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Stock Market Volatility and Terrorism: New Evidence from the Markov Switching Model

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Abstract: Terrorism in Pakistan poses a significant risk towards the lives of people by violent destruction and physical damage. In addition to human loss, such catastrophic activities also affect the financial markets. The purpose of this study is to examine the impact of terrorism on the volatility of the Pakistan stock market. The financial impact of 339 terrorist attacks for a period of 18 years (2000–2018) is estimated w.r.t. target type, days of the week, and surprise factor. Three important macroeconomic variables namely exchange rate, gold, and oil were also considered. The findings of the EGARCH (1, 1) model revealed that the terrorist attacks targeting the security forces and commercial facilities significantly increased the stock market volatility. The significant impact of terrorist attacks on Monday, Tuesday, and Thursday confirms the overreaction of investors to terrorist news. Furthermore, the results confirmed the negative linkage between the surprise factor and stock market returns. The findings of this study have significant implications for investors and policymakers.

Keywords: days of the week effect, Pakistan stock exchange, terrorist events

1 Introduction

Terrorism is one of the emerging issues of international security in the 21st century, where attacks not only on military but civilians (both individuals and businesses) were noticed (Markoulis and Katsikides 2020). Any threat or use of illegitimate power and sternness to achieve any economic, religious, political, or other social purpose is termed as terrorism or terrorist activities (LaFree and Dugan 2007). The

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motive behind these activities is common i.e. causing damaging national resources, creating a disturbance, or seeking attention (Khan et al. 2020). Such terrorist activities affect national as well as the global economy, create uncertainty and increases risks, and ultimately slows economic growth. There are evidence of their impact global (Becker and Murphy 2001), regional (Aslam et al. 2018; Das, Kannadhasan, and Bhattacharyya 2019) and national (Aslam, Eom, and Kang 2014; MengYun et al. 2018) levels. Terrorist activities besides creating panic, fear, and insecurity (Aslam and Kang 2015), also generates shocks for economies resulting in destruction (Yehuda and Hyman 2005). But empirical evidence is needed (Bevilacqua, Morelli, and Uzan 2020; Rosenfeld 2010) as literature is scant. Although, multiple factors resulting to stock market volatility including national credit policy, inflation, stocks' volume, etc. (French 1980), investors' risk, herd behavior, trade rate of currency, etc. (Imran, Rafique, and Aslam 2020) are extensively explored in the literature. The negative nexus of terrorism with a nation's economy reduces investors' confidence which decreases trade figures and foreign direct investment (Aksoy and Demiralay 2019; Jain and Grosse 2009; Johnston and Nedelescu 2006). The ultimate adverse influence of these activities reaches the backbone of countries, i.e. stock markets (Eldor and Melnick 2004; Irshad et al. 2019). Multiple studies (Arin, Ciferri, and Spagnolo 2008; Carter and Simkins 2004; Charles and Darné 2006; Hadi, Katircioglu, and Adaoglu 2020; Nikkinen et al. 2008; Zhou, Huang, and Chen 2020) reported close association among these activities and volatility of stock markets. The regulatory authorities should act as a cornerstone to buffer the financial markets from terrorist attacks so that efficiency and effectiveness can be ensured, and adaptability to new circumstances is guaranteed.

One of the deadliest terrorist activities in the West, The Twin Towers (9/11) witnessed halting financial markets, with closure of Nasdaq and the New York Stock Exchange (Bevilacqua, Morelli, and Uzan 2020). Shortly after the said attacks, stock markets plunged to protracted bear market owing to enduring deterioration of investors' confidence. The aftermath of these attacks implied higher cross-market connections, had impact on investors' sentiments and more sensitive response to shocks in the US market (Mun 2005). Investigations on the impact of 9/11 attacks and other such tragic events were seen on capital markets (Chen and Siems 2004; Maillet and Michel 2005), linking terrorist activities with stock markets (Abadie and Gardeazabal 2003; Chen and Siems 2004; Papakyriakou, Sakkas, and Taoushianis 2019; Wisniewski 2016), or connecting terrorist activities with substitutions of volatility (Chong 2011; Essaddam and Karagianis 2014; Shaikh 2019). Post 9/11 attacks, Pakistan played a vital role in fight against terrorism and resultantly increase in terrorist activities were noticed in different parts of the country. Economy was adversely affected, stock markets slumped but in 2000 a rapid growth was noticed, which continued till 2007. Then in 2008 an increase in terrorist activities was seen due to political instability. Democratic government resumed in 2014 and stock market gushed by crossing 3000 points. In the same year military operation against terrorists occasioned in improvement of law and order situation and improvement in stock market performance was seen in 2017 by touching 5000 points. The figures of Pakistan Stock Exchange (PSX) accounted 560 listed firms and US$98 billion market capitalization and PSX was reclassified as Morgan Stanley Capital International (MSCI) emerging market, and Financial Times Stock Exchange (FTSE) classified it as Secondary Emerging Market. Considering, PSX's performance, investigations about effect of terrorism seems imperative and was noted by multiple authors (Ahmed and Farooq 2008; Aslam and Kang 2015; Suleman 2012).

The distinguishing nature of this study as compared to the previous literature is to find out the effect of 339 destructive events on stock returns from 2000 to 2018. The effects are concerned with target type, days of the week, and a surprise factor of terrorist activities. The target of activities was divided into five categories namely private citizens & property, religious figures/institutions, commercial facilities, military & police force, and government (general/diplomatic). The effect of activities was then examined pertaining Monday to Friday (five-day working week in Pakistan followed by estimation of surprise factor i.e. days among two successive activities). Additionally, three macroeconomic variables of oil, gold, and exchange rate were considered to observe changes in returns. The results in this study suggest that the impact of terrorism diversifies with altering types of targets, days of the week, and surprise factor. These results are helpful for investors to design investment and portfolio management, and government for policy framework in order to improve the market efficiency to absorb the impact of such disruptions.

2 Literature Review

The response of stock markets towards terrorist attacks is an emerging issue in recent literature (Asteriou and Siriopoulos 2000; Athanassiou, Kollias, and Syriopoulos 2006; Christofis et al. 2013; Goel, Cagle, and Shawky 2017; Guidolin and La Ferrara 2010; Malik, Zhilong, and Ashraf 2019; Rigobon and Sack 2005; Zakaria, Jun, and Ahmed 2019). There were several studies conducted to empirically test the effect of terrorist attacks on the volatility of stock market (Drakos 2010; Eldor and Melnick 2004; Essaddam and Mnasri 2015; Hobbs, Schaupp, and Gingrich 2015; Karolyi and Martell 2010; Zussman and Zussman 2006) and negative effect of terrorism on stock markets returns were reported. The simultaneous effect of both volatility and market returns was also studied in various studies (Arin, Ciferri, and Spagnolo 2008; Barros, Caporale, and Gil-Alana 2009; Bautista 2003; Nguyen and Enomoto 2009; Nikkinen et al. 2008) and negative impact was reported. The extent of attacks varies with respect to country, the severity and type of attack (Aslam et al. 2018). Also, it was noticed that impact on stock markets is directly proportional to the attack severity (Aslam and Kang 2015; Eldor and Melnick 2004). However, being efficient financial markets have the capacity to absorb such shocks quickly (Chen and Siems 2004; Christofis et al. 2013; Coleman 2012; Nikkinen et al. 2008; Peleg et al. 2011). The literature mostly suggested limited impact of terrorist attacks on financial markets, and the duration is termed as shorter (Arin et al. 2008; Brounen and Derwall 2010; Chen and Siems 2004; Chesney, Reshetar, and Karaman 2011; Essaddam and Mnasri 2015). The permanent impact of stock markets was also reported scarcely in the literature (Eldor and Melnick 2004). Also, a greater effect of attacks was reported in stock markets of emerging economies, and vice versa (Arin et al. 2008). Most of the literature refers to developed countries while less work is conducted till date about emerging and developing nations.

The effect of terrorist events differs with stock market size, development and maturity (Berrebi and Klor 2010; Kollias, Papadamou, and Stagiannis 2011; Nikkinen et al. 2008). Various studies have reported the effects on stock markets of UK, US, Spain, Israel etc. (Arin et al. 2008; Butt, Masood, and Javaria 2020; Chen and Siems 2004; Coleman 2012; Karolyi and Martell 2010; Kollias et al. 2011; Masood, Javaria, and Petrenko 2020; Zussman and Zussman 2006). However, there are very few studies pertaining to Pakistan that examine the impact of terrorism on volatility of stock markets. Few of the noteworthy studies reported effect of 9/11 attacks (Ahmed and Farooq 2008), news of terrorist attacks (Suleman 2012), negative impact of terrorism (Aslam and Kang 2015) on the volatility of the market. It was also observed in previous studies that impact is short-term and the market recovers in a day and severity of an attack, being an important factor has a strong relationship with the magnitude of effect (Aslam, Eom, and Kang 2014).

3 Data and Methodology

3.1 Data

For this study, five datasets were used namely terrorist attacks, KSE-100 Index, Oil, Gold, and Exchange rates from 01-Jan-2000 to 31-Dec-2018.[1] The complete nexus of

1 Since this was the last date for data availability on terrorism events at Global Terrorism Database (GTD).

13,030 terrorist attacks causing 21,241 deaths and 36,761 injuries were reported in Pakistan as per the figures reported by Global Terrorism Database (GTD).[2] The GTD is one of the comprehensive terrorism databases containing information of 120 variables of transnational or international attacks. The timings of attacks were also considered. Any attack after the closing time of the stock market (3:30 PM) was considered on the next trading day (Aslam and Kang 2015). Furthermore, attacks on weekends and those with unknown or zero reported causalities were not included in analysis.

Table 1: Frequency distribution of major terrorist attacks (2000–2018).

Day of the week	No. of incidents	Target type	No. of incidents
Monday	74	Private citizens & property	93
Tuesday	44	Religious figures/Institutions	42
Wednesday	60	Commercial facilities	79
Thursday	74	Military and police force	74
Friday	87	Government (General/Diplomatic)	51
Total	339	Total	339

Source: GTD database.

A total of 339 major attacks were selected for analysis on the basis of number of injuries and casualties sharing the characteristics of attacks such as attack date, days of the week, and target type. The frequency distribution w.r.t. days of the week and target type of considered attacks are provided in Table 1. The highest number of attacks were reported on Fridays (87), followed by Mondays (74) and Thursdays (74). The terrorists mostly attacked on private citizens and their property (93), commercial facilities (79), and military and police forces (74).

The daily prices of KSE-100 Index, exchange rate of (PKR/USD), gold, and oil (Brent Oil) were collected from the Wharton Research Data Services[3] (WRDS) database which corresponds to 4627 observations.

The log returns of KSE-100 Index, exchange rate of (PKR/USD), gold, and oil (Brent Oil) were calculated by using Eq. (1).

2 At the University of Maryland, Global Terrorism Database (GTD) began in 2001. Initially, it was assembled by the "Pinkerton Global Intelligence Services" (PGIS) that was an open source database comprising information associated with terrorist attacks from 1970 to 2017. The information is relied on the reports from different open media sources and added after verification of the credible sources. The National Consortium for the "Study of Terrorism and Responses to Terrorism" (START) makes the GTD available via this online interface.

3 See Wharton Research Data Services (WRDS).

$$R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \tag{1}$$

where, $\boldsymbol{P_{i,\ t}}$ is the price at the day end, and $\boldsymbol{P_{i,\ t-1}}$ is the index price at period $\boldsymbol{t-1}$.

The summary statistics (measures of central tendency, shape, and dispersion) of KSE-100 Index, exchange rate, gold, and oil are depicted in Table 2. The KSE-100 index fluctuates from −7.74 to 8.51% with an average of 0.07% from 2000 to 2018. The fat tail of KSE-100 index returns can be confirmed by skewness (−0.2643). The average daily returns of gold (0.06%) remains higher than oil (0.04%) and exchange rate (0.02%). Although, the stock market of Pakistan offers highest average returns, but oil market depicts highest volatility of 2.56% as compared to others. Furthermore, the null hypothesis of normal distribution is rejected on the basis of Jarque-Bera test.

Table 2: Summary statistics (2000–2018).

Variable	R_{KSE}	R_{GOLD}	R_{OIL}	R_{ER}
Mean	0.0007	0.0006	0.0004	0.0002
Median	0.0010	0.0001	0.0010	0.0000
Maximum	0.0851	0.0820	0.1717	0.0953
Minimum	−0.0774	−0.0960	−0.3134	−0.0541
Std. Dev.	0.0134	0.0121	0.0256	0.0034
Skewness	−0.2643	0.2301	−1.1180	8.2516
Kurtosis	6.5353	10.8769	17.4419	241.7912
Jarque-Bera	2463.378	12002.61	41174	11045725
Probability	0.0000	0.0000	0.0000	0.0000
Observations	4627	4627	4627	4627

Source: Author's estimations

In agreement, the histogram of KSE-100 index returns superimposed by normal distribution is presented in Figure 1. It can be noticed that the returns exhibit fat tails and did not follow the normal distribution. As compared to normal distribution curve (orange) the histogram is peaked around zero. There are large number of small positive returns and small number of large positive returns noticed in the KSE-100 index.

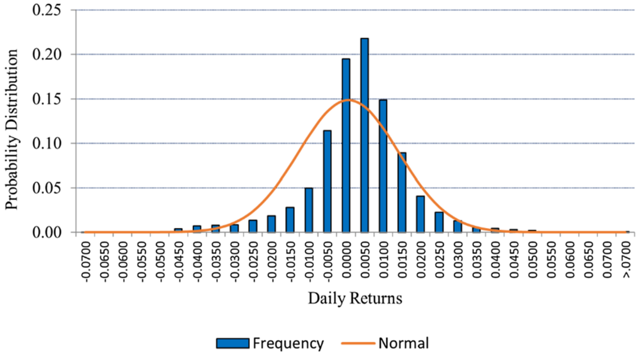

Figure 1: Histogram of daily KSE-100 returns and the normal distribution (2000–2018).

3.2 Stationarity Test

Since our study objective demand time series analysis, it is necessary to establish the stationarity of variables. In this regard we use Augmented Dicky Fuller (ADF) test to establish the order of integration. The results are presented in Table 3. The outcome of three models, i.e. without intercept, with intercept, and having both trend and intercept, show that all the variables used in estimation are stationary at 99 percent confidence level.

Table 3: Augmented Dicky Fuller test for unit root.

Model	ADF test statistics			
	R_{KSE}	R_{GOLD}	R_{OIL}	R_{ER}
$\Delta Rt = \delta R_t - 1 + \mu_t$	−61.0812***	−66.5922***	−65.5931***	−37.3383***
$\Delta R^t = \alpha + \delta R_t - 1 + \mu_t$	−61.0812***	−66.7454***	−65.5985***	−34.3871***
$\Delta Rt = \alpha + \beta T + \delta R_t - 1 + \mu_t$	−61.2229***	−66.7508***	−65.5981***	−34.4499***

*, **, *** denotes Significance at 90%, 95% & 99% confidence level.

3.3 Volatility Clustering

An important prerequisite to apply GARCH family of models is that we need to establish the presence of volatility clustering. Figure 2 shows the log return of KSE-100 index for the period January 1, 2000 to December 31, 2018. It is evident from visual inspection that periods of high volatility are followed by high volatility (e.g. 2008) and same holds for low volatility (e.g. 2013) periods. This advocates the presence of volatility clustering. The overall returns vary between –7.75% and +8.5% with an average of 0.07%.

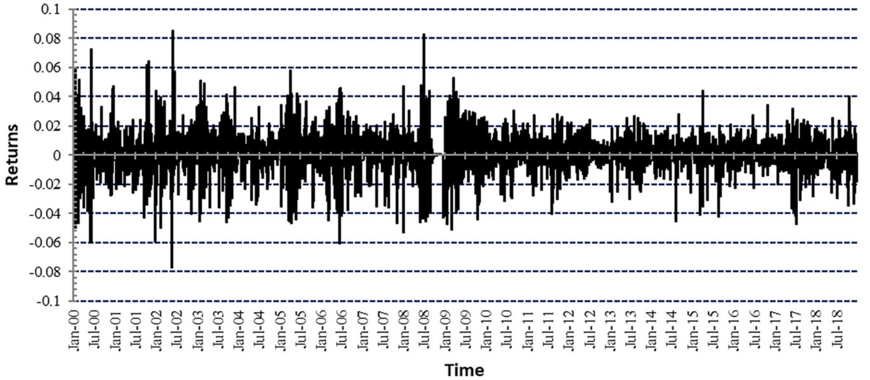

Figure 2: KSE-100 index % returns during Jan 1, 2000 – Dec 31, 2018.

3.4 ARCH Test

After establishing the evidence of clustering and hetroskedasticity from visual inspection of KSE-100 index series, we proceed to present the results of ARCH effect test which is essentially a white noise test but for the squared series. ARCH test is similar to Lagrange Multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). First, we estimate a linear model as defined in Eq. (2), which is then used to obtain residuals û.

$$RKSE, t = \alpha + \beta RKSE, t - 1 + \mu t \tag{2}$$

The squared residuals are regressed on its q lags to test the ARCH of order p (Eq. (3)).

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 \ldots\ldots + \alpha_3 u_{t-p}^2 + v_t \tag{3}$$

We test the null of homoscedasticity of residuals using LM statistic which is number of observations (T) times the R-squared of Eq. (8). Table 4 presents the results of ARCH(1) model and we reject the null of homoscedasticity at 99 percent confidence level. This establishes the presence of heteroskedasticity in our series based on T*R-squared vale of 500.99 and rejection of the null hypothesis.

Table 4: Findings of testing of ARCH effect.

Heteroskedasticity test: ARCH			
F-statistic	561.6193	Prob. F (1,4623)	0.0000
T*R-squared	500.9991	Prob. Chi-Square (1)	0.0000

Source: Author's estimation.

Considering the presence of clustering and conditional hetroskedasticity in our stationary series we proceed to choose Exponential GARCH model (EGARCH) model proposed by Nelson (1991) which solved the important shortcoming ARCH/GARCH. An EGARCH model not only addresses conditional heteroscedasticity, or volatility clustering, in an innovations process but also captures the asymmetric news effects. The specification for the conditional variance is given below.

3.5 Exponential GARCH (EGARCH) Model

In EGARCH model, variance depends on both the size and sign of lagged residual (Nelson 1991). In other words, it allows bad news (unfavorable) and good news (favorable) to have a different impact on volatility, and it allows big news to have greater impact on volatility. Furthermore, the dependent side is the log of the conditional variance which implies that the leverage effect is exponential, rather than quadratic. Generally, the specification for the conditional variance in EGARCH (1, 1) model can be postulated as:

$$log\,(\sigma^2{}_t) = \omega + \alpha|Z_{t-1}| - E|Z_{t-1}|) + \gamma Z_{t-1} + \delta log\,(\sigma^2{}_{t-1}) \tag{4}$$

where ω, α, β and γ are parameters for conditional variance estimation. The value of $\gamma \neq 0$ represent asymmetry effect in the variance. A significant negative (positive) value of γ confirms that negative realizations of the innovation generate more (less) volatility than positive realization. The parameter δ indicates the impact of the last period measures on the conditional variance, reflecting the weight of previous period's conditional volatility in the conditional volatility at time t. the parameter α measures the effect of previous period in the information set and explains the past-standardized residuals' influence on the current volatility.

3.6 Effect of Terrorist Attacks on Stock Market Volatility

As the purpose of this study is to capture the impact of terrorist attacks on volatility of stock market. Therefore, we incorporate that variables of interests (terrorist attacks) in the variance equation while the other variables of Gold, Oil and Exchange rates are incorporated in the mean equation. The EGARCH model will simultaneously model the mean and variance of KSE-100 index return series with the following specification.

$$Rt = \alpha + \beta_1 R_{Oil} + \beta_2 R_{Gold} + \beta_3 R_{ER} + \epsilon t \tag{5}$$

$$\epsilon t \sim iid\ N(0,\ \sigma_t^2) \tag{6}$$

where

$$Z_t = \epsilon_t / \sigma_t \tag{8}$$

Z_t is standard Gaussian, [ε_t ~ EGARCH], $R_{Oil,}$ $R_{Gold,}$ *and* R_{ER} represent the daily returns of oil, gold and exchange rate in Eq. (5).

To estimate the separate impact of target type and day of the week, we add series of dummy variables in EGARCH (1, 1) model by categorizing the terrorist attacks into two groups. A brief discussion of variance equations for every group is given below.

3.6.1 Target Type Effect

To find out the impact of different targets, 339 terrorist attacks are classified into five most common target types, namely Private Citizens & Property, Religious Figures/Institutions, Commercial Facilities, Military and Police Force and

Government (General/Diplomatic). Five distinct dummy variables are defined for each category as follows

$$TGT_{i,t} = \begin{cases} 1, \textit{if Target Type is } i \\ 0, \textit{ otherwise} \end{cases} \tag{9}$$

where i = *Private Citizens & Property, Religious Figures/Institutions, Commercial Facilities, Military and Police Force and Government (General/Diplomatic).*

$$log\left(\sigma^2 t\right) = \omega + \alpha|Zt - 1| - E|Zt - 1|) + \gamma Zt - 1 + \delta log\left(\sigma^2 t - 1\right) + \sum_{i=1}^{5} \beta_i TGT_{i,t} \tag{10}$$

3.6.2 Days of the Week Effect

Just like target types, the data revels certain patterns of terrorist attacks on different days of the week. To estimate the impact of these attacks on KSE-100 with respect to different days of the week, following five dichotomous dummy variables (i.e. for Monday to Friday) are defined as follows:

$$DAY_{i,t} = \begin{cases} 1, \textit{ if the day of terrorist attack is } i \\ 0, \textit{ otherwise} \end{cases} \tag{11}$$

where, i = Monday, Tuesday, Wednesday, Thursday, Friday

The above mentioned five dummy variables are incorporated in the following EGARCH (1, 1) model:

$$log\left(\sigma^2 t\right) = \omega + \alpha|Zt - 1| - E|Zt - 1|) + \gamma Zt - 1 + \delta log\left(\sigma^2 t - 1\right) + \sum_{i=1}^{5} \beta_i DAY_{i,t} \tag{12}$$

3.6.3 Surprise Effect

Finally, the simple regression methodology is used to examine the terrorist event surprise factor.The daily return of benchmark index is employed as a dependent variable while surprise factor (number of days) the difference between two terrorist events is used asan independent variable. The association between market returns and the surprise factor is hypothesized in Eq. (6).

$$R_{KSE,t} = \alpha + \beta\left(Surprise\_Factor\right) + \mu_i \tag{13}$$

3.7 Effect of Terrorist Attacks on Stock Market Volatility – A Markov Switching Model

We also consider tha effect of terrorist attack on stock market volatility may be asymmetric in nature. This stems from the argument that the direction and magnitude effect may differ across high and low volatility regimes of the market. In order to explore it we use Markov-Switching model with two regimes ($\boldsymbol{S_t}$ where t = 0, 1), i.e. high and low volatility regimes. Hence we assume that variance ($\boldsymbol{\sigma_{st}}$ where t = 0, 1) and coefficients of terrorist attack ($\boldsymbol{Z_{st}}$ where t = 0, 1) are regime-dependent. Here we run two separate models where this would be target type in the first model while day of the attack in the second model. It means that these parameters evolve around the regimes. The specification of our MS (2) models is as under

$$\sigma^2 t = \boldsymbol{\beta}_0 + \boldsymbol{\beta_{st}} TGT_{i,st} + \boldsymbol{\theta} \sum_{\boldsymbol{i}=1}^{3} \Delta \boldsymbol{X_i} + \boldsymbol{\varepsilon} \tag{14}$$

where $\boldsymbol{Z_{i,t}}$ are state dependent switching variables that is target type (five most common target types, namely Private Citizens & Property, Religious Figures/Institutions, Commercial Facilities, Military and Police Force and Government (General/Diplomatic) and day of the week in second model (Monday to Friday)). $\boldsymbol{X_{i,t}}$ are non-switching variables i.e. prices of Gold & Oil and Exchange rate. The probabilities of switching between regimes will be

$$S_t = \begin{cases} 0 \; with\, probability\, p_{00} \\ \\ 0 \; with\, probability\, p_{11} \end{cases} \tag{15}$$

and the probabilities of switching between two regimes can be expressed as:

$$P_r = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} and \; \sum_{j=1}^{M} p_{ij} = 1 \; for \; i = 1 \; and \; i = 0 \tag{16}$$

$\boldsymbol{p_{00}}$ and $\boldsymbol{p_{11}}$ are the probabilities of remaining in regimes 1 and 0 respectively, while $\boldsymbol{p_{01}}$ is the probability of switching from regime 0 to 1 and $\boldsymbol{p_{10}}$ is the probability of switching from regime 1 to 0.

4 Empirical Findings

4.1 Target Type and Stock Market Volatility

First, we estimate Eq. (10) for effect of target type on stock market volatility. As discussed in the data section we classify terrorist attacks into five categories namely; Private Citizens and Property, Commercial Facilities, Government, Military & Police Force and Religious. Each of these is a dummy variable taking the value “1” if terrorist attack was targeted on that category and 0 otherwise. In addition, we control for Exchange rate, Gold and Oil Prices. Results of EGARCH estimation are presented in Table 5.

All the variables appear with expected signs in mean equation where Exchange Rate is statistically significant. Its coefficient depicts that a 1% increase in exchange rate, depreciation of Pak Rupee, leads to decrease in stock market volatility by 27 percent. It is evident that investors would prefer to adjust their investment portfolio to increase dollar holdings for better returns in the expectation of further depreciations. In variance equation the coefficient of γ is negative and significant at 99 percent, showing existence of asymmetry in response of volatility to good and bad news. The coefficient, –0.0962, essentially means that the absolute effect of bad news is relatively more intense that good news. Further the ARCH and GARCH effects are statistically significant and the sum of their coefficients is close to unity indicating stationarity of GARCH model.

Table 5: EGARCH estimates of terrorist target on stock market volatility.

Variable	Coefficient	Std. Error
Mean Variance		
C	0.0014***	0.0002
GOLD	0.0064	0.0108
OIL	0.0012	0.0045
ER	−0.2793***	0.0420
Variance equation		
ω	−1.0808***	0.0654
α	0.3646***	0.0196
γ	−0.0962***	0.0098
δ	0.9100***	0.0065
Commercial facilities	1.5736***	0.1840
Military and police force	0.6070***	0.1420
Private citizens & property	−0.2446	0.1247
Religious	0.0556	0.1712
Government (General/Diplomatic)	0.2354	0.1954
Observations	4627	
Akaike info criterion	−6.0138	
Schwarz criterion	−6.0263	

s*, **, *** denotes Significance at 90%, 95% &99% confidence level.

The coefficients on target variables also appear with expected signs except Private Citizens & Property which is statistically insignificant. The coefficients with Commercial and Military & Police force dummy variables are statistically significant at 99 percent significance level and show that stock market volatility increases with such events. All other targets seem to be insignificant in having an effect on volatility of stock market. In relative terms an attack on commercial locations (1.58) has more severe effect on volatility than on security personnel (0.61). While the first leads to disruption of business activity the second category is basically an attack on country's security which also leads to unfavorable environment for investments.

Our results are in line with the literature like for example A. Karolyi (2006) highlighted that increased security costs and damages to corporate assets leads to changes in investment strategies and thus price changes. Larobina and Pate (2009) also argued that terrorist activities lead to disruption of supply chains, loss of life & communication and hence increased cost of doing business. Jain and Grosse (2009) linked terrorism with reduced Foreign Direct Investment, decreased trade activities and disruption to business processes. Terrorism creates an unstable economic environment in any country. Attacks particularly on commercial setups lead to disruption of routine business process and increases the risk for corporates. This in turn creates an unfavorable environment for investments. Hence the volatility of stock market increases. Similar is the case for attacks on security personnel, military or police force, which compromises the security conditions. For sustainable economic conditions it is necessary to have stable security conditions in a country. Terrorist activities increase the level of uncertainty which may then translate into increased volatility in stock returns.

4.2 Day of the Week and Stock Market Volatility

As already highlighted in methodology section we also explored the day of the week effect in case of terrorist attacks, considering that empirical literature already shows that day of the week anomaly exists in case of Pakistan Stock Exchange (Hussain et al. 2011; Rasheed, Sohail, and Nafees 2019). As discussed in data and methodology, we use dummy variable for each business day which takes the value of "1" if a terrorist attack took place during that day, while it is "0" otherwise. The results of EGARCH (1, 1) estimates are presented in Table 6.

The dummy variables included to capture day of the week effect are also significant at 99% confidence level and appear with expected signs except Friday which is insignificant. The findings show that an attack on Monday or Tuesday have high detrimental effect, a coefficient of 0.66 and 0.47 respectively, meaning an increased volatility by 66 and 47 percent. This is intuitive as these are start of working days and any such event will have serious consequences for business and investment. The leading effect is in case of Thursday which is an increased volatility of 68 percent.

Table 6: EGARCH estimates of attack days-of the week effect on stock market volatility.

Variable	Coefficient	Std. Error
Mean Variance		
C	0.0013***	0.0002
GOLD	−0.0339***	0.0089
OIL	0.0299***	0.0040
ER	−0.1642	0.0699
Variance equation		
ω	−0.9686***	0.0589
α	0.3436***	0.0177
γ	−0.0870***	0.0093
δ	0.9208***	0.0059
Monday	0.6578***	0.0768
Tuesday	0.4669***	0.1043
Wednesday	−1.2686***	0.3194
Thursday	0.6822***	0.1325
Friday	−0.1572	0.1473
Observations	4627	
Akaike info criterion	−6.0238	
Schwarz criterion	−6.0363	

*, **, *** denotes Significance at 90%, 95% &99% confidence level.

4.3 Surprise Effect Analysis

Finally, we present the estimates of surprise factor which is essentially a variables showing number of days between two consecutive events. With more uneventful days between two terrorist attacks, the surprise factor increases, which may lead to stronger response to an attack as against a generally unstable security conditions when such attacks are expected by the general public and government authorities. The results are presented in Table 7.

Table 7: Surprise effect analysis during 2000–2018.

Variable	Coefficients	Std. Error
Intercept	0.0025***	0.0009
Surprise factor	−0.0006***	0.0001
Durbin-Watson test:		
DW	1.8430	
Breusch–Pagan test:		
F-statistic	1.1948	
No. of observations	339	

*, **, *** denotes significance at 90%, 95% & 99% confidence level.

Considering the Durbin-Watson (DW = 1.84) and Breusch–Pagan (F-stat = 1.19) test statistic, the model is free from autocorrelation and heteroskedasticity. The coefficient with surprise factor is statistically significant at 99 percent level of significance. The coefficient shows that with increased gap between two events leads to larger adverse effect on stock returns. Evidently a gap of one uneventful day leads to increase in an effect of 0.06 percent. Our results are in line with literature where for example (Taleb 2007) highlighted that unpredictable, infrequent and high-impact occurrences are usually not expected. The author emphasized that with more uneventful days leading to more gap in severe events people develop 'collective blindness', making these events more hazardous. (Griffin and Tversky 1992) showed that psychological biases gain strength during periods of uncertainty. As is evident from results as well, with more number of uneventful days the repercussion of a terrorist attacks is more severe. With less gap in events people tend to treat them as routine occurrences unless directly affected. (Gul et al. 2010) termed this to be cold-blood attitude of investors. However, it seems to be a natural human phenomenon. Countries with more unrest tend to have people with higher tolerance level for such activities.

4.4 Markov-Switching Results of Stock Market Volatility

We also applied Markov Switching Model to examine the differing impact of these terrorist activities across various regimes of Volatility. The results are placed in Table 8. These results also strengthen the EGARCH model estimates and show that during both regimes an attack on any of the targets increases volatility which seems to be theoretically plausible. However, the coefficient with commercial facilities is not statistically significant for low volatility regime (Regime 1). Another logical outcome of the switching results show that an attack on any of these facilities during high volatility regime (Regime 2) increases volatility more than during the low volatility regime (Regime 1). This being an intuitive outcome considering that during high volatility periods the security situation and economic conditions are already unstable.

The switching probabilities also present persistence of both regimes in their specific states but the probability of low volatility to stay in low volatility regime (98.4 percent) is higher than the probability of high volatility to stay in high volatility period (96.6 percent). Hence a high volatility regime has a probability of 3.4 percent for switching to low volatility state.

Similar to our Target Type analysis we also used Markov Switching Model to examine the differing impact of days of the week across various regimes of Volatility. The results placed in Table 9 show that an attack on any of the days in a week

Table 8: Markov switching results with target type.

Variable	Coefficient	Std. Error
Regime 1		
Commercial facilities	0.00339	0.004339
Military and police force	0.008858***	0.001955
Private citizens & property	0.007632***	0.001353
Religious	0.006807***	0.001678
Government (General/Diplomatic)	0.007491***	0.002557
Log(Sigma)	0.0072467	0.0001355
Regime 2		
Commercial facilities	0.022635***	0.007505
Military and police force	0.018007***	0.007738
Private citizens & property	0.013786***	0.00631
Religious	0.018475***	0.00853
Government (General/Diplomatic)	0.009028***	0.019545
Log(Sigma)	0.0183597	0.0004396
Non-switching variables		
GOLD	0.027215*	0.012817
OIL	0.001307	0.006454
ER	0.132306***	0.047894
Switching probabilities	$\begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} 0.984 & 0.016 \\ 0.034 & 0.966 \end{bmatrix}$	
Portmanteau test – Standardized residual	8.9745 [*P*-value: 0.1029]	
Portmanteau test – Standardized squared residual	7.3238 [*P*-value: 0.1174]	

*, **, *** denotes significance at 90%, 95% &99% confidence level.

lead to increased volatility. However, a cross comparison of each day across the low volatility (Regime 1) and high volatility (Regime 2) regimes show that relative increase in volatility due to an event during high volatility state is larger during Regime 2. This is again a plausible result considering that an already volatile economic condition triggers more panic among investors if the security situation worsens.

Finally, we used portmanteau test of Ljung and Box (1978) on the standardized and standardized squared residuals for autocorrelation in both the models. The results show that models have no issue of autocorrelation. However, the *P*-values barely fail to reject the null of white noise, leading us to assign equal importance to EGARCH results for their interpretations, especially considering that they are generally in line with the markov-switching results. Additionally, these regimes based estimates show overreaction by investors where any such event during high volatility period increases volatility more than low volatility periods. This further strengthens results based on GARCH family, since such overreaction leads to

Table 9: Markov switching results with attack days-of the week.

Variable	Coefficient	Std. Error
Regime 1		
Monday	0.007061***	0.000927
Tuesday	0.00801***	0.000858
Wednesday	0.007592***	0.00126
Thursday	0.007492***	0.001293
Friday	0.007558***	0.000687
Log(Sigma)	0.007254	0.000136
Regime 2		
Monday	0.022985***	0.003879
Tuesday	0.015768***	0.002053
Wednesday	0.011268***	0.000909
Thursday	0.017006***	0.002407
Friday	0.015795***	0.002631
Log(Sigma)	0.018372	0.000439
Non-switching variables		
GOLD	0.027114*	0.014117
OIL	0.000679	0.007215
ER	0.1319***	0.043002
Switching probabilities	$\begin{bmatrix} 0.984 & 0.016 \\ 0.034 & 0.966 \end{bmatrix}$	
Portmanteau test – Standardized residual	9.727 [*P*-value: 0.1008]	
Portmanteau test – Standardized squared residual	7.3118 [*P*-value: 0.1097]	

*, **, *** denotes Significance at 90%, 95% &99% confidence level.

volatility clustering, which is the main reason for applying EGARCH model. Our findings are in line with the studies of (Hussain et al. 2011; Rasheed, Sohail, and Nafees 2019; Veronesi 1999).

5 Conclusion and Recommendations

Terrorism, apart from being a threat to the nation, damages the country image, economic growth, and financial markets. Pakistan is also among countries affected by the stigma of terrorism. The financial impact of 339 terrorist activities categorized on the basis of target type, days of the week, and surprise factor was estimated for a period of 18 years (2000–2018). The effect differs w.r.t. days of the week, target type and surprise factor. Highest attacks were reported on Fridays, followed by Mondays and Thursdays with most attacks on private citizens and their properties, commercial facilities, followed by military and police forces. More interestingly, terrorist attacks with larger surprise factors have a significantly larger negative impact on stock returns, ceteris paribus.

Despite limitations, this study has important managerial implications for investors and regulators. Particularly the institutional investors having a large pool of flexible cash flows, are interested in the market's movements instead of individual stocks. By considering the influence of terrorist attacks on stock market volatility regarding the days of the week, the target of the terrorists and surprise factor, the investors could manage their investment and portfolio strategies. The findings reveal that terrorist attacks on commercial facilities are essentially destructive for the stock market. The firms can minimize the impacts of terrorist shocks by reducing the incentive to attack by increasing their own security (Frey 2009). Furthermore, an improvement in credibility and information dissemination can improve the market efficiency to absorb the impacts of such shocks. Furthermore, Military and other security forces should take extra precautions to protect commercial facilities. For instance, on June 29, 2020, Pakistan Stock Exchange (PSX) was the target of a terrorist attack. The situation was brought under control in less than 12 min as security forces (Police and Rangers), dealt with the situation effectively and in a timely manner. As a result of this, The Stock Exchange continued to function normally and did not close for even a minute. Finally, an integrated anti-terrorism policy from security and exchange commissions and defense institutions to provide a timely, rapid and effective response to such terrorist events would be beneficial to minimize the financial impacts. The high-frequency data have complex attributes. The study can be extended to analyze the impact of such terrorist events on trading behavior by using intra-day prices. Furthermore, the reaction of different industries can also be considered.

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