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Original citation & hyperlink:
Park, JS & Newaz, MK 2018, 'Do terrorist attacks harm financial markets? A meta-analysis of event studies and the determinants of adverse impact' Global Finance Journal, vol. 37, pp. 227-247.
https://dx.doi.org/10.1016/j.gfj.2018.06.003

DOI 10.1016/j.gfj.2018.06.003
ISSN 1044-0283

Publisher: Elsevier

Do terrorist attacks harm financial markets?

A meta-analysis of event studies and the determinants of adverse impact

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ABSTRACT

This study reassesses the common belief that terrorist attacks destabilize financial markets, by analyzing event studies covering 10,576 individual attacks and 141,665 nonattack days across 72 stock and foreign exchange markets in 36 countries from 1996 to 2015. The meta-analysis reveals that terrorist attacks have almost no impact on stock markets and only marginal effect on foreign exchange markets, though effects vary with individual attacks and markets. The number of fatalities slightly raises the likelihood of adverse impact, while the number of wounded and the magnitude of recent attacks slightly decrease it. The markets are hit less hard when attack-day returns are positive, but variance is more likely to increase in the short term. Also, the impact of an attack is stronger when the market is performing extremely well or poorly.

JEL classifications:

C22

G14

G15

F50

Keywords:

Terrorism

Terrorist attack

Stock market

Foreign exchange market

Event studies

Quantile regression

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1.Introduction

The effects of terrorism on financial markets have not received much attention from academics and policy makers until recently, despite the common belief that terrorist attacks can lower prices while creating uncertainty about the future and consequently increasing market volatility. Since the terrorist attacks of 9/11 changed the scope of terrorism as a geopolitical risk that threatens the global economy and financial markets, the existing literature has mainly focused on a very limited number of terrorist events, particularly the 9/11 U.S. attacks in 2001, the 3/4 Madrid bombings in 2004, the 7/7 London bombings in 2005, and the 11/13 Paris attacks in 2015. Most studies use the event study method and regression models and focus on stock markets, and less frequently on foreign exchange and other financial markets.

Karolyi (2006) surveys the earlier research, most of which focused on a single episode like the 9/11 attacks, and concludes that terrorist attacks are associated with negative abnormal market returns. Likewise, other single-country studies, which usually adopt regression models, conclude that terrorist attacks hurt financial markets. For example, Eldor and Melnick (2004) investigate the stock and foreign exchange markets in Israel using linear regression models and reveal significant negative impact on returns. Aslam and Kang (2013), using a similar model, show significant negative stock return just after terrorist attacks in Pakistan. Mansoor and colleagues (2017) reveal that terrorist attacks depreciate Turkish currency.

Most of the studies that cover a wider range of countries or attacks also present evidence of adverse impacts. For instance, Chen and Siems (2004) adopt the event study method and show that the majority of 36 stock indices reacted negatively to the 9/11 attack. Arin, Ciferri, and Spagnolo (2008) report that all of the six stock markets they tested (Indonesia, Israel, Spain, Thailand, Turkey, and the UK) suffered from decreasing returns after terrorist attacks. Johnston and Nedelescu (2005), also using event studies, conclude that the 9/11 and 3/4 Madrid attacks had predominantly negative impacts on the financial sectors of 14 countries. Chesney and colleagues (2011), using both event studies and regression models, investigate 77 attacks in 25 countries and show that two-thirds of the attacks decreased market returns in at least one stock market. The scale of adverse impact may differ with the characteristics of specific financial markets (Johnston & Nedelescu, 2005) and attacks (Eldor & Melnick, 2004; Karolyi & Martell, 2006). On the other hand, their impact on the economy in general is estimated as negative (Abadie & Gardeazabal, 2003; Eckstein & Tsiddon, 2004; Shahzad, Zakaria, Rehman, Ahmed, & Fida, 2016), and company-targeted attacks also decrease the company's share prices (Karolyi & Martell, 2006).

Studies on volatility are relatively rare and commonly use volatility regression models. They mostly agree that terrorist attacks increase market volatility. For instance, Arin et al. (2008) and Chuliá et al. (2009) show that terrorist attacks predominantly destabilize financial markets. Increased volatility after attacks may last longer than a week at both country (Mnasri & Nechi, 2016) and firm levels (Essaddam & Karagianis, 2014).

In contrast, other studies argue that adverse impacts do not always occur. Chen and Siems (2004) examine the response of U.S. stock markets to 14 attacks, but find no evidence of lowered returns. They conclude that U.S. financial markets are more flexible and liquid and recover quicker than other global financial markets; hence the minimal reaction to terrorist attacks. Kollias, Papadamou, and Stagiannis (2011) present similar evidence of the flexibility of the UK stock market compared with the relatively smaller Spanish stock market. Brounrn and Derwall (2010) find that the impact of terrorist attacks other than the 9/11 attack seems mild and brief if there is any, and Kollias, Manou, Papadamou, and Stagiannis (2011) find that whether the markets react to attacks depends on the attributes of the individual attack. Looking at 21 foreign exchange markets, Narayan and colleagues (2017) show that market reactions are diverse in terms of appreciation and depreciation of currencies.

This contrasting evidence may arise because comprehensive research on a large number of attacks and their impacts on financial markets is still in its infancy, despite the hundreds of terrorist attacks happening globally each year. Studies on foreign exchange or other financial markets are rare. Both popular methods, event studies and regression models, have been used on a small number of well-known attacks and markets. The event studies rarely make any comparison with nonattack days, and almost all the regression-based studies examine the conditional mean of market returns rather than the different parts of return distribution, e.g., median or quantiles of return distribution. The only exception is the study by Chesney et al. (2011), one of whose methods is based on value at risk (i.e., the lower tail). Further meta-analysis, for example to test the significant impact of attack days against nonattack days or to find what determines the impact of terrorist attacks, is rarely carried out.

Therefore, we intend to answer the following research questions: (1) Do terrorist attacks decrease stock returns or the value of domestic currency, or increase the variance of returns? (2) Does a large-scale attack have a higher chance of harming markets? (3) What attributes of the attack and the market determine whether a particular terrorist attack has an adverse impact? (4) Do terrorist attacks differently affect strong or weak markets?

This study makes four contributions. First, we explore one of the most comprehensive datasets, covering 10,576 individual terrorist attacks across 72 stock and foreign exchange markets between 1996 and 2015. Second, we reanalyze the results of event studies to verify the adverse impact of terrorist attacks and also to find the determinants. Third, we compare results for attack days with those for nonattack days and those from volatility models to check that our findings are robust. Last, we use a quantile regression model to see how terrorist attacks affect different return quantiles.

The remainder of this study is organized as follows. Section 2 describes the dataset, which includes data on both terrorist attacks and financial markets. Section 3 explains the method and Section 4 reports the results. Section 5 concludes.

2. Data

In this study, the stock market and the foreign exchange market are represented by the price index of a country's main stock market and its real effective exchange rate (REER), observed daily for 36 countries over the period from January 1, 1996 to December 31, 2015 (Table 1).[1] The five strongest performers in the stock markets are Indonesia, Mexico, India, Denmark, and South Africa, while the value of domestic currencies increases by the largest percentage in the Czech Republic, Switzerland, China, the United States, and Israel. The financial market statistics (market capitalization, the value of stock traded, and the turnover of the stock markets) are obtained from the World Bank, and the geographical distribution of foreign currency turnover is from the Bank for International Settlements (BIS, 2016).

A total of 10,833 terrorist attack days during the same period are collected from the Global Terrorism Database (GTD), the most extensive dataset of terrorism attacks, maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism at the University of Maryland, United States. This database is time-stamped only by year, month, and day, so terrorist attacks happening on the same day cannot be ordered; we thus consolidate them as an attack day. This will not be an issue, since this study focuses on daily data. The impact of attacks during market closure is captured by the empirical

[1] The REER represents the price of local currency as the trade-weighted average of exchange rates among trade partners. The depreciation of currency is not always bad; it could decrease export prices and eventually restore competitiveness. The data source is Datastream. We do not conduct industry-level or firm-level analysis owing to the lack of comparative industry indices across the sample countries.

models. After removing attacks that do not have sufficient observations for the event study, we use 10,576 attack days in the subsequent analyses.

<Insert Table 1 here>

The daily terrorism index is calculated following Cukierman (2004), Eckstein and Tsiddon (2004), and Arin et al. (2008) as the natural logarithm of [e + the numbers of attacks, wounded, and killed in a day]. This index is used to categorize large-scale attacks and to represent the magnitude of the attacks. India, the Philippines, Thailand, Turkey, and Russia are the five countries most heavily attacked, while Denmark, Finland, Taiwan, Croatia, and Norway suffered the least over the sample period.

3. Methods

This study employs six empirical methods to investigate the research questions. First, we test for equality of mean returns and variances between attack days and nonattack days. The alternative hypothesis is that attack days exhibit smaller returns or larger variances. We also test the next-day data after each terrorist attack against nonattack days.[2] This method provides collective but only descriptive evidence about the adverse impact of the terrorist attacks, as it does not consider different circumstances in the financial markets before or after individual attacks.

Second, we employ the event study method to compare the impact of attack and nonattack days as events. Unlike typical event studies, our study applies the same method not

[2] Financial market returns are known to be approximately normal, so the need for alternative tests such as Bartlett tests is minimal. We use next-day data to capture the effects of attacks that may have happened during market closure. In the subsequent analyses, the effect of these attacks is captured by cumulative abnormal returns in the event studies and lagged variables in the regression models.

only to all attack days but also to all nonattack days in the dataset. We then compare the results for attack and nonattack days over the whole dataset and across different countries. To investigate the effect of attack size, we identify attacks with index scores in the top ten percent, that is, large-scale attacks, and investigate whether they make a stronger adverse impact on financial markets.

Our event study approach estimates a mean-return model for an estimation window preceding individual terrorist attacks and identifies forecast errors within that window, including the attack day. Forecast errors are classified as abnormal returns, and then cumulative abnormal returns (CAR) are calculated. We follow the method described by Campbell, Lo, and MacKinlay (1997)[3] to test whether the sign of CAR is negative at a 5% significance level. We also test for equality in the variances of abnormal returns between estimation and event windows to find the impact of events on variances. The mean-return (r_{it}) model for the event study is an autoregressive model of order 3, which uses three lags of returns as explanatory variables, with 100-day estimation and 6-day event windows, i.e., [-100,-1] and [0,5]:[4]

[3] We omit the technical details of event study as it is one of the most commonly used methods (Chesney et al., 2011).

[4] This pure autoregressive setup removes the difficulty of finding proper control variables. The choice of the number of lags follows Eldor and Melnick (2004). Tests with a model with 5 lags produce very similar results. Six days is the midpoint of the window lengths tested by Chen and Siems (2004) and is also used by Chesney et al. (2011). Our test with a 3-day window generates a similar result except for the tests for equality of variance, where 3 days may not be sufficient. Panel A in Table A3 presents the results when we add the returns on the MSCI World Index to control for global market performance. The results are not dissimilar.

$$r_{it} = \alpha_i + \sum_{l=1}^{3} \beta_{li} r_{it-l} + \varepsilon_{it} \ , \quad (1)$$

where ε_{it} is the error term with zero mean and variance of σ_{it}^2 at time t in market i.

Third, in the first part of the meta-analysis, if strong adverse impact is not found in the original tests in the event studies, we adopt binomial tests to statistically test the marginal impact of attacks on the markets against nonattack days. A binomial distribution is defined as the probability (P) of a random variable X having a value of k:

$$P(X = k) = \binom{N}{k} p^k (1 - p)^{N-k} \ , \quad (2)$$

where N is the number of trials, k is the number of successes, and p is the probability of success for a single trial in a population.

We use the binomial tests to evaluate two separate hypotheses. The first is that the probability of observing a significant adverse impact (i.e., decrease in return or increase in variance after an event) is identical (a) between attack and nonattack days or (b) between large-scale attacks and nonattack days. That is, attacks or even large-scale attacks do not increase the chance of adverse market conditions. The proportion of event days with adverse impact in nonattack days is defined as p, and then the probability of having at least k events with adverse impact in N attack days is calculated. The second hypothesis is that the probability of observing a significant adverse or favorable impact is 0.5 (p=0.5) regardless of whether an event is a nonattack, attack, or large-scale attack. In other words, there are equal chances of significant adverse (downward or more volatile) or favorable (upward or less volatile) movement even after attacks or large-scale attacks. Simply put, the probability differential between the two types of impact is zero. Both tests are done at the 5% significance level.

Fourth, as the second part of the meta-analysis, we identify the determinants of the adverse impact of terrorist attacks using two different models, classifying adverse impacts according to the results from the event study. First, we use the extreme value model, a binary dependent variable model, specifying attack days with significant adverse impact as one type of market response and those without adverse impact as the other type. Then we model the probability of adverse effect by the following cumulative distribution function of the extreme value distribution of Type I i.e. Gompit (Johnson, Kotz, & Balakrishnan, 1995).

$$\mathrm{P}(\mathrm{y_i} = 1|\mathbf{x_i}, \boldsymbol{\delta}) = \exp\left(-\mathrm{e}^{-\mathrm{x_i}'\boldsymbol{\delta}}\right), \tag{3}$$

where the probability that a binary variable y takes on the value of 1 or 0 depends on the determinants x and the coefficient δ. This model assumes that the maximum impact of individual attacks is generated by an arbitrary distribution, of which asymmetry may provide a better fit than probit or logit models. Second, we use a linear least squares model where the CARs or their test statistics in the event studies are defined as the strength of the adverse impact and used as the dependent variable in a regression model.[5]

The potential determinants of adverse impact (x) are selected from attack-side and recipient (or market)-side variables. The numbers of victims killed and wounded are expected to have a positive relationship with significant adverse impact. On the other hand, the market's recent experience of similar attacks (calculated as the number of attacks, killed, or wounded in the past 100 days) is expected to have a negative relationship with the adverse impact, since recent experience may reduce the impact of the latest attack. Since attack-day returns may have a certain relationship with adverse impact, they are added along with the sign and size dummies.

Fifth, as a robustness check for the findings from the meta-analysis of event studies, we apply a mean-volatility model to the observations belonging to each individual country. In this study, the autoregressive model above is accompanied by a popular asymmetric volatility

[5] This second model is used for comparison purposes only, since the test statistics (t or F) have their own distributions, so typical postestimation statistical tests could be invalid.

model, the exponential GARCH (EGARCH) model (Nelson, 1991). We add the current and previous-day terrorism indices up to lag 5, which account for the size and the timing of attacks, to both return and variance equations. To assess the impact of a terrorist attack, we use the Wald test for the significance of the sum of the coefficients of the terrorism indices. This model can utilize all aggregated information regarding one country and analyze the impact of terrorist attacks on both mean return and volatility at the same time, but it ignores specific circumstances preceding individual attacks.

$$ln(\sigma_{it}^2) = \omega_i + \gamma_{1i}\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_{2i}\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \gamma_{3i}\, ln(\sigma_{it-1}^2) + \sum_{l=0}^{5}\gamma_{li}T_{it-l}\,, \tag{4}$$

where T is the terrorism index.

Last, we apply the quantile regression model (Koenker & Bassett, 1978) to investigate whether different quantiles of market return react to attacks in different ways. The quantile regression model specifies the relationship between a specific quantile of market returns, i.e., their conditional medians instead of means, and the set of explanatory variables. The vector of regression estimators for quantile θ (η(θ)) is the solution to the following minimization problem:

$$\widehat{\eta(\theta)} = \text{argmin}_{\eta(\theta)}\left(\sum_{t:r_t>c_t^{\prime}\eta(\theta)}\theta\left|r_t - c_t^{\prime}\,\eta(\theta)\right| + \sum_{t:r_t<c_t^{\prime}\eta(\theta)}(1-\theta)\left|r_t - c_t^{\prime}\,\eta(\theta)\right|\right). \tag{5}$$

That is, the estimators minimize a weighted sum of the absolute deviation where r_t is split at proportions θ below and (1- θ) above. $c_t^{\prime}$ is a vector of the explanatory variables used in the event studies but includes 5 lags of the terrorism index. This study employs autoregressive variables, and thus it actually becomes a quantile autoregressive model (Koenker & Xiao, 2006) that is estimated by linear programming. The impact of terrorist attacks on a different θ can be tested by the significance of the sum of the coefficients of the terrorism index. Three quantiles, namely, 0.1, 0.5, and 0.9, are used in this study; the quantile of 0.1 represents underperforming markets (the bottom 10% of observations in terms of return), and that of 0.9 represents well-performing markets. In addition, we use two slope equality tests (0.1 vs. 0.5 and 0.5 vs. 0.9) to confirm that the two extreme quantiles are different from the middle quantile.

4. Results

At the aggregate level, market returns do not differ statistically between attack days and nonattack days, as is shown by the tests for equality in mean return in both stock and foreign exchange markets (Table 2). At the level of individual countries, only 3 out of 72 financial markets, Brazil, Taiwan, and the UK, show significant adverse impact on attack days. There is also only one market, Australia, that has statistically lower next-day returns after attacks (Atk+1) than after nonattack days. This descriptive evidence suggests that the adverse impact of terrorist attacks on market returns does not exist, particularly in the very short term.

<Insert Table 2 here>

On the other hand, market volatilities are relatively strongly affected by terrorist attacks (Table 3). However, the sign is mixed. The aggregated data show that terrorist attacks are associated with significantly higher volatility (U) on postattack days than on nonattack days in the stock markets, but lower volatility (D) on both attack and postattack days than on nonattack days in the foreign exchange markets. In addition, the individual financial markets have widely mixed signs and magnitudes of responses. Roughly equal numbers of markets show stabilizing and destabilizing effects of terrorist attacks, so the evidence here is not decisive. True, we do not control for different circumstances around individual attacks in the tests for equality, but the large number of observations may be sufficient to support the findings reasonably at the aggregated level. The evidence from these tests essentially suggests that the effect of terrorist attacks is not dominantly adverse and could be marginal or absent.

<Insert Table 3 here>

The meta-analysis of the event studies on all attack and nonattack days confirms this suggestion (Table 4). First, the event studies alone do not produce a clear pattern, as the postevent cumulative abnormal returns are almost equally divided between significantly negative (23–26%) and positive returns (24–28%) in the individual stock and foreign exchange markets. Second, the binomial tests on the aggregated results show that only in the foreign exchange markets is there a significantly higher chance of adverse impact after terrorist attacks than after nonattack days (under NvA). Only some individual markets are more clearly and adversely affected by terrorist attacks, specifically the stock markets in France and Israel and the foreign exchange markets in China, India, Israel, and Thailand.

Even larger-scale attacks do not produce statistical difference from nonattack days (Nv10). In terms of the probability of adverse effect on individual markets, the scant impact of 1,057 large-scale attacks contrasts with several previous findings that high-profile terrorist attacks significantly reduce returns (Charles & Darné, 2006; Chen & Siems, 2004; Hobbs, Schaupp, & Gingrich, 2016). In the aggregated data on the stock markets, we even observe a higher probability of upward movement after attacks. This may evidence a solid and quick recovery or even overshoot within the event windows, which may indicate the strong flexibility of the markets. The benchmark EGARCH models (EG) for each market do not show any more significant or dominant results than the event studies.

<Insert Table 4 here>

Nor do terrorist attacks, including large-scale attacks, increase volatility in the stock markets (Table 5). The only marginal evidence for adverse impact appears in the foreign exchange markets, where significantly higher volatilities are more probable after attacks than after nonattack days. Even for individual markets, there is not much evidence for an adverse impact. Only Japan and Mexico show a higher chance of greater volatilities in stock markets after attacks, and only Austria, China, Germany, Greece, India, and Israel see volatilities increase in their foreign exchange markets.

<Insert Table 5 here>

The reason for this slightly stronger impact on the foreign exchange markets than the stock markets could be that the former is inherently more efficient or less resilient in responding to a shock. On the other hand, significant probability differentials (under DvU) tend to disappear when only large-scale attacks are tested. This could be because, particularly in less frequently attacked countries, subsample size becomes a bit too insufficient to identify the probability differential when significant impact on volatility is rarer than significant impact on mean return, as is the case in our sample. The benchmark EGARCH models present similar results: stronger adverse impact on foreign exchange markets, but generally weak and mixed impacts overall.

In summary, terrorist attacks do not universally nor commonly have adverse impacts (Panel A in Table 6), but do have marginally significant impacts on foreign exchange markets. The evidence for this marginal adverse impact is clear only in aggregate data; individual attacks and markets often register heterogeneous results. Specifically, the marginally significant impacts take the form of higher probability of return decrease or volatility increase after attacks than after nonattack days, or significantly higher probability of having lower returns or larger variance than of having higher returns or smaller variance after attacks. Also, the adverse impact is stronger on volatilities than on mean returns.

The evidence from the binomial distribution—that terrorist attacks marginally increase the probability of adverse impact in relation to nonattack days—is compatible with Chesney and colleagues' (2011) evidence of a negative effect from the conditional distribution of attack-day returns on previous-day ones. Both studies show that terrorist attacks are likely to affect the probability distribution, if anything, so most of the time the adverse impact is unlikely to happen.

However, there could be alternative ways to reconcile our finding with those of other, more limited-scale studies. First, although terrorist attacks are known to have stronger impacts than natural disasters (Brounrn & Derwall, 2010; Chesney et al., 2011), market recovery could also be strong and quick (see Johnston & Nedelescu, 2005). Then, the adverse impact may not be easily captured by the event study method or regression models, which usually adopt event windows or lags of a few days. Second, similarly, financial markets could be essentially resilient to this type of shock. Investors may know or have experienced that unlike wars or coups, terrorist attacks are temporary and recovery follows soon after, so they may never respond at all, even at the beginning. However, this explanation is less likely, as past experience is relevant (see below and Table 7). Third, financial constraints such as short-selling bans may prevent excessive market reaction to negative shocks.[6] Fourth, the impact may be limited to certain industries (Apergis & Apergis, 2016; Hobbs et al., 2016; Kolaric & Schiereck, 2016). Fifth, the technical limitations of our methods may play a role here, but the benchmark models produce essentially very similar outcomes.

Sixth, the development of the finance and banking sector over time could make some markets flexible enough not to suffer from terrorist attacks (Chen & Siems, 2004), or other country-specific factors could explain our findings, since the adverse impact appears particularly strong in several countries (Panel A in Table 6), such as China, India, and Israel.

[6] Short-selling bans may not actually affect the market reaction to terrorist attacks. The meta-analysis by year (Tables A1 and A2) and the comparison between countries that imposed short-selling bans and those that did not in 2008 and 2009 (Panels B and C in Table A3, respectively) do not show an apparent difference.

However, there are minimal cross-sectional correlations between these development factors—market capitalization/GDP, stock traded/GDP, and stock and foreign market turnovers (Panel B in Table 6)—and significant adverse impacts on return or variance (Panel C in Table 6), and none of these correlations are statistically significant. Only stock market turnover is moderately positively related (0.22) to adverse impact on foreign exchange markets. This could indicate that market liquidity or development may make foreign exchange markets more susceptible to terrorist attacks, possibly owing to the role of foreign investors.

<Insert Table 6 here>

Last, event-level characteristics may have affected the outcomes (Table 7). We investigate both attack-side and recipient-side factors using two different models (the extreme value and the linear least squares) and the results are much the same. First, the numbers of killed and wounded victims (Kld and Wnd) on the attack day have marginally significant but opposite impacts on stock returns on the following days: the number killed raises the probability of adverse impact, but the number wounded reduces it. Stock investors may weight deaths more heavily but get used to nonfatal attacks. However, this pattern is not evident in the foreign exchange markets. Second, the experience and severity of recent attacks (100T) decrease the likelihood of adverse impact on the foreign exchange markets. That is, investors in these markets discount the impact of the subsequent attacks. But this response is not shared by stock investors.

Market returns on attack days (R) are more strongly related to the probability of adverse impact over subsequent days. Positive-return markets are less likely to suffer drops, while negative-return markets are more likely to be hit hard. On the other hand, attack-day returns are nonlinearly related to the likelihood of adverse impact on short-term market volatility.[7] Markets with either high or low returns are likely to be made more volatile by terrorist attacks, perhaps because they require a relatively large market adjustment, possibly mean-reverting. The results of the recipient-side variables here imply that the different quantiles of return distribution may react differently to attacks.

<Insert Table 7 here>

Finally, the quantile regression model of returns indeed shows that the impact of attacks is stronger in both tails of the return distribution (Table 8). In both stock and foreign exchange markets, both the top and the bottom 10% of observations are more strongly affected by the attacks than are the quantile of 0.5 and the benchmark volatility models. That is, the financial markets are more vulnerable when they are performing extremely well or extremely poorly. This finding is verified by the significant results of the slope equality tests, which show that the two extreme quantiles (0.9 and 0.1) react statistically differently from the median quantile (0.5). However, whether the impact is adverse or favorable varies across countries and markets, and thus it again confirms that terrorist attacks are weakly linked to adverse movements in financial markets in general. Similar patterns recur in the volatility models.

<Insert Table 8 here>

5. Conclusion

In summary, unlike most of the previous literature, this study does not find strong and universal evidence that terrorist attacks adversely affect financial markets. Attack days and

[7] Unlike the results for market returns, where the coefficient of the slope dummy (D×R) is smaller than that of the returns (R), in market variances, the relatively large negative coefficient of the slope dummy overcomes the positive coefficient of current returns (R) when R is negative.

even the following days do not have statistically smaller returns nor larger variances than nonattack days in the aggregated data. Adverse effects are seldom found even in individual markets.

In foreign exchange markets the probability of decreasing returns and increasing variance after terrorist attacks are marginally significantly larger than after nonattack days. However, very few of the individual foreign exchange markets show this significant adverse impact; and even so, the signs are quite mixed. Nor do large-scale attacks have stronger adverse impacts.

Whether an attack harms a financial market is determined by its magnitude and the market's past experience of terrorist attacks and by the market conditions when the attack happens. For example, in stock markets (but not foreign exchange markets) the number of victims killed increases the chance of significant adverse impact while that of wounded victims decreases it. In foreign exchange markets (but not stock markets) recent attacks decrease that probability. And in both markets, down-trending markets are more likely to suffer from declines after attacks while up-trending markets are less likely to do so. Both extremely well and poorly performing markets are likely to have higher volatility after attacks.

The findings of this study of a comprehensive dataset imply that we cannot normally expect a terrorist attack to decrease market returns or increase volatility. Its impact will at most marginally increase the probability of adverse impact compared with nonattack days. The probability of no response or a favorable market movement will still be fairly high. Country-specific or event-specific studies or studies based on a small sample will pick up only part of the true impact of terrorist attacks and may wrongly forecast their outcomes. Also, this study adds another dimension to the study of terrorist attacks. That is, if we are looking for significant impacts, we should focus on extremely well or poorly performing markets. Our findings may also help the decision making of investors who worry about the impact of these supposedly random and adverse external events.

On the other hand, it should be noted that we use event studies of individual attacks and nonattack days to identify adverse impacts from daily data, and then adopt meta-analysis to draw conclusions. This study may be still subject to the technical limitations of these approaches, despite our efforts to check robustness. The use of a lower or higher frequency dataset and/or other methods, like panel studies, could verify the findings of this study. Also, future research may need to focus on the conditional distribution and the extreme tails of returns to find more significant impact and identify determinants.

References

Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque country. *American Economic Review*, *93*(1), 113–132.

Apergis, E., & Apergis, N. (2016). The 11/13 Paris terrorist attacks and stock prices : The case of the international defense industry. *Finance Research Letters*, *17*, 186–192. https://doi.org/10.1016/j.frl.2016.03.002

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*(3), 164–167. https://doi.org/10.1016/j.econlet.2008.07.007

Aslam, F., & Kang, H.-G. (2013). How different terrorist attacks affect stock markets. *Defence and Peace Economics*, *26*(6), 634–648. https://doi.org/10.1080/10242694.2013.832555

Beber, A., & Pagano, M. (2013). Short-selling bans around the world : Evidence from the 2007–09 crisis. *Journal of Finance*, *68*(1), 343–381.

BIS. (2016). Triennial central bank survey—Foreign exchange turnover in April 2016. *Bank of International Settlements Review*, 15-16. Retrieved from www.bis.org

Brounrn, D., & Derwall, J. (2010). The impact of terrorist attacks on international stock markets. *European Financial Management*, *16*(4), 585–598. https://doi.org/10.1111/j.1468-036X.2009.00502.x

Campbell, J. Y., Lo, A. W., & MacKinlay, C. A. (1997). *The econometrics of financial markets*. Princeton, NJ: Princeton University Press.

Charles, A., & Darné, O. (2006). Large shocks and the September 11th terrorist attacks on international stock markets. *Economic Modelling*, *23*(4), 683–698. https://doi.org/10.1016/j.econmod.2006.03.008

Chen, A. H., & Siems, T. F. (2004). The effects of terrorism on global capital markets.

European Journal of Political Economy, *20*(2), 349–366. https://doi.org/10.1016/j.ejpoleco.2003.12.005

Chesney, M., Reshetar, G., & Karaman, M. (2011). The impact of terrorism on financial markets: An empirical study. *Journal of Banking and Finance*, *35*(2), 253–267. https://doi.org/10.1016/j.jbankfin.2010.07.026

Chuliá, H., Climent, F., Soriano, P., & Torró, H. (2009). Volatility transmission patterns and terrorist attacks. *Quantitative Finance*, *9*(5), 607–619. https://doi.org/10.1080/14697680802637882

Cukierman, A. (2004). Comment on: "Macroeconomic consequences of terror: Theory and the case of Israel." *Journal of Monetary Economics*, *51*(5), 1003–1006. https://doi.org/10.1016/j.jmoneco.2004.05.002

Eckstein, Z., & Tsiddon, D. (2004). Macroeconomic consequences of terror: Theory and the case of Israel. *Journal of Monetary Economics*, *51*(5), 971–1002. https://doi.org/https://doi.org/10.1016/j.jmoneco.2004.05.001

Eldor, R., & Melnick, R. (2004). Financial markets and terrorism. *European Journal of Political Economy*, *20*(2), 367–386. https://doi.org/10.1016/j.ejpoleco.2004.03.002

Essaddam, N., & Karagianis, J. M. (2014). Terrorism, country attributes, and the volatility of stock returns. *Research in International Business and Finance*, *31*, 87–100. https://doi.org/10.1016/j.ribaf.2013.11.001

Hobbs, J., Schaupp, L. C., & Gingrich, J. (2016). Terrorism, militarism, and stock returns. *Journal of Financial Crime*, *23*(1), 70-86. https://doi.org/10.1108/JFC-01-2015-0002

Johnson, N. L., Kotz, S., & Balakrishnan, N. (1995). *Continuous univariate distributions: Volume 2* (2nd ed.). New York: Wiley. Retrieved from https://openlibrary.org/books/OL1433543M/Continuous_univariate_distributions

Johnston, R. B., & Nedelescu, O. M. (2005). The impact of terrorism on financial markets:

An empirical study. *Journal of Banking and Finance*, *13*(1), 7–25. https://doi.org/10.1016/j.jbankfin.2010.07.026

Karolyi, G. A. (2006). *The consequences of terrorism for financial markets : What do we know ?* SSRN Working Paper Series, May. Retrieved from https://ssrn.com/abstract=904398

Karolyi, G. A., & Martell, R. (2006). Terrorism and the stock market. *International Review of Applied Financial Issues and Economics*, *2*(2), 285–314. https://doi.org/10.2139/ssrn.823465

Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica*, *46*(1), 33. https://doi.org/10.2307/1913643

Koenker, R., & Xiao, Z. (2006). Quantile autoregression. *Journal of the American Statistical Association*, *101*(475), 980–990. https://doi.org/10.1198/016214506000000672

Kolaric, S., & Schiereck, D. (2016). Are stock markets efficient in the face of fear? Evidence from the terrorist attacks in Paris and Brussels. *Finance Research Letters*, *18*, 306–310. https://doi.org/10.1016/j.frl.2016.05.003

Kollias, C., Manou, E., Papadamou, S., & Stagiannis, A. (2011). Stock markets and terrorist attacks: Comparative evidence from a large and a small capitalization market. *European Journal of Political Economy*, *27*(SUPPL. 1), S64-S77. https://doi.org/10.1016/j.ejpoleco.2011.05.002

Kollias, C., Papadamou, S., & Stagiannis, A. (2011). Terrorism and capital markets: The effects of the Madrid and London bomb attacks. *International Review of Economics and Finance*, *20*(4), 532–541. https://doi.org/10.1016/j.iref.2010.09.004

Mansoor, M., Mustofa, J., & Ugur, G. (2017). The impact of terrorist attacks on foreign exchange rate: Case study of Turkish lira versus pound sterling. *Economies*, *5*(1), 5. https://doi.org/10.3390/economies5010005

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

Narayan, P. K., Narayan, S., Khademalomoom, S., & Phan, D. H. B. (2017). Do terrorist attacks impact exchange rate behavior? New international evidence. *Economic Inquiry*, *56*(1), 547–561. https://doi.org/10.1111/ecin.12447

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, *59*(2), 347–370. Retrieved from http://links.jstor.org/sici?sici=0012-9682(199103)59:2%3C347:CHIARA%3E2.0.CO;2-V

Shahzad, S. J. H., Zakaria, M., Rehman, M. U., Ahmed, T., & Fida, B. A. (2016). Relationship between FDI, terrorism and economic growth in Pakistan: Pre and post 9/11 analysis. *Social Indicators Research*, *127*(1), 179–194. https://doi.org/10.1007/s11205-015-0950-5

Table 1

Descriptive statistics—financial markets and terrorist attacks.

Panel A: Total or Average (T/A)

					Stock	Forex	Days	Num	Wnd	Kld	Tind
					0.0002	0.0000	10833	21847	49703	25509	1.072

Panel B: Individual Countries

ID	Country	Price index	Start	Obs	Stock	Forex	Days	Num	Wnd	Kld	Tind
AT	Austria	ATX	11/04/1996	5146	0.0002	0.0000	14	17	12	1	1.001
AU	Australia	ASX200	11/04/1996	5146	0.0002	0.0000	38	41	33	8	1.004
BL	Belgium	BEL20	11/04/1996	5146	0.0002	0.0000	16	23	24	9	1.002
BR	Brazil	BOVESPA	02/01/2006	2609	0.0001	-0.0001	15	15	11	9	1.003
BU	Bulgaria	SOFIX	14/04/2006	2535	-0.0003	0.0000	11	12	30	8	1.002
CA	Canada	TSX Comp	11/04/1996	5146	0.0002	0.0000	41	42	51	8	1.004
CL	Chile	IGPA General	29/03/2007	2286	0.0001	-0.0001	43	54	30	3	1.009
CN	China	Shanghai A	03/06/2002	3544	0.0002	0.0001	83	109	947	786	1.038
CR	Croatia	CROBEX	30/01/2008	2067	-0.0005	0.0000	5	5	4	0	1.001
CZ	Czech	PX	10/04/2000	4104	0.0001	0.0001	15	16	25	2	1.002
DN	Denmark	OMXC20	11/04/1996	5146	0.0004	0.0000	7	8	8	2	1.001
FI	Finland	OMXH	11/04/1996	5146	0.0003	0.0000	10	11	2	9	1.001
FR	France	FAC40	11/04/1996	5146	0.0002	0.0000	370	689	390	186	1.040
GE	Germany	DAX30	11/04/1996	5146	0.0003	0.0000	141	176	192	22	1.015
GR	Greece	Athex Comp.	11/04/1996	5146	-0.0001	0.0000	373	573	71	10	1.033
HK	Hong Kong	Hang Seng	29/10/1996	5003	0.0001	0.0000	5	5	64	0	1.001
HU	Hungary	BUX	19/01/1999	4423	0.0003	0.0000	6	6	1	3	1.001
ID	Indonesia	IDX Comp.	14/05/2003	3297	0.0007	-0.0002	199	239	791	242	1.045
IN	India	NIFTY500	11/04/1996	5146	0.0004	-0.0001	2751	7414	19541	11088	1.738
IR	Ireland	ISEQ Overall	11/04/1996	5146	0.0002	0.0000	133	145	15	3	1.009
IS	Israel	TA125	09/04/2002	3583	0.0004	0.0000	505	959	2777	668	1.136
JP	Japan	NIKKEI225	11/04/1996	5146	0.0000	0.0000	44	53	3	0	1.003
ML	Malaysia	KLCI	31/10/2001	3697	0.0003	-0.0001	30	35	8	6	1.004
MX	Mexico	IPC	31/07/2001	3763	0.0005	-0.0002	72	89	284	134	1.015
NL	Netherland	AEX	11/04/1996	5146	0.0001	0.0000	20	20	17	9	1.002
NO	Norway	Oslo All	11/04/1996	5146	0.0004	0.0000	6	7	76	78	1.001
PH	Philippines	PSEi	16/01/2001	3903	0.0004	0.0000	1545	3450	5789	3203	1.428
RS	Russia	RTS	31/03/2003	3329	0.0002	-0.0003	890	1382	4681	2210	1.254
SA	South Africa	JSE All	11/04/1996	5146	0.0004	-0.0002	105	149	298	125	1.017
SP	Spain	IBEX35	11/04/1996	5146	0.0002	0.0000	380	614	2489	271	1.049
SZ	Switzerland	SMI	11/04/1996	5146	0.0002	0.0001	19	22	24	15	1.002
TK	Turkey	BIST100	27/01/2010	1547	0.0002	-0.0003	380	808	1954	897	1.255
TL	Thailand	Bangkok SET	15/09/1999	4252	0.0003	0.0000	1400	3108	6339	2167	1.369
TW	Taiwan	TAIEX	16/04/1999	4360	0.0000	0.0000	6	7	21	2	1.001
UK	UK	FTSE100	11/04/1996	5146	0.0001	0.0000	779	1064	1811	174	1.079
US	US	S&P500	11/04/1996	5146	0.0002	0.0000	376	480	890	3151	1.040

Note: All data end on December 31, 2015. “Stock” and “Forex” represent the average of log returns of the stock index and the real effective exchange rates, respectively. “Num” is the total number of terrorism attacks. “Wnd” and “Kld” are the total numbers of victims wounded and killed, respectively. “Tind” is the average value of the terrorism index, which is calculated as ln(e+Num+Wnd+Kld). The number of attack days used in the subsequent analysis is smaller than the number in this table because the event studies exclude any attack that does not have 100 daily observations (the estimation window) before the attack day.

Table 2

Attack vs. nonattack days—tests for equality in mean returns.

	Obs			Stock								Forex							
ID	Total	N	A	N	A	Atk	D	U	Atk+1	D	U	N	A	Atk	D	U	Atk+1	D	U
T/A	152241	141665	10576	0.0002	0.0004	1.5304			0.0776			0.0000	-0.0001	-1.4698			0.5925		
AT	5039	5026	13	0.0002	-0.0066	-1.1405			-1.2336			0.0000	-0.0004	-0.5835			-0.9428		
AU	5039	5003	36	0.0002	0.0029	1.3372			-1.9233	*		0.0000	0.0003	0.1813			-0.0809		
BL	5039	5023	16	0.0001	0.0023	0.5754			-0.2050			0.0000	0.0003	0.4302			0.2776		
BR	2503	2488	15	0.0001	-0.0096	-2.6454	*		0.1231			-0.0001	0.0004	0.1706			-0.1555		
BU	2429	2418	11	-0.0003	0.0027	1.0859			2.1118		*	0.0000	-0.0014	-1.1324			-0.8046		
CA	5039	4999	40	0.0002	-0.0012	-0.6681			-0.4461			0.0000	-0.0015	-1.3071			0.1076		
CL	2180	2137	43	0.0001	0.0012	0.9707			0.4243			-0.0001	0.0008	0.8327			0.2893		
CN	3438	3356	82	0.0002	0.0040	2.5460		*	-0.9538			0.0001	0.0001	-0.0378			1.1803		
CR	1961	1957	4	-0.0004	0.0033	1.2332			0.1215			0.0000	-0.0007	-0.3433			1.0865		
CZ	3998	3983	15	0.0001	0.0012	0.5176			-0.8686			0.0001	-0.0003	-0.4093			-0.6848		
DN	5039	5032	7	0.0004	0.0056	3.0835		*	1.7626		*	0.0000	-0.0009	-0.9450			-0.5744		
FI	5039	5030	9	0.0003	-0.0032	-0.7753			-1.1794			0.0000	0.0014	1.0077			-0.8501		
FR	5039	4701	338	0.0001	0.0013	1.6771		*	0.1037			0.0000	-0.0002	-1.5880			0.6502		
GE	5039	4916	123	0.0003	-0.0006	-0.6324			-0.7240			0.0000	0.0004	1.7760		*	-1.0044		
GR	5039	4670	369	-0.0002	0.0007	0.7658			-0.1464			0.0000	0.0002	1.5315			-1.5634		
HK	4897	4892	5	0.0001	-0.0154	-1.1763			0.4462			0.0000	-0.0012	-0.8262			-0.2078		
HU	4317	4311	6	0.0003	0.0085	4.5627		*	-1.4267			0.0000	-0.0005	-0.3227			-0.4530		
ID	3191	2997	194	0.0007	-0.0004	-1.0184			-0.3775			-0.0002	-0.0003	-0.3769			0.1429		
IN	5039	2331	2708	0.0008	0.0001	-1.5588			-0.0771			-0.0001	-0.0001	-0.1475			-0.4241		
IR	5039	4908	131	0.0001	0.0019	1.8377		*	1.0897			0.0000	-0.0003	-1.0757			0.6853		
IS	3477	2994	483	0.0003	0.0005	0.2306			-0.8628			0.0000	0.0001	0.3264			-0.4999		
JP	5039	4999	40	0.0000	-0.0001	-0.0349			0.4627			0.0000	-0.0006	-0.7431			-0.0115		
ML	3591	3561	30	0.0002	-0.0001	-0.2848			1.2281			-0.0001	-0.0002	-0.2288			1.4862		
MX	3657	3589	68	0.0006	-0.0012	-1.3556			0.2872			-0.0001	-0.0023	-1.2302			0.7492		
NL	5039	5021	18	0.0001	-0.0007	-0.2284			0.0514			0.0000	-0.0002	-0.4198			1.2026		
NO	5039	5033	6	0.0003	0.0027	0.6863			-0.8588			0.0000	0.0027	1.6937		*	-0.3387		
PH	3797	2270	1527	0.0004	0.0004	0.0750			0.8134			-0.0001	0.0001	1.8328		*	1.2187		
RS	3223	2359	864	-0.0001	0.0008	1.0724			-0.8378			-0.0003	-0.0003	-0.2109			0.2616		
SA	5039	4944	95	0.0004	-0.0005	-0.7502			0.4315			-0.0002	-0.0005	-0.3551			0.5113		
SP	5039	4682	357	0.0002	0.0002	0.0676			-1.6152			0.0000	0.0000	0.1404			0.0058		
SZ	5039	5022	17	0.0002	0.0018	0.9028			1.9110		*	0.0001	-0.0009	-1.4503			-0.4934		
TK	1441	1068	373	0.0002	0.0002	0.0640			0.2742			-0.0003	-0.0004	-0.0656			0.9209		
TL	4146	2752	1394	-0.0001	0.0009	2.5189		*	0.4658			0.0000	0.0001	0.9881			0.2249		
TW	4254	4248	6	0.0000	-0.0131	-1.5257			-1.6398			0.0000	-0.0020	-1.6781	*		-1.1877		
UK	5039	4268	771	0.0001	0.0000	-0.3735			-0.2995			0.0001	-0.0003	-2.2961	*		1.8383		*
US	5039	4677	362	0.0002	0.0000	-0.3698			1.1830			0.0001	-0.0001	-0.6875			2.2752		*
				Sig		19%			11%			Sig		14%			6%		
				D%		3%			3%			D		6%			0%		
				U%		17%			8%			U		8%			6%		

Note: Statistical differences between attack ("A") and nonattack ("N") days are tested by equality of mean tests. The test statistics are presented under "Atk" for attack vs. nonattack days and "Atk+1" for attack+1 vs. nonattack days. "D" and "U" indicate whether the alternative hypothesis is that the statistics for attack days are smaller or larger against the null hypothesis of equality, respectively. * shows rejection of the null hypothesis at the 5% significance level. “T/A” is total or average, and “Obs” is the number of observations. “Sig” is the proportion of rejection in the individual markets. “D%” and “U%” show the proportion of rejection in the individual markets for each alternative hypothesis.

Table 3

Attack vs. nonattack days—tests for equality in variances.

	Obs			Stock								Forex							
ID	Total	N	A	N	A	Atk	D	U	Atk+1	D	U	N	A	Atk	D	U	Atk+1	D	U
T/A	152241	141665	10576	2.0E-04	2.0E-04	1.0146			1.0320		*	2.0E-05	1.9E-05	0.9283	*		0.9265	*	
AT	5039	5026	13	1.9E-04	4.6E-04	2.3595		*	5.4517		*	1.6E-06	6.1E-06	3.7433		*	1.6145		
AU	5039	5003	36	9.6E-05	1.5E-04	1.5828		*	0.9585			4.4E-05	1.0E-04	2.3259		*	0.9514		
BL	5039	5023	16	1.5E-04	2.3E-04	1.5222			1.3017			3.2E-06	6.4E-06	2.0055		*	1.9004		*
BR	2503	2488	15	3.1E-04	2.0E-04	0.6499			0.5662			1.1E-04	1.2E-04	1.1577			1.0233		
BU	2429	2418	11	1.6E-04	8.2E-05	0.5064			0.2441	*		6.2E-06	1.7E-05	2.7499		*	0.4411		
CA	5039	4999	40	1.2E-04	1.7E-04	1.3576			1.9257		*	2.6E-05	5.6E-05	2.1691		*	1.5585		*
CL	2180	2137	43	7.6E-05	5.5E-05	0.7196			0.5556	*		4.7E-05	4.6E-05	0.9977			0.6749		
CN	3438	3356	82	2.7E-04	1.8E-04	0.6850	*		1.3999		*	8.0E-06	1.6E-05	2.0131		*	1.1456		
CR	1961	1957	4	1.6E-04	3.7E-05	0.2355			2.0711			4.2E-06	1.4E-05	3.3072		*	0.4863		
CZ	3998	3983	15	2.0E-04	6.4E-05	0.3263	*		1.4568			1.6E-05	1.5E-05	0.9219			0.6182		
DN	5039	5032	7	1.6E-04	2.0E-05	0.1247	*		0.1204	*		3.8E-06	7.1E-06	1.8507			0.4562		
FI	5039	5030	9	3.3E-04	1.9E-04	0.5596			1.5967			5.1E-06	1.7E-05	3.3858		*	1.4037		
FR	5039	4701	338	2.2E-04	1.7E-04	0.7954	*		0.7134	*		3.5E-06	3.6E-06	1.0206			1.2007		*
GE	5039	4916	123	2.3E-04	2.3E-04	0.9659			0.9479			5.1E-06	4.9E-06	0.9562			1.4642		*
GR	5039	4670	369	3.6E-04	4.6E-04	1.2859		*	1.2418		*	5.8E-06	3.7E-06	0.6319	*		0.8387	*	
HK	4897	4892	5	2.7E-04	8.7E-04	3.1678		*	0.4867			5.9E-06	1.2E-05	1.9424			0.9522		
HU	4317	4311	6	2.4E-04	1.9E-05	0.0815	*		1.2252			3.4E-05	1.0E-05	0.2961			0.2651		
ID	3191	2997	194	1.9E-04	1.9E-04	1.0327			1.3448		*	3.0E-05	2.8E-05	0.9259			0.7811	*	
IN	5039	2331	2708	2.7E-04	2.1E-04	0.7973	*		0.7936	*		1.6E-05	2.3E-05	1.4896		*	1.5377		*
IR	5039	4908	131	1.8E-04	1.2E-04	0.6570	*		0.7250	*		8.6E-06	7.9E-06	0.9133			0.8309		
IS	3477	2994	483	1.3E-04	1.5E-04	1.1083			0.8572	*		2.0E-05	2.7E-05	1.3165		*	1.4267		*
JP	5039	4999	40	2.3E-04	1.8E-04	0.8138			3.1306		*	4.4E-05	2.9E-05	0.6715			1.8302		*
ML	3591	3561	30	5.4E-05	2.8E-05	0.5198	*		1.4706			1.3E-05	1.9E-05	1.4956		*	2.7505		*
MX	3657	3589	68	1.5E-04	1.2E-04	0.7670			2.1866		*	5.1E-05	2.0E-04	3.8807		*	1.9897		*
NL	5039	5021	18	2.1E-04	2.6E-04	1.2004			0.8832			4.6E-06	3.7E-06	0.7908			0.8494		
NO	5039	5033	6	1.8E-04	7.0E-05	0.3818			0.5581			2.0E-05	1.5E-05	0.7557			0.5781		
PH	3797	2270	1527	1.5E-04	1.5E-04	0.9884			0.8529	*		1.2E-05	1.2E-05	0.9980			1.1536		*
RS	3223	2359	864	4.9E-04	4.3E-04	0.8908	*		0.9044	*		7.7E-05	2.4E-05	0.3179	*		0.2919	*	
SA	5039	4944	95	1.5E-04	1.4E-04	0.9127			0.8080			8.5E-05	5.4E-05	0.6319	*		1.1174		
SP	5039	4682	357	2.2E-04	2.1E-04	0.9417			0.8144	*		2.4E-06	2.9E-06	1.2203		*	1.4414		*
SZ	5039	5022	17	1.5E-04	5.6E-05	0.3812	*		0.9940			2.1E-05	7.1E-06	0.3436	*		0.5429		
TK	1441	1068	373	2.2E-04	1.9E-04	0.8776			0.9548			3.0E-05	3.7E-05	1.2295		*	1.4123		*
TL	4146	2752	1394	2.0E-04	1.4E-04	0.6690	*		0.7436	*		9.2E-06	8.3E-06	0.9000	*		0.8621	*	
TW	4254	4248	6	1.9E-04	4.5E-04	2.3038		*	3.8444		*	6.7E-06	8.4E-06	1.2464			0.2328		
UK	5039	4268	771	1.5E-04	1.1E-04	0.7210	*		0.7841	*		1.7E-05	1.7E-05	0.9691			1.1254		*
US	5039	4677	362	1.5E-04	1.7E-04	1.1308			0.8484	*		9.6E-06	7.9E-06	0.8182	*		0.8148	*	
				Sig		47%			58%			Sig		56%			50%		
				D%		33%			36%			D		17%			14%		
				U%		14%			22%			U		39%			36%		

Note: Statistical differences between nonattack days (N) and attack days (A) are tested by equality of variance tests. The test statistics are presented under "Atk" for attack vs.

nonattack days and “Atk+1” for attack+1 vs. nonattack days. “D” and “U” indicate whether the alternative hypothesis is that the statistics in attack days are smaller or larger against the null hypothesis of equality, respectively. * shows rejection of the null hypothesis at the 5% significance level. “T/A” is total or average, and “Obs” is the number of observations. “Sig” is the proportion of rejection in the individual markets. “D%” and “U%” show the proportion of rejection in the individual markets for each alternative hypothesis.

Table 4

Meta-analysis of the event studies—mean returns.

					Stock													Forex												
		Obs			N		A		10		NvA		Nv 10		DvU			N		A		10		NvA		Nv 10		DvU		
ID	Total	N	A	10	D	U	D	U	D	U	D	U	D	U	A	10	EG	D	U	D	U	D	U	D	U	D	U	A	10	EG
T/A	152241	141665	10576	1057	35735	35270	2737	2527	238	291				*	D	U		36001	36344	2713	2669	278	267	*						
					0.25	*0.25*	*0.26*	*0.24*	*0.23*	*0.28*								*0.25*	*0.26*	*0.26*	*0.25*	*0.26*	*0.25*							
AT	5039	5026	13		1326	1277	1	6										1268	1319	5	6									
AU	5039	5003	36	1	1294	1288	12	8	1	0								1310	1247	14	9	0	1							
BL	5039	5023	16	1	1229	1232	3	2	0	0								1322	1355	3	3	0	0							
BR	2503	2488	15		629	670	2	6										603	594	4	4									
BU	2429	2418	11	1	573	587	3	2	0	1								578	601	3	5	0	0							
CA	5039	4999	40	1	1311	1217	8	14	1	0								1342	1337	5	13	1	0					U		D
CL	2180	2137	43		536	547	10	13										555	545	11	8									
CN	3438	3356	82	27	837	786	19	19	8	4								828	868	36	11	2	14	*			*	D	U	U
CR	1961	1957	4		457	483	2	0										501	498	2	1									U
CZ	3998	3983	15	1	1037	955	4	5	1	0								977	998	5	2	0	1							
DN	5039	5032	7		1283	1235	2	2										1318	1363	3	3									
FI	5039	5030	9		1288	1273	0	4									D	1312	1322	3	1									
FR	5039	4701	338	8	1156	1198	111	78	2	3	*				D			1243	1245	88	98	3	2							
GE	5039	4916	123	3	1261	1248	36	32	0	1								1290	1310	23	44	2	0		*			U		D
GR	5039	4670	369		1199	1178	103	90									U	1183	1219	87	103									
HK	4897	4892	5	1	1283	1285	1	0	0	0								1292	1271	0	3	1	0							
HU	4317	4311	6		1121	1086	3	0										1049	1052	0	1									
ID	3191	2997	194	7	739	678	43	44	0	6						U		691	685	49	49	0	3							
IN	5039	2331	2708	527	665	550	698	664	119	144							D	585	584	695	684	148	139	*		*				
IR	5039	4908	131		1234	1217	37	31										1311	1301	38	41									
IS	3477	2994	483	46	753	748	144	115	9	18	*			*	D			758	711	137	125	11	10	*						
JP	5039	4999	40		1293	1235	8	14									D	1223	1345	12	10									
ML	3591	3561	30		844	854	7	5										863	899	7	8									
MX	3657	3589	68	3	862	892	16	22	2	1								895	843	16	17	0	1							
NL	5039	5021	18	1	1244	1249	4	3	0	1								1332	1350	1	5	0	0							
NO	5039	5033	6	1	1273	1197	1	0	0	0								1288	1229	2	1	0	0							U
PH	3797	2270	1527	159	547	537	393	349	32	37							U	529	559	364	353	37	32							
RS	3223	2359	864	58	572	562	218	202	17	13								553	602	202	214	18	7						D	
SA	5039	4944	95	5	1217	1259	21	23	2	3								1262	1244	23	20	0	0							
SP	5039	4682	357	9	1179	1211	101	82	1	5								1238	1261	100	97	4	4							
SZ	5039	5022	17	1	1237	1228	5	5	0	1								1200	1259	3	5	1	0							
TK	1441	1068	373	44	279	266	103	81	6	12								266	279	98	96	11	11							
TL	4146	2752	1394	136	693	673	331	320	32	38								683	688	376	334	35	35	*						
TW	4254	4248	6	1	1067	1059	1	3	1	0								1056	1082	1	3	1	0							
UK	5039	4268	771	8	1076	1088	192	193	1	1								1085	1082	202	204	1	4							
US	5039	4677	362	7	1141	1222	94	90	3	2								1212	1197	95	88	2	3							

Note: This table presents the results of a meta-analysis of event studies on nonattack days (N), attack days (A), and large-scale (10% largest) attack days (10), with a 100-day estimation and a 6-day event window. The main figures show the number of days with significant decrease (D) or increase (U) of the market returns due to an attack. NvA compares nonattack days with attack days by testing the probability that decrease (D) or increase (U) in return is equal in both groups. Nv10 does the same but with large-scale attacks instead. * indicates significance at the 5% level. DvU tests whether the probabilities of observing D and U are equal or one of them is favored in each group of event days, at the 5% significance level. “Obs” is the number of observations. “T/A” is either total or average. The numbers in italics show the proportion of significant event days (D or U) in each group (N/A/10). EG shows the results from the EGARCH model. The results by year are presented in Table A1 in the appendix.

Table 5

Meta-analysis of the event studies—variances.

	Obs				Stock													Forex												
	Obs				N		A		10		NvA		Nv10		DvU			N		A		10		NvA		Nv10		DvU		
ID	Total	N	A	10	D	U	D	U	D	U	D	U	D	U	A	10	EG	D	U	D	U	D	U	D	U	D	U	A	10	EG
T/A	152241	145481	10576	1057	15362	16439	1283	1195	113	125	*				D			14087	15218	1150	1206	109	128	*	*		*			
					0.11	*0.11*	*0.12*	*0.11*	*0.11*	*0.12*								*0.10*	*0.10*	*0.11*	*0.11*	*0.10*	*0.12*							
AT	5039	5026	13		532	604	1	2										417	538	1	5				*					
AU	5039	5003	36	1	475	559	2	5	0	0								443	551	2	5	0	0							
BL	5039	5023	16	1	533	613	3	2	0	0								378	517	3	3	0	0							
BR	2503	2488	15		220	264	0	2										417	316	3	2									
BU	2429	2418	11	1	446	319	2	1	0	0								624	293	3	1	1	0							
CA	5039	4999	40	1	486	563	2	7	0	0								350	494	8	4	0	0	*						
CL	2180	2137	43		284	267	7	2										204	219	5	7									
CN	3438	3356	82	27	361	425	7	6	2	4								316	317	3	13	1	4		*			U		
CR	1961	1957	4		239	179	1	0										159	214	0	1									
CZ	3998	3983	15	1	511	449	2	2	0	0								513	455	2	2	0	0							U
DN	5039	5032	7		540	586	1	1										414	528	0	2									
FI	5039	5030	9		488	546	1	0										439	486	0	1									
FR	5039	4701	338	8	429	560	34	37	1	2								356	509	27	36	1	3				*			
GE	5039	4916	123	3	539	573	9	11	0	1								416	511	11	20	0	0		*					
GR	5039	4670	369		562	561	39	48										449	459	26	47				*			U		U
HK	4897	4892	5	1	446	504	0	0	0	0								374	496	2	1	0	1							
HU	4317	4311	6		432	415	0	0										578	500	0	0									
ID	3191	2997	194	7	446	371	31	31	0	2							D	542	377	30	27	1	1							
IN	5039	2331	2708	527	323	318	353	312	60	55							D	274	242	358	312	58	64	*	*			D		U
IR	5039	4908	131		472	560	10	15										347	478	9	19							U		
IS	3477	2994	483	46	321	291	52	57	1	6								336	288	37	62	4	7		*			U		U
JP	5039	4999	40		476	566	6	10				*						524	567	2	6									
ML	3591	3561	30	3	451	442	3	6	0	2								296	415	0	5	0	1					U		U
MX	3657	3589	68		404	432	4	14				*			U		U	364	394	3	11							U		
NL	5039	5021	18	1	491	605	4	3	0	0								369	522	2	0	1	0							
NO	5039	5033	6	1	577	574	1	0	0	0								493	526	0	0	0	0							
PH	3797	2270	1527	159	266	232	205	152	21	12	*				D		D	194	233	154	157	17	13	*						
RS	3223	2359	864	58	308	291	113	95	9	8								382	301	136	110	3	9							
SA	5039	4944	95	5	580	633	11	14	1	2								506	570	12	11	1	2							D
SP	5039	4682	357	9	451	566	29	44	0	2								379	505	21	36	1	1					U		
SZ	5039	5022	17	1	554	602	0	0	0	0							D	588	520	0	1	0	0							D
TK	1441	1068	373	44	110	112	34	36	2	5								116	129	29	35	4	4							
TL	4146	2752	1394	136	359	308	202	145	15	19					D		D	309	324	164	147	15	17							D
TW	4254	4248	6	1	344	456	0	1	0	0								502	520	0	0	0	0							
UK	5039	4268	771	8	443	520	71	84	0	3								330	422	71	88	0	1							
US	5039	4677	362	7	463	573	43	50	1	2								389	482	26	29	1	0							

Note: This table presents the results of a meta-analysis of event studies on nonattack days (N), attack days (A), and large-scale (10% largest) attack days (10), with a 100-day estimation and a 6-day event window. The main figures show the number of days with significant decrease (D) or increase (U) of market variances due to an attack. NvA compares nonattack days with attack days by testing whether the probabilities of decrease (D) or increase (U) in return are equal in both groups. Nv10 does the same but with large-scale attacks instead. * indicates significance at the 5% level. DvU tests whether the probabilities of observing D and U are equal or one of them is favored in each group of event days, at the 5% significance level. “Obs” is the number of observations. “T/A” is either total or average. The numbers in italics show the proportion of significant event days (D or U) in each group (N/A/10). EG shows the results from the EGARCH model. The results by year are presented in Table A2 in the appendix.

Table 6

Adverse impact by country and its correlation with market/economic factors.

Panel A: Summary of adverse impact

ID	SM	SV	EM	EV	Sum
AT	0	0	0	1	1
AU	0	0	0	0	0
BL	0	0	0	0	0
BR	0	0	0	0	0
BU	0	0	0	0	0
CA	0	0	0	0	0
CL	0	0	0	0	0
CN	0	0	1	1	2
CR	0	0	0	0	0
CZ	0	0	0	0	0
DN	0	0	0	0	0
FI	0	0	0	0	0
FR	1	0	0	0	1
GE	0	0	0	1	1
GR	0	0	0	1	1
HK	0	0	0	0	0
HU	0	0	0	0	0
ID	0	0	0	0	0
IN	0	0	1	1	2
IR	0	0	0	0	0
IS	1	0	1	1	3
JP	0	1	0	0	1
ML	0	0	0	0	0
MX	0	1	0	0	1
NL	0	0	0	0	0
NO	0	0	0	0	0
PH	0	0	0	0	0
RS	0	0	0	0	0
SA	0	0	0	0	0
SP	0	0	0	0	0
SZ	0	0	0	0	0
TK	0	0	0	0	0
TL	0	0	1	0	1
TW	0	0	0	0	0
UK	0	0	0	0	0
US	0	0	0	0	0
T/A	2	2	4	6	14

Panel B: Market/economic factors

ID	CAP	TRD	TOV	FOV
AT	107.62	81.05	75.17	0.29
AU	28.34	11.34	39.32	1.86
BL	66.00	23.75	39.71	0.35
BR	49.09	26.04	54.47	0.31
BU	15.21	2.43	19.04	0.03
CA	112.86	79.92	72.70	1.32
CL	103.28	14.73	13.78	0.11
CN	51.90	92.36	183.01	1.12
CR	38.59	2.04	5.41	
CZ	20.76	11.79	65.43	0.06
DN	55.75	32.06	56.29	1.55
FI	134.73	117.69	91.12	0.21
FR	77.96	62.79	82.75	2.78
GE	45.40	55.31	126.78	1.78
GR	41.16	21.00	46.50	0.02
HK	795.92	443.09	54.82	6.71
HU	20.75	15.18	72.56	0.05
ID	33.56	10.82	34.88	0.08
IN	76.06	48.37	75.05	0.52
IR	51.42	6.55	13.50	0.03
IS	71.89	27.24	37.71	0.12
JP	77.77	88.35	111.97	6.13
ML	136.87	41.88	30.75	0.12
MX	30.49	8.11	27.27	0.31
NL	90.49	94.33	108.59	1.30
NO	52.16	41.01	77.82	0.61
PH	55.22	9.29	16.62	0.05
RS	40.63	30.19	47.73	0.69
SA	211.39	57.31	27.11	0.32
SP	81.27	107.61	133.77	0.51
SZ	216.01	134.29	1.09	2.39
TK	28.72	43.62	158.31	0.34
TL	66.55	52.24	79.75	0.17
TW	159.24	98.01	62.67	
UK	120.84	94.35	78.15	36.94
US	124.65	222.97	186.51	19.53
T/A	96.96	64.14	66.89	2.61

Panel C: Correlation table

	CAP	TRD	TOV	FOV
SM	-0.042	-0.062	-0.046	-0.042
SV	-0.082	-0.052	0.004	0.022
EM	-0.084	-0.045	0.197	-0.112
EV	-0.110	-0.062	0.218	-0.132
T/A	-0.080	-0.055	0.093	-0.066

Note: Panel A summarizes the number of adverse impacts discovered in each country in the meta-analysis (Tables 4 and 5). The prefixes S and E are for stock and foreign exchange markets, respectively. M and V indicate mean return and variances, respectively. Panel B shows 15-year (2000–2015) average values of stock market capitalization per GDP (CAP, in %), the value of stock traded per GDP (TRD, in %), stock market turnover ratio (TOV), and the daily average distribution of foreign exchange turnover (FOV, in %). Panel C is the table of correlation between the variables in Panels A and B. No correlation is significant at the 5% level. T/A is total or average.

Table 7

The determinants of the adverse impact of terrorist attacks.

	Return			Variance		
Stock	EV	CAR	T	EV	CAR^2	F
c	-0.4907***	-0.0013	-0.2699**	-1.0941***	0.0006***	0.7293***
Kld	-0.0075	0.0015*	0.1017*	0.0462	0.0000	0.0031
Wnd	-0.0363*	-0.0010*	-0.0525	-0.0149	0.0001	-0.0044
100T	0.0105	0.0004	-0.0254	-0.0258	0.0000	-0.0649
Trend	0.0029	0.0000	0.0100*	-0.0004	0.0000***	0.0057
R_t	-19.6403***	-1.2051***	-69.4705***	20.0243***	0.1269***	34.6726***
D_t	0.2419***	0.0028***	0.6635***	-0.0221	0.0003**	-0.0198
$D_t{\times}R_t$	-2.6762	0.4003***	23.9018***	-59.5709***	-0.2185***	-104.6672***
R^2	0.0763	0.1672	0.1435	0.0996	0.0792	0.0813

	Return			Variance		
Forex	EV	CAR	T	EV	CAR^2	F
c	-0.2934***	0.0006	-0.0922	-0.8572***	0.0000	1.7341***
Kld	-0.0108	0.0002	0.0524	-0.0074	0.0000	-0.1020
Wnd	0.0001	-0.0002	-0.0577	0.0058	0.0000	0.0061
100T	-0.1019***	-0.0005	-0.1247	-0.1520***	0.0000	-0.2853*
Trend	-0.0036	0.0000	0.0050	0.0017	0.0000	-0.0183
R_t	-52.6821***	-1.2150***	-212.2467***	81.6690***	0.0412***	116.0863***
D_t	0.2469***	0.0005*	0.6623***	-0.0490	0.0000*	-0.5959***
$D_t{\times}R_t$	-25.0917**	0.4588***	59.3903***	-188.9171***	-0.0734***	-433.6373***
R^2	0.0691	0.1517	0.1199	0.0793	0.0806	0.0208

Note: This table presents the estimation results of the binary extreme value (EV) and least squares models (CAR, CAR^2, T and F) of the adverse impact of terrorist attacks. The dependent variables are the measures of significant adverse effect from the event studies. EV adopts a dummy for significant adverse impact on return or variance. CAR uses the negativity of 6-day cumulative abnormal returns and CAR^2 uses their squares as a proxy for variance. T and F use the test statistics used in the event studies. Kld and Wnd are the numbers of killed and wounded victims. 100T is the average of the terrorism index over 100 days preceding an attack. R is market returns and R_{t-1} is previous-day returns. D is a dummy for negative returns. D×R is an interaction term (or a slope dummy). R^2 in EV is McFadden R^2, which is calculated from likelihood values. R^2 in the other models are the adjusted R^2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 8

Impact on the different quantiles of return.

	Stock						Forex					
ID	EG	0.1	0.5	0.9	15	59	EG	0.1	0.5	0.9	15	59
AT	-0.0213	-0.1136 D	-0.0277	0.1516 U			-0.0006	-0.0090 D	-0.0005	0.0051 U		
AU	-0.0009	0.0078	-0.0040	0.0302	X	X	0.0020	0.0094 U	0.0024	0.0178 U		
BL	0.0095	0.0209 U	0.0079	0.0213			-0.0003	0.0008	-0.0006	-0.0012	X	
BR	-0.0219	0.0017	-0.0235 D	-0.0732 D			-0.0058	0.0011	-0.0108 D	0.0064		X
BU	0.0021	0.0156	0.0067 U	-0.0142	X		-0.0005	0.0026	-0.0006	-0.0030 D	X	
CA	-0.0043	-0.0428	-0.0077	-0.0025			-0.0042 D	-0.0002	-0.0059	-0.0086 D		
CL	-0.0022	0.0059	-0.0022	-0.0070	X		0.0007	-0.0009	0.0051	-0.0093		
CN	0.0011	0.0035	-0.0011	-0.0048 D			0.0010 U	0.0008	0.0012 U	0.0017 U		
CR	0.0235	-0.0311 D	0.0078	0.0861 U	X	X	0.0106 U	-0.0156 D	-0.0001	0.0106 U	X	
CZ	-0.0090	0.0094	0.0018	0.0057			0.0031	0.0105 U	0.0076 U	-0.0054 D		X
DN	0.0121	-0.0327	0.0287 U	0.1171 U	X	X	-0.0029	-0.0234 D	-0.0007	0.0125 U	X	X
FI	-0.0340 D	-0.0622 D	-0.0457	-0.0580 D	X	X	0.0017	-0.0143 D	-0.0002	0.0090 U	X	X
FR	0.0018	0.0097 U	0.0019	-0.0035			-0.0004	-0.0005	-0.0003	-0.0005		
GE	0.0005	0.0002	0.0022	-0.0001	X		-0.0013 D	-0.0053 D	-0.0008	-0.0004		X
GR	0.0137 U	-0.0101	0.0028	0.0410 U			-0.0003	-0.0011	-0.0001	0.0016 U		
HK	-0.0040	0.0078 U	-0.0109 D	-0.0139 D	X	X	-0.0012	-0.0070 D	-0.0122 D	-0.0019 D	X	X
HU	0.0060	0.0153	-0.0091	-0.0262	X		-0.0034	-0.0077	-0.0072	-0.0109 D		X
ID	-0.0011	-0.0016	-0.0018	0.0012	X		-0.0009	-0.0031 D	0.0000	0.0036	X	X
IN	-0.0008 D	0.0024 U	-0.0006	-0.0036 D		X	0.0000	-0.0009 D	-0.0001	0.0006 U		
IR	-0.0042	0.0187	0.0002	0.0004			-0.0015	0.0017	0.0001	-0.0023		
IS	-0.0001	-0.0010	0.0004	0.0002			0.0001	-0.0018 D	0.0000	0.0007		
JP	-0.0316 D	-0.0614 D	-0.0137	-0.0031		X	0.0085	-0.0008	0.0062	0.0024		
ML	0.0016	0.0159	-0.0009	0.0032			0.0031	-0.0138	0.0014	0.0130		
MX	-0.0049	-0.0065	-0.0029	0.0111 U	X		0.0000	0.0035	0.0005	-0.0022	X	X
NL	0.0078	0.0452 U	0.0179	0.0095 U		X	0.0002	-0.0085	-0.0001	0.0011	X	
NO	-0.0032	0.0159 U	-0.0051 D	-0.0245 D	X	X	0.0011 U	0.0076 U	0.0010 U	-0.0053 D	X	X
PH	0.0013 U	0.0032 U	0.0003	-0.0012	X		0.0002	0.0007 U	0.0000	0.0000	X	
RS	-0.0010	-0.0002	0.0006	-0.0025			0.0001	0.0017 U	0.0000	-0.0014 D		X
SA	-0.0001	0.0069	-0.0003	-0.0075 D			0.0008	0.0075	-0.0002	-0.0086 D		X
SP	0.0013	-0.0030	0.0008	0.0035			0.0001	-0.0008	0.0000	0.0008		X
SZ	0.0017	0.0169	0.0157 U	0.0106			-0.0023	-0.0009	-0.0008	-0.0010		X
TK	-0.0004	0.0023 U	0.0002	-0.0006			0.0001	-0.0024 D	0.0003	0.0013		X
TL	-0.0007	0.0042 U	0.0004	-0.0040 D	X	X	0.0000	0.0006 U	-0.0001	-0.0002	X	X
TW	-0.0403	-0.0829 D	-0.0327 D	-0.0111	X		-0.0019	0.0015	-0.0020 D	-0.0023		X
UK	-0.0002	0.0026	0.0011	-0.0039			0.0001	-0.0004	0.0004	0.0004		
US	0.0004	0.0002	0.0002	0.0047			0.0002	0.0015 U	0.0007 U	-0.0001		
Sig	0.14	0.39	0.19	0.39	0.42	0.28	0.14	0.47	0.19	0.44	0.33	0.47
D%	0.08	0.14	0.11	0.22			0.06	0.28	0.08	0.22		
U%	0.06	0.25	0.08	0.17			0.08	0.19	0.11	0.22		

Note: This table summarizes the estimation results of the quantile regression model. The results from the mean-volatility model (EG) are also presented as a benchmark for mean return. The numbers are the sum of the coefficients of the terrorism indices from t=0 and t=-5. “U” and “D” after the estimates indicate whether the estimates are significant in increasing or decreasing the corresponding statistics at the 5% significance level, respectively. In the quantile regression models, “0.1,” “0.5,” and “0.9” are the quantiles. “15” indicates the results of the slope equality tests of the current-day terrorist index between quantiles 0.1 and 0.5; “59” indicates the results of the tests between quantiles 0.5 and 0.9. “X” indicates significant difference at the 5% level. “Sig” in the bottom panel indicates the percentage of countries that are significantly affected by terrorist attacks. “D%” and “U%” are the percentages of significantly negatively and positively affected countries, respectively.

Appendix

Table A1

Meta-analysis of the event studies—mean returns by year.

					Stock												Forex											
		Obs			N		A		10		NvA		Nv10		DvU		N		A		10		NvA		Nv10		DvU	
ID	Total	N	A	10	D	U	D	U	D	U	D	U	D	U	A	10	D	U	D	U	D	U	D	U	D	U	A	10
T	152241	141665	10576	1057	35270	35735	2527	2737	238	291							36344	36001	2669	2713	278	267						
					0.25	*0.25*	*0.24*	*0.26*	*0.23*	*0.28*							*0.26*	*0.25*	*0.25*	*0.26*	*0.26*	*0.25*						
1996	1653	1512	141	11	299	538	30	57	4	5				*	U		460	337	31	30	1	3						
1997	5165	4837	328	45	1289	1370	81	93	13	10							1238	1385	93	103	12	19				*		
1998	5220	5052	168	19	1277	1364	44	50	5	4							1260	1141	45	31	1	5						
1999	5453	5164	289	24	1244	1261	62	80	5	6							1255	1109	69	80	8	8		*				
2000	6046	5722	324	29	1652	1305	99	80	8	11							1591	1639	94	85	14	7			*			
2001	6422	6091	331	43	1374	1678	74	93	8	12							1664	1464	88	81	21	7			*			D
2002	7131	6867	264	45	1970	1567	55	65	10	12							1706	1862	67	72	15	11						
2003	7731	7417	314	60	1625	1880	63	93	13	18		*			U		1885	1934	96	81	18	14	*					
2004	8122	7875	247	54	1859	2068	52	69	9	18							2069	2003	53	56	8	10						
2005	8060	7703	357	59	1910	2126	76	103	5	23				*	U	U	2003	2008	98	97	15	15						
2006	8304	7903	401	58	1699	2040	91	106	11	13							1982	1991	105	123	15	15		*				
2007	8710	8299	411	57	2191	2138	106	117	15	20							2120	2221	107	94	17	13						
2008	9048	8281	767	68	2544	2095	201	203	20	17							2396	2397	224	218	16	23						
2009	9135	8381	754	64	1655	1927	140	174	8	17					U		1860	1702	160	177	12	16		*				
2010	9277	8543	734	49	1958	2107	174	170	12	13							2243	2164	190	173	15	9						
2011	9360	8649	711	40	2424	2170	194	162	9	11							2281	2102	185	176	13	10						
2012	9396	8488	908	64	1808	2011	181	244	11	22		*		*	U	U	1921	2309	215	236	12	17						
2013	9396	8385	1011	81	2206	2049	281	266	21	17							2153	2115	242	257	19	19						
2014	9396	8329	1067	94	2282	2090	241	267	22	19							2220	2128	251	281	21	25						
2015	9216	8167	1049	93	2004	1951	282	245	29	23	*						2037	1990	256	262	25	21						

Note: This table presents the results of a meta-analysis of event studies on nonattack days (N), attack days (A), and large-scale (10% largest) attack days (10), with a 100-day estimation and a 6-day event window. The main figures show the number of days with significant decrease (D) or increase (U) of the market returns due to an attack. NvA compares nonattack days with attack days by testing whether the probabilities of decrease (D) or increase (U) in return are equal in both groups. Nv10 does the same but with large-scale attacks instead. * indicates significance at the 5% level. DvU tests whether the probabilities of observing D and U are equal or one of them is favored in each group of event days, at the 5% significance level. “Obs” is the number of observations. “T” is total. The numbers in italics show the proportion of significant event days (D or U) in each group (N/A/10).

Table A2

Meta-analysis of the event studies—variances by year.

					Stock												Forex											
					N		A		10		NvA		Nv10		DvU		N		A		10		NvA		Nv10		DvU	
Year	Obs	N	A	10	D	U	D	U	D	U	D	U	D	U	A	10	D	U	D	U	D	U	D	U	D	U	A	10
T	152241	141665	10576	1057	15362	16439	1283	1195	113	125	*				D		14087	15218	1150	1206	109	128	*	*		*		
					0.11	*0.12*	*0.12*	*0.11*	*0.11*	*0.12*							*0.10*	*0.11*	*0.11*	*0.11*	*0.10*	*0.12*						
1996	1653	1512	141	11	97	157	6	31	1	4		*		*	U		176	190	34	16	4	2	*		*		D	
1997	5165	4837	328	45	331	733	32	50	7	8	*		*	*	U		347	629	29	45	4	5					U	
1998	5220	5052	168	19	711	794	16	20	2	4							760	576	34	7	2	0	*				D	
1999	5453	5164	289	24	539	329	37	23	5	2					D		541	403	19	20	1	1						
2000	6046	5722	324	29	635	833	41	58	4	4							340	718	23	31	2	2						
2001	6422	6091	331	43	655	613	49	39	6	5	*						523	447	41	23	6	7	*				D	
2002	7131	6867	264	45	724	867	32	22	6	2							714	788	24	28	2	4						
2003	7731	7417	314	60	724	492	19	26	1	4							511	665	23	35	5	5						
2004	8122	7875	247	54	735	741	43	26	10	4	*		*		D		782	752	21	25	6	3						
2005	8060	7703	357	59	595	815	31	32	6	5							499	531	44	20	7	8	*			*	D	
2006	8304	7903	401	58	1057	987	73	49	9	8	*				D		879	599	36	57	6	10		*			U	
2007	8710	8299	411	57	759	1271	62	48	8	11	*			*			724	1077	81	61	10	7	*		*			
2008	9048	8281	767	68	941	1764	110	138	5	12	*				U		517	1582	45	167	4	21		*		*	U	U
2009	9135	8381	754	64	1219	222	136	23	6	4	*				D		1342	361	130	52	12	3		*			D	D
2010	9277	8543	734	49	1152	812	104	93	5	10		*					790	962	75	97	5	6						
2011	9360	8649	711	40	683	1412	45	89	1	8				*	U	U	1017	1104	66	81	2	4						
2012	9396	8488	908	64	1245	517	114	41	6	0					D	D	908	473	86	67	6	6		*				
2013	9396	8385	1011	81	867	989	100	181	9	12		*			U		892	1113	121	155	7	13		*			U	
2014	9396	8329	1067	94	808	1145	109	109	9	6							808	1348	116	116	10	10						
2015	9216	8167	1049	93	885	946	124	97	7	12					D		1017	900	102	103	8	11						

Note: This table presents the results of a meta-analysis of event studies on nonattack days (N), attack days (A), and large-scale (10% largest) attack days (10), with a 100-day estimation and a 6-day event window. The main figures show the number of days with significant decrease (D) or increase (U) of the market variances due to an attack. NvA compares nonattack days with attack days by testing whether the probabilities of decrease (D) or increase (U) in return are equal in both groups. Nv10 does the same but with large-scale attacks instead. * indicates significance at the 5% level. DvU tests whether the probabilities of observing D and U are equal or one of them is favored in each group of event days, at the 5% significance level. “Obs” is the number of observations. “T” is total. The numbers in italics show the proportion of significant event days (D or U) in each group (N/A/10).

Table A3

Meta-analysis of the event studies—alternative specification and short-selling.

					Stock						Forex						
		Obs			Return			Variance			Return			Variance			
	ID	Total	N	A	D	U	DvU	D	U	DvU	D	U	DvU	D	U	DvU
Panel A	T	152241	141665	10576	2324	2502	U	1522	1223	D	2635	2692		1132	1216	U
All					*0.22*	*0.24*		*0.14*	*0.12*		*0.25*	*0.25*		*0.11*	*0.11*	
	AT	5039	5026	13	5	3		1	3		6	4		1	5	
	AU	5039	5003	36	8	7		1	4		11	12		2	7	
	BL	5039	5023	16	2	8		3	2		3	3		2	3	
	BR	2503	2488	15	6	2		1	2		4	5		3	2	
	BU	2429	2418	11	1	3		2	1		5	2		2	1	
	CA	5039	4999	40	10	6		1	7	U	7	7		5	3	
	CL	2180	2137	43	10	9		8	4		9	12		3	6	
	CN	3438	3356	82	15	19		11	10		11	35	U	3	13	U
	CR	1961	1957	4	1	2		1	1		1	2		0	1	
	CZ	3998	3983	15	2	5		3	1		1	6		3	2	
	DN	5039	5032	7	3	2		1	1		2	2		0	2	
	FI	5039	5030	9	4	1		1	1		1	3		0	3	
	FR	5039	4701	338	77	89		41	40		93	84		30	38	
	GE	5039	4916	123	27	27		10	16		43	24	D	12	18	
	GR	5039	4670	369	85	99		37	51		104	84		35	47	
	HK	4897	4892	5	0	0		0	0		3	0		1	1	
	HU	4317	4311	6	0	1		0	0		2	0		1	0	
	ID	3191	2997	194	34	46		35	26		50	48		32	30	
	IN	5039	2331	2708	628	635		428	326	D	676	683		357	309	D
	IR	5039	4908	131	23	36		17	6	D	38	35		9	19	U
	IS	3477	2994	483	109	117		56	66		126	131		39	63	U
	JP	5039	4999	40	13	7		7	11		7	10		3	5	
	ML	3591	3561	30	7	6		4	5		7	6		0	6	U
	MX	3657	3589	68	16	18		9	8		15	17		3	12	U
	NL	5039	5021	18	4	4		4	3		5	2		1	1	
	NO	5039	5033	6	0	4		1	1		0	3		1	0	
	PH	3797	2270	1527	327	357		240	165	D	368	383		143	167	
	RS	3223	2359	864	190	204		144	92	D	221	194		131	103	D
	SA	5039	4944	95	12	21		10	14		19	23		10	13	
	SP	5039	4682	357	84	88		33	33		90	102		20	33	U
	SZ	5039	5022	17	6	2		1	0		3	3		1	1	
	TK	1441	1068	373	68	88		46	36		96	108		30	41	
	TL	4146	2752	1394	291	300		222	148	D	322	354		166	149	
	TW	4254	4248	6	3	1		0	1		4	1		0	0	
	UK	5039	4268	771	175	197		105	85		202	210		62	83	U
	US	5039	4677	362	78	88		38	53		80	94		21	29	
Panel B	T	3090	2914	176	38	48		23	20		43	47		16	18	
Ban	AU	515	511	4	0	1		0	0		0	1		0	0	
	CA	515	506	9	2	2		0	2		2	2		0	2	
	GR	515	422	93	25	23		8	14		27	18		13	9	
	NL	515	513	2	0	1		1	0		0	0		1	0	
	UK	515	470	45	8	13		11	3	D	11	18		1	6	
	US	515	492	23	3	8		3	1		3	8		1	1	
Panel C	T	2575	2475	100	23	27		5	24	U	28	29		6	25	U
No Ban	CZ	515	512	3	0	1		1	0		0	1		1	0	
	FI	515	514	1	0	1		0	0		1	0		0	0	
	HK	515	514	1	0	0		0	0		1	0		0	1	
	HU	515	512	3	0	1		0	0		1	0		1	0	
	IS	515	423	92	23	24		4	24	U	25	28		4	24	U

Note: This table presents the results of a meta-analysis of event studies on nonattack (N) and attack (A) days, with a 100-day estimation and a 6-day event window. The mean-return model now additionally employs the event-day return on the MSCI World Index. In all panels, the main figures show the number of days with significant decrease (D) or increase (U) of the market return or variances due to an attack. DvU tests whether the probabilities of observing D and U are equal or one of them is favored in each group of event days, at the 5% significance level. "Obs" is the number of observations. "T" is total. The numbers in italics show the proportion of significant event days (D or U). Panels B and C show the results with countries that imposed short-selling bans in 2008 and lifted them in 2009 (Panel B) and those that did not (Panel C), respectively. The classification of the two groups follows Beber and Pagano (2013).