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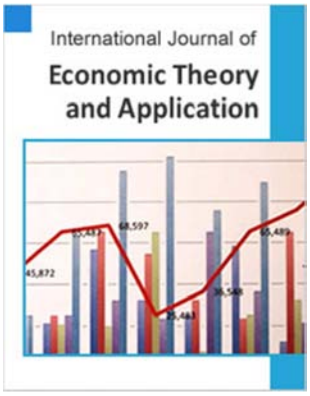

Quantifying the Impact of Terrorism on Financial Markets of Pakistan

Ayesha Nazuk[1, *], Asma Shamshad[2]

[1]School of Social Sciences and Humanities, National University of Sciences and Technology, NUST, Sector H-12, Islamabad, Pakistan
[2]Nori Patient Welfare Trust (Nori Cancer Hospital), Previously Student of National University of Sciences and Technology, NUST Business School, Islamabad, Pakistan

Email address

ayesha.nazuk@s3h.nust.edu.pk (A. Nazuk), spectacular_iris@hotmail.com (A. Nazuk), asmashamshad@hotmail.com (A. Shamshad)
[*]Corresponding author

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Abstract

Terrorism is one of the grave global issues that demands corrective action to avoid its detrimental consequences. Pakistan has been facing serious challenges of terrorism and there is a need to measure the damage done by this perilous ailment. Terrorism can impact a country in multiple manners however; this study focuses on measuring the association of terrorism on financial markets of Pakistan. This study analyzes the impact of terrorism on Karachi Stock Exchange 100 as it represents all sectors of the Karachi Stock Exchange and includes the largest companies on the basis of their market capitalization. This study also analyzes impact of terrorism on Pakistan Euro/PKR exchange rate. Generalized Auto Regressive Conditional Hetroscedasticity has been used to conclude that, in post-9-11 regime, Pakistan's stock market is not responsive to number of attacks per day and number of deaths shows no effect both in pre-9-11 and post-9-11 era. Moreover, in post-9-11 regime Pakistan's stock market has shown increased response to attack in a major city. In post-9-11 regime, foreign exchange market of Pakistan is less responsive to number of attacks per day in the post-9-11 regime as compared to post-9-11 regime. Moreover, attacks per day and number of deaths showed no effect on foreign exchange market of Pakistan both for pre-9-11 and post-9-11 regime.

1. Introduction

Terrorism is a plague that has infected many countries of the world and it has affected many aspects such as tourism industry, sports and financial markets. No 'formal' definition of terrorism is universally accepted and therefore the elements and dimensions of terrorism remain unpacked. Different legal systems and government agencies define terrorism in their own way.

US statute (Title 22, U.S.C. § 2656f(d)) contains the following definitions related to terrorism:

a. "The term 'terrorism' means premeditated, politically motivated violence perpetrated against noncombatant[1] targets by sub-national groups or clandestine agents, usually intended to influence an audience.
b. The term 'international terrorism' means terrorism involving citizens or the territory of more than one country.

1 For purposes of this definition, "noncombatant" includes civilians and military personnel who at the time of the incident are unarmed or not on duty.

It is possible to believe that terrorist activities have an insignificant effect on stock prices, since the terrorist attacks destroy a small fraction of the assets of a country and that too of firms in particular. But the empirical studies conducted throughout the world tell a different tale[2].

Let us begin our discussion by considering as to how stocks or stock markets might be affected by terrorist activities. The reasons for effect may be that:

1) The assets and resources of companies were destroyed/damaged directly by terrorist attacks or are under the likelihood (or direct threat) of future terrorist attacks.
2) The sentiments that stakeholders have, related to attacks, may affect companies. Two examples of such industries heavily affected by terrorist attacks are transport and tourism.
3) The prices of individual stocks reflect the hopes and fears of investors and the reaction to terrorist attacks is very much emotional. Anticipation about future of the stock prices can bring down/impact the prices significantly as explains Karolyi (2006); as the terrorist attacks have high liquidity so terrorists attacks and other alike events can have bad consequences for stocks and bonds. Such events can revert buying and selling decisions and in some cases investors even leave from the market in search of safer financial instruments

The main challenge according to Chesney, Reshetar and Karaman (2010) is to predict the patterns, probability and the financial consequences of terrorist attacks. The purpose of this study is to attempt this quantification. Current study is especially relevant, since it focuses on Pakistan, a frontline state in the "War against Terrorism". Pakistan has been facing terrorist attacks and threats for many years now, with an increase in number and intensity after 9/11.

Abadie and Gardeazabal (2003) analyzed the effects of terrorism on economic activity for Basque country. They considered several variables such as terrorist activity, regional data on GDP, investment, population density, sectorial production, human capital, oil prices, stock prices, firm size, book equity, and dividends, interest rates, bonds and macroeconomic announcements. The three models namely; Fama-French Three-Factor Model, Market Model and the Constant-Mean-Return Models were applied. Abadie and Gardeazabal (2003) proved that terrorism induced 10% decline in per capita GDP in the Basque Country.

Arin et al. (2008) did a comprehensive analysis of six different financial markets Indonesia, Israel, Spain, Thailand, Turkey and United Kingdom. According to Arin et al. (2008), terror has a significant impact on both stock markets and the stock market volatility, and magnitudes of these effects are larger in emerging markets.

Brounrn and Derwall (2010) studied eight of the most economically significant countries in the world (namely Canada, France, Germany, Italy, Japan, the Netherlands, the UK, and the US) to reveal that terrorist attacks produce mildly negative price effects. In order to compare natural and manned disaster they compared these price reactions to earthquakes and found that price declines following terror attacks are more prominent. They opined that reactions are strongest for local markets and for industries that are directly affected by the attack and that the 9/11 attacks were the only attacks that caused long-term effects on financial markets, especially in terms of industries' systematic risk.

Chen and Siems (2004), conducted a global study which revealed that global capital markets today are tightly inter-linked; news spreads rapidly, with quick spillover, or contagion, effects. Also that modern U.S. capital markets have become more resilient than they were in the past and that these markets recover sooner from terrorist/military attacks than other global capital markets. In the paper Chen and Siems (2004) analyzed two recent terrorist/military attacks—the 9/11 terrorist attacks and Iraq's invasion into Kuwait.

Eldor and Melnick (2004) also tried to see the impact of the various nefarious forms of terrorism. They investigated how stock and foreign exchange markets react to terror. They took into account the location, type of attack and target, number of casualties, and the number of attacks per day for his study of terror attacks between 1990 and 2003 in Israel. They concluded that "suicide attacks" have a permanent effect on both the stock and foreign exchange market. Same was the effect of the "numbers of victims", while "location of attack" had no effect on either market. In other words deaths of individuals, which no doubt is a serious event, effects the financial markets most intensely.

Gul et al. (2010) examined the effect of each kind of terrorist activity on stock, foreign exchange and money markets using daily data for a period of 2.5 years. They found that terrorists' activities in Pakistan had adversely and significantly affected the performance of KSE while insignificantly but adversely affected both foreign exchange market and the KIBOR rate. The finding that foreign exchange markets are insignificantly affected might be due to the shorter span of data being analyzed.

2. Current Study

This study is an exploratory research aimed at determining the immediate effect of news of terrorist activity/activities (activities that occurred within Pakistan from 1998 to 2010) on the: (a) Stock Markets of Pakistan and (b) Foreign Exchange Markets of Pakistan. This study conducted as a comparative study of the effects: (a) Prior to 9/11 attacks (i.e. prior to 11th Sept, 2001) and (b) after 9/11 attacks period (post 11th Sept, 2001).

2.1. Stock Market Studied

For the purpose of current study we have analyzed Karachi Stock Exchange (KSE) as it is largest and representative unit of financial market of Pakistan. KSE-100 is also reflective of the equity market of Pakistan that helps investors to develop impression. KSE-100 is representative of the largest

2 Studies by Arin et al. (2008), Chesney, Reshetar & Karaman (2010) and Eldor & Melnick (2004) all conclude that stock markets are significantly affected by terrorist activities

companies with reference to market capitalization.

2.2. Foreign Exchange Market Studied

The Euro was introduced to world financial markets as an accounting currency in 1999, replacing the former European Currency Unit (ECU). It is the official currency of 17 of the 27 member states of the European Union (EU) and is the second largest reserve currency as well as the second most traded currency in the world after the US$. As of June 2010, with more than €800 billion in circulation, the Euro has the highest combined value of banknotes and coins in circulation in the world, having surpassed the U.S. dollar (As of 30 October 2009) (Keating, 2011).

Keeping in mind the interest that Euro has gained as a currency not just around the world but also in Pakistan we focus on Euro/Pak Rupee exchange rate for our analysis.

2.3. Data on KSE - 100 Index

The KSE – 100 Index data daily closing prices were obtained from Yahoo-Finance website for the period 1st January, 1998 to 31st December 2010. This totals to 3168 observations.

The logarithmic daily index returns were calculated using formula:

Rt =LOG(Pt) - LOG(Pt-1)

Where;

Rt = Return on the KSE - 100 index for period t

Pt = Price of KSE – 100 Index at the end of period t

Pt-1 = Price of the KSE – 100 Index at the end of period t-1.

Data on Euro/PkR Exchange Market

The daily Euro/PkR exchange rate (ask and bid prices) data was obtained from OANDA[3] website for the period 15th December, 1998 to 31st December 2010. This totals to 4400 observations. The mid-point quote was then calculated for the exchange rate.

The logarithmic daily returns for Euro/PkR exchange rate (mid-point quote) were calculated using formula:

Rt =LOG(Et) - LOG(Et-1)

Where;

Rt = Return on the Euro/PkR exchange rate (mid-point quote) for period t

Et = Euro/PkR exchange rate (mid-point quote) at the end of period t

Et-1 = Euro/PkR exchange rate (mid-point quote) at the end of period t-1.

Data on Terrorist Activities

The data on terrorist events was collected for the following characteristics of the attacks that we use in our study to represent the intensity and psychological impact of an attack:

1. Number of attacks per day
2. Location
3. Number of fatalities/deaths in an attack

We collected information about the above mentioned characteristics from two websites:

a. GTD (Global Terrorism Database) by Center for Terrorism and Intelligence Studies (CETIS)[4].
   a). For the period 1st January, 1998 to 31st December, 2003. This totals to 202 attacks in the span of six years.
b. WITS (Worldwide Incidents Tracking System) by the National Counter Terrorism Center (NCTC) of US Government.
   b). For the period 1st January, 2004 to 31st December, 2010. This totals to 6943 attacks in a span of seven years.

Together the data totals to 7145 terrorist attacks in a span of thirteen years.

2.4. ARCH and GARCH Models

Heteroskedasticity biases the Ordinary Least Square estimated standard errors of the slope estimates, which means that the t tests will not be reliable. The multi-sample version or the F-test, used to check significance of overall regression model, will also not reliable. Heteroskedasticity is said to be conditional if we cannot know in advance the periods in which volatility will be higher (or lower). The ARCH and GARCH models, which stand for Autoregressive Conditional Heteroskedasticity and Generalized Autoregressive Conditional Heteroskedasticity respectively, are designed to deal with this type of volatility clustering. The term ‘autoregressive’ here means a model in which the dependent variable ‘Y’ is dependent on one or more lagged (past) values of itself i.e. ‘Y_{t-1}, Y_{t-2} ….

2.5. GARCH Model

The GARCH model has the same mean equation but generalizes the ARCH model so as to cater for hetroscasticity and volatility clustering. By volatility clustering we mean that we have stratums of data in which the variance can be classified as similar. Furthermore we know that broadly speaking probability distributions can be classified as platykurtic, mesokurtic and leptokurtic where mesokurtic implies normality assumption. Usually stock prices have leptokurtic distribution due to price spikes and the GARCH model accommodates this.

3. Testing, Model Building and Post-testing

Since our analysis consist of both the stock market represented by KSE – 100 Index return series and the foreign exchange market in particular the Euro/PkR exchange rate return series we divide coming section into two sections; 3.1 for KSE – 100 Index returns and 3.2 for the Euro/PkR exchange rate.

3.1. KSE - 100 Index Return Series

In this section analysis for KSE-100 Index Return has been discussed.

3 https://www.oanda.com/currency/converter/

4 https://www.start.umd.edu/gtd/

3.1.1. Testing of KSE-100 Index Return Series

The testing phase consists of graphical as well as descriptive tests. We perform a sequence of tests to determine which modeling technique is appropriate for our financial time series data namely the KSE 100 Index dataset.

Graphical analysis of a time series data can give important insights about the data. Interestingly many researchers avoid this important step and hence sometimes the findings are misleading e.g. using ARCH/GARCH model in the absence of volatility.

We begin our graphical analysis with tests for normality. This is achieved by plotting the probability distribution graph of KSE – 100 Index returns with reference to the normal probability distribution graph at that standard deviation.

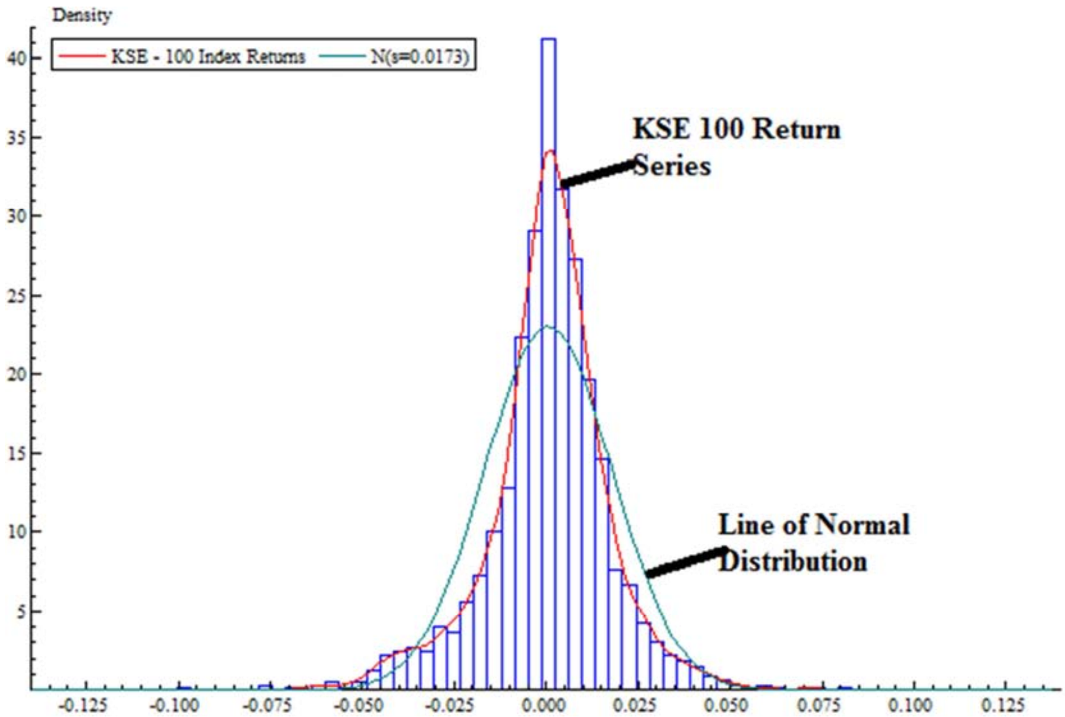

Figure 1. *Probability Distribution Graph of KSE – 100 Index Returns.*

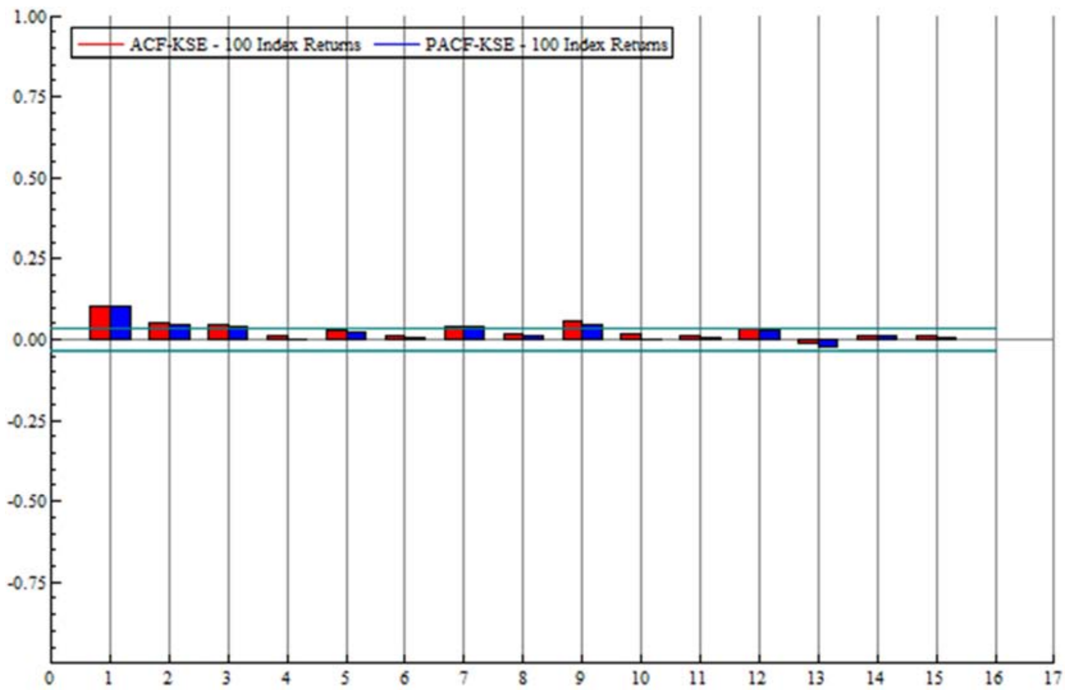

Figure 2. *Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Stock Index returns[5].*

5 In all ACF/PACF graphs the first rectangles at each lag represent autocorrelations while the second rectangles represent partial autocorrelations.

It is clear that the two distribution (red for KSE – 100 probability distribution and green for normal probability distribution in green at standard deviation‘s’ = 0.0173) do not match. The data is leptokurtic (tall peaked and long tailed) as opposed to the normal bell shaped distribution.

Next we look at the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Stock Index returns to look for signs of serial autocorrelations (the correlation between observations of a time series separated by some time units, in our case days) in the KSE – 100 Index returns.

The two parallel lines above and below the line at Y=0 are known as Upper Confidence Level (UCL) and Lower Confidence Level (LCL) respectively. If the data is random then the plot should be within the UCL and LCL (which is the 95% confidence interval). If it goes beyond UCL or LCL we conclude that some correlation exists in the data. Clearly the graph for KSE – 100 Index returns data is outside the UCL (at lag 1 this is most evident) and LCL which means correlation exists in the data.

Now to inquire about the presence of volatility we plot the actual series for the ‘KSE-100 Index returns’.

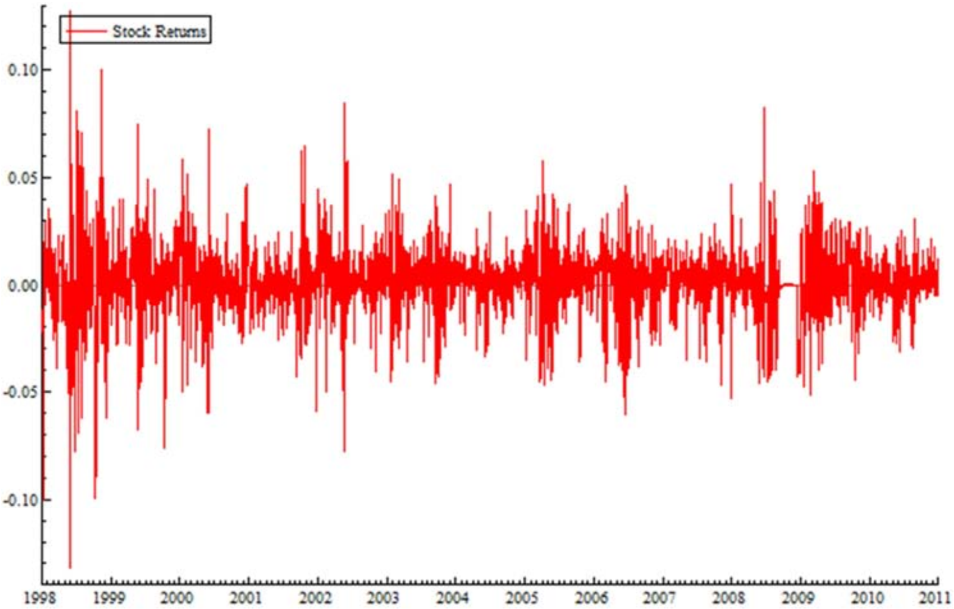

Figure 3. *Actual series plot for Index returns for daily KSE-100 Index data from 01/01/1998 to 31/12/2010.*

This graph shows that the volatility is greater for some periods than others. If the data pattern was in the form of a single band above and below the ‘0’ we would conclude that the volatility is not changing hence constant or “homoskedastic”.

Also we can observe, the volatility is in form of clusters, i.e. periods of high volatility is followed by periods of low volatility. This is indicative of ‘Auto Regressive Conditional Heteroskedasticity Effect’.

We can more clearly observe the ARCH Effect by the help of plotting ACF/PACF of the squares of the KSE – 100 Index returns.

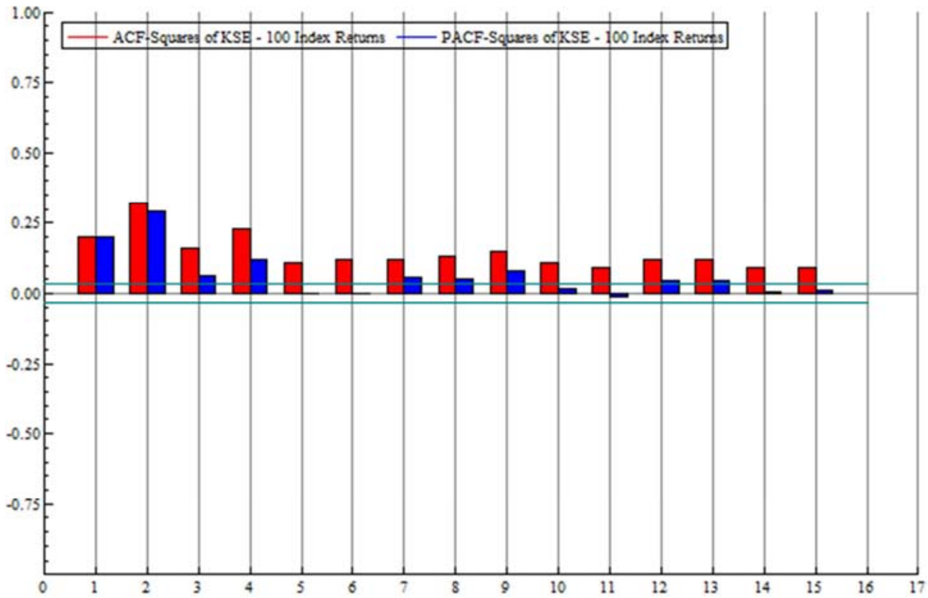

Figure 4. *Auto Correlation Function and Partial Auto Correlation Function for the squares of the KSE – 100 Index returns.*

The ACF/PACF shows that there exists autocorrelation in the squares of the KSE – 100 Index returns indicating existence of ARCH Effect in the financial time series.

3.1.2. Descriptive Testing

To further investigate the data we perform descriptive tests on KSE – 100 Stock returns.

The descriptive tests we perform for normality is the Jarque-Bera test (Jarque & Bera, 1980).

Table 1. *Jarque Bera Test for KSE-100 Returns.*

Test	Statistic	P-Value
Jarque-Bera	3506.3	0.00000

Jarque-Bera test is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness. The null hypothesis being the data is from a normal distribution which is rejected in our case as p-value is significant (at 0) implying we can reject the null hypothesis thus the data is non-normal. It confirms the observation of the graphical pre-test for normality.

Descriptive testing for Autocorrelations in KSE -100 Return Series

We perform the Engle's Lagrange Multiplier (LM) ARCH Test to determine whether our data has Autoregressive Conditional Heteroskedasticity. The results for 2, 5 and 10 lags are given below:

Table 2. *Engle's Lagrange Multiplier (LM) ARCH Test for KSE-100 Returns.*

Test	F-Statistics	p-value
ARCH 1-2 test	F(2,3162) = 220.00	[0.0000]**
ARCH 1-5 test	F(5,3156) = 107.62	[0.0000]**
ARCH 1-10 test	F(10,3146)= 60.491	[0.0000]**

The null hypothesis of the LM ARCH test in that "there is no arch effect for up to k lags" which can be rejected if the p-value is significant. The table shows the F-statistic are together with p-value in square brackets. The results indicate that there is ARCH effect in the squares of our time series for up to 10 lags. The LM ARCH Test confirms ARCH effect for the squares of KSE – 100 Index returns.

The testing phase makes it clear that the Classical Linear Regression Model (CLRM) is not the appropriate choice at all for modeling our data. The two critical assumptions of CLRM are violated by our dataset and that the GARCH type model (which actually is meant to incorporate these two critical assumptions) is the suitable choice for modeling our KSE – 100 Index returns.

3.1.3. Model Building for KSE - 100 Index Return Series

We build the GARCH model for KSE – 100 Index returns and then apply it to two subsamples; the pre 9-11 subsample and the post 9-11 subsample respectively.

In order to model the KSE – 100 returns we first identify the Autoregressive (AR) terms that we need to model for our mean equation of the GRACH model. Recall that the mean equation is:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \ldots + \alpha_q Y_{t-q} + \varepsilon_t$$

By identifying the AR we are determining the lags of dependent variable (Y_t) that it, (Y_t) itself, is dependent upon.

For this we look at the ACF and PACF of the series. We observe that some lags, up to 9, show signs of autocorrelation. The process is therefore an AR (9) process, where 9 is the order denoted by 'q'. We also note that only the AR terms 1, 2, 3, 7 and 9 are significant as they fall outside the 95% confidence bounds. Hence we include only these terms in our mean equation namely Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-7} and Y_{t-9} as independent variables.

We also include the independent variables that are associated with terrorist attacks into equation namely:

1. D_{Maj} - dummy variable representing 'major city'
   a. '1' for major city by urban population
2. $X_{A/D}$ - representing 'No. of attacks/day'
3. X_D representing 'No. of deaths'

Our mean equation then takes the form:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \alpha_3 Y_{t-3} + \alpha_7 Y_{t-7} + \alpha_9 Y_{t-9} + \gamma_1 D_{Maj} + \gamma_2 X_{A/D} + \gamma_3 X_D + \varepsilon_t$$

Recall that the variance equation of GARCH model has the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_p \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2$$

GARCH (1,1) works remarkably well with most financial time series data so we apply GARCH (1, 1) i.e. p=1 and q=1 to estimate our variance equation.

Our variance equation is thus:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

The results for mean equation are as follows:

Table 3. *GARCH (1, 1) for KSE-100 Returns (Pre 9-11 Regime).*

Name of Independent Variable/Constant	Independent Variable/Constant	Coefficient	t-prob
KSE - 100 Index Returns_Lag 1	Y_{t-1}	0.064167	0.066*
KSE - 100 Index Returns_Lag 2	Y_{t-2}	0.0816364	0.019*
KSE - 100 Index Returns_Lag 3	Y_{t-3}	0.0295214	0.375
KSE - 100 Index Returns_Lag 7	Y_{t-7}	0.01869	0.545
KSE - 100 Index Returns_Lag 9	Y_{t-9}	0.00487448	0.888
Intercept	Constant	-3.18E-06	0.995
Major City	D_{Maj}	0.00448696	0.08*
No. of Attacks/Day	$X_{A/D}$	-0.00292418	0*
No. of Deaths	X_D	3.93E-05	0.903

* At 10% significance level

The results for variance equation are as follows:

Table 4. *Variance Equation Results by GARCH (1, 1) for KSE-100 Returns (Pre 9-11 Regime).*

Name of Coefficient	Value	t-prob
alpha_0	9.95E-06	0.06*
alpha_1	0.149888	0*
beta_1	0.83257	0*

* At 10% significance level
No. of observations = 872

The results for mean equation are as follows:

Table 5. *Results of GARCH (1, 1) for KSE-100 Returns on Post 9-11 Subsample.*

Name of Independent Variable	Independent Variable	Coefficient	t-prob
KSE - 100 Index Returns_Lag 1	Y_{t-1}	0.0532903	0.028*
KSE - 100 Index Returns_Lag 2	Y_{t-2}	0.0157005	0.493
KSE - 100 Index Returns_Lag 3	Y_{t-3}	0.0400938	0.06*
KSE - 100 Index Returns_Lag 7	Y_{t-7}	0.0348092	0.095*
KSE - 100 Index Returns_Lag 9	Y_{t-9}	0.0318167	0.095*
Intercept	Constant	0.00205185	0*
Major City	D_{Maj}	-0.000934576	0.036*
No. of Attacks/Day	$X_{A/D}$	-7.80E-05	0.31
No. of Deaths	X_D	4.05E-06	0.881

* At 10% significance level

The results for variance equation are as follows:

Table 6. *Variance Equation Results by GARCH (1, 1) for KSE-100 Returns (Post 9-11 Regime).*

Name of Coefficient	Value	t-prob
alpha_0	5.53E-06	0.011*
alpha_1	0.228192	1
beta_1	0.771808	0*

* At 10% significance level
No. of observations = 2286

3.2. Euro/PkR Exchange Rate Returns

In this section we discuss the analysis for Euro/PKR exchange rate returns.

3.2.1. Testing for Euro/PkR Exchange Rate Returns

As with KSE – 100 Index return series the testing phase consists of graphical as well as descriptive tests. We perform a battery of tests to determine which modeling technique is appropriate for our financial time series data namely the Euro/PkR exchange rate return series.

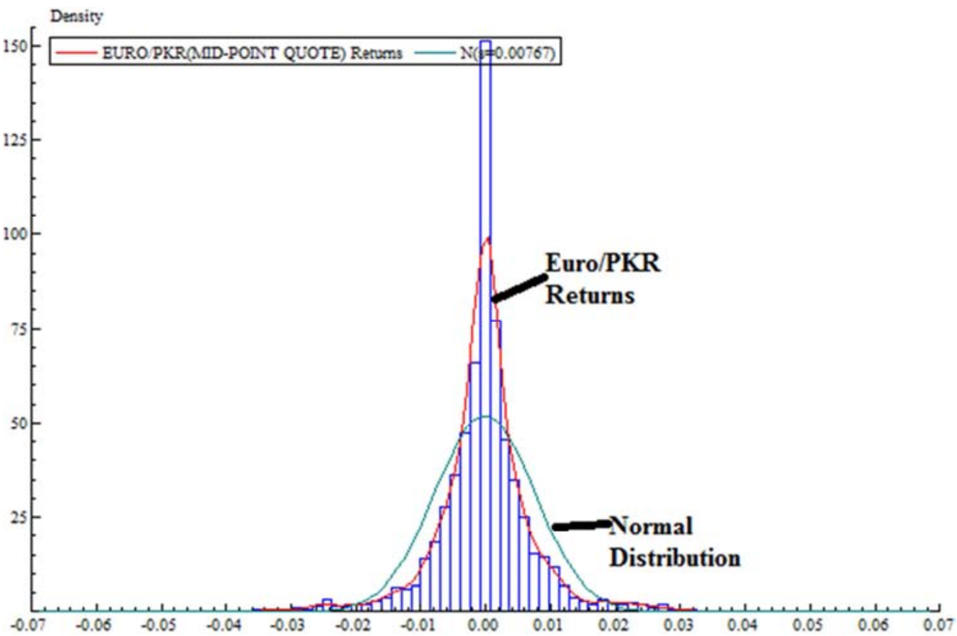

Figure 5. *Probability distribution plot for returns for daily Euro/PkR exchange rate from 15/12/1998 to 31/12/2010 against the normal probability distribution in green at standard deviation 's' = 0.00767.*

We perform test for normality by help of probability distribution graph of the Euro/PkR exchange rate return series with reference to the normal probability distribution graph at that standard deviation.

Euro/PkR exchange rate return series is leptokurtic (tall peaked and long tailed) as opposed to the normal bell shaped distribution.

Next we look at the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Euro/PkR exchange rate return to look for signs of serial autocorrelations (the correlation between observations of a time series separated by some time units, in our case days).

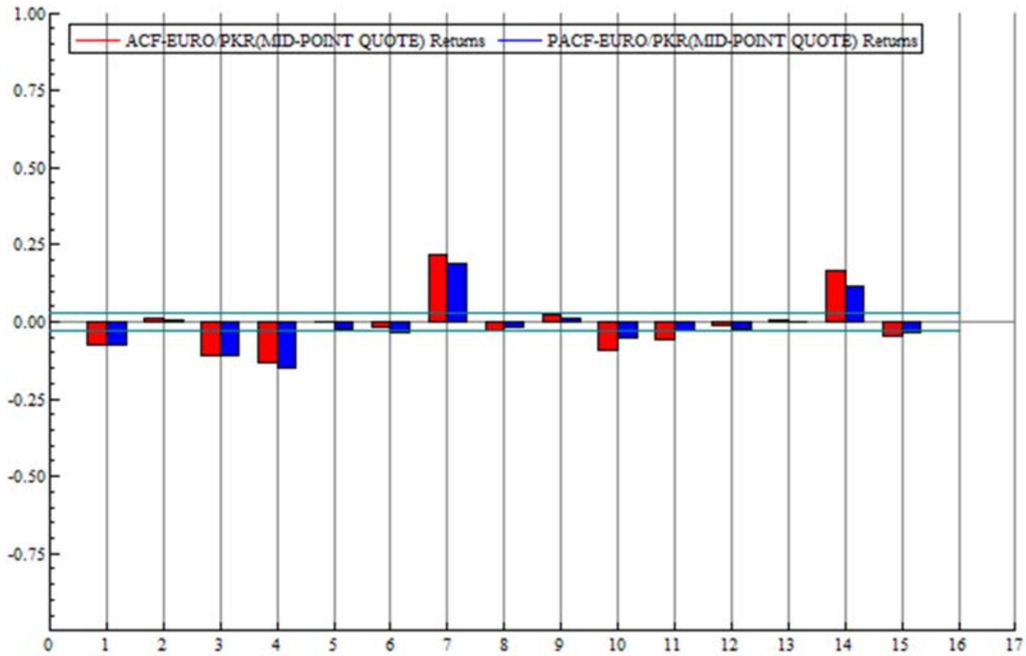

Figure 6. *Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the Euro/PkR exchange rate return.*

Clearly the graph for returns data is outside the UCL (at lag 7 and 14 this is most evident) and LCL which means correlation exists in the data. This means an Autoregressive model type is required.

Graphical testing for Auto Regressive Conditional Heteroskedasticity/ARCH Effect

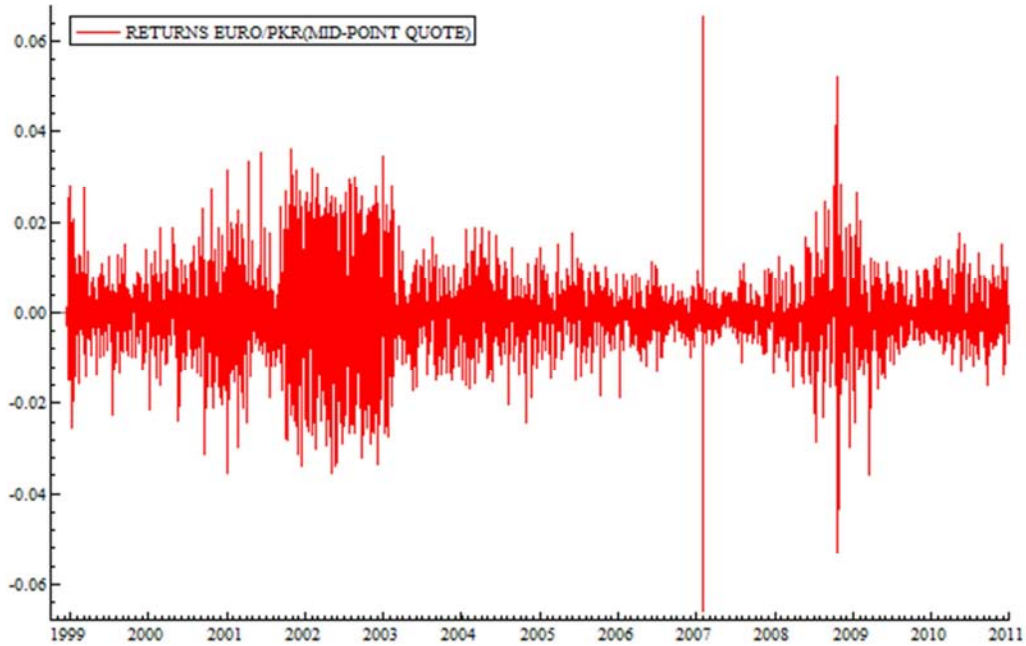

Figure 7. *Actual series plot for returns for daily Euro/PkR exchange rate data from 15/12/1998 to 31/12/2010.*

This graph shows that the volatility is greater for some periods than others meaning the volatility is changing hence "heteroskedastic". Also we can observe, the volatility is in form of clusters, i.e. periods of high volatility is followed by periods of low volatility which means there is "Auto Regressive Conditional Heteroskedasticity Effect' in data.

ACF/PACF Method

We can more clearly observe the ARCH Effect by the help of plotting ACF/PACF of the squares of the Euro/PkR exchange rate returns

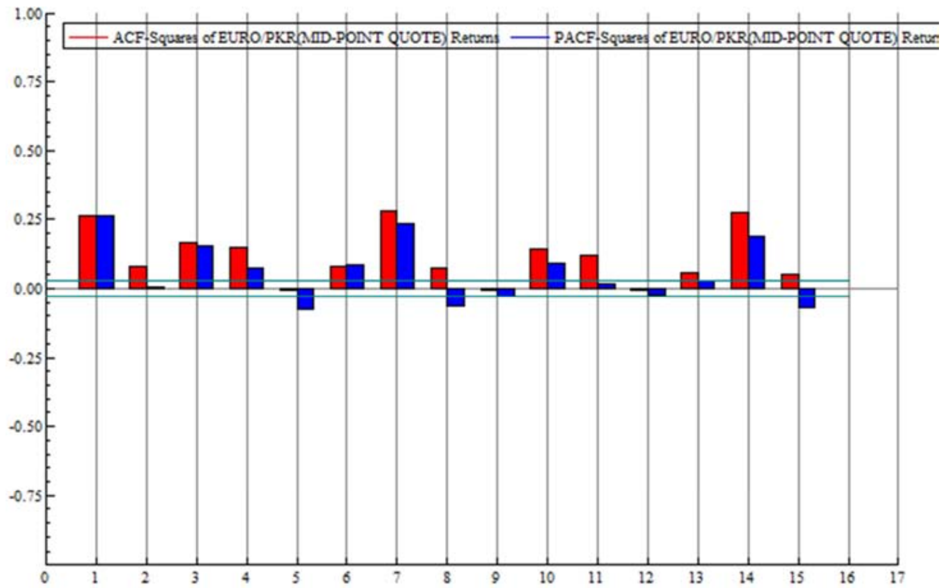

Figure 8. *ACF/PACF of the squares of the Euro/PkR exchange rate returns.*

The ACF/PACF correlogram clearly shows that there exists autocorrelation in the squares of the returns indicating existence of ARCH Effect in our financial time series. The presence of ARCH effect violates a critical assumption of the CLRM namely that the error variances are constant.

3.2.2. Descriptive testing of Euro/PKR Returns

To further investigate our data we perform descriptive tests on our return series. The descriptive test we perform for normality is the Jarque-Bera test which proves that the Euro/PkR exchange rate returns are not normally distributed.

Table 7. *Jarque Bera Test for Euro/PkR exchange rate returns.*

Test	Statistic	P-Value
Jarque-Bera	9506.1	0.00000

Descriptive testing for Autoregressive Conditional Heteroskedasticity

Engle's Lagrange Multiplier (LM) ARCH Test

We perform the Lagrange Multiplier (LM) ARCH Test to determine whether our data has Autoregressive Conditional Heteroskedasticity. The results for 2, 5 and 10 lags are given below:

Table 8. *Lagrange Multiplier (LM) ARCH Test for Euro/PkR exchange rate returns.*

Test	F-Statistics	p-value
ARCH 1-2 test	F(2,4394) = 167.27	[0.0000]**
ARCH 1-5 test	F(5,4388) = 99.840	[0.0000]**
ARCH 1-10 test	F(10,4378)= 89.157	[0.0000]**

The null hypothesis of the LM ARCH test in that "there is no arch effect for up to k lags" which can be rejected if the p-value is significant. The table shows the F-statistic are together with p-value in square brackets. The results indicate that there is ARCH effect in the squares of our time series for up to 10 lags. The LM ARCH Test confirms ARCH effect for the squares of our Euro/PkR exchange rate returns.

The testing phase makes it clear that the Classical Linear Regression Model is not the appropriate choice at all for modeling our data. The two critical assumptions of CLRM are violated by our dataset and that the GARCH type model (which actually is meant to incorporate these two critical assumptions) is the suitable choice for modeling our Euro/PkR exchange rate returns.

3.2.3. Model Building for Euro/PkR Exchange Rate Return Series

We build the GARCH model for Euro/PkR exchange rate returns and then apply it to two subsamples; the pre 9-11 subsample and the post 9-11 subsample respectively. We first identify the Autoregressive (AR) terms that we need to model for our mean equation of the GRACH model. By identifying the AR we are determining the lags of dependent variable (Y_t) that it, (Y_t) itself, is dependent upon.

For this we look at the ACF and PACF of the series

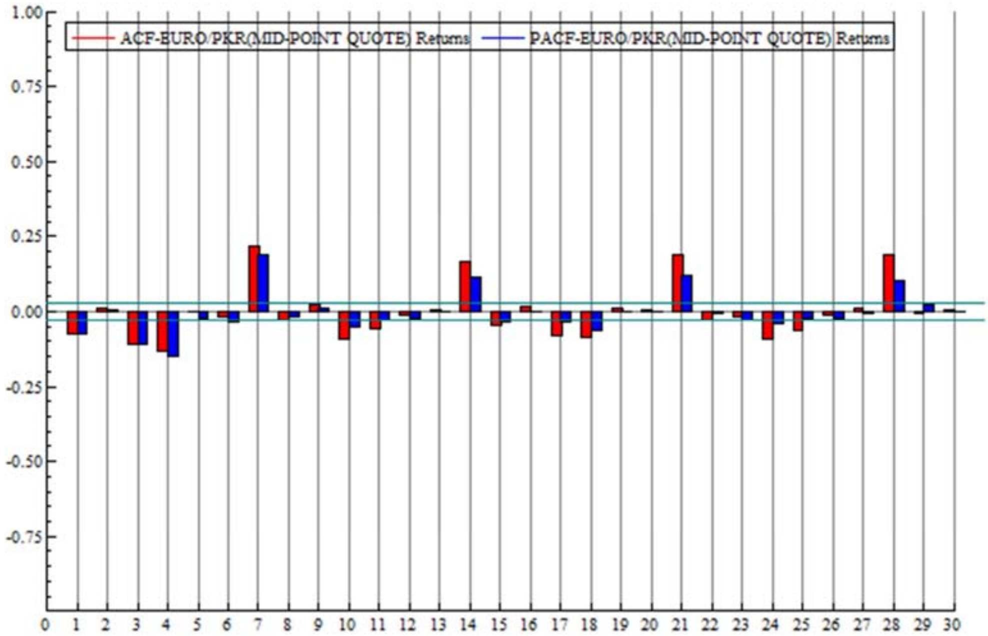

Figure 9. *ACF and PACF of Euro/PkR Exchange Rate Return Series.*

We observe that some lags, up to 28, show signs of autocorrelation. The process is therefore an AR (28) process, where 28 is the order denoted by 'q'. We also note that only the AR terms 1, 3, 4, 6, 7, and 10, 11, 14, 15, 17, 18, 21, 23, 24, 26 and 28 are significant as they fall outside the 95% confidence bounds. Hence we include only these terms in our mean equation. We also include the independent variables that are associated with terrorist attacks into equation namely:

1. D_{Maj} - dummy variable representing 'major city'
   a. '1' for major city by urban population
2. $X_{A/D}$ - representing 'No. of attacks/day'
3. X_D representing 'No. of deaths'

Our mean equation then takes the form:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_3 Y_{t-3} + \alpha_4 Y_{t-4} + \alpha_6 Y_{t-6} + \alpha_7 Y_{t-7} + \alpha_{10} Y_{t-10} + \alpha_{11} Y_{t-11} + \alpha_{14} Y_{t-14} + \alpha_{15} Y_{t-15} + \alpha_{17} Y_{t-17} + \alpha_{18} Y_{t-18} + \alpha_{21} Y_{t-21} + \alpha_{23} Y_{t-23} + \alpha_{24} Y_{t-24} + \alpha_{26} Y_{t-26} + \alpha_{28} Y_{t-28} + \gamma_1 D_{Maj} + \gamma_2 X_{\frac{A}{D}} + \gamma_3 X_D + \varepsilon_t$$

The variance equation i.e. eq. (2) of GARCH model has the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_p \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2$$

We apply GARCH (2, 1) i.e. p=2 and q=1 to estimate our variance equation. Our variance equation is thus:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2$$

The results for mean equation are as follows:

Table 9. *Results of GARCH (2, 1) on Pre 9-11 Subsample (1998-01-01 to 2001-11-08).*

Name of Independent Variable/Constant	Independent Variable/Constant	Coefficient	t-prob
EURO/PKR(MPQ) Returns_Lag 1	Y_{t-1}	0.0138127	0.627
EURO/PKR(MPQ) Returns_Lag 3	Y_{t-3}	-0.0440975	0.089*
EURO/PKR(MPQ) Returns_Lag 4	Y_{t-4}	-0.0102825	0.677
EURO/PKR(MPQ) Returns_Lag 6	Y_{t-6}	-0.0275592	0.404
EURO/PKR(MPQ) Returns_Lag 7	Y_{t-7}	0.0291181	0.393
EURO/PKR(MPQ) Returns_Lag 10	Y_{t-10}	-0.00294828	0.907
EURO/PKR(MPQ) Returns_Lag 11	Y_{t-11}	0.0395472	0.111
EURO/PKR(MPQ) Returns_Lag 14	Y_{t-14}	0.00814542	0.811
EURO/PKR(MPQ) Returns_Lag 15	Y_{t-15}	0.0642371	0.02*
EURO/PKR(MPQ) Returns_Lag 17	Yt-17	0.0186383	0.468
EURO/PKR(MPQ) Returns_Lag 18	Yt-18	-0.0337921	0.16
EURO/PKR(MPQ) Returns_Lag 21	Yt-21	0.0119724	0.697
EURO/PKR(MPQ) Returns_Lag 23	Yt-23	-0.0339696	0.124
EURO/PKR(MPQ) Returns_Lag 24	Yt-24	0.00330208	0.896

Name of Independent Variable/Constant	Independent Variable/Constant	Coefficient	t-prob
EURO/PKR(MPQ) Returns_Lag 26	Yt-26	-0.0114961	0.659
EURO/PKR(MPQ) Returns_Lag 28	Yt-28	0.0255444	0.507
Intercept	Constant	0.000174519	0.315
Major City	DMaj	-0.00114898	0.344
No. of Attacks/Day	XA/D	0.000858072	0.006*
No. of Deaths	XD	-9.59E-05	0.572

* At 10% significance level

The results for variance equation are as follows:

***Table 10.** Variance Equation for GARCH (2, 1) on Pre 9-11 Subsample (1998-01-01 to 2001-11-08).*

Name of Coefficient	Value	t-prob
alpha_0	4.05E-07	0.17
alpha_1	0.0504541	1
beta_1	0.54835	0.087*
beta_2	0.401196	0.436

* At 10% significance level
No. of observations = 972

The results for mean equation are as follows:

***Table 11.** Results of GARCH (2, 1) on Post 9-11 Subsample (2001-11-09 to 2010-12-31).*

Name of Independent Variable/Constant	Independent Variable/Constant	Coefficient	t-prob
EURO/PKR(MPQ) Returns_Lag 1	Y_{t-1}	0.00723758	0.626
EURO/PKR(MPQ) Returns_Lag 3	Y_{t-3}	-0.0556949	0*
EURO/PKR(MPQ) Returns_Lag 4	Y_{t-4}	-0.0499172	0.001*
EURO/PKR(MPQ) Returns_Lag 6	Y_{t-6}	-0.00810492	0.531
EURO/PKR(MPQ) Returns_Lag 7	Y_{t-7}	0.104369	0*
EURO/PKR(MPQ) Returns_Lag 10	Y_{t-10}	-0.0222741	0.12
EURO/PKR(MPQ) Returns_Lag 11	Y_{t-11}	0.00179381	0.894
EURO/PKR(MPQ) Returns_Lag 14	Y_{t-14}	0.070686	0.003*
EURO/PKR(MPQ) Returns_Lag 15	Y_{t-15}	-0.0301098	0.027*
EURO/PKR(MPQ) Returns_Lag 17	Yt-17	-0.031123	0.02*
EURO/PKR(MPQ) Returns_Lag 18	Yt-18	-0.0134441	0.341
EURO/PKR(MPQ) Returns_Lag 21	Yt-21	0.077546	0.001*
EURO/PKR(MPQ) Returns_Lag 23	Yt-23	-0.0156603	0.148
EURO/PKR(MPQ) Returns_Lag 24	Yt-24	-0.0213639	0.118
EURO/PKR(MPQ) Returns_Lag 26	Yt-26	-0.0163966	0.12
EURO/PKR(MPQ) Returns_Lag 28	Yt-28	0.0927242	0*
Intercept	Constant	-0.000113274	0.249
Major City	DMaj	0.000147872	0.46
No. of Attacks/Day	XA/D	-6.12E-05	0.131
No. of Deaths	XD	-3.05E-06	0.871

At 10% significance level

The results for variance equation are as follows:

***Table 12.** Results of GARCH (2, 1) on Post 9-11 Subsample (2001-11-09 to 2010-12-31).*

Name of Coefficient	Value	t-prob
alpha_0	9.28E-07	0.003*
alpha_1	0.109454	1
beta_1	0.180686	0.015*
beta_2	0.70986	0.004*

* At 10% significance level
No. of observations = 3399

4. Conclusions

We started with the objective to quantify the impact of terrorism on financial markets of Pakistan using the ARCH GARCH family of models as our financial time series data (for both stock and foreign exchange markets) violated some critical assumptions that Classical Linear Regression Model make about the underlying data.

The main conclusion that we draw using GARCH modeling for:

a. Stock market returns:
   1. Number of attacks per day have a very significant negative impact prior to 9-11 attacks but has no significant impact after the 9-11 attacks.
   2. Location: Attack in a major city has a slightly significant positive impact prior to 9-11 attacks but a highly significant negative impact after 9-11 attacks.
   3. Number of fatalities/deaths has no significant effect before or after 9-11 attacks.

b. Foreign exchange market returns:

1. Number of attacks per day has a moderately significant positive impact prior to 9-11 attacks but has no significant impact after the 9-11 attacks.
2. Location: Attack in a major city has no significant effect before or after 9-11 attacks.
3. Number of fatalities/deaths has no significant effect before or after 9-11 attacks.

In this study we have investigated the impact of various characteristics of the news of a terrorist event on stock and foreign exchange markets of Pakistan. A more detailed study may be attempted that would include other economic and that effect the stock and foreign exchange markets. This study can also be extended by using a modeling technique known as Auto Regressive Distributed Lag Model. This type introduces lags in the independent variables (the Xs) so that for any terrorist event, the effect of a particular characteristic (of event), on the dependent variable may be noted for many time intervals to follow, example the effect that was seen the next day, etc. We also recommend that a further study of the reasons as to why a particular effect (positive or negative) was observed for a terrorist event variable, be investigated. Also the study can be performed to see the sector wise impact on the stock market to determine sectors affected and whether the effect was positive or negative and for what characteristics of a terrorist activity. We also propose that another interpolation technique known as the "Wavelet Transform" be applied to interpolate missing values for stocks market data. We suggest that modeling can refined by applying various GARCH models with different orders of p and q and other models belonging to the GARCH family. These models may be compared for accuracy using Akaike Information Criteria (AIC), Schwarz Bayesian Information Criteria (BIC) and other model selection criteria.

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