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Terrorism and Stock Market Nexus: New Evidence from Wavelet Analysis

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Abstract: *This study examines the impact of terrorism on Karachi stock market returns. Daily data of KSE100 index from 1st July 1999 to 31st December 2015 is used for the empirical analysis. The objective of this paper is to examine the change in systematic risk in response to the terrorist activities. Multiscale data derived from Maximal Overlap Discrete Wavelet Transformation (MODWT) was used to test the heterogeneous market hypothesis. The results showed no relationship between Terrorism and increase in the systematic risk for KSE100 index returns mainly in short-run.*

Keywords: Terrorism, KSE100 index, wavelet, decomposition, MODWT.

Introduction

Over the two decades several studies have examined the financial markets response to terrorist attacks and concluded that the financial markets reacted differently and these terror events showed mixed influence on stock markets; in some studies it was noted that terror attacks have limited and short lived impacts Chen and Siems (2004); Cam (2008); Chesney, Reshtar, and Karaman (2011) and conclude that the financial systems and institutions have become robust and can absorb terror shocks without influencing stock returns. On the contrary Eldor and Melnick (2004); Eckstein and Tsiddon (2004); Drakos (2004); Arin, Ciferri, and Spagnolo (2008); Apergis and Apergis (2016); Mnasri and Nechi (2016); Arif and Suleman (2017) have shown that after every terror attacks both the systematic risk and idiosyncratic risk increase substantially and their effect remains for the longer period.

Both of these contradicting conclusions may well be due to the fact that there are several time scales involved in the relationships and for the true understanding of the relationship between terrorism and stock market returns, conventional analyses may not be adequate to incorporate the time scale structured relationships. Therefore, this research attempt to empirically investigate the relation between terrorism and stock market returns by using wavelets analysis. Wavelet analysis will enables us to filter out different time scales of variation in the data. Enhancement of Fourier analysis into Wavelet analysis, which allow decomposing of time series data at different frequencies, by localizing each frequency in its time domain, is a powerful tool, which makes it probable to quantify correlations between time series at different time horizons.

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This research study contributes to the body of research on this subject by investigating the impact of terrorist attacks on market returns at different time-scale which has not been attempted before. This research will be useful for investors who take investment decisions in the stock markets where exist diverse subgroups of investors incline toward various time horizon for their investment decisions. There are intraday traders, commercial banks, international portfolio managers, large multinational corporations, domestic central banks, and hedging strategist. All these market players are recognizably not quite the same from the perspective of investment time duration. A true dynamic structure of the relationship between terrorist attacks and stock market returns is a need to cater the diversity in the investment time span among investors, which should allow variation over different time scales associated with those distinctive investment time spans. Due to the absence of analytical tool, almost all earlier studies have only focused on long and short-run, two-time-scale analysis. Recently, wavelet analysis pulled in consideration as a means of filling this gap.

Wavelet analysis will enable researcher to use various time scale data of terrorism and stocks returns and will allow to research the connection between terrorism and stock returns whether expected stock returns react distinctively to the terrorist assault over the diverse time horizons. This approach relies upon a wavelet multiscaling procedure that separates a given time series on a scale-by-scale premise. The primary favorable position of wavelet analysis is the adaptability it gives in demonstrating financial market heterogeneity by breaking down the data into a several time scales and the capacity to deal with nonstationary data, localization in time, and the resolution of the signal in terms of time scale of investigation. Since it is likely that there are the various basic decision-making time scales among dealers, the genuine dynamic structure of the connection between the stock returns and terrorist attacks itself will change over various time scales related with those distinctive horizons. Wavelet analysis expands past examinations that were just contrasted and compared the short run and the long run relation.

Wavelet analysis has been used in studying the relationship between share price and exchange rate (Tiwari, Bhanja, Dar, & Islam, 2014), stock market returns comovement (Rua & Nunes, 2009), macroeconomic variables and stock markets return (Jammazi, 2012) etc. but have not seen any literature where wavelet analysis has been used to study the impact of terrorist attack on stock market returns. This is the first attempt to investigate the relationship between stock returns and terrorism, using wavelet analysis and hence examines stock returns and terror over the different time scales.

This paper first introduce wavelet analysis with the focus on its features useful for analysing the impact of terror attacks on stock market returns. It begins with Fourier analysis, and then the paper moves to the main features of wavelet analysis largely focusing on the application of time series analysis. Finally, results and conclusion is presented.

Wavelet Analysis

Fourier Transform

Wavelet analysis has its origin in Fourier analysis. Fourier analysis help to represent any wave function as a sum of infinite sine and cosine functions called the Fourier representation. It means that any function $f \varepsilon L^2 [-\pi, \pi]$ can be represented as:

$$f(x) = \frac{1}{2}a_0 + \sum_{j=1}^{\infty} (a_j sin\,(jx) + b_j cos\,(jx)) \tag{1}$$

The sines and cosines function in equation 1 are Fourier basis functions and are exceptionally useful for representing a stationary time series. By reducing the summation in equation 1 to some finite upper limit can still be use to well-approximate the function.

$$H_J(x) = \frac{1}{2}a_0 + \sum_{j=1}^{n} (a_j sin\,(jx) + b_j cos\,(jx)) \tag{2}$$

Above equation (2) representing Fourier series can be use to present any $L^2[-\pi, \pi]$ function with the help of two basis sine and cosines functions. However, in case of changing frequencies over time Fourier analysis fails to represent the actual function truly and it average out the changing frequencies over the whole function. It happens because equation (1) consist of sine and cosine functions which are periodic in nature. To overcome this limitation Short Time Fourier Transform (STFT), also known as Windowed Fourier Transform (WFT) was introduced to measure the variation in frequency of a signal. The major advantage of WFT is that simultaneously it can give information about signal frequency and time domains. WFT allows, to divide a signal into several segments, and frequency of each segment is analysed separately. The thought behind window is to localize the signal in time. WFT gives information about both when and what frequencies a signal event occurs but with limited accuracy. The problem of WFT is that once a window size is chosen it remain same for all frequencies another problem with WFT is that if a change in the frequency occur within the width of window it will remain unable to analyse the signal.

Wavelet Transform

A wavelet is a small wave which grows and decays in a finite time period and it is denoted by $\psi(.)$. Any wave such as sine wave, which grows and decay repeatedly over an infinite time period can be represented as a sum of these wavelets. For a function to be classified as a wavelet it must have following properties:

- The integral of $\psi(.) is 0$:

$$\oint_{-\infty}^{\infty} \psi(u)du = 0 \tag{3}$$

- The integral of the square of $\psi(.)$ is unity:

$$\oint_{-\infty}^{\infty} \psi^2(u)du = 1 \tag{4}$$

- Admissibility condition of $\psi(.) is 0$:

$$C_\psi = \oint_{-\infty}^{\infty} \frac{|\Psi(f)|^2}{f} df \quad satisfies \quad 0 < C_\psi < \infty \tag{5}$$

Equation (3) discloses that any journeys the wavelet function ψ makes over zero, must be counterbalanced by journeys beneath zero. Equation (4)suggest that ψ must have some displacement from its starting point. Equation (5) state that the signal to be analysed can be reconstructed if admissibility condition satisfied.

Fourier Transform v/s Wavelet Transform

Although wavelet analysis has its root in Fourier analysis, the two analytical techniques have some similarity and some dissimilarity. Here we will only discuss the distinctive advantages of wavelet analysis over Fourier analysis. Unlike fourier transformation, Wavelet transformation allow decomposition of data into several time scales rather than frequency domain. This characteristic of wavelet transformation enable researcher to investigate the behavior of the signal over various time scales. Wavelet analysis allow varying windows which is useful for isolating signal discontinuities using short basis functions, and for detailed frequency analysis long basis functions can be used. Finally, wavelet analysis handle non-stationary data very efficiently.

Discrete Wavelet Transform

Discrete Wavelet Transform (DWT)is a powerful tool for a time-scale multi-resolution analysis on time series and it is due to its favorable characteristics it has attracted researchers attention. Despite the fact that DWT has been around for a long while, just of late it has been taken as a guarantee by the researcher to aid data examination for time series. DWT has the power to separate an original time series into various time-scale components, each of which may convey significant information of the original time series. It has been used by researchers for a wide range of analyses on the decomposition of an original time series in audio and video information, image data and medical time series information, and obtained superior results but not much practiced in the area of evaluation of stock prices and yields. Moreover, no research has examined the impact of terrorism on the stock market index using decomposed data by DWT.

Discrete wavelet transform transforms a time series using a set of basis functions called wavelets. It separates time series data components into different frequencies at different time scales. For any time series, the number of repetition of the event in a unit time is called frequency of the time series and the time interval between the repetitions of the event for the time series is called time scale. For instance, a time series with a frequency of five events in a minutes represents a time interval (scale) of 12 seconds. Therefore, when DWT is applied to a time series data it decomposed the original time series at different scales (interval) and different series are generated which separated hidden but meaningful sub-series of the original time series. This decomposed series, which may convey the information in a more meaningful manner are then used for the test of hypothesis.

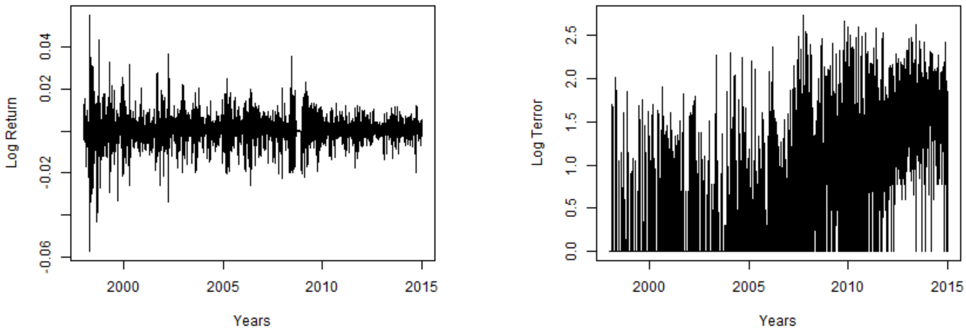
Data & Methodology

We used daily data (5 days per week) from Yahoo Finance for KSE100 index for a total of 4149 observations. We define daily returns as logarithmic differences of stock indices. For terrorism impact factor index we used publicly available information on terrorist event mainly provided by Global Terrorism Index (2012); GTD (2016), and followed Arif and Suleman (2017) in defining terror index as the natural logarithm of (1 + 3 * number of human casualties + 0.5 * number of people injured + number of terrorist attacks + property damage) occurred each day. Data for the terror events are collected from the GTD Database. The terror events that occurred during the weekend are summed up to the next following Monday's figure. For financial data we used daily stock price from Yahoo Finance over the period 1999(Jul) to 2015(Dec), for a total of 4149 observations.

In Figure 1a & 1b, we plotted the KSE100 index daily log return and daily log TIF time series for Pakistan. Figure 1 shows the significant fluctuations in both the series. Log return series shows a large variation during the 1999 - 2000 period, this is the period when political situation in Pakistan was very volatile (corruption cases against political leaders, Kargil war, army coup and deposition of Prime minister etc.) Similarly in 2002 volatility and brisk movement remaining the key features, a positive shift in economy's fundamentals helped to sustain abnormal gains throughout the year. Similarly 2007-2008 have also been event filled for Karachi Stock Exchange. It reached to its highest benchmark of 14,814 index point on December 26, 2007, a day prior to the death of previous Prime Minister Benazir Bhutto, when the record plunged. However, it recuperated rapidly and accomplished a noteworthy milestone when KSE-100 Index passed the psychological level of 15,000 without precedent for its history and crested 15,737.32 on 20 April 2008. In May 2008, unexpected rise in the interest rate by State Bank of Pakistan brought end to the upward journey of KSE-100 index and brought a sharp fall and it dropped one-third from an all-time high. Moreover, mistrust on Pakistan's coalition government to tackle Taliban militants worsens concern about the country's economic miseries. In August 28 to December 14, Karachi Stock Exchange set a floor for stock prices to halt a plunge. In Figure **??** we can note that after Lal Masjid Operation July 2007, the intensity of terror impact factor has increased and it continued till the end of the studied period which show the retaliation from the terrorist group against the series of military operation launched against them, during different periods details of which are as follows, South Waziristan Operation 1 (January 2008 May 2008), South Waziristan Operation 2 (June 2009 Decmber 2009), Orakzai and Kurram Operations (September 2009 June 2010), Momand Operation (November 2009), Bajaur Operation (August 2008 February 2009), Swat Operation (May 2009 July 2009), Operation Zarb-e-Azb (June 2014). However, after launching of Zarb-e-Azb the hint of decline in the terrorist attack can be noted.

The graph of both time series show that there is a high frequency change on daily bases which justify for the use of daily data for the testing of the hypothesis and analyzing the relationship between terrorism and stock returns. The data analysis based on daily observations will also allow us to analyze the relationship more accurately in the shorter period.

Figure 1
Two studied time-series



(a) Daily KSE100 Index Log return

(b) Log terror impact factor

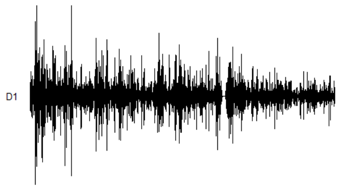
Wavelet Decomposition

Several researches have studied the relationship between terrorism and stock market movement but none of these researches have assumed that in the datasets of these variables there are many periods, and not just one time scale can be set up as an appropriate time scale in a particular study (Raza, Sharif, Wong, & Karim, 2016).

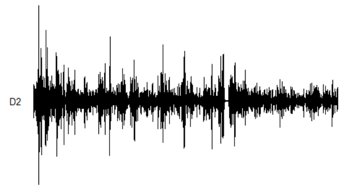
Subsequently, to investigate the co-movement of terrorism and stock market, this research use time-frequency-based approach 'wavelets' which allow investigation of time series data at different time horizon. It is an intrinsic attribute of wavelets to take care of non-stationary data and does not require pre-processing of the data. Figure-2 and 3 exhibit the multi-resolution analysis (MRA) of order $J = 6$ for SM and TR by utilizing Maximal overlap discrete wavelet transform (MODWT) using Daubechies (1992) least asymmetric (LA) wavelet filter. The plot of orthogonal components $(D_1, D_2, ..., D_6,)$ show the different filtered frequency components of the original series in details. The empirical results show that the high frequencies are found in the shorter period of both series. Moreover, the variation in SM and TR has become more stable in the longer periods.

Table 1 presents the Energy Decomposition for SM and TR at each scale. Using this energy decomposition we can explain the relationship between studied quantity in five periods, D1 represent daily, D2 represents mid of the week, D3 represents weekly, D4 fortnightly and D5 represents monthly time scales (period). From the table **??** it can be noted that most of the variance in both the studied variables exist in D1 D2 and D3. The variance in the series of SM occurred 44.29%, 24.31%, 13.84%, 6.90% and 4.69% in daily, half weekly, weekly, fortnightly and monthly respectively. In contrast the variance in TR series transpire 12.33%, 6.91%, 2.817%, 1.57%, and 1.24% in daily, half weekly, weekly, fortnightly and monthly respectively.

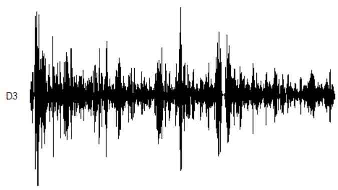
Figure 2
MODWT decomposition of SM on $J = 6$ wavelet level



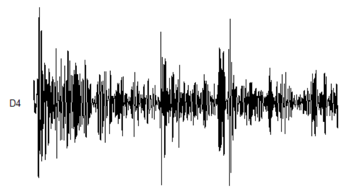
(a) $D_1 = 1 - 2\ days$



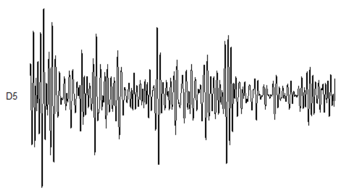
(b) $D_2 = 2 - 4\ days$



(c) $D_3 = 4 - 8\ days$

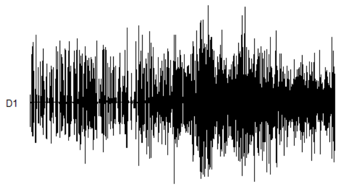


(d) $D_4 = 8 - 16\ days$

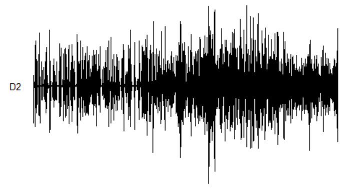


(e) $D_5 = 16 - 32\ days$

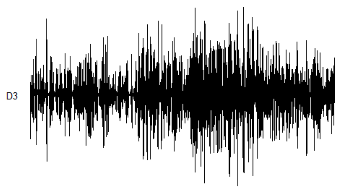
Figure 3
MODWT decomposition of TR on $J = 6$ wavelet level



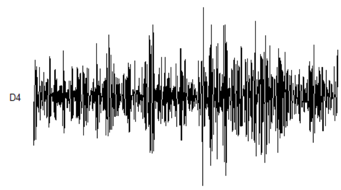
(a) $D_1 = 1 - 2\ days$



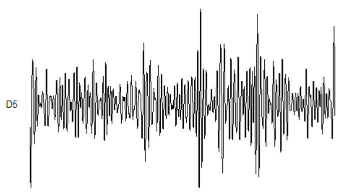
(b) $D_2 = 2 - 4\ days$



(c) $D_3 = 4 - 8\ days$



(d) $D_4 = 8 - 16\ days$



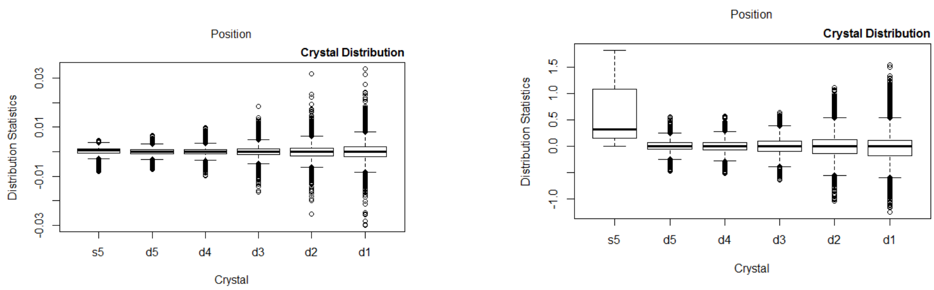
(e) $D_5 = 16 - 32\ days$

Table: 1
Energy Decomposition for SM and TR

Wavelet Scales	**TR**	**SM**
D1 (1-2 day cycles)	12.33%	44.29%
D2 (2-4 day cycles)	6.91%	24.31%
D3 (4-8 day cycles)	2.87%	13.84%
D4 (8-16 day cycles)	1.57%	6.90%
D5 (16-32 day cycles)	1.24%	4.69%
S5 (above 32 days cycles)	75.05%	5.95%

Source: Authors' estimations.

Figure 4
Crystal energy distribution for SM and TR



(a) SM (b) TR

Figure 4 presents crystal distribution of both TR and SM series. MODWT technique is used to draw the Crystal distribution which is a box plot. This distribution show that most of the energy is in the D1, D2, and D3 crystal for both TR and SM. Therefore for the studied data it can be assumed that decompose data for D1, D2, and D3 are the most suitable for further causal study and determination of the true relation between terrorism and stock market returns.

ARDL Model

Finally at this juncture to extract more meaningful results from this study we minutely investigated the impact of terrorism on stock market returns by utilizing decomposed time series data for different time-scale using following econometric model:

$$SMD_t = \alpha + TRD_t + e_t \tag{6}$$

We employed Autoregressive-Distributed Lag (ARDL) bounds tests approach, introduced by Pesaran, Shin, and Smith (2001) to investigate the relationship between terrorism and the stock market index. The extent of long term as well as short-term dynamics between terrorism and stock market returns were assessed .

The ARDL model is a regression of one variable on its own past and on the present and past values of a number of other variables. The ARDL has various practical advantages: first, this approach to testing the existence of a relationship between the variables is applicable regardless whether the underlying regressors are stationary. The variables are not required to be I(0) or I(1) or fractionally integrated. The ARDL model does not require a unique level of integration of the variables that is no unit root pre-test is required. (A stochastic process is said to be stationary if its mean and variance are constant over time, i.e. time invariant. By contrast, a non-stationary time series will have a time-varying mean or a time-varying variance or both which renders many alternative statistical tests invalid). Second, the ARDL model takes sufficient numbers of lags into consideration to capture the data generating process in a general-to-specific modeling framework.

In addition to the above two mentioned advantages, Narayan and Narayan (2006) reaffirm that the ARDL co-integration model is efficient and unbiased and at the same time, is able to capture the short-run and long-run components of the model simultaneously.

Specifically, the ARDL models used in this study are as follows:

$$\Delta SM_t = \alpha + \sum_{i=1}^{k} \phi_i \Delta SM_{t-i} + \sum_{j=0}^{k} \beta_j \Delta TR_{t-j} + \delta_1 SM_{t-1} + \delta_2 TR_{t-1} + e_t \tag{7}$$

Where SM is stock market movement decomposed series on 1-2 day, 2-4 days, 4-8 days, 8-16 days, and 16-32 days time horizon. Similarly we used terror index (TR) movement for equal time horizon. e_t and Δ are the white noise term and the first difference operator, respectively. An appropriate lag selection is done based on Akakie Information Criterion (AIC). The bounds testing procedure based on the F-statistic was used to test the null hypothesis of no cointegration, against the alternative of the existence of cointegration. The calculated F-statistics lies above the upper level of the band, the null is rejected, indicating cointegration. If the calculated F-statistics is below the upper critical value, we cannot reject the null hypothesis of no cointegration.

If there is a cointegration between the variables, Eq. (8) presents the long-run model and Eq. (9) shows the short-run dynamics:

$$SM_t = \alpha + \sum_{i=1}^{m} \phi_i SM_{t-i} + \sum_{j=0}^{n} \beta_j TR_{t-j} + \mu_t \tag{8}$$

$$\Delta SM_t = \alpha + \sum_{i=1}^{k} \phi_i \Delta SM_{t-i} + \sum_{j=0}^{k} \beta_j \Delta TR_{t-j} + \psi ECT_{t-1} + \zeta_t \tag{9}$$

where ψ is the coefficient of error correction term (ECT). It shows how quickly variables converge to equilibrium and it should have a statistically significant coefficient with a negative sign.

Empirical Analysis

Unit Root Test Results

ARDL technique allows its use without considering the order of the data series which is either I(0), I(1) but it should not be generated by I(2) process (Pesaran et al., 2001). Therefore, it is mandatory to test the level of stationarity. For this reason we utilize the Augmented Dickey Fuller (ADF) unit root test to check the stationary of the data series. The results of the ADF tests are presented in Table 2. It is evident from the ADF results that all series are integrated at I(0). Vitally, none of the data series are I(2) or above. Subsequently, we are supported for utilizing the ARDL estimators.

Table 2
ADF Unit Root Test

	C				C & T			
	I(0)		**I(1)**		**I(0)**		**I(1)**	
	t-stats	p-values	t-stats	p-values	t-stats	p-values	t stats	p values
SMD1	-35.120	0.000	-37.862	0.000	-35.115	0.000	-37.857	0.000
SMD2	-26.765	0.000	-30.768	0.000	-26.761	0.000	-30.764	0.000
SMD3	-23.203	0.000	-32.429	0.000	-23.201	0.000	-32.425	0.000
SMD4	-18.754	0.000	-29.286	0.000	-18.752	0.000	-29.282	0.000
SMD5	-12.705	0.000	-24.182	0.000	-12.703	0.000	-24.179	0.000
TRD1	-32.239	0.000	-36.945	0.000	-32.235	0.000	-36.940	0.000
TRD2	-27.138	0.000	-30.689	0.000	-27.135	0.000	-30.686	0.000
TRD3	-23.458	0.000	-32.110	0.000	-23.455	0.000	-32.107	0.000
TRD4	-17.134	0.000	-31.424	0.000	-17.132	0.000	-31.420	0.000
TRD5	-12.063	0.000	-26.066	0.000	-12.061	0.000	-26.063	0.000

Source: Author's estimation

After confirmation of stationarity of all series at order I(0) following Pesaran et al. (2001) who supported the testing of the relationship between variables independent of whether the underlying regressors are mutually cointegrated, simply I(1)or simply I(0). we proceed with ARDL bounds testing procedure for establishing the long-run relationship between terrorism and stock market returns. Their fundamental statistical procedure was the well-known Wald or F-statistic. They stated that it is not important to know the integration/cointegration status of the fundamental regressors if the calculated F-statistic or Wald statistics is greater than the critical value bounds, and an irrefutable inference can be drawn. However, knowledge of the order of the integration of the underlying variables is required before definitive inferences can be made if the F-statistic or Wald statistics is lesser than critical value bounds, without which the inference will be inconclusive.For this purpose we estimated Eq. 7 by OLS techniques and joint F-statistics is calculated and are presented in Panel-B of Table 3. The F-statistics is well beyond the critical value at 1% level of significance. So we proceed with ARDL bond test and it is reported in table 3.

AIC criteria was used to determine the optimum level of lag selection. Base on the bond test results for all five models (Table 3) the null hypothesis of no long-run relationship was rejected. In other words, existence of no cointegration in the series of data is rejected. Hence ARDL bounds test analysis shows evidence of a long-run equilibrium relationship between the terrorism and stock returns.

Table 3
The long-run estimates ARDL Models

	Dependent Variables				
Panel- A: Long-run Estimates					
Regressors	SMD1	SMD2	SMD3	SMD4	SMD5
Lag Length	12,0	12,0	11,0	12,0	12,0
TRD1	0.00003	-	-	-	-
TRD2	-	-0.00001	-	-	-
TRD3	-	-	-0.00003	-	-
TRD4	-	-	-	-0.00016	-
TRD5	-	-	-	-	-0.00012
F-Statistics calculated	3523.04	1228.351	681.773	534.045	202.805
Upper Bound Critical Value	7.84(0.001)	9.63(0.001)	9.63(0.001)	9.63(0.001)	9.63(0.001)

Source: Author's estimation

The results of the bi-variate long run estimates between terrorism and stock market index are presented in Table 3. Results show that in long run for 2-4 days, 4-8 days, 8-16 days and 16-32 days cycle; terrorism has a negative and insignificant impact on stock market index. However, for 1-2 days cycle terrorism has a positive but again insignificant impact on stock market index. Moreover, very small coefficients of the terrorism in all the five models further support the conclusion that the terrorism has insignificant effect on stock market index.

Conclusion

In this paper, we explore the empirical evidence of the impact of terrorism on Pakistan stock market index. The novelty of this paper lie in the fact that it has used the continuous wavelet approach to examine a causal relationship between the terrorism and the return series of share price index. We used decomposed time frequency data for 2-4 days, 4-8 days, 8-16 days and 16-32 days cycle. To the best of our knowledge, we can proclaim that this is a first ever study that has used this approach to investigate the terrorism and stock price index nexus. We use daily data of KSE100 index from January 1, 2000 to December 2014. We noted from energy decomposition and crystal energy distribution for terror and stock market index data that the most of variation in the data exist during the 1-2 day, 2-4 day, and 4-8 day cycle. After running the test for the given time-frequency, results support that terror events do not influence Pakistani equity market index significantly over different time scales.

The result, reinforce that continued existence of terrorism in reality for extended period prepare the minds of people for it and terrorism becomes a common factor in business risk assessment, and financial markets sensitivity to terrorism incidents relatively becomes insensitive. Furthermore, this study illustrate that when a man-made disaster becomes a 'natural' part of the environment, market disruptions and consumer confidence may not be affected. In other words, market sensitivity to terrorism erode over time as terrorism becomes a routine element and is discounted by traders in financial markets.

Moreover, it is noticeable that now in Pakistan terrorism has become a part of the routine life and investors have already discounted its risk and the affect i.e. "Normalization of Terror". It indicates that the market is unresponsiveness to terror attack over time. Consequently, it is concluded that Karachi stock market is functioning in an efficient way and market has already discounted stock price for terror risk.

References

Apergis, E., & Apergis, N. (2016). The impact of 11/13 paris terrorist attacks on stock prices: Evidence from the international defence industry. *Applied Economics Letters*, *24*(1), 45–48. doi: 10.1080/13504851.2016.1158914

Arif, I., & Suleman, T. (2017). Terrorism and stock market linkages: An empirical study from a front-line state. *Global Business Review*, *18*(2), 365–378. Retrieved from https://doi.org/10.1177%2F0972150916668604 doi: 10.1177/0972150916668604

Arin, K. P., Ciferri, D., & Spagnolo, N. (2008). The price of terror: The effects of terrorism on stock market returns and volatility. *Economics Letters*, *101*, 164-167.

Cam, M.-A. (2008). The impact of terrorism on united states industries. *Economic Papers: A Journal of Applied Economics and Policy*, *27*(2), 115–134. doi: 10.1111/j.1759-3441.2008.tb01031.x

Chen, A. H., & Siems, T. F. (2004). The effects of terrorism on global capital markets. *European Journal of Political Economy*, *20*(2), 349–366. doi: 10.1016/j.ejpoleco.2003.12.005

Chesney, M., Reshtar, G., & Karaman, M. (2011). The impact of terrorism on financial markets an empirical study. *Journal of Banking and Finance*, *35*, 253-267.

Drakos, K. (2004). Terrorism-induced structural shifts in financial risk: Sirline stocks in the aftermath of the September 11th terror attacks. *European Journal of Political Economy*, *20*(2), 435–446. doi: 10.1016/j.ejpoleco.2003.12.010

Eckstein, Z., & Tsiddon, D. (2004). Macroeconomic consequences of terror: Theory and the Case of Israel. *Journal of Monetary Economics*, *51*, 971-1002.

Eldor, R., & Melnick, R. (2004). Financial markets and terrorism. *European Journal of Political Economy*, *20*, 367-386.

Global Terrorism Index. (2012). *Global Terrorism Index 2012* [Report]. Retrieved from http://reliefweb.int/sites/reliefweb.int/files/resources/2012-Global-Terrorism-Index-Report.pdf

GTD. (2016). *Global terrorism database.* Retrieved from http://https//www.start.umd.edu/gtd/

Jammazi, R. (2012). Oil shock transmission to stock market returns: Wavelet-multivariate markov switching GARCH approach. *Energy*, *37*(1), 430–454. doi: 10.1016/j.energy.2011.11.011

Mnasri, A., & Nechi, S. (2016). Impact of terrorist attacks on stock market volatility in emerging markets. *Emerging Markets Review*, *28*, 184–202. doi: 10.1016/j.ememar.2016.08.002

Narayan, P. K., & Narayan, S. (2006). Savings behaviour in Fiji: An empirical assessment using the ARDL approach to cointegration. *International Journal of Social Economics*, *33*(7), 468–480.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326. doi: 10.1002/jae.616

Raza, S. A., Sharif, A., Wong, W. K., & Karim, M. Z. A. (2016). Tourism development and environmental degradation in the United States: Evidence from wavelet-based analysis. *Current Issues in Tourism*, *20*(16), 1768–1790. Retrieved from https://doi.org/10.1080%2F13683500.2016.1192587 doi: 10.1080/13683500.2016.1192587

Rua, A., & Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, *16*(4), 632–639. doi: 10.1016/j.jempfin.2009.02.002

Tiwari, A. K., Bhanja, N., Dar, A. B., & Islam, F. (2014). Time–frequency relationship between share prices and exchange rates in India: Evidence from continuous wavelets. *Empirical Economics*, *48*(2), 699–714. doi: 10.1007/s00181-014-0800-3