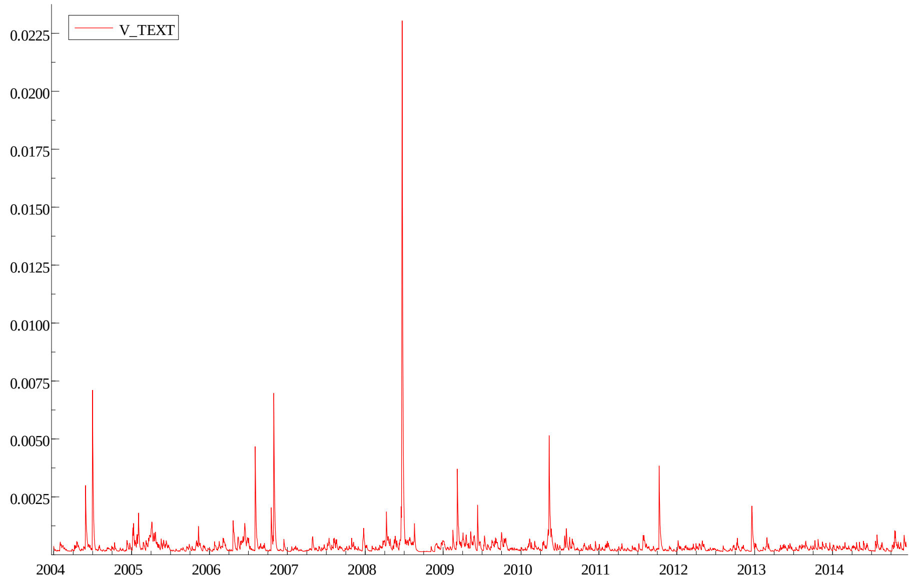
$\boldsymbol{h_t = 0.47 + 0.24\, \varepsilon_{t-1}^2 + 0.65\, h_{t-1}}$ *(Conditional Variance Equation)*

Conditional mean equation illustrates that the returns depends on its own 1 lag only where the conditional variance equation illustrate that it depends on 1 lag of the square of the disturbance term and 1 lag of the square of the variance as the data series is showing symmetric effects under the t-distribution. The value of persistence is 0.89, depicting that persistence of a shock takes a long time to decay. *Table 4.58* is acquainting the descriptive statistics analysis for the volatility:

Table 4.58 Volatility of Textile Sector

Mean	*0.000388*
Median	*0.000268*
Maximum	*0.023041*
Minimum	*0.000135*
Std. Dev.	*0.000721*
Skewness	*18.47512*
Kurtosis	*470.9627*
Jarque-Bera	*24835782*
Probability	*0*
Sum	*1.049198*
Sum Sq. Dev.	*0.001405*
Observations	*2705*

The mean value of volatility of the returns in *Textile Sector* is 0.0388%, value of the median is 0.0268%, the maximum value 2.304%, and maximum fall in the value of the returns is 0.00136% the spread of the data from the mean value is 0.072%, data series is positively skewed, and the distribution of return series is leptokurtic while significance of *Jarque-Bera* is stating that null hypothesis of the normal distribution has been rejected. *Graph 4.58* is explaining the behavior of the volatility series from 2004 to 2014:



The graph 4.58 is explaining the spread of the volatility series over the time that the spread of the volatility lies between -0.0013% to +2.03%. Normal and small fluctuations in the volatility observed throughout the period from 2004 to 2014 except for the second quarter of 2008.

4.8.2 Event Study

This section discusses the response of daily returns against events. For this purpose data has divided split into two splits, the control period consists of 60 days, while estimation window and event period consist of 11 days; event window from 5 days before and 5 days after the event day. These splits actually depict the behavior of daily returns based on past history of 60 days. *Table 4.59* is informing the average abnormal returns (AAR) against the terrorist events along with t-stats:

Table 4.59 Event Window Textile Sector: Terrorist Attacks

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.000211*	*-0.183410*	*0.000090*	*0.073419*
-4	*0.000584*	*0.507397*	*0.000828*	*0.672244*
-3	*-0.000879*	*-0.763606*	*-0.000648*	*-0.526350*
-2	*0.001399*	*1.215975*	*0.001489*	*1.209331*
-1	*0.000084*	*0.072680*	*0.000495*	*0.402039*
0	*-0.001944*	*-1.689305**	*-0.001657*	*-1.346023*
1	*0.000722*	*0.627479*	*0.000705*	*0.572311*
2	*0.001073*	*0.932585*	*0.001646*	*1.337001*
3	*0.000957*	*0.831500*	*0.000960*	*0.779992*
4	*-0.002542*	*-2.209742***	*-0.002724*	*-2.212901***
5	*-0.000349*	*-0.302914*	*-0.000493*	*-0.400185*

*Significance Level: *10% **5% ***1%*

The table 4.59 is acquainting the *AAR* and *t-states* around the terrorism events under *Capital Asset Pricing Model (CAPM)* and *Mean Adjusted Returns Model (MARM)*. Results are depicting the terrorist events are significant on events day under *CAPM* and are significant on 4th day after the event under both *CAPM* and *MAR* models in 11 days event window at any level of significance for the *Textile Sector* under both *CAPM* and *MAR model*.

Table 4.60 is explains the AAR against political events:

Table 4.60 Event Window Textile Sector: Political Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.001022*	*-0.565681*	*-0.000773*	*-0.451049*
-4	*-0.001788*	*-0.990238*	*-0.001700*	*-0.992349*
-3	*0.001177*	*0.651491*	*0.001445*	*0.843181*
-2	*0.001108*	*0.613532*	*0.001407*	*0.821433*
-1	*-0.000646*	*-0.357915*	*-0.000120*	*-0.070125*
0	*-0.004953*	*-2.742509***	*-0.004180*	*-2.439731***
1	*-0.000200*	*-0.110706*	*-0.000386*	*-0.225273*
2	*-0.000702*	*-0.388977*	*-0.000090*	*-0.052247*
3	*-0.000531*	*-0.294236*	*-0.000702*	*-0.409717*
4	*0.001657*	*0.917436*	*0.002080*	*1.213925*
5	*-0.001489*	*-0.824434*	*-0.000824*	*-0.480853*

*Significance Level: *10% **5% ***1%*

The table 4.60 portrayed *AAR* and *t-stats* around the political events under *CAMP* and *MARM* for *Textile Sector*. The above table is depicting that overall political events are significant at 5% level of significance on the event day for both *CAMP* and *MARM models* However after the event day, the impact of the political events turns insignificant.

Table 4.61 is acquainting the *AAR* against financial crises events:

Table 4.61 Event Window Textile Sector: Financial Crises Events

	CAPM		*MEAN AD.*	
DAY	*AAR*	*t-test*	*AAR*	*t-test*
-5	*-0.016445*	*-4.274364***	*-0.013927*	*-3.832352***
-4	*-0.015542*	*-4.039490***	*-0.015396*	*-4.236399***
-3	*-0.018346*	*-4.768335***	*-0.017849*	*-4.911535***
-2	*-0.016294*	*-4.235175***	*-0.015252*	*-4.197045**
-1	*-0.010826*	*-2.813718***	*-0.009429*	*-2.594695***
0	*-0.011533*	*-2.997475***	*-0.012647*	*-3.479972***
1	*-0.012118*	*-3.149577***	*-0.013114*	*-3.608647***
2	*-0.007309*	*-1.899757***	*-0.007682*	*-2.113802***
3	*-0.006173*	*-1.604420**	*-0.006658*	*-1.832008**
4	*-0.011913*	*-3.096429***	*-0.011095*	*-3.053046***
5	*-0.014655*	*-3.809067***	*-0.016590*	*-4.564979***

*Significance Level: *10% **5% ***1%*

The table 4.61 is acquainting the behavior of the *Textile Sector* around the financial crises events. The results indicate that returns series have significant reaction over the financial crises events. As financial crises events turns significant at 5% level of significance on all the days[38] under both *CAMP* and *MAR models*.

38 The significant impact of the financial crises events on the returns of Automobile Sector starts at 5th day and lasts for more than 100 days.

4.7.3 *Event Day Analysis*

In this methodology day dummies has been introduced to observe the impact of two different kinds of events: i.e., terrorism and political events, on the returns and volatility. Day dummies illustrate D_i **=** 1 if the event occurs and 0 otherwise, where ***i = -5, -4, …, 0, …, 4, 5*** for the terrorist events and ***i = -2, -1, 0, 1, 2*** for the political event: *Tables 4.62& 63* are acquitting the response of returns and volatility against the terrorist events for *Textile Sector:*

Table 4.62 Event Day Analysis of Textile Sector: Terrorist Attacks[39]

Number of Observations		*2705*												
Date	*1/1/2004*		*12/31/2014*											
RETURN														
	C	*T_B_5*	*T_B_4*	*T_B_3*	*T_B_2*	*T_B_1*	*T_0*	*T_1*	*T_2*	*T_3*	*T_4*	*T_5*	*AR(1)*	*MA(1)*
				-			-					-		
Coefficient	*0.0005850*	*0.0004490*	*0.0012350*	*0.0005390*	*0.0016620*	*0.0006260*	*0.0017410*	*0.0008560*	*0.0016700*	*0.0005460*	*-0.0028850*	*0.0005870*	*0.1147170*	
Std. Error	*0.0005500*	*0.0013680*	*0.0013780*	*0.0013750*	*0.0013750*	*0.0013750*	*0.0013780*	*0.0013750*	*0.0013750*	*0.0013750*	*0.0013780*	*0.0013690*	*0.0191540*	
				-			-				-	-		
t-Statistic	*1.0633140*	*0.3284600*	*0.8964710*	*0.3922070*	*1.2090760*	*0.4553830*	*1.2633860*	*0.6220210*	*1.2152570*	*0.3969090*	*2.0933220***	*0.4292130*	*5.9893340*	
VOLATILITY														
Coefficient	*0.000408*	*0.000036*	*0.000002*	*-0.000022*	*-0.000026*	*-0.000051*	*-0.000078*	*-0.000065*	*-0.000049*	*-0.000037*	*-0.000005*	*0.000049*	*0.688740*	*0.301411*
Std. Error	*0.000042*	*0.000030*	*0.000043*	*0.000047*	*0.000049*	*0.000050*	*0.000050*	*0.000050*	*0.000049*	*0.000047*	*0.000043*	*0.000030*	*0.017051*	*0.022433*
t-Statistic	*9.73878*	*1.19431*	*0.04527*	*-0.46786*	*-0.53731*	*-1.03428*	*-1.57600*	*-1.30443*	*-0.99317*	*-0.78078*	*-0.12660*	*1.60644*	*40.39293*	*13.43633*
WALD TEST		*RETURNS*			*VOLATILITY*									
		Chi-			*Chi-*									
Test Statistic	*F-statistic*	*square*	*DW*	*F-statistic*	*square*	*DW*								
Value	*3.823592*	*49.7067*	*2.01*	*268.628*	*3760.791*	*2.012*								
df	*(13, 2691)*	*13*		*(14, 2690)*	*14*									
Probability	*0.000*	*0.000*		*0.000*	*0.000*									

39 Significance Level: *10% **5% ***1%

Table 4.63 Event Day Analysis of Textile Sector: Political Events[40]

Number of Observations		*2705*						
Date	*1/1/2004*			*12/31/2014*				
RETURN								
	C	*P_B_2*	*P_B_1*	*P_0*	*P_1*	*P_2*	*AR(1)*	*MA(1)*
Coefficient	*0.00093*	*0.00132*	*-0.00011*	*-0.00662*	*0.00156*	*-0.00020*	*0.11587*	
Std. Error	*0.00047*	*0.00157*	*0.00157*	*0.00157*	*0.00157*	*0.00157*	*0.01913*	
t-Statistic	*1.98254*	*0.84243*	*-0.06711*	*-4.21472***	*0.99118*	*-0.13036*	*6.05692*	
VOLATILITY								
Coefficient	*0.00038*	*-0.00002*	*-0.00002*	*-0.00005*	*0.00013*	*0.00006*	*0.68823*	*3.09E-01*
Std. Error	*0.00004*	*0.00003*	*0.00005*	*0.00005*	*0.00005*	*0.00003*	*0.01700*	*2.23E-02*
t-Statistic	*10.70227*	*-0.51993*	*-0.32498*	*-0.98346*	*2.77851***	*1.82599**	*40.49301*	*1.38E+01*

WALD TEST		*RETURNS*			*VOLATILITY*	
Test Statistic	*F-statistic*	*Chi-square*	*DW*	*F-statistic*	*Chi-square*	*DW*
Value	*8.557282*	*59.90097*	*2.01*	*477.0634*	*3816.507*	*2.003*
Df	*(7, 2697)*	*7*		*(8, 2696)*	*8*	
Probability	*0.000*	*0.000*		*0.000*	*0.000*	

*40 Significance Level: *10% **5% ***1%*

In tables 4.62 and 4.63, the table 4.62 is explaining the impact of terrorist events on the returns and volatility of the *Textile Sector*, *T_B_5* represents the 5th day before the terrorist event and *T_0* represents the event day, where *T_5* represents the 5th day after the events day. The returns and volatility series are depending on their own 1st lags and volatility also depending on the 1st lag of the error term. For the returns series, *T_4* is significant at 10% level of significance, indicating that a significant impact of terrorist attacks on the returns of 4th day while this impact turns insignificant right after a day. Moreover, volatility remains insignificant for all remaining 5 days against the terrorist attacks, as no day dummy turns significant at any level of significance.

The table 4.63 is acquainting the impact of political events on the returns and volatility of the *Textile Sector*, *P_B_2* represents the 2nd day before the occurrence of a political event, *P_0* explains the day when an event takes place, *P_2* explains the 2nd day after the occurrence of a political event. Returns and volatility series are depending on their own 1st lag and volatility also depending on 1st lag of the error term. Results show that political events are significant on the event day at 5% level of significance however they turn insignificant after the event day. Political events on volatility are significant on 1st and 2nd day after the event day at first and second level of significance respectively.

4.7.4 Impulse Indicator Saturation

In this methodology, one dummy variable is generated against each observation and a general unrestricted model runs for the both returns and volatility series. Further, significance of events has been gauged for returns and volatility. *Table 4.64* is explaining the results of the returns and volatility series against political and terrorism events:

Table 4.64 Impulse Indicator Saturation: Textile Sector

	Co-Breaks		Significance⁰	Significance¹	Significance²	Significance³	Persistence
Terrorist Attacks	*70*	*Returns*	*72*	*26*	*16*	*15*	*1 d 6 mins*
		Volatility	*118*	*43*	*14*	*10*	*1 d 318 mins*
Political Events	*77*	*Returns*	*124*	*7*	*2*	*2*	*1 d 144 mins*
		Volatility	*94*	*49*	*5*	*0*	*2 d 126 mins*

[0]on day significant [1] after 1 day significant [2]after 2 days significant [3]after 3 days significant, at 5% level of significance

The table 4.64 above explains the results obtained through Impulse Indicator Saturation, depicts that out of total 217 terrorist attacks 72 attacks found to be significant in returns series on the event day, of these events 26, 16 and 15 number of events are significant on 1^{st}, 2^{nd} and 3^{rd} day respectively after the event day. On average the persistence of the significanct terrorist attacks is 1 day and 6 minutes of a working day. There are 118 significant terrorist attacks in the volatility of the returns series of which

43, 14 and 10 number of events are significant on 1st, 2nd and 3rd day respectively after the event day. On average persistence of significant terrorist attacks is 2 day and 318 minutes of a working day. Moreover, 70 numbers of co-breaks captured against the terrorist events. In political events, out of 160, there are 124 events that are significant on the event day under return series, of which 7, 2 and 2 are significant after the event day on 1st, 2nd and 3rd day respectively in return series. There are 94 political events that are significant in volatility on the event day, of which 49, 5 and 0 are significant on 1st, 2nd and 3rd day respectively after the event day. On average persistence of significant political events is 1 day and 144 minutes in returns, and 2 days and 126 minutes in volatility of a working day. Moreover, 77 co-breaks captured against political events.

CHAPTER V

CONCLUSION AND POLICY IMPLICATIONS

There is abundant can of worms that Pakistan is confronting from last one and half decade in the form of political instabilities and dreading terrorist attacks. Voluminous political instabilities especially in number of political assassinations, justice movements and long marches have recorded during this era. Terrorist attacks are not only causing causalities, injuries and loss to the economy; they are also spawning a dicey and precarious situation for the market shareholders. Moreover, *Pakistan* linkages with international market have also become a reason for the transfer of foreign perils into the country. In the presence of en masse considered situations, stock market can represent the aggregate reflecting behavior of the people.

This study observed the impact of terrorist attacks, political events and financial crises events on eight divergent sectors of *Pakistan Stock Exchange (PSX).* To meet the objectives of this study, 217 terrorist attacks, 160 political events and 2 financial crises events were being undertaken. Under the different employed methodologies, the reaction on daily frequency data from 2004 to 2014 of eight different sectors of *PSX* has examined against the considered events for both returns and volatility of the stock returns.

In the event study methodology, terrorist attacks significantly impacts the returns in cement, oil and gas, food and textile sectors, although the impact of terrorist attacks turns insignificant right after a day. Political events show a significant impact on the returns of all the sectors. Most of the political events are significant on the event day, although the impact turns insignificant right after a day. For the financial crises events, all the sectors show a significant long lasting response. However, the rebounding period lies between 20 to 100+ days for all the sectors against the financial crises events.

In the event day analysis, four divergent sectors: automobile, food, telecommunication and textile shows significant reaction on returns over the terrorist attacks, however the results are not significant on the event day. Whereas, the volatility of the stock returns in the telecommunication and oil and gas development show a significant reaction over the terrorist attacks. Returns in all the sectors against the political events have shown significant reaction but the volatility has not shown the significant reaction in automobile, food and chemical sector.

Both employed methodologies showing that sectors of *PSX* are more reactant to the political events as compare to the terrorist attacks which contradicts *(Aslam, 2013)* and *(Hassan, 2014)* for *KSE-100* index. This can be reasoned as might be financial sectors are more reactant to the terrorist attacks as compare to the non-financial sectors. Moreover the results are depicting the true situation against the political events alike *(Zach, 2003)* and *(Clark et al. 2008).* Moreover, contradictory results has been obtained under non parametric event study and parametric event study (Event Day Analysis). Even within the same methodology two models are depicting different results. Therefore, impulse indicator saturation is being employed to capture the breaks, co-breaks and level shifts. Moreover, to capture the persistence period in level shifts due to political events and terrorist attacks.

According to the Impulse Indicator Saturation, on average in all the sectors 107 number of events are significant out of the 160 political events in returns series on the event day; however 76 political events are significant on the event day in the volatility series. However maximum rebounding period in the returns series is maximum 1 day and 351 minutes of a working day among all the sectors against the political events, where rebounding period in the volatility series is up to 2 days and 220 minutes of a working day against the political events. Sugar sector found to be safes sector in the presence of political instabilities and food sector is most risky sector among all. Moving towards the reaction over the terrorist attacks, in all sectors on average 84 terrorist attacks have shown a significant reaction on the event day in the returns series where 100 terrorist attacks out of 217 total terrorist attacks have shown a significant reaction on the event day in the volatility series. The maximum rebounding period in the returns series against terrorist attacks is 1 day and 79 minutes of a working day whereas in the volatility series maximum rebounding period among all the sectors is 2 days and 66 minutes of a working day. Food sector reacts most and textile sector found to be the least reactive against the terrorist attacks. The *Impulse Indicator Saturations (IIS)* computes better results as it captures almost all the level shifts. The results obtained through *IIS* are comparatively better than all the methods of events study as the results obtained though *IIS* are much easier to compute and interpret.

Policy Implications

- In the presence of political instabilities and terrorism, food sector shows highest reaction in this sample period.
- In the presence of terrorist attacks food and textile sector may be risky as they are highly reactant to the terrorist attacks.
- In the presence of financial crises, chemical sector rebounding period is comparatively less than the other sectors.

- In the presence of political instabilities, sugar sector is less reactant to political events in this sample.

Research Limitations

- All the events have not included in the present study to avoid the issue of events overlapping.
- Study could not deal with some of the events overlapping issue.

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