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Behaviors of Stocks and Fear Index from Terrorist Attacks: Empirical Evidence from SENSEX and NVIX

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Abstract

This study examines the impacts of domestic and counter-terrorist attacks on India's securities markets after collecting time series data of SENSEX and NVIX during the period 1980-2015 for the empirical work. We employ the conditional volatility framework to estimate stock market volatility around the terrorist events, presenting empirical results that corroborate earlier studies and report a significant impact of terrorist activities on investors' sentiment. Stock market volatility remains volatile for pre- and post-terrorist events. This paper is the first empirical research investigating the impact of terrorist attacks on stock market performance in an emerging economy like India, such as stock returns and investors' fear-gauge-index (NVIX). The implications of the study underpin a forward-looking direction on stock market volatility and investors' behavior towards risky capital investment decisions.

Key words: terrorist attacks; India securities market; NVIX; SENSEX; volatility index

JEL classifications: G10; G14

1. Introduction

Human civilization in the 21st century has faced numerous challenges regarding political tensions, global wars, social unrest, counter-terrorism, domestic violence, and religious ideology, which have had profound effects on human behavior and economic growth of society. The market economy is subject to the internal and external business environments, which are influenced by the degree of political system and human civilization. The consumption and investment of any economy mainly depend upon its political and economic environments, and issues like social

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unrest, state and religious ideologies, and terrorist attacks have serious effects on future consumption and investment (e.g., Jackson, 2008). The current states of consumption and investment closely follow social and economic events with societal unrest and counter-terrorism the main concerns for any market economy. Therefore, prospective investments and savings may eventually be disrupted due to these global events.

The main purpose of terrorist attacks is to interrupt the human mindset and influence the economic environment of the target country. A terrorist attack aims to create fear among people and can result in human and property losses. Thus, it impacts human civilization, consumption, and investment patterns of civilians. Moreover, terrorist attacks disrupt short-term operational business activities and eventually, but gradually, spread into supply chain finance.

This empirical paper aims to analyze how terrorist attacks affect short- and long-run consumption and investment in a given emerging market. The Republic of India has been the target of terrorist groups and rival countries in order to disrupt its economic system by injecting the counter-terrorism and moist domestic activity. Several terrorist groups are in operations across the border of the country and keep targeting India's major cities and workplaces. India has been attacked several times by terrorist groups, including Jammu and Kashmir (J&K), Sri-Lanka, Bangladesh, PoK-Pakistan. Major cities like Delhi, Mumbai, Kolkata, and Chennai have been severely affected due to terrorist attacks during the past four decades. In fact, both Mumbai and J&K remain the primary targets for terrorist attacks in the form of creating cross-border tensions and investors' fear in the finance city. BSE (Bombay Stock Exchange) and NSE (National Stock Exchange) are the two main stock exchanges located in Mumbai, with the former as India's oldest recognized stock exchange.

The present work documents the information content of 121 major terrorist attacks that happened in India over the past 35 years. As stock market performance is an important indicator of an economy's investment and saving patterns, we examine the relationship between financial development (stock market behavior and investors' fear index) and terrorist events followed by cross-border terrorism and border tension. We consider the historical stock returns of BSE Sensex and NSE Nifty volatility indices as key indicators for financial disruptions after terrorist attacks. As a unique empirical study on an emerging economy (India), it considers a wide array of indicators, such as the number of people killed, the number of people wounded, days around the T-attacks, target location, attack type, group certainty, weapons used, and day-of-the-week and month-of-the-year effects. The study also examines the impact of terrorist attacks on the NVIX index, which is an accurate measure of investors' fear and greed (e.g., Whaley, 2009).

Financial economists are keen to learn behavioral biases in asset pricing models. In the financial economics literature over the past three decades, scholars have reported different market anomalies, e.g. day-of-the-week effects, January effects, election cycle effects, etc. A closer search of this stream of the literature highlights in the past two decades that researchers have paid much attention to building theoretical and empirical models to explain greatly debated market anomalies, such as excess volatility, over-reaction, and under-reaction (e.g., Barberis et al., 1998; Lam et al., 2010 and 2012; Guo et al., 2017). Scholars have described how market anomalies exist due to behavioral biases. These anomalies tend to occur in the presence of investors' heuristic biases influenced by investors' conservatism and representativeness heuristics as well as excessive weights of small/large samples, neglecting recent past/new information. For instance, Lam et al. (2010) document excess volatility, over-reaction, and under-reaction in their Pseudo-Bayesian model, presenting some quantitative relationship patterns between market anomalies and behavioral biases based on certain weights induced by investors' conservatism and representativeness heuristics. Taking into the account such heuristic biases, their study finds the presence of some interesting anomalies in the market: excess volatility, short-term under-reaction, long-term over-reaction, larger autocorrelation, and momentum profit. Adding to this, some studies examine investors' behavior around the September 11 attacks and global financial crises, with supportive evidence of excess volatility and over/under reactions subject to investors' conservatism and representativeness heuristics (e.g., Wong et al., 2011 and Guo et al., 2017). To contribute to this emerging literature stream on market anomalies around serious global attacks, this paper analyzes equity market behavior before and after major terrorist attacks and shows some empirical evidence on investors' heuristics biases gauged from the volatility index (NVIX).

Existing studies have shown equity returns and volatility behavior in the form of international portfolio selection, stock and volume correlations, and investor sentiment (e.g., Tauchen and Pitts, 1983; Adler and Dumas, 1983; Darrat et al., 2011; Yang et al., 2014; Wang et al., 2017), as well as international asset pricing and contagion (e.g., Errunza and Losq, 1985; Fields and Janjigian, 1989). More specifically, equity market returns and political and macroeconomic changes under global terrorism have been explored by Enders and Sandler (1991; 1996; 2005). Enders et al. (1992; 2006) examine the impact of terrorism on the international tourism market and foreign direct investment (FDI) flow. Some have empirically explored the impact of terrorism on domestic and transnational stock markets (e.g., Carter and Simkins, 2004; Hon et al., 2004; Chen and Siems, 2004; Drakos, 2004; Mun, 2005; Glaser and Weber, 2005). Others report that contagion impacts exist in equity markets that are followed by negative abnormal returns, high volatility, and an increase in idiosyncratic risk.

Some studies find that political events and terrorist attacks (ISIS) have negative impacts on stock markets, the macro-economy, global equity market linkages, defense and airline industries, and regional economies (e.g., Drakos and Kutan, 2003; Amihud and Who, 2004; Chen and Siems, 2004; Drakos, 2004; Eckstein and Tsiddon, 2004; Hon et al., 2004; Nikkinen et al., 2008; Abadie and Gardeazabal, 2008; Khan and Estrada, 2016). Jackson (2008) examines the September 9/11 attack on the U.S. economy, reporting the variety of facets of the economy, higher the catastrophic nature of such terrorist attacks. The financial market remained closed for four days and corrected due to such events. The consumer confidence index (CCI) declined significantly and resulted in one more crisis (2007-08). Overall, the U.S. economy became stronger in fighting against such attacks in the future.

Nguyen and Enomoto (2009) describe stock returns and volatility behavior under acts of terrorism, administering their study on KSE and TSE (Pakistan and Iran, respectively). They observe significant, but different, stock shifts and fluctuations in volatility among the two markets. Krieger and Meierrieks (2010) argue that unemployment, poverty, inequality, and dissatisfaction in terms of social spending and welfare regimes result in less domestic terrorism and vice versa. The directional causality is two-way, higher the spending and generous welfare regimes.

Some recent pioneering works in developed and emerging markets also have shown some interesting results, such as the impacts of terrorism and investor sentiment, stock market volatility and returns, global arms business, the market efficiency of options, internationalization networking of financial institutions, corporate governance, and other issues (e.g., Larocque et al., 2010; Nikkinen and Vahama, 2010; Karolyi and Martell, 2010; Kollias et al., 2011; Kis-Katos et al., 2011; Akerman and Seim, 2014; Padhi and Shaikh, 2014; Aslam and Kang, 2015; Apergis and Apergis, 2016; Shaikh, 2017 and 2018; Smaraidos et al., 2018; Warin and Sanger, 2018). Unlike most recent studies, this paper is a unique empirical research on the impacts of terrorist attacks on stock market performance in an emerging economy (India), such as stock returns and investors' fear-gauge-index (NVIX).

The remainder of the paper is organized as follows. Section 2 describes the data and shows summary statistics. Section 3 presents the empirical model. Section 4 discusses the results. Section 5 summarizes and concludes the study.

2. Data Sources and Summary Statistics

This study employs the Global Terrorism Database (GTD) prepared in terms of Study on Terrorist Attacks Response to Terrorism (START). The GTD database is prepared by the University of Maryland (U.S.A.) and spans from 1970 to 2015. The present work considers only those terrorist attacks that occurred in India during the period 1982-2015. The essential criterion for sampling the terrorist attacks is that the event caused 10 or more human fatalities. Hence, the sampling procedure shows a total of 121 terrorist attacks with 3148 fatalities and 6557 wounded civilians. The data on these 121 terrorist attacks contain information on the date of the terrorist attack, target location, terrorist group name, types of weapons, attack type, and the number of people killed and wounded. To analyze the impacts of such terrorist attacks on India's financial system, we consider daily stock indices and market volatility.

This study examines the BSE Sensex stock index and the NSE Nifty VIX index. The former one explains the return behavior on such terrorist attacks, and the latter one gauges investors' fear from the terrorist events. The sample periods of BSE and of Nifty VIX (NVIX) cover 1982-2015 and 2007-2015, respectively. NVIX is India's future stock market volatility index calculated on a real-time basis. VIX is the trademark of the Chicago Board of Options Exchange (CBOE), and the same methodology is employed to calculate India VIX (i.e., NVIX). NVIX is the implied volatility estimate calculated based on options prices written on the Nifty stock index. NVIX forecasts equity market volatility for the next 30 calendar days.

Table 1 reports the summary statistics of the BSE Sensex stock index and associated stock market volatility followed by the number of people killed and wounded. Table 1 presents the descriptive measures based on 121 terrorist attacks that took place over the last 35 years in India. The terrorist attacks resulted in a total of 9,705 fatalties with each attack averaging 80 fatalities. The sample presents the highest level of the BSE stock index at 28,559 with peak volatility of 26.60%. The maximum positive returns are 12.34% (absolute returns of 13.66%) with an average yield of 0.18%. The standard deviation of change in the stock index is higher than the level series, representing the most significant movement in the stocks over the period. Similarly, the standard deviation of crude returns is lower than asymmetric returns, implying that a terrorist attack causes a negative impact on stock prices. Moreover, the JB-stats clearly show that returns are non-normally distributed, which describe the marginal effects of abnormal events (e.g., terrorist attacks) and investors' behavior. On average, 26 people were killed and 54 people were wounded for each of the 121 terrorist attacks. The maximum casualties were 1004 people. One observes that market volatility remains high after the maximum number of fatalities and vice versa.

Table 1. Summary Statistics

	Index - SE	Change - BSE	Returns	Absolute Returns ABR	Volatility VOL (%)	Number of people killed NKILL	Number of people wounded NWND	Total Fatalities
Mean	5258.54	2076.53	0.18	1.80	331.58	26.00	54.00	80.00
Maximum	28559.62	74355.00	12.34	13.66	2660.42	187.00	817.00	1004.00
Minimum	225.55	-57042.00	-13.66	0.03	56.00	11.00	11.00	22.00
Std. Dev.	5667.68	15703.80	2.85	2.21	356.28	25.98	84.43	110.41
Skewness	1.67	0.51	-0.30	2.92	3.76	3.84	6.65	10.48
Kurtosis	5.18	9.01	10.02	13.49	20.81	20.38	57.43	77.81
JB-stat	80.13793	187.0512	250.3565	726.5181	1883.933	1819.377	15828.36	17647.74
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total						3148	6557	9705
T-attacks	121	121	121	121	121	121	121	121

Notes: The table shows the descriptive statistics on the BSE index in differences, stock returns, absolute returns = ABR, volatility (%) = VOL (%), and people killed = NKILL and wounded = NWND. The table reports a summary of the stock index and fatalities based on 121 major terrorist attacks in India.

3. Empirical Model

For the information content of terrorist attacks on investors' behavior, we consider data on stocks and volatility index. Let R_t^{SENSEX} be the daily log-transformed BSE $SENSEX$ index returns, P_t^{SENSEX} is the current Sensex index level, and P_{t-1}^{SENSEX} is the previous days' level of the Sensex index. Hence, we have:

$$R_t^{SENSEX} = ln\left(\frac{P_t^{SENSEX}}{P_{t-1}^{SENSEX}}\right) \tag{1}$$

Similarly, R_t^{NVIX} is the log-transformed returns on investors' fear gauge index (NVIX):

$$R_t^{NVIX} = ln\left(\frac{P_t^{NVIX}}{P_{t-1}^{NVIX}}\right) \tag{2}$$

Regression model

The following regression specifications are expressed in terms of the OLS dummy regression framework. The variance equation is expressed in terms of ARCH(1) and GARCH(1) specifications. Moore (2011) employs the GARCH model to examine the volatility and spillover correlations between market and industry-specific stocks. Chang et al. (2018) also use the GRACH model to estimate the volatility of the Hong Kong stock exchange followed by connect program.

$$h_t = \omega_0 + \sum_{j=0}^{p} \omega_i \in_{t-1}^2 + \sum_{k=0}^{q} \omega_i h_{t-1} + u_t \tag{3}$$

$$R_t^{SENSEX} = \alpha_0 + \beta R_{t-1}^{SENSEX} + \theta_1 nkill_t + \theta_2 nwnd_t + \mu_i D_t^i + \in_t \tag{4}$$

$$\begin{aligned} R_t^{NVIX} = \delta_0 + \beta` R_t^{Nifty} + \lambda R_{t-1}^{NIVX} + \theta_1 nkill_t \\ + \theta_2 nwnd_t + \nu_i D_t^i + \in_t \end{aligned} \tag{5}$$

Equation (3) measures stock market volatility. Volatility is triggered following the outcome of a terrorist attack. This equation models volatility for stocks and the fear index separately. The non-negative and statistically significant estimate exhibits persistence of stock market volatility (see Tables 2 and 3). The ARCH(1) and GARCH(1) coefficients are validated based on Bollerslev-Wooldridge robust standard errors and covariance.

Equation (4) models the stock market returns based on the BSE $SENSEX30$ stock index under various indicators of terrorist attacks. The slope coefficients θ_1, θ_2, and μ_i measure the effects of various terrorist attacks on India's capital market. We add R_{t-1}^{SENSEX} to the right-hand side to control for autocorrelation. Similarly, equation (5) measures investors' overreactions on terrorist attacks as gauged in the volatility index (i.e., NVIX). In this equation, slope $\beta`$ measures the association between Nifty50 index and NVIX index as one of the control variables.

Table 2. Variable Descriptions and Definitions

α_0	Intercept term in the mean equation
β	Slope of one-period lagged returns on the SENSEX index
λ	Slope of one-period lagged returns on the Nifty Volatility index (NVIX)
μ_i	Estimate on the dummy variable; an indicator/dummy of terrorist attacks (BSE)
ν_i	Estimate on the dummy variable; an indicator/dummy of terrorist attacks (NVIX)
$\theta_1 and \theta_2$	Estimate on human fatalities
D_t^i	Dummy that assumes 1 and otherwise 0, based on the following indicators:
IDAY	Day of terrorist attack; it is a categorical variable that assumes 1 for day of attack and otherwise 0
AIDAY	+1, +5, i.e. after the terrorist attack; again, it is a dummy variable that measures effects of a terrorist attack in the window of +1 and +5 days after day of attack
CT	CT is a dummy variable, it is 1 for a specific location of a terrorist attack and otherwise zero CT1 = Delhi; CT4 = Kolkata CT2 = Mumbai; CT5 = Amritsar, J&K and PoK CT3 = Madras; CT6 = others
AT	Attack Type; AT is a dummy variable that captures the general method of attack and often reflects the broad class of tactics used AT1 = Armed Assault AT2 = Bombing/Explosion AT3 = Others
GC	Gang Certain; GC is a dummy variable that captures the certainty of a gang attack and its affiliation GC1 = Sikh Extremists GC2 = Babbar Khalsa International (BKI) GC3 = United Liberation Front of Assam (ULFA) GC4 = Communist Party of India - Maoist (CPI-Maoist) GC5 = Indian Mujahideen (IM), Hizbul Mujahideen (HM) GC6 = Others
WT	Weapon Type; WT is also a dummy variable that measures the effect of weapon(s) used in the attack WT1 = Automatic firearm WT2 =Explosives/Bombs/Dynamite WT3 = Others

Source: GTD Database, Retrieved from https://www.start.umd.edu/gtd/, University of Maryland.

Hypotheses of the models

Hypothesis H_1: Regression equation (4) models stock market behavior under various indicators of terrorist attacks. The number of people killed and wounded after any terrorist attack creates more instability in the market. Human losses should negatively affect stock market volatility. Hence, the slope coefficient should be negative and statistically significant. Other indicators of terrorist attacks expressed in the form of dummies should also be negative and statistically significant.

Hypothesis H_2: Regression equation (5) models investors' overreaction in the

Nifty volatility index (NVIX). Terrorist activity and fear of future attacks create uncertainty in financial markets. Hence, in the short run after a recent terrorist attack, the slope on the various indicators should be positive and statistically significant. Moreover, if any seasonal terrorist attack pattern holds in India's securities market, then the estimates on day-of-the-week and month-of-the-year dummies should be positive and statistically significant.

Hypothesis H_3: The intercept term captures the presence of any other economic and social indicators for stock market performance. The significant positive (negative) intercept terms imply that there are some other economic, social, and political factors that influence stock market performance.

4. Empirical Evidence and Discussions

This study examines investors' behavior in India's securities market in the event of terrorist activities that have occurred across the country over the past three decades. The novel aspect of the work is that this is the first attempt in the context of India to explore the effects of terrorist activity on the stock market and investors' sentiment. Table 2 presents the outcome of a terrorist attack in the form of stock market volatility. However, there is no strong reason to believe that short- and long-run economic disruptions occur due to cross-border tensions and terrorist activities (e.g., Abadie and Gardeazabal, 2008; Apergis and Apergis, 2016; Bilson et al., 2012 and Drakos, 2004). The U.S., the Middle East, South Africa, and Asia have all faced the challenges of terrorist attacks. The uncertainties of cross-border wars and terrorist activities have brought forth the need for new surveillance technology and greater budgets for defense, cyber security, and biological terrorist attacks. Speaking collectively, many nations spend billions of dollars in the name of surveillance, and directly or indirectly this monetary burden impacts economic resources of a country.

Table 3. Stock Market and Terrorist Attacks 1982-2015

Model 1: Stock Market surrounding Terrorist Attacks

Mean equation						
Returns	Intercept	$R_{(-1)}$	NKILL	NWND	IDAY	A1DAY
Coefficient	0.069^{a}	0.110^{a}	0.009	0.001	$-0.202^{§}$	0.028
Z-stat	4.80	8.83	1.49	0.55	-1.77^{c}	0.24
	C	$R_{(-1)}$	NKILL	NWND	IDAY	A5DAY
Coefficient	0.067^{a}	0.110^{a}	0.009	0.001	$-0.200^{§}$	0.043
Z-stat	4.54	8.83	1.48	0.56	-1.75^{c}	0.72

Variance equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
0.036^{a}	0.103^{a}	0.887^{a}	-14013.26	2.03
5.43	11.63	97.42	Other Stats	
C	ARCH	GARCH	LL	DW-stat
0.036^{a}	0.103^{a}	0.887^{a}	-14013.01	2.03
5.43	11.64	97.45		

Table 3. (cont'd)

Model 2: Stock Market and T-attack Locations

Mean Equation									
Returns	Intercept	$R_{(-1)}$	NKILL	NWND	CT1	CT2	CT3	CT5	CT6
Coefficient	0.070^{a}	0.110^{a}	0.012^{c}	0.003	$-0.111^{§}$	$-1.570^{§}$	$-0.985^{b§}$	$-0.201^{§}$	$-0.272^{§}$
Z-stat	4.90	8.81	1.75	1.05	-0.19	-1.13	-2.49	-0.76	-1.16

Variance Equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
0.036^{a}	0.103^{a}	0.887^{a}	-14010.65	2.03
5.42	11.64	97.27		

Model 3: Stock Market and T-attack Types

Mean equation							
Returns	Intercept	$R_{(-1)}$	NKILL	NWND	AT1	AT2	AT3
Coefficient	0.070^{a}	0.110^{a}	0.013^{b}	0.001	$-0.450^{c§}$	$-0.287^{§}$	$-0.686^{a§}$
Z-stat	4.90	8.84	2.16	0.32	-1.87	-1.21	-3.84

Variance equation				
Intercept	ARCH	GARCH	LL	DW-stat
0.036^{a}	0.103^{a}	0.887^{a}	-14011.94	2.03
5.44	11.63	97.38		

Model 4: Stock Market and Gang Certainty

Mean Equation											
Returns	Intercept	$R_{(-1)}$	NKILL	NWND	GC1	GC2	GC3	GC4	GC5	GC6
Coefficient	0.070^{a}	0.110^{a}	0.009	0.002	$-0.021^{§}$	0.045	0.304	$-0.509^{§}$	$-0.470^{§}$	$-0.095^{§}$
Z-stat	4.87	8.84	1.29	0.63	-0.05	0.06	0.96	-1.26	-1.49	-0.38

Variance Equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
0.037^{a}	0.104^{a}	0.886^{a}	-14011.24	2.03
5.43	11.64	97.00		

Model 5: Stock Market and Type of Weapon

Mean equation							
Returns	Intercept	$R_{(-1)}$	NKILL	NWND	WT1	WT2	WT3
Coefficient	0.070 [a]	0.110 [a]	0.011 [c]	0.001	-0.265[§]	-0.163[§]	-0.762[§]
Z-stat	4.87	8.85	1.74	0.33	-1.20	-0.69	-0.90

Variance equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
0.037 [a]	0.103 [a]	0.887 [a]	-14012.78	2.03
5.43	11.63	97.16		

Notes: This table reports the estimates of equation $R_t^{SENSEX} = \alpha_0 + \beta R_{t-1}^{SENSEX} + \theta_1 nkill_t + \theta_2 nwnd_t + \mu_i D_t^i + \in_t$ with variance equation $h_t = \omega_0 + \sum_{j=0}^{p} \omega_i \in_{t-1}^2 + \sum_{k=0}^{q} \omega_i h_{t-1} + u_t$. Here, [a]1%, [b]5%, and [c]10% levels of significance; § = estimates calculated per each hypothesis.

Table 4. NVIX-Investors' Fear and Terrorist Attacks 2007-2015

Model 1: NVIX-Investors' Fear and T-attacks

Mean Equation							
Returns	Intercept	R(Nifty)	$RNVIX_{(-1)}$	NKILL	NWND	IDAY	A1DAY
Coefficient	0.020	-2.530 [a]	-0.086 [a]	-0.126 [a]	0.040[#]	1.403	-1.519[#]
Z-stat	0.20	-14.48	-3.92	-2.89	1.35	1.04	-1.42

Variance Equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
1.257 [b#]	0.127 [a]	0.847 [a]	-6437.681	2.16
2.07	3.81	28.88		

Model 2: NVIX-Investors' Fear and T-attack types

Mean Equation								
Returns	Intercept	R(Nifty)	$RNVIX_{(-1)}$	NKILL	NWND	AT1	AT2	AT3
Coefficient	-0.016	-2.52 [a]	-0.095 [a]	-0.073 [b]	-0.007	5.060 [a#]	4.060 [b#]	-1.854
Z-stat	-0.12	-14.41	-3.45	-2.38	-0.28	4.55	2.12	-0.91

Variance Equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
3.255 [a]	0.127 [a]	0.807 [a]	-6725	2.16
3.22	3.16	19.50		

Model 3: NVIX-Investors' Fear and T-attacks by Location

Mean Equation							
Returns	Intercept	R(Nifty)	$RNVIX_{(-1)}$	CT1	CT2	CT5	CT6
Coefficient	0.014	-2.513 ^{a}	-0.085 ^{a}	0.138$^{\#}$	3.140 $^{a\#}$	7.439 $^{a\#}$	-1.089
Z-stat	0.14	-14.28	-3.85	0.26	4.58	46.62	-0.72

Variance Equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
1.463 ^{b}	0.138 ^{a}	0.832 ^{a}	-6439.7	2.16
2.19	3.78	25.16		

Model 4: NVIX-Investors' Fear and T-attacks and Weapon type

Mean Equation						
Returns	Intercept	R(Nifty)	$RNVIX_{(-1)}$	WT1	WT2	WT3
Coefficient	0.018	-2.518 ^{a}	-0.087 ^{a}	2.433 $^{a\#}$	1.021$^{\#}$	-9.900 ^{a}
Z-stat	0.18	-14.32	-3.98	2.71	0.86	-29.99

Variance equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
1.464 ^{b}	0.137 ^{a}	0.832 ^{a}	-6438.1	2.16
2.19	3.78	25.14		

Model 5: NVIX-Investors' Fear and Gang Certain

Mean Equation							
Returns	Intercept	R(Nifty)	$RNVIX_{(-1)}$	GC3	GC4	GC5	GC6
Coefficient	0.010	-2.532 ^{a}	-0.086 ^{a}	20.937 $^{a\#}$	-1.347	0.643 $^{a\#}$	3.184$^{\#}$
Z-stat	0.10	-14.48	-3.89	15.03	-0.68	2.02	1.20

Variance Equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
1.303 ^{b}	0.128 ^{a}	0.845 ^{a}	-6440.1	2.16
2.10	3.79	28.12		

Table 4. (cont'd)

Model 6: NVIX-Investors' Fear and T-attacks from North India and South India

Mean Equation							
Returns	Intercept	R(Nifty)	RNVIX$_{(-1)}$	NKILL	NWND	NI	SI
Coefficient	-0.016	-1.998 [a]	-0.093 [a]	-0.106 [b]	0.014[#]	0.443[#]	3.102 [a#]
Z-stat	-0.12	-11.60	-3.38	-2.46	0.64	0.10	2.34

Variance Equation			Other Stats	
Intercept	ARCH	GARCH	LL	DW-stat
3.221 [a]	0.126 [a]	0.809 [a]	-6726.3	2.16
3.17	3.14	19.45		

Model 7: NVIX-Investors' Fear and T-attacks based on day-of-the-week

Mean Equation							
Returns	Intercept	R	RNVIX$_{(-1)}$	MON	TUE	WED	FRI
Coefficient	0.012	-2.528 [a]	-0.087 [a]	0.789[#]	1.795[#]	2.266[#]	-8.431 [a]
Z-stat	0.11	-14.46	-3.94	1.49	0.67	1.32	-4.40

Variance Equation				
Intercept	ARCH	GARCH	LL	DW-stat
1.285 [b]	0.127 [a]	0.846 [a]	-6438.646	2.15
2.09	3.80	28.54		

Notes: This table reports the estimates of equation $R_t^{NVIX} = \delta_0 + \beta` R_t^{Nifty} + \lambda R_{t-1}^{NIVX} + \theta_1 nkill_t + \theta_2 nwnd_t + \nu_i D_t^i + \in_t$ with variance equation $h_t = \omega_0 + \sum_{j=0}^{p} \omega_i \in_{t-1}^2 + \sum_{k=0}^{q} \omega_i h_{t-1} + u_t$. Here, [a]1%, [b]5%, and [c]10% levels of significance; # - signifies the estimates calculated per each hypothesis.

Model 1 of Table 2 describes the behavior of India's securities market affected due to terrorist attacks that resulted in enormous amounts of fatalities. One of the important insights out of the empirical results is that total fatalities due to terrorist attacks marginally affect stock market returns. The results are identical across the variants of Models 2 to 5. However, for IDAY, the terrorist attack day does have a significant impact on market behavior. Once the terrorist attack takes place the news spreads in the market, and it is reflected in the fair price of the stocks. This can be clearly seen from the estimates on IDAY; it appears to be -0.202 and is statistically significant. Moreover, the market reverts to its normal level one day later after the day of the attack (e.g., Jackson, 2008).

Model 2 presents the stock market behavior based on the location of terrorist attacks in India. There are six classified cities considered as hubs for business and finance in India. It is apparent from the estimates that the terrorist attacks positioned in these cities negatively impacted investors' earnings from stock trading. The slope of all six locations appears to be negative; in fact, the highest one is for the Mumbai terrorist attack, and the second highest one is for the Madras attack (e.g., Wong et al., 2011).

Model 3 reports the stock market returns and volatility as a direct consequence of terrorist Attack-Type (AT). There are mainly three types of terrorist attacks under observation: AT1, AT2, and AT3. The results show that the returns are negative and statistically significant due to attack type. They imply that investors have high concerns on the strategic attack type administered by the terrorist group. The statistically significant slope indicates that succeeding the attack-type market report negative returns of -0.686-point basis.

Model 4 offers the stock market behavior under gang-certainty (GC). For the sake of convenience, we analyze six terrorist groups and observe that markets' overreaction is more when a terrorist group declares responsibility. Here, the GC1, GC4, GC5, and GC6 terrorist group dummies are negative, indicating that group certainty contains some information that explains a market rally in the short run.

Model 5 presents the effects of weapon-type (WT) used in the terrorist attack on the investing community. Three weapons are identified in the present work: WT1, WT2, and WT3. When a terrorist attack employes WT3, it shows the highest negative impact on the stock market. Market participants are more affected when WT3 is used.

Figure 1. Fatality and Stock Market Volatility

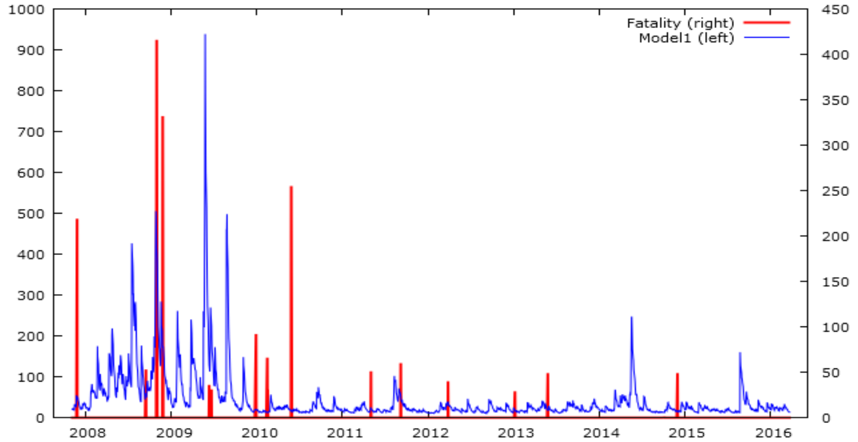
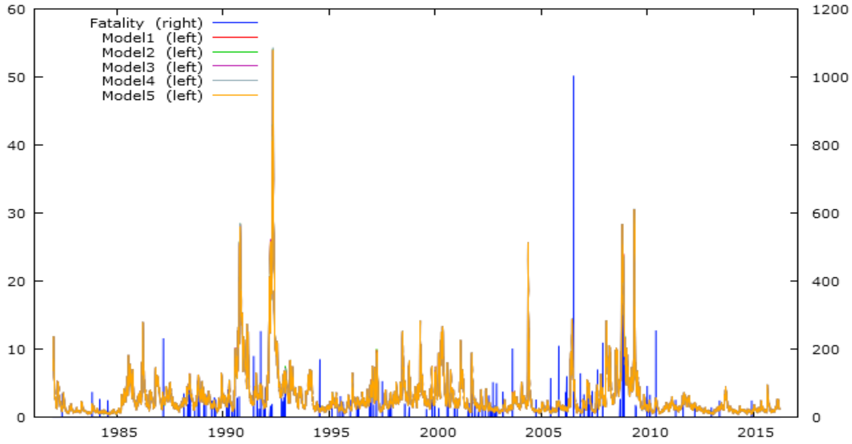


Figure 2. Stock Market Volatility and T-Attacks



The variance equation in all the models reports positive slopes on the ARCH and GARCH specifications. The results indicate that stock market volatility increases due to terrorist attacks in India. Terrorist activities dislocate the social system, and the social system effects on the economic system and economic growth cause the financial services. Hence, cross-border tension and terrorist activities indirectly impact financial development.

Stock market performance is an indicator of the functioning of a country's financial system. Looking at the log-likelihood values of the GARCH model, the highest value appears for Model 2, which explains that the location of the terrorist attack matter for investors. The model shows that Mumbai remains the primary target for most terrorist attacks; the reason is that Mumbai is India's financial capital and is highly populated. Figures 1 and 2 illustrate stock market volatility under Model 1 and through Model 1-5. The market was very volatile in 2008, 2009, and 2010, as the highest fatalities occurred under the shadow of terrorist attacks (e.g., Guo et al., 2017). Figure 2 exhibits the increased number of terrorist attacks with higher amounts of fatalities during 1990-1995. The same is true during the period 2005-2010.

Figure 3. The Performance of BSE Followed by T-Attacks 1985-2015

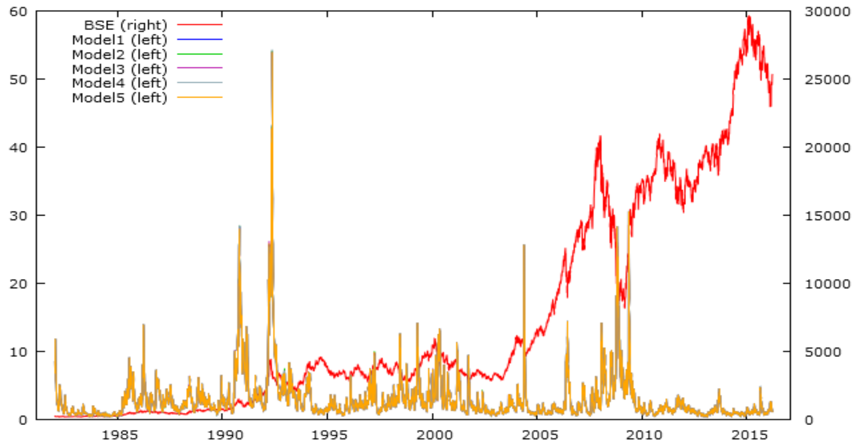


Figure 3 presents the time series plot of the BSE stock index and stock market volatility under terrorist activities from 1985 to 2015. Between 1990 to 1995, stock market volatility was over 50%, and the BSE index was trading below 5000 points. On the other hand, market volatility was about 30% and the BSE index traded below 10,000 points between 2005 and 2010. Volatility was lower for 2010 to 2015, and BSE reached a peak of nearly 30,000 points.

Model 2 demonstrates the behavior of expected stock market volatility due to terrorist attack types. AT1 and AT2 show a significant impact on investors' fear index. The results also note that the nature of a terrorist attack matters for market participants. The slope signifies that the NVIX level rises by 4 to 6 basis points under type of terrorist attack.

Model 3 presents the NVIX changes followed by the location of the terrorist attack. One can see that location of the terrorist attack matters as the slope appears to be positive and statistically significant. Expected stock market volatility increases from 0.138 to 7.439 basis points depending on the location. When the location target is Mumbai, investors' fear goes up by 3.14 basis points. One of the essential structures of terrorist attacks found to be located in the state of J&K and Punjab. When an attack occurs in these locations, volatility can reach a high level.

Figure 4. Investors' Fear Gauge and T-Attacks

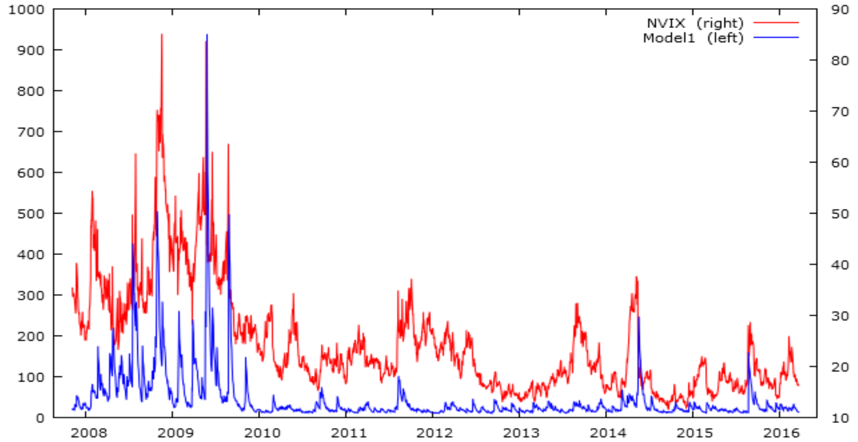
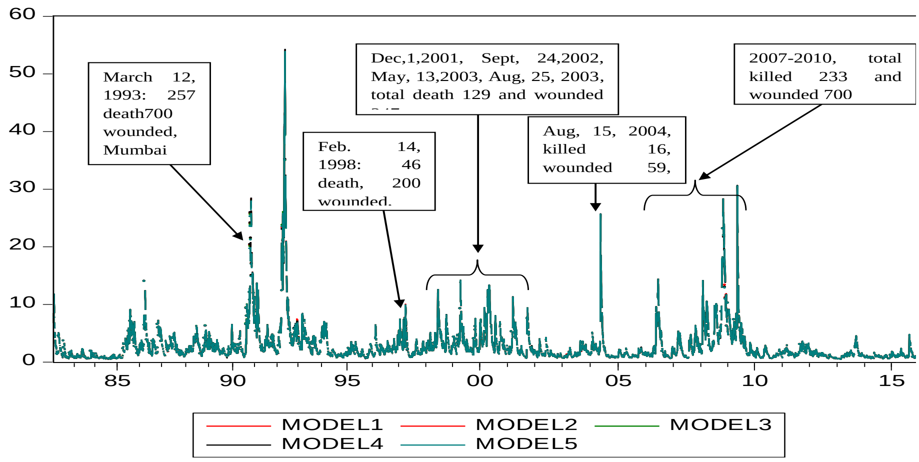


Figure 5. Major T-Attacks in India and Stock Market Volatility



Model 4 shows expected stock market volatility based on the type of weapon (WT) used in the terrorist attack, and one can see that weapon type does contain information to explain market volatility. Model 5 considers gang certainty (GC) in the terrorist attack. A positive estimate on the GC dummy indicates that group identity influences market behavior after a terrorist attack. One of the interesting outcomes reported under Model 6 is that stock market volatility remains on the higher side when the terrorist attacks are located in the southern part of India. Moreover, the study documents seasonal patterns of terrorist attacks on the financial market. Model 7 exhibits that Monday, Tuesday, and Wednesday have clear day-of-the-week effects from terrorist attacks, presenting positive and significant effects on investors' sentiment and their portfolio planning. The results imply that investors' concern is very high on a terrorist attack when it takes place on these particular days. Furthermore, month-of-the-year terrorist attack patterns are also observed in Model 8. January, February, September, October, November, and December are months reporting increased terrorist attacks, and such attacks translate into increased expected stock market volatility in the short run.[1]

Figure 4 exhibits the time series plot of NVIX and stock market volatility. It can be seen that stock market volatility appears higher under a terrorist attack, and one can understand that expected stock market volatility remains greater than realized volatility (e.g., Wong et al., 2011). One of the likely reasons behind this pattern is investors' overreaction on a terrorist attack and aggressive trading. Stock market volatility and Nifty VIX appears to be more volatile during the years 2008, 2009, and 2010. An interesting observation from 2014 and onward is that stocks' ex-post volatility and expected stock market volatility are in equilibrium. Figure 5 shows the stock market volatility through regression Model 1-5. One can see that market uncertainty remains higher after a terrorist attack.

5. Summary and Conclusion

Global terrorism is now a common threat to any country. In Asia, India remains the main target for social and economic disruptions through cross-border terrorism and domestic Naxalite movement. The country's financial development over the past four decades has been severely affected due to cross-border and domestic terrorist activities. According to the GTD database, J&K, Punjab, and Maharastra (Mumbai) are the primary targets for terrorist attacks. Thus, this paper is the first to examine the impact of cross-border and domestic terrorist attacks on stock market performance in an emerging economy like India. Empirical analysis has been carried out herein for 121 major terrorist attacks that happened across the country during the past four decades (1982-2015). To deeply investigate the effects of terrorist attacks on stock returns and investors' fear-gauge-index, this study specifically takes into consideration some indicators, such as the number of people killed, the number of people wounded, days around the T-attacks, target location, attack type, group certainty, and weapon(s) used.

Based on time series data of SENSEX and NVIX and the conditional volatility framework, the empirical results highlight that terrorist activities have had detrimental effects on the functioning of the country's financial market in that market volatility moves higher around terrorist attacks. For most of the terrorist attacks, the stock market has reported negative returns and greater expected stock market volatility. The results are in line with earlier studies that show a significant impact of terrorist activities on investors' sentiment. Stock market volatility remains extremely unstable around terrorist attacks and post-terrorist attacks. This study reveals that the market is temporarily distracted due to a terrorist attack, but it then goes back to normal one day after the attack.

The implications of the study underpin a forward-looking direction on stock market volatility and investors' behavior towards risky capital investment decisions. It should be noted that although time series data since 1980 provide a clear view of stock market behaviors, the period between 1980 and 2000 may not present real behaviors given the fact that media coverage was almost negligible during that time (e.g., Lam et al., 2010). After this period, we can see greater visibility and heightened coverage by international and local media news due to Internet-based social networking channels. How have terrorist attacks severely impacted financial markets' performances in developed and emerging markets in recent years? This could be an interesting area for comparative empirical analysis in future research.

Notes

1. Due to space constraints, Model 8 results are not reported herein, but are available upon request.

References

Abadie, A. and J. Gardeazabal, (2008), "Terrorism and the World Economy," *European Economic Review*, 52(1), 1-27.

Adler, M. and B. Dumas, (1983), "International Portfolio Choice and Corporation Finance: A Synthesis," *The Journal of Finance,* 38(3), 925-984.

Akerman, A. and A. L. Seim, (2014), "The Global Arms Trade Network 1950-2007," *Journal of Comparative Economics,* 42(3), 535-551.

Amihud, Y. and A. Woh, (2004), "Political News and Stock Prices: The Case of Saddam Hussein Contracts," *Journal of Banking and Finance*, 28(5), 1185-1200.

Apergis, E. and N. Apergis, (2016), "The 11/13 Paris Terrorist Attacks and Stock Prices: The Case of the International Defense Industry," *Finance Research Letters*, 17, 186-192.

Aslam, F. and H. G. Kang, (2015), "How Different Terrorist Attacks Affect Stock Markets," *Defence and Peace Economics,* 26(6), 634-648.

Barberis, N., A. Shleifer, and R. Vishny, (1998), "A Model of Investor Sentiment," *Journal of Financial Economics*, 49(3), 307-343.

Bilson, C., T. Brailsford, A. Hallett, and J. Shi, (2012), "The Impact of Terrorism on Global Equity Market Integration," *Australian Journal of Management,* 37(1), 47-60.

Carter, D. A. and B. J. Simkins, (2004), "The Market's Reaction to Unexpected, Catastrophic Events: The Case of Airline Stock Returns and the September 11th Attacks," *The Quarterly Review of Economics and Finance,* 44(4), 539-558.

Chang, T.-Z., S. Chen, H. Gu, and A. Jiang, (2018), "A Market Volatility Analysis of the Shanghai-Hong Kong Stock Connect Program," *International Journal of Business and Economics*, 17(2), 113-121.

Chen, A. H. and T. F. Siems, (2004), "The Effects of Terrorism on Global Capital Markets," *European Journal of Political Economy,* 20(2), 349-366.

Darrat, A. F., B. Li, and O. Benkato, (2011), "The Relationship between Volatility and Expected Returns: Some Evidence for Australia," *International Journal of*

Business and Economics, 10(1), 27-43.

Drakos, K. and A. M. Kutan, (2003), "Regional Effects of Terrorism on Tourism in Three Mediterranean Countries," *Journal of Conflict Resolution*, 47(5), 621-641.

Drakos, K., (2004), "Terrorism-Induced Structural Shifts in Financial Risk: Airline Stocks in the Aftermath of the September 11th Terror Attacks," *European Journal of Political Economy*, 20(2), 435-446.

Eckstein, Z. and D. Tsiddon, (2004), "Macroeconomic Consequences of Terror: Theory and the Case of Israel," *Journal of Monetary Economics*, 51(5), 971-1002.

Enders, W. and T. Sandler, (1991), "Causality between Transnational Terrorism and Tourism: The Case of Spain," *Studies in Conflict and Terrorism*, 14(1), 49-58.

Enders, W. and T. Sandler, (1996), "Terrorism and Foreign Direct Investment in Spain and Greece," *Kyklos*, 49(3), 331-352.

Enders, W. and T. Sandler, (2005), *The Political Economy of Terrorism*, Cambridge, UK: Cambridge University Press.

Enders, W., A. Sachsida, and T. Sandler, (2006), "The Impact of Transnational Terrorism on US Foreign Direct Investment," *Political Research Quarterly*, 59(4), 517-531.

Enders, W., T. Sandler, and G. F. Parise, (1992), "An Econometric Analysis of the Impact of Terrorism on Tourism," *Kyklos*, 45(4), 531-554.

Errunza, V. and E. Losq, (1985), "International Asset Pricing Under Mild Segmentation: Theory and Test," *The Journal of Finance*, 40(1), 105-124.

Fields, M. A. and V. Janjigian, (1989), "The Effect of Chernobyl on Electric-Utility Stock Prices," *Journal of Business Research*, 18(1), 81-87.

Glaser, M. and M. Weber, (2005), "September 11 and Stock Return Expectations of Individual Investors," *Review of Finance*, 9(2), 243-279.

Guo, X., M. McAleer, W. K. Wong, and L. Zhu, (2017), "A Bayesian Approach to Excess Volatility, Short-Term Underreaction and Long-Term Overreaction During Financial Crises," *The North American Journal of Economics and Finance*, 42, 346-358.

Hon, M. T., J. Strauss, and S. K. Yong, (2004), “Contagion in Financial Markets after September 11: Myth or Reality?” *Journal of Financial Research*, 27(1), 95-114.

Jackson, O. A., (2008), “The Impact of the 9/11 Terrorist Attacks on the US Economy,” *Journal of 9/11 Studies*, 20(1), 1-27.

Karolyi, G. A. and R. Martell, (2010), “Terrorism and the Stock Market,” *International Review of Applied Financial Issues and Economics*, 2(2), 285-314.

Khan, A. and M. A. Estrada, (2016), “The Effects of Terrorism on Economic Performance: The Case of Islamic State in Iraq and Syria (ISIS),” *Quality and Quantity*, 50(4), 1645-1661.

Kis-Katos, K., H. Liebert, and G. G. Schulze, (2011), “On the Origin of Domestic and International Terrorism,” *European Journal of Political Economy*, 27, S17-S36.

Kollias, C. E., S. Papadamou, and A. Stagiannis, (2011), “Stock Markets and Terrorist Attacks: Comparative Evidence from A Large and A Small Capitalization Market,” *European Journal of Political Economy*, 27, S64-S77.

Krieger, T. and D. Meierrieks, (2010), “Terrorism in the Worlds of Welfare Capitalism,” *Journal of Conflict Resolution*, 54(6), 902-939.

Lam, K., T. Liu, and W. K. Wong, (2010), “A Pseudo-Bayesian Model in Financial Decision Making with Implications to Market Volatility, Under-And Overreaction,” *European Journal of Operational Research*, 203(1), 166-175.

Lam, K., T. Liu, and W. K. Wong, (2012), “A New Pseudo-Bayesian Model with Implications for Financial Anomalies and Investors’ Behavior,” *Journal of Behavioral Finance*, 13(2), 93-107.

Larocque, D., G. Lincourt, and M. Normandin, (2010), “Macroeconomic Effects of Terrorist Shocks in Israel,” *Defence and Peace Economics*, 21(4), 317-336.

Moore, T., (2011), “The Volatility Spillover from the Market to Disaggregated Industry Stocks: The Case for the US and UK,” *International Journal of Business and Economics*, 10(1), 61-68.

Mun, K.-C., (2005), “Contagion and Impulse Response of International Stock Markets around the 9-11 Terrorist Attacks,” *Global Finance Journal*, 16(1), 48-68.

Nguyen, A. P. and C. E. Enomoto, (2009), “Acts of Terrorism and their Impacts on

Stock Index Returns and Volatility: The Cases of the Karachi and Tehran Stock Exchanges," *International Business and Economics Research Journal*, 8(12), 75-86.

Nikkinen, J. and S. Vähämaa, (2010), "Terrorism and Stock Market Sentiment," *Financial Review*, 45(2), 263-275.

Nikkinen, J., M. M. Omran, P. Sahlström, and J. Äijö, (2008), "Stock Returns and Volatility Following the September 11 Attacks: Evidence from 53 Equity Markets," *International Review of Financial Analysis*, 17(1), 27-46.

Padhi, P. and I. Shaikh, (2014), "On the Relationship of Implied, Realized and Historical Volatility: Evidence from NSE Equity Index Options," *Journal of Business Economics and Management*, 15(5), 915-934.

Shaikh, I., (2017), "The 2016 U.S. Presidential Election and the Stock, FX and VIX Markets," *The North American Journal of Economics and Finance*, 42, 546-563.

Shaikh, I., (2018), "Investors' Fear and Stock Returns: Evidence from National Stock Exchange of India," *Engineering Economics*, 29(1), 4-12.

Smaraidos, V., G. Thanasas, and A. Filiou, (2018), "The Impact of Corporate Governance on Earnings Management in Emerging Economies: The Greek Evidence," *International Journal of Comparative Management*, 1(3), 317-330.

Tauchen, G. E. and M. Pitts, (1983), "The Price Variability-Volume Relationship on Speculative Markets," *Econometrica: Journal of the Econometric Society*, 51(2), 485-505.

Wang, L., B. Liu, R. Gupta, J. J. Su, and B. Li, (2017), "Return Predictability in Australian Managed Funds," *International Journal of Business and Economics*, 16(1), 1-19.

Warin, T. and W. Sanger, (2018), "Connectivity and Closeness Among International Financial Institutions: A Network Theory Perspective," *International Journal of Comparative Management*, 1(3), 225-254.

Whaley, R. E., (2009), "Understanding the VIX," *The Journal of Portfolio Management*, 35(3), 98-105.

Wong, W. K., H. E. Thompson, and K. Teh, (2011), "Was There Abnormal Trading in the S&P 500 Index Options Prior to the September 11 Attacks?" *Multinational Finance Journal*, 15(3/4), 1-46.

Yang, Z., R. Su, Q. Zhang, and Y. Sun, (2014), "Managers' Incentives, Earnings Management Strategies, and Investor Sentiment," *International Journal of Business and Economics*, 13(2), 157-80.