HOW DO STOCK MARKETS AND BOND MARKETS IN A COUNTRY BEHAVE IN RESPONSE TO TERRORIST ATTACKS?

by

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(Under the Direction of William Lastrapes)

ABSTRACT

We study the effects of terrorist attacks (as exogenous shocks) on equity returns, bond returns, and the correlation between the two. One would expect terrorism to cause (or at least, Granger cause) a short-term negative response in equity returns in the affected country, most likely due to increased risk perception. This is not entirely a new question; similar ideas have been published before (Chen & Siems 2004, Charles & Darné 2006). However, past studies have focused mostly on equity markets in major developed countries, with fewer papers examining equities in developing countries or bonds. In this paper, we show that the best predictor of equity market response is the number of fatalities caused by a terrorist attack, and that the best predictor of bond market response is the mean equity market return prior to the attack. We also show that equity markets and bond markets move together in response to terrorist attacks.

INDEX WORDS: Stock Markets, Equity Markets, Bond Markets, Terrorism, Event Study

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DEDICATION

To my incredibly talented professors, who taught me more than I thought possible and pushed me to reach my full potential, this would not be possible without each one of you.

To my friends and my family, who have offered their unwavering support and their constant willingness to entertain my thoughts and ideas, I am deeply grateful.

To the men and women who work tirelessly to combat terrorism at home and abroad, your sacrifice and commitment do not go unnoticed.

To God, for His unending blessings.

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CHAPTER 1

INTRODUCTION

In a post-September 11, 2001 world, terrorism is a pervasive fear in the American zeitgeist. The horrific events of 9/11 led to irreversible changes in culture and in the economy. One particularly relevant change was the heightened perception of terrorism risk, which decreased the expected value of a variety of economic transactions. In the United States especially, the size of insured losses exceeded any reasonable estimate of potential loss, which led insurers and reinsurers to stop covering terrorism losses until Congress stepped in to ameliorate the situation, passing the Terrorism Risk Insurance Act (TRIA) in November 2002 (Webel 2013). As Webel notes, the increased uncertainty from terrorism posed a serious threat to real estate, construction, transportation, energy, and utility sectors of the economy.

The effects of 9/11 on equity markets in the United States and around the world are well documented (Chen & Siems 2004, Charles & Darné 2006); namely, that there were abnormally negative equity returns both in US markets and in international markets. Though the United States was the direct target of the attacks, interestingly enough, the US did not experience the most severe equity market response. Instead, as Chen & Siems (2004) note, of the ten largest equity markets in existence on September 11, 2001, the New York Stock Exchange (NYSE) experienced the second-*smallest* event-day abnormal return (although the authors do add an important caveat that the event day for US markets was September 17, whereas the event day for foreign markets was September 11 or September 12). Thankfully, this kind of market closure is not an issue in the rest of our events, as no other attack comes close to 9/11 in terms of total fatalities: 2,997 vs. 344 in the next highest event (Appendix A), or in terms of total insured losses: $25.1 billion vs. $1.2 billion (both in 2014 dollars) in the next highest event (Insurance Information Institute 2015).

In another example of high-profile attacks, Kollias et al. (2011) examined the effects of the Madrid bombings of March 2004 and the London bombings of July 2005 on each country's respective equity markets. The authors take a very thorough look at the effects of each event, looking not just at the "headline" numbers in equity markets but also the sector-level response in each market. In both cases (Madrid and London), the authors find that most sectors in the respective equity markets experienced negative returns following the attack.

This paper makes a few novel contributions to our understanding of terrorism's effects on financial markets. We compile a larger list of terrorist events than has already been used. The Global Terrorism Database (GTD), cited by Drakos (2010), is the most comprehensive database of terrorist events to our knowledge. We use casualties as an initial measure for severity of attack; however, it is possible that there are other variables that are better correlated with significance of abnormal returns. In our analysis, we examine casualties as a standalone variable, and we also use its component parts (fatalities and non-fatal injuries) broken up in to separate variables. Though Eldor & Melnick (2004) use casualties as an explanatory variable for market response to terrorism, their study is confined only to Israel. Thus, to our knowledge, this paper is the first to use casualties, fatalities, and injuries as explanatory variables for abnormal return in a multi-country sample of terrorist events.

Another way in which we differ from Chesney et al. (2011) — and align more with Eldor & Melnick — is that Chesney et al. study the responses in European and American markets to terrorist events overseas, whereas we are more interested in the responses in venue-country markets; that is, markets in the country that is attacked (to borrow terminology from Bandyopadhyay et al. (2014)). This presents an obvious data problem in that many terrorist attacks occur in countries with insufficient (or unobservable[1]) financial infrastructure; however, this is not as much of an issue as one might expect.

The importance of correlations between assets is not to be understated: the convenient assumption of independence can sometimes lead to disastrous results. As Chiang et al. (2007) note, "The apparent high correlation coefficients during crisis periods implies that the gain from international diversification by holding a portfolio consisting of diverse stocks from these contagion countries declines, since these stock markets are commonly exposed to systematic risk." Correlation analysis has been conducted previously on equity and bond markets in response to crisis (Filis et al. (2011) and Chiang et al. (2007)); however, to our knowledge, this paper is the first to examine the response of equity-bond correlation to terrorist attacks. By investigating the responses of equities, bonds, and the correlations between them, we hope to develop a deeper and more thorough understanding of the short-term responses of financial markets to terrorist attacks.

Chapter 2 reviews the literature in greater depth. Chapter 3 describes the data obtained for this paper and the methods used to analyze market responses. Chapter 4 presents the results, and Chapter 5 contains discussion and conclusion.

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[1] There are multiple possible explanations for unobserved financial activity, especially in emerging markets in Asia and Africa. By one estimate (Schneider & Enste 2000), the "shadow" economy in OECD countries usually averages 10-25% of the officially measured economy, whereas in African and Asian economies, this figure is closer to 45-50%. Additionally, alternative financial systems, such as hawala networks (Jost & Sandhu), are more prominent in these economies, where they are unobservable to us in official statistics.

CHAPTER 2

LITERATURE REVIEW

Rigorous studies of specific terrorist events are quite valuable to understanding causes and effects in the context of an individual attack; however, this approach is limited in its ability to draw more general conclusions. Abadie & Gardeazabal have made strides in this arena with their 2003 case study on conflict in the Basque country (and later with their 2008 larger-scope work, "Terrorism and the world economy", which is briefly discussed later).

In their 2003 paper, Abadie & Gardeazabal look at the Basque country of Spain and its tumultuous history of conflict and terrorism primarily catalyzed by the Basque separatist group ETA. Over a time window of approximately 30 years, the authors draw several conclusions — two of which are particularly notable here.

The first finding is that the Basque country experienced a 10% decrease in per-capita GDP due to terrorist activity relative to a synthetic control region. The second finding is that during a period of cease-fire in 1998 and 1999, businesses with a sizable amount of activity in the Basque country experienced higher equity returns than businesses considered to have little investment in the Basque country.

The second finding is remarkable, because it approaches the effects of terrorism on financial markets from a different angle. Many studies begin in some "normal" state of the market or economy, and then examine the effects of a terrorist event — equity market response, GDP response, FDI response, etc. But with this second finding, Abadie & Gardeazabal examine a region where the long-run "normal" has been constant threats of terrorism, and a cease-fire is a distinctly positive change. This cease-fire, though technically one event, allows us to make broader inference about the state of Basque equities during the 30-year window of ETA terrorist activity; namely, that terrorism was pushing down equity prices below where they would have been in the event of a lasting truce.

In a more general paper, Eldor & Melnick (2004) investigate the effects of terrorist attacks in Israel on the Tel Aviv Stock Exchange (TASE). The authors distinguish a number of variables about the attacks themselves, and focus less on sector-level market reaction. Another difference between this paper and the Abadie & Gardeazabal paper discussed earlier is that Eldor & Melnick restrict their focus to financial market responses, leaving aside broader macroeconomic responses. As a positive tradeoff to this narrower focus, Eldor & Melnick examine a large number of terrorist events (n=639) relative to other papers discussed here. This enables them to draw conclusions about location of attack, type of attack, and other notable pieces of data incumbent to any terrorist event. For example, the authors find that the effect of location was insignificant, but the type (or method) of attack made a striking difference — suicide attacks left a permanent negative influence on the TASE and on foreign exchange markets.

Given that terrorism is inherently emotional, it is worthwhile to ask if there is a behavioral and/or psychological element to help explain the effects of terrorism on financial markets. Indeed, Abadie & Gardeazabal (2008) highlight a finding by Becker & Murphy (2001) that the attacks of September 11, 2001 cost the US economy an estimated 0.06% of its total productive resources. Abadie & Gardeazabal contrast this with their 2003 work (discussed earlier) showing that terrorism in the Basque country reduced per-capita GDP by approximately

10%. The implicit question: how can terrorism, which destroys a miniscule fraction of the overall capital stock, have such a profound effect?

Drakos (2010) sets out to answer this question in his paper fittingly titled, "Terrorism activity, investor sentiment, and stock returns." Drakos, like Eldor & Melnick, makes a concerted effort to move beyond any one singular event and instead to look at the broader trend of terrorism and its effects on markets. Using data provided by the Global Terrorism Database (GTD), Drakos shows that terrorist attacks with a moderate to major psychosocial impact have a negative effect on returns beyond what is expected for a generic terrorist attack of unspecified psychosocial impact. This result is noteworthy in that it helps to understand the apparent paradox set up by Abadie & Gardeazabal (2008). However, it certainly does not answer the question entirely, since Drakos' work only resolves the question in a short-run event window, and he does not address reversals either.

A long-run answer to this question is discussed more in Abadie & Gardeazabal's 2008 paper: the reduced expected returns incumbent in terrorism, combined with a high degree of transnational capital mobility, often leads to reduced foreign direct investment (FDI) over a longer timeframe. Bandyopadhyay et al. (2014) corroborate the finding that terrorism results in lower FDI in "venue" countries, or countries where terrorist attacks take place. Bandyopadhyay et al. also subdivide terrorism into two kinds: transnational (source country of terror is different from the venue country of terror) and domestic (source and venue are the same country). Across both sides of this division, the result still holds that terrorism results in lower FDI.

These long-run effects, though important to understand, are difficult to study in the context of financial markets alone. This is not to say that markets cannot form long-term expectations; instead, it is that in the short run, markets form long-run expectations, but we cannot evaluate the accuracy of these expectations in the short run. Markets may assess the present discounted value of an asset, and the heightened risk perception immediately following a terrorist attack may cause investors to decrease their risk-adjusted expectations out of an abundance of caution. Later, as more information becomes available about the severity of an attack, investors may rule out extreme possibilities based on this new information. This evaluation of longer-run macroeconomic data distinguishes Abadie & Gardeazabal (2008), but here we restrict our focus to the short-term market responses. Perhaps the most comprehensive paper to date on the short-run effects of terrorist attacks on financial markets is “The impact of terrorism on financial markets: An empirical study,” by Chesney et al. (2011).

In their paper, Chesney et al. make a number of important contributions to the literature on terrorism and financial markets. First and foremost, they use a broader scope of events than most other papers. They use a list of 77 major terrorist events dating back to 1994 in countries around the globe, and for each event, they look at the reaction across many different financial markets. This contrasts with the approach taken by Chen & Siems (2004), who looked at a small list of events in a lot of markets, and it also contrasts with the approach taken by Eldor & Melnick (2004), who looked at a long list of events in only two primary markets.

Another way in which Chesney et al. expand their approach beyond previous literature is that they included bond markets and commodity markets in their paper. Their findings in the commodities market may run counter to the conventional wisdom: they find that the worldwide response in these markets to terrorist events is sometimes positive and sometimes negative. As the authors write, “Given that gold is usually considered to be a ‘safe-haven’ asset, these empirical results remain difficult to explain.” The authors produce a similarly mixed result in major bond indices.

CHAPTER 3

DATA AND METHODS

The first source of data for this paper is the aforementioned Global Terrorism Database (GTD) at the University of Maryland. We use GTD to generate a list of all terrorism events (n=585) in the database with at least 100 total casualties (injuries and fatalities combined). We chose a 100-casualty cutoff partially out of search convenience and also to maximize the probability that each event would generate a notable market response (perhaps due to increased news coverage, etc.). The implicit assumption here is a direct link between casualties and relevance. The definition of a terrorist attack used by GTD is that an event must meet at least two of the following three criteria: i) The act must be aimed at attaining a political, economic, religious, or social goal; ii) There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience than the immediate victims; iii) The action must be outside the context of legitimate warfare activities, i.e. the act must be outside the parameters permitted by international humanitarian law (particularly the admonition against deliberately targeting civilians or non-combatants).

For each event, GTD includes data on date, location, casualties, perpetrators, and targets. For our purposes, we are only interested in the date of the attack, the country of the attack, the number of injuries, and the number of fatalities. Given this list of events, we combine events in the same country on the same day into one observation, since our equity market data has daily frequency instead of intraday frequency. Once this intraday national aggregation is complete, the list of events shrinks to 538 observations. We note that most of these reductions come from a single attack over multiple locations (for example, 9/11 is originally categorized as four separate events instead of one multi-plane attack).

Next we retrieve daily frequency data for major equity and corporate bond indices in each country that is attacked. Since most of the relevant data are foreign, we use Datastream for these equity and bond indices. Note that this differs from some of the existing literature discussed above in that we are looking at market responses in the country that is attacked (as opposed to market responses in the major developed countries that are not direct victims of the attack). Of the 538 events on the list, only 113 occurred in a time and place with daily frequency equity and bond index data. Events that occurred earlier in history (i.e. 1970 instead of 2000) or in less developed countries (i.e. Iraq instead of the United Kingdom) were more likely to be dropped due to data unavailability. We also note that the bond index data are not uniformly available from the same data source — most bond index data are taken either from Citigroup indices or J.P. Morgan indices. A full list of all 113 events can be found in Appendix A.

The main tool in this paper is an event study approach to understanding market responses to terrorism events. To keep the details consistent across events, we look at all of our data to determine an appropriately sized estimation window such that all events can have the same length of estimation. We use an estimation window of 120 trading days. Given the inherent surprise nature of terrorism, we choose an event window of 3 trading days, which begins on the day of the attack. This is in line with previous literature on terrorism, where relatively short event windows are commonplace. Terrorism is inherently unexpected, and we are inclined to assume that within the country that is victim to a terrorist attack, news of the attack spreads pretty quickly. This is particularly plausible given our self-imposed constraint of only allowing terrorism events with 100 or more total casualties.

We base our event study on the approach outlined in Campbell et al. (1997) and Chen & Siems (2004), and in this framework we can calculate cumulative abnormal return (CAR) during the event window for each attack in our sample. The CAR effectively measures how much market behavior deviates from "normal" behavior during a terrorism event. Our data are originally given in levels and then we calculate daily returns using the following definition:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{1}$$

where $P_{i,t}$ is the price level of market i at day t and $R_{i,t}$ is the return of market i at day t.

To quantify exactly what normal behavior looks like, we use a constant-mean-return model of normal market performance, stipulated as follows:

$$R_{i,t} = \mu_i + \xi_{i,t} \text{ where } E(\xi_{i,t}) = 0 \text{ and } Var(\xi_{i,t}) = \sigma^2_{\xi_i} \tag{2}$$

$$R_t \overset{i.i.d.}{\sim} N(\mu, \Sigma_\xi) \tag{3}$$

Regarding the choice of a constant-mean-return model, we note that Brown and Warner (1980) showed that this model detects abnormal returns no less frequently than more sophisticated models, and that there is no gain in power by using a more sophisticated model. Formally, we assume that daily returns are independently and identically distributed under the multivariate normal, where R_t is the (N x 1) vector of returns at time t (where N = 113). Importantly, Campbell et al. (1997) assert that inferences made under the i.i.d. multivariate normal assumption here are robust to deviations from this assumption.

We then define an abnormal return as follows:

$$\varepsilon_{i,t}^{*} = R_{i,t} - E\left[R_{i,t}|X_t\right] \tag{4}$$

where $\varepsilon_{i,t}^{*}$ is the abnormal return of asset i in time t, R_t is the realized return of asset i in time t, and $E\left[R_{i,t}|X_t\right]$ is the expected return of asset i in time t, conditional on information in X_t. Since we are using the constant-mean-return model of market performance, X_t is simply the constant mean return of asset i. We compute the constant mean return of asset i by computing the daily return for each of the 120 trading days in the estimation window of asset i, and then taking the simple arithmetic mean (using Equation 1) over the 120 days.

We can use the CAR and the standardized CAR (SCAR) to tell us more about market reaction to terrorism. We define a CAR as follows:

$$\widehat{CAR}_i(\tau_1, \tau_2) \equiv \gamma' \varepsilon_i^{*} \tag{5}$$

where (τ_1, τ_2) is the event window, γ is a $\left((\tau_2 - \tau_1 + 1)\times 1\right)$ vector of ones, and ε_i^{*} is the vector of abnormal returns over the event window. The variance of a CAR is given by:

$$Var\left[\widehat{CAR}_i(\tau_1, \tau_2)\right] \equiv \sigma_i^2(\tau_1, \tau_2) \tag{6}$$

Our null hypothesis, when dealing with CARs, is that market behavior during an event is no different from behavior during the pre-event estimation window. However, it is very important to caveat that if the event itself causes variance inflation during the event window, then we will not pick that up in our inference, and thus the statistical (and economic) significance of our estimates may be overstated.

Regardless, if we assume the null hypothesis is true, then CARs have the following distribution:

$$\widehat{CAR}_i(\tau_1, \tau_2) \sim N\left(0, \sigma_i^2(\tau_1, \tau_2)\right) \tag{7}$$

To test the null hypothesis, we use standardized CARs, or SCARs, which are constructed as follows:

$$\widehat{SCAR}_i(\tau_1, \tau_2) = \frac{\widehat{CAR}_i(\tau_1, \tau_2)}{\sigma_i(\tau_1, \tau_2)} \overset{a}{\sim} N(0,1) \tag{8}$$

Since our estimation window is 120 days (well over 30 days), we can use the asymptotic result that SCARs follow a standard normal distribution. However, our analysis does not end with calculating CARs and SCARs; rather, we incorporate other data about each attack (such as fatalities and injuries) to see if there are variables that help predict the CAR for an attack. To do this, we use the following regression models: For the full model — Reg. (1) in Table 1 and Reg (1) in Table 3 — we use Equation 9 below.

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_4 X_{i4} + \beta_5 X_{i5} + \beta_6 X_{i6} + \beta_7 X_{i7} + \sum_{j=1}^{16} \eta_j X_{i,j+7} + \varepsilon_i \tag{9}$$

In Eq. 9, Y_i is the CAR (of equities in Table 1; of bonds in Table 3) of event i. X_{i1} is the number of fatalities of event i, and X_{i2} is the number of non-fatal injuries of event i. (X_{i3} is the number of total casualties of event i, which is the sum of the fatalities and non-fatal injuries, but X_{i3} is not used in Reg. (1) in Table 1 or Table 3, since it is perfectly collinear with X_{i1} and X_{i2}.) X_{i4} is an indicator equal to unity if event i occurs on a trading day (0 if not). X_{i5} is the equity-bond correlation of event i during the pre-event estimation period, X_{i6} is the mean equity return of event i during the pre-event estimation period, and X_{i7} is the mean bond return of event i during the pre-event estimation period. The term $\sum_{j=1}^{16} \eta_j X_{i,j+7}$ represents the country dummy variables for event i.

For Table 1, the remaining five regressions differ as follows:

- Reg. (2) drops X_{i5}, X_{i6}, and X_{i7} from Reg. (1), keeping all other terms.
- Reg. (3) drops X_{i1} and X_{i2} from Reg. (1) and replaces with X_{i3}, keeping all other terms.
- Reg. (4) drops X_{i5}, X_{i6}, and X_{i7} from Reg. (3), keeping all other terms.
- Reg. (5) includes only X_{i1} and the country dummies.
- Reg. (6) includes only X_{i1}.

For Table 3, the remaining five regressions differ as follows:

- Reg. (2) drops X_{i5}, X_{i6}, and X_{i7} from Reg. (1), keeping all other terms.
- Reg. (3) drops X_{i1} and X_{i2} from Reg. (1) and replaces with X_{i3}, keeping all other terms.
- Reg. (4) drops X_{i5}, X_{i6}, and X_{i7} from Reg. (3), keeping all other terms.
- Reg. (5) includes only X_{i6} and the country dummies.
- Reg. (6) includes only X_{i6}.

We also want to examine whether or not there is a significant relationship between equity CAR and bond CAR in the wake of an attack. It is not immediately obvious, ex-ante, which way such a correlation might go: one could argue that equities and bonds should move together in response to an attack if investors think that these two markets are similarly affected. On the other hand, one could also argue that equities and bonds should move in opposite directions following an attack, as investors will flee equities in favor of bonds in a flight to safety.

To examine these correlations, we use a number of methods. First and foremost, we run OLS regressions of bond CARs on equity CARs and bond SCARs on equity SCARs at the individual event level. Then, we run the same regressions using country averages. To see how the equity-bond correlation changes in response to an attack, we compute the equity-bond correlation for the estimation window of each event, and then we compute the equity-bond correlation for the event window of each event. Then we use a paired t-test and a non-parametric Wilcoxon signed-rank test to see if there is a statistically significant difference between estimation-window equity-bond correlations and event-window equity-bond correlations.

CHAPTER 4

RESULTS

First, we turn our attention towards the relationship between market response and characteristics of the terrorist attacks. We want to allow for the fact that terrorist attacks can vary widely in their severity; thus, we seek to use a number of attributes of terrorist attacks as explanatory variables for equity market response and bond market response: country of attack, fatalities, injuries, and binary indicator for whether or not the attack occurred on a trading day. Table 1, below, displays several versions of an OLS regression (Eq. 9) for the dependent variable equity CAR. We construct a similar table for bond CARs in Table 3.

Table 1: Regressions for Equity CAR

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
Fatalities[a]	-27.32*** (9.906)	-25.90** (10.00)	—	—	-25.38** (9.883)	-21.21*** (7.992)
Injuries[a]	-2.787 (5.354)	-3.121 (5.330)	—	—	—	—
Casualties[a]	—	—	-8.181* (4.861)	-8.032* (4.828)	—	—
Trading Day[b]	0.017 (0.599)	-0.243 (0.593)	0.117 (0.610)	-0.131 (0.600)	—	—
Est. Period E-B Corr.[b]	2.105 (1.600)	—	1.787 (1.627)	—	—	—
Est. Period Equity Return	-3.223* (1.804)	—	-3.167* (1.841)	—	—	—
Est. Period Bond Return	0.8107 (2.227)	—	0.8481 (2.274)	—	—	—
Intercept[b]	-6.338** (2.764)	-4.369 (2.493)	-6.253 (2.822)	-4.517 (2.533)	-4.690* (2.399)	-0.235 (0.232)
Country Dummies	Yes	Yes	Yes	Yes	Yes	No
R^2	0.2368	0.1919	0.1956	0.1561	0.1874	0.0597
Adjusted R^2	0.0502	0.0268	0.0010	-0.0055	0.0419	0.0512
p-value	0.215	0.3064	0.4113	0.5044	0.2169	0.0091
N	113	113	113	113	113	113

*** = Statistical significance at 1%
** = Statistical significance at 5%
* = Statistical significance at 10%
[a] = Estimates displayed 10^6 times larger than actual value
[b] = Estimates displayed 10^2 times larger than actual value

There are a couple of important takeaways here. In Table 1, where we are regressing equity CARs on the set of variables, we note that the number of fatalities caused by a terrorist attack is always a statistically significant predictor of equity market response (and always significantly negative, at that). Interestingly, the number of non-fatal injuries is never significant, and when fatalities and injuries are combined to form casualties, the resulting variable is much less statistically significant than fatalities alone. This is somewhat consistent with the findings of Eldor & Melnick, who found that fatalities and injuries, when included as separate variables (as shown in regressions 1 and 2 in Table 1), both take significantly negative coefficients in predicting equity market response. A table of coefficients for each of the individual country dummies in each regression can be found in Appendix B. To illustrate the economic significance of our results on equity CARs, consider the question of how many additional fatalities or casualties would be required to generate a 10% decrease (increase in absolute value) of the average event equity CAR, as shown below in Table 2.

Table 2: Economic Significance of Equity CAR Results

Reg.	Coeff.[c]	Avg Equity CAR[c]	10% Decrease[c]	Fatalities required	Increase from average[1]	Casualties required	Increase from average[2]
(1)	-2.732	-389.1	-38.91	14.24	19.64%	—	—
(2)	-2.590			15.02	20.71%	—	—
(3)	-0.818			—	—	47.56	17.15%
(4)	-0.803			—	—	48.44	17.46%
(5)	-2.538			15.33	21.14%	—	—
(6)	-2.121			18.35	25.29%	—	—

[1] Average fatalities of an event is 72.53
[2] Average casualties of an event is 277.4
[c] = Estimates displayed 10^5 times larger than actual value

As we can see in Table 2, to generate a 10% decrease in equity CAR (in other words, an equity CAR that is 10% more severe) of an average event, then ceteris paribus, a 20-25% increase in fatalities or a 17-18% increase in casualties would accomplish that. This result is colored by the fact that the set of events we are considering have at least 100 casualties, but still, within the context of a major terrorist attack, it is plausible to consider 15 more fatalities or 48 more casualties.

Table 3: Regressions for Bond CAR

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
Fatalities[a]	-1.633 (7.105)	-0.455 (7.368)	—	—	—	—
Injuries[a]	0.348 (3.840)	1.058 (3.926)	—	—	—	—
Casualties[a]	—	—	-0.087 (3.397)	0.732 (3.481)	—	—
Trading Day[b]	0.462 (0.430)	0.237 (0.437)	0.470 (0.426)	0.244 (0.432)	—	—
Est. Period E-B Corr.[b]	-0.124 (0.115)	—	-0.150 (0.114)	—	—	—
Est. Period Equity Return	-3.910*** (1.293)	—	-3.906*** (1.287)	—	-3.797*** (1.215)	-2.131* (1.134)
Est. Period Bond Return	-0.7619 (1.597)	—	-0.7589 (1.589)	—	—	—
Intercept[b]	-2.486 (1.982)	-1.606 (1.837)	-2.479 (1.972)	-1.615 (1.826)	-1.950 (1.692)	0.082 (0.177)
Country Dummies	Yes	Yes	Yes	Yes	Yes	No
R^2	0.2471	0.1592	0.2466	0.1589	0.2343	0.0308
Adjusted R^2	0.0631	-0.0126	0.0727	-0.0022	0.0973	0.0221
p-value	0.1672	0.5527	0.1307	0.4820	0.0539	0.0630
N	113	113	113	113	113	113

*** = Statistical significance at 1%
** = Statistical significance at 5%
* = Statistical significance at 10%
[a] = Estimates displayed 10^6 times larger than actual value
[b] = Estimates displayed 10^2 times larger than actual value

It is also noteworthy in Table 3 that there is not a single permutation of fatalities, injuries, and casualties that is a statistically significant predictor of bond market response to terrorist attacks. Across equities and bonds alike, whether or not a terrorist attack occurs on a trading day is of little to no importance in predicting equity CARs or bond CARs. Including the mean daily return in the equity market during the 120-trading-day estimation period preceding the terrorist attack is significantly helpful both to the equity response (at the 10% significance level) and to the bond response (at the 1% significance level). It is a little puzzling that the only variable of any statistical significance in predicting bond market response is the equity market average return prior to the event — a curious addition to the equity-bond correlation discussion, no doubt. (None of the country dummies are statistically significant in any regression in Table 3.) This result is robust to the inclusion or exclusion of data from Mexico and Nigeria, where the equity-bond correlation is extremely high (Table 9). It is also interesting that for equity markets, once we narrow down the regression just to the number of fatalities, removing the country dummies improves the adjusted R^2 and the p-value of the model, whereas for bond markets, removing the country dummies decreases the adjusted R^2 and increases the p-value. To learn more about the relationship between equity and bond market responses to terrorist attacks, we turn next to Figure 1, which illustrates the relationship between bond CARs and equity CARs.

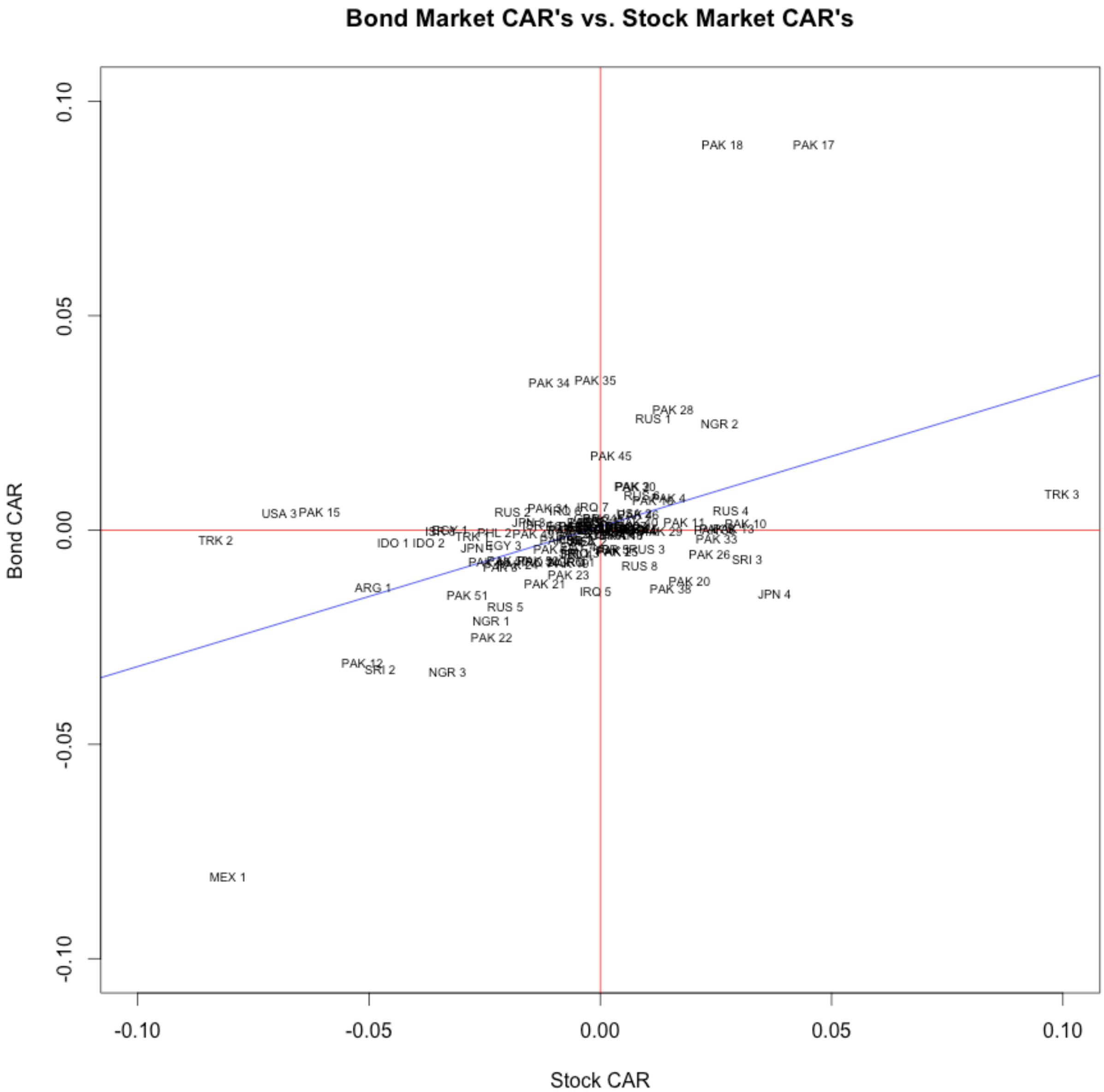

Figure 1a: Equity and bond CARs for each event, with event names used to plot the points. Blue line is the OLS regression line ($R^2 = 0.2049$, $p < 0.001$).

To see if the above relationship is solely a function of three outliers (MEX 1, PAK 17, PAK 18), we remove these three observations from the data set and re-run the regression. The results are as follows:

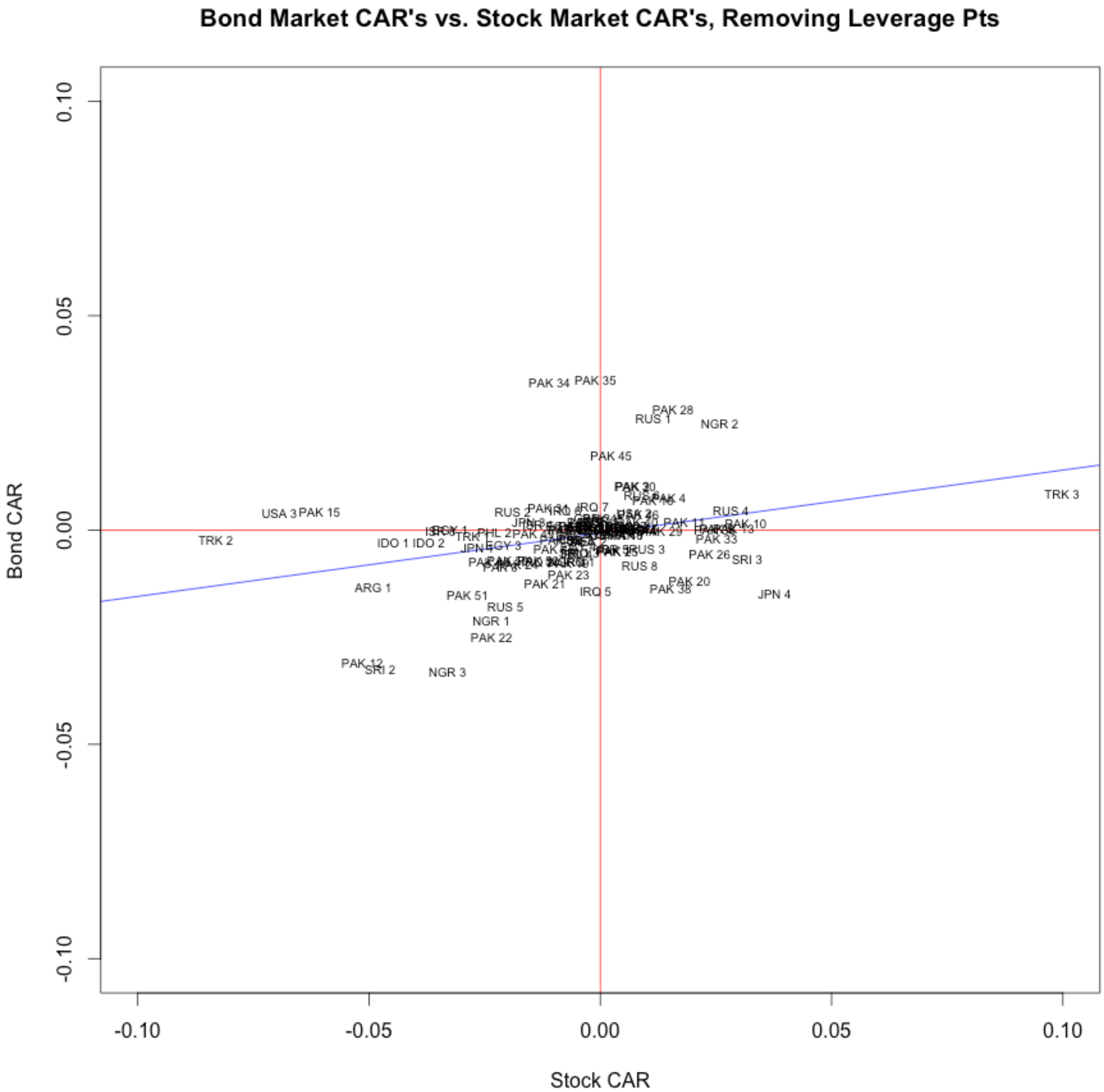

Figure 1b: Equity and bond CARs for each event, with event names used to plot the points. Blue line is the OLS regression line ($R^2 = 0.1035$, $p < 0.001$). Three outlier events (MEX 1, PAK 17, PAK 18) have been removed from Figure 1 due to potential leverage effects.

Figure 2 shows the relationship between bond SCARs and equity SCARs across events. The red lines represent statistical significance at the 5% level under the null hypothesis that SCARs are distributed N(0,1), so events that fall outside the red lines are statistically significant.

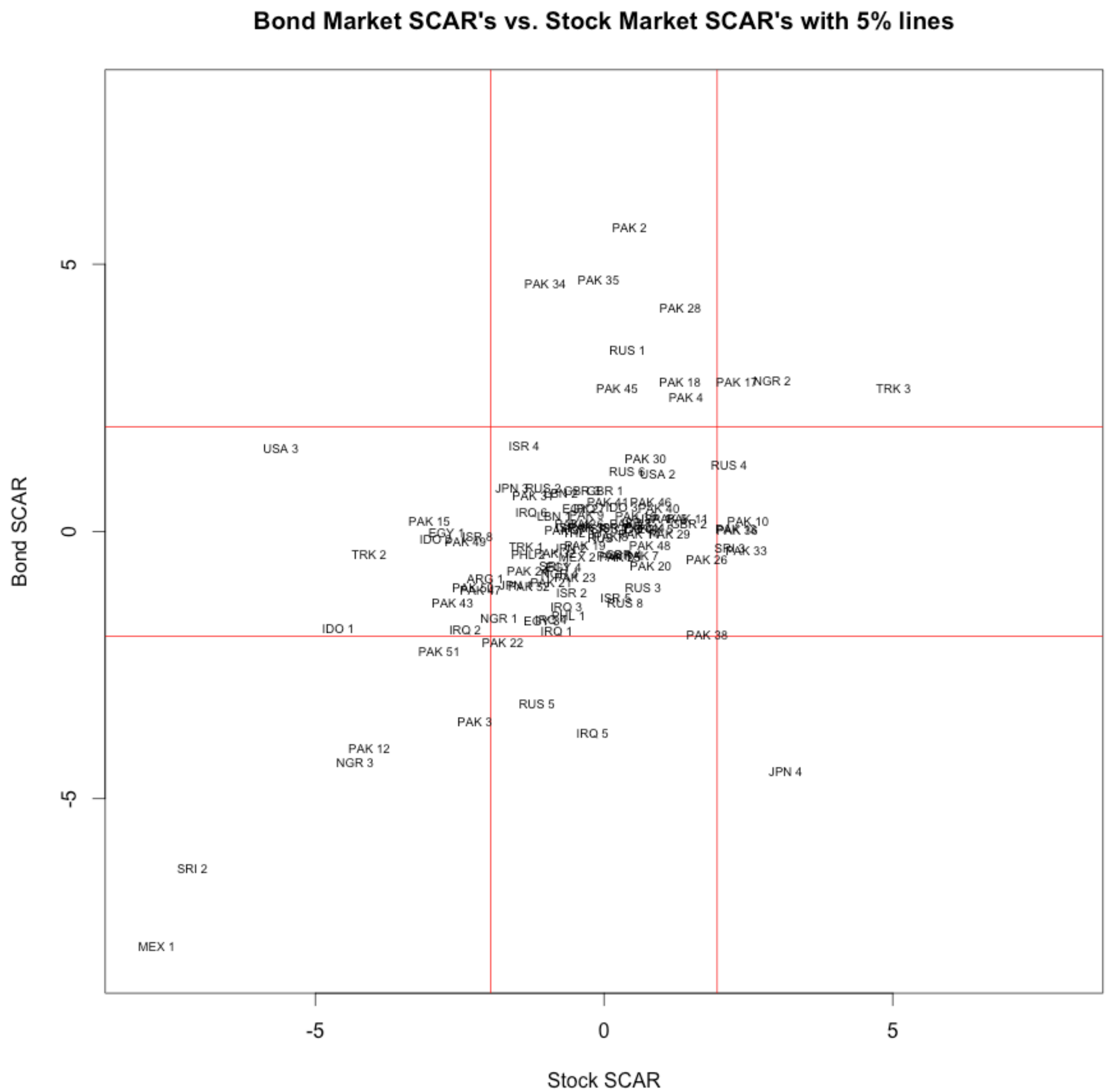

Figure 2: Equity and bond SCARs for each event, with event names used to plot the points. Red lines indicate the two-tailed 5% significance level (z = ±1.96)

If we look at Figure 2, imagine that we number the nine regions sequentially across rows (so that Region 1 is in the northwest corner, Region 3 is in the northeast corner, Region 7 is in the southwest corner, and Region 9 is in the southeast corner). Table 4 gives a textual depiction of how events are distributed across these nine regions.

Table 4: Distribution of Events Across Regions of Significance

	Equity SCAR sig. negative	Equity SCAR insignificant	Equity SCAR sig. positive	Row Totals
Bond SCAR sig. positive	0	8	3	11
Bond SCAR insignificant	13	73	6	92
Bond SCAR sig. negative	6	3	1	10
Column Totals	19	84	10	113

Table 5a: Average Fatalities by Region of Significance

	Equity SCAR sig. negative	Equity SCAR insignificant	Equity SCAR sig. positive	Row Averages
Bond SCAR sig. positive	N/A	34.7500	27.3333	32.7273
Bond SCAR insignificant	290.9231	45.4247	68.1667	81.5978
Bond SCAR sig. negative	27.5000	54.6667	0.0000	32.9000
Column Averages	207.7368	44.7381	49.1000	72.5310

Table 5b: Average Casualties by Region of Significance

	Equity SCAR sig. negative	Equity SCAR insignificant	Equity SCAR sig. positive	Row Averages
Bond SCAR sig. positive	N/A	151.1250	164.3333	154.7273
Bond SCAR insignificant	470.6923	278.7123	198.5000	300.6087
Bond SCAR sig. negative	129.5000	180.3333	671.0000	198.9000
Column Averages	362.9474	263.0476	235.5000	277.4071

There are a couple of things that stand out from Table 4 worth noting on first pass. For one, there are 29 events (25.7%) with equity SCARs significantly different from zero, and 21 events (18.6%) with bond SCARs significantly different from zero. We also note that of the (statistically) significant equity SCARs, they are distributed approximately 2:1 negative to positive, whereas the significant bond SCARs are distributed approximately evenly between negative and positive. As we see in Figures 1 and 2, and in Table 4, the trend of equity-bond correlation appears to be positive on the whole. Table 5 gives a better illustration of the severity of events in each region of Table 4. We note from Table 5 that events with significantly negative equity SCARs have more fatalities and casualties, on average, than events with significantly positive equity SCARs. This pattern is also true for bonds, but with a much smaller difference.

Past literature does not really examine the equity CARs and bond CARs of markets in the venue country of attacks on an individual event basis. Chesney et al. look at European responses to attacks that are mostly outside of Europe. Chesney et al. find that European markets, examined on the all-sector composite level, do not experience significantly positive responses to terrorist attacks. However, they do find that responses in the aero/defense, pharma/biotech, and oil/gas sectors are sometimes positive and sometimes negative. So it is not entirely unreasonable to think that a country with an economy largely comprised of these sectors might experience a positive equity market response to a terrorist attack. Eldor & Melnick, and also Drakos, look at regression estimates of model parameters over a data set of many attacks, but never at individual attack responses. Table 6 shows the OLS regression estimates of the line graphed in Fig. 1.

Table 6: OLS Regressions of Abnormal Bond Returns on Abnormal Equity Returns Per Event

Parameter	Bond CAR	Bond CAR	Bond CAR	Bond SCAR	Bond SCAR	Bond SCAR
Equity CAR	0.3269*** (0.0611)	0.1474*** (0.0417)	0.1237*** (0.0450)	—	—	—
Equity SCAR	—	—	—	0.4946*** (0.0813)	0.3896*** (0.0856)	0.3488*** (0.1014)
Intercept	0.0009 (0.0015)	-0.0008 (0.0010)	-0.0014 (0.0012)	0.0175 (0.1600)	-0.0228 (0.1571)	-0.1880 (0.2089)
Leverage Points Included?	Y	N	N	Y	N	N
Pakistan Included?	Y	Y	N	Y	Y	N
R^2	0.2049	0.1035	0.1151	0.2502	0.1611	0.1694
Adjusted R^2	0.1978	0.0952	0.0998	0.2434	0.1533	0.1551
p-value	4.804e-07	6.091e-04	8.020e-03	1.689e-08	1.390e-05	1.087e-03
N	113	110	60	113	110	60

*** = Statistical significance at 1%
** = Statistical significance at 5%
* = Statistical significance at 10%

Leverage points refer to MEX 1, PAK 17, and PAK 18, which may exert leverage over the regression estimates.

We can also examine this relationship on a per-country basis instead of a per-event basis. We simply take means over countries and then perform the same regressions shown in Table 6; the results are shown in Table 7.

Table 7: OLS Regressions of Abnormal Bond Returns on Abnormal Equity Returns Per Country

Parameter	Bond CAR	Bond CAR	Bond CAR	Bond CAR	Bond SCAR	Bond SCAR	Bond SCAR	Bond SCAR
Equity CAR	0.5199*** (0.1426)	0.5131*** (0.1509)	0.2263** (0.0979)	0.2123* (0.1026)	—	—	—	—
Equity SCAR	—	—	—	—	0.8929*** (0.1922)	0.8943*** (0.2039)	0.5781* (0.2922)	0.5651* (0.3147)
Intercept	0.0010 (0.0025)	0.0008 (0.0028)	0.0001 (0.0015)	-0.0003 (0.0016)	0.2588 (0.2713)	0.2619 (0.2968)	0.0977 (0.3022)	0.0785 (0.3369)
Pakistan Included?	Y	N	Y	N	Y	N	Y	N
Mexico & Nigeria Included?	Y	Y	N	N	Y	Y	N	N
R^2	0.4698	0.4523	0.2916	0.2631	0.5900	0.5787	0.2314	0.2118
Adjusted R^2	0.4345	0.4132	0.2371	0.2017	0.5627	0.5486	0.1723	0.1461
p-value	0.0024	0.0043	0.0377	0.0607	0.0003	0.0006	0.0695	0.0978
N	17	16	15	14	17	16	15	14

*** = Statistical significance at 1%
** = Statistical significance at 5%
* = Statistical significance at 10%

The tables and figures above, taken together, demonstrate that in response to a terrorist attack, equity markets and bond markets in the venue country usually move together. This result may be colored by the particular set of events for which we have data, or by the fact that events in one country (Pakistan) comprise a disproportionately large share of the sample. However, as shown Tables 6 and 7, the results are robust to the inclusion or exclusion of Pakistani events, and the results are also robust to the inclusion or exclusion of three notable leverage points. As shown in Table 9, the equity-bond correlations in Mexico and Nigeria are unusually high, but the signs of the results are robust to the inclusion or exclusion of Mexico and Nigeria, and the results remain statistically significant, albeit at a lower level of significance.

As a follow-up question, we would like to see how the correlation between daily equity and bond returns *changes* between the estimation period and the event window. This is a question distinct from the previous analysis because here, we compute the correlation in daily returns and then examine the change in the correlation, whereas before we examined equity changes and bond changes separately and then looked at how those changes were related to each other. We compute the equity-bond correlation in the estimation period, then we compute separately the equity-bond correlation in the event window, and then we use paired difference tests to test for statistically significant change. Table 8 shows the results of these (two-tailed) tests.

Table 8: Change in Equity-Bond Correlations on a Per-Event Basis

	Per-Event Basis		Per-Country Basis	
	Paired t-test	Wilcoxon signed rank test	Paired t-test	Wilcoxon signed rank test
Test Statistic	t = 0.7923	V = 3461	t = 1.3109	V = 105
p-value	p = 0.4299	p = 0.4917	p = 0.2084	p = 0.1901

The paired t-test and the Wilcoxon signed rank test, a nonparametric paired differences test, both test to see if the mean difference between two columns (in this case, the correlations in the estimation period and the event window, respectively) is significantly different from zero. The only difference between these tests is that the Wilcoxon test is non-parametric, so it requires no distributional assumptions. Regardless, we do not observe a statistically significant change in correlation between the estimation period and the event window. Table 9 displays the mean correlations by country for estimation period and event window.

Table 9: Equity-Bond Correlations by Country

COUNTRY	Estimation Period Corr	Event Window Corr	Difference
Argentina	0.6421	0.6649	0.0227
Egypt	0.0221	-0.4523	-0.4745
Great Britain	0.3655	-0.0323	-0.3978
Indonesia	0.0296	0.0143	-0.0153
Iraq	-0.1004	-0.4247	-0.3243
Israel	-0.1045	-0.0040	0.1004
Japan	0.0271	-0.0627	-0.0899
Lebanon	0.0133	-0.3672	-0.3805
Mexico	0.9993	1.0000	0.0007
Nigeria	0.9943	0.9954	0.0011
Pakistan	0.0255	0.0473	0.0217
Philippines	0.2764	0.8976	0.6212
Russia	0.2112	0.1008	-0.1103
Sri Lanka	0.0856	-0.1060	-0.1917
Thailand	0.0957	-0.3254	-0.4211
Turkey	0.3776	0.7225	0.3448
United States	0.2740	0.0220	-0.2520

CHAPTER 5

DISCUSSION

We showed in Chapter 4 that equity markets and bond markets in the venue country usually move together. Intuitively, this result makes sense if we think about investing in developing countries as a riskier proposition with less granular data available. If a terrorist attack happens in, say, Pakistan or Sri Lanka (to pick example countries with relatively less developed financial systems and lower media profiles in the West), investors may not have many other pieces of information about the situation, and they may not want to wait around for more information to become publicly available. This is, of course, one of many stories that could be conjured up to explain this finding. It is also puzzling, as mentioned previously, how estimation-window equity market returns are the only statistically significant predictor of bond CARs, and negatively so at that. Why is it that equity returns matter more to bond markets than bond returns?

Previous literature may point to an answer. Kwan (1996) shows that equity returns lead bond returns on an individual firm basis. Downing et al. (2009), citing Kwan, document several steps taken to improve transparency in the bond market — most notably, the development of the Trade Reporting and Compliance Engine (TRACE) — and yet they show that equities are still more informationally efficient than bonds using intraday data. Beber et al. (2009) disentangle the difference between flight-to-quality and flight-to-liquidity among bond investors, and they find that in times of market distress, investors chase liquidity as the more immediate concern (over credit quality). Taking these findings together, one possible explanation is that equities can price in the information more quickly than bonds. Further research into this explanation using intraday data would be helpful in supporting or refuting this conjecture.

Regarding the ability to predict equity CARs, it is very interesting how fatalities are such a statistically significant predictor of equity CARs, even though when a terrorist attack first happens, it is not immediately clear how many people are killed or injured. One could easily imagine that in response to a terrorist attack, investors see images or read reports in the news and make an intuitive evaluation of the severity of the attack, and make an investing response to terrorism accordingly.

Further directions for this research that would be of value would be to identify the major investing partnerships (on a country-by-country basis) of each country included in the sample, and then look at the correlations between a victim country's response to terror and the responses of its major trading and investing partners. Another avenue of inquiry worth pursuing would be an examination of capital controls in the countries where terrorism occurs — do countries with stricter capital controls experience more muted market responses to terrorism? Kim & Singal (2000) show that countries with looser capital controls experience more informationally efficient equity markets, but it may be the case that some terrorist events result in muted market responses for reasons other than informationally inefficient markets. Thus, a study of capital controls and market responses to terrorism would be useful for disentangling this putative effect from other possible explanations. Lastly, in the age of social media, it would be useful to see how the social media reaction and the market reaction to a terrorist event are related. The threat of terrorism is sure to be with us for the foreseeable future, unfortunately, but by understanding its effects on financial markets, we may better plan to hedge against its ill effects.

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APPENDIX A

FULL EVENT LIST

DATE	NAME	COUNTRY	CITY	FATALITIES	INJURED
7.18.94	ARG 1	Argentina	Buenos Aires	85	236
12.24.13	EGY 5	Egypt	Mansoura	16	130
1.1.11	EGY 4	Egypt	Alexandria	23	97
4.24.06	EGY 3	Egypt	Dahab	18	87
7.23.05	EGY 2	Egypt	Sharm el-Sheikh	91	110
10.7.04	EGY 1	Egypt	Taba	34	159
7.7.05	GBR 4	Great Britain	London	56	784
6.15.96	GBR 3	Great Britain	Manchester	0	200
2.9.96	GBR 2	Great Britain	London	2	100
12.21.88	GBR 1	Great Britain	Lockerbie	270	0
9.9.04	IDO 4	Indonesia	Jakarta	10	182
8.5.03	IDO 3	Indonesia	Jakarta	15	149
10.12.02	IDO 2	Indonesia	Kuta	202	300
7.27.96	IDO 1	Indonesia	Jakarta	5	149
11.14.13	IRQ 7	Iraq	Sadiyah	33	80
10.5.13	IRQ 6	Iraq	Baghdad	43	75
5.11.13	IRQ 5	Iraq	Shirqat	4	101
3.11.13	IRQ 4	Iraq	Dibis	6	120
2.3.13	IRQ 3	Iraq	Kirkuk	36	70
1.23.13	IRQ 2	Iraq	Tuz Khormato	43	75
1.16.13	IRQ 1	Iraq	Kirkuk	18	90
8.19.03	ISR 8	Israel	Jerusalem	19	100
12.1.01	ISR 7	Israel	Jerusalem	10	171
8.9.01	ISR 6	Israel	Jerusalem	16	130
6.1.01	ISR 5	Israel	Tel Aviv	22	100
9.4.97	ISR 4	Israel	Jerusalem	7	192
7.30.97	ISR 3	Israel	Jerusalem	15	170
3.4.96	ISR 2	Israel	Tel Aviv	13	105
8.21.95	ISR 1	Israel	Jerusalem	6	100
4.19.95	JPN 4	Japan	Yokohama	0	671
3.20.95	JPN 3	Japan	Tokyo	13	5500
6.27.94	JPN 2	Japan	Matsumoto	7	500
10.9.90	JPN 1	Japan	Osaka	0	106
8.23.13	LBN 2	Lebanon	Tripoli	48	300
8.15.13	LBN 1	Lebanon	Beirut	30	300
1.31.13	MEX 2	Mexico	Mexico City	37	101
9.15.08	MEX 1	Mexico	Morelia	8	101
3.18.13	NGR 4	Nigeria	Kano	39	75
10.28.12	NGR 3	Nigeria	Malali	3	100
6.18.12	NGR 2	Nigeria	Damaturu	8	99

8.26.11	NGR 1	Nigeria	Abuja	24	81
9.29.13	PAK 52	Pakistan	Peshawar	43	101
9.22.13	PAK 51	Pakistan	Peshawar	87	131
7.26.13	PAK 50	Pakistan	Parachinar	60	152
3.3.13	PAK 49	Pakistan	Karachi	45	151
2.16.13	PAK 48	Pakistan	Quetta	91	169
1.10.13	PAK 47	Pakistan	Quetta	139	238
2.17.12	PAK 46	Pakistan	Parachinar	40	64
1.31.12	PAK 45	Pakistan	Jogi	43	62
9.15.11	PAK 44	Pakistan	Mayar Jandool	93	122
8.19.11	PAK 43	Pakistan	Jamrud	57	123
5.13.11	PAK 42	Pakistan	Shabqadar	82	140
4.3.11	PAK 41	Pakistan	Dera Ghazi Khan	52	102
3.8.11	PAK 40	Pakistan	Faisalabad	25	101
12.25.10	PAK 39	Pakistan	Bajaur district	48	72
12.6.10	PAK 38	Pakistan	Mohmand district	52	60
11.11.10	PAK 37	Pakistan	Islamabad	15	100
11.5.10	PAK 36	Pakistan	Darra Adam Khel	96	27
9.3.10	PAK 35	Pakistan	Quetta	66	150
9.1.10	PAK 34	Pakistan	Lahore	40	200
7.9.10	PAK 33	Pakistan	Mohmand district	106	115
7.1.10	PAK 32	Pakistan	Lahore	44	175
4.17.10	PAK 31	Pakistan	Kohat	43	64
4.5.10	PAK 30	Pakistan	Timergara	46	100
3.12.10	PAK 29	Pakistan	Lahore	47	100
3.8.10	PAK 28	Pakistan	Lahore	14	113
2.18.10	PAK 27	Pakistan	Khyber district	31	100
1.1.10	PAK 26	Pakistan	Shah Hassan Khel	100	87
12.28.09	PAK 25	Pakistan	Karachi	45	100
12.7.09	PAK 24	Pakistan	Lahore	51	150
11.10.09	PAK 23	Pakistan	Charsadda	34	100
10.28.09	PAK 22	Pakistan	Peshawar	120	200
10.9.09	PAK 21	Pakistan	Peshawar	42	100
5.27.09	PAK 20	Pakistan	Lahore	30	200
4.5.09	PAK 19	Pakistan	Chakwal	25	140
3.30.09	PAK 18	Pakistan	Manawan	12	90
3.27.09	PAK 17	Pakistan	Jamrud	57	158
9.20.08	PAK 16	Pakistan	Islamabad	61	200
8.21.08	PAK 15	Pakistan	Islamabad	64	100
3.11.08	PAK 14	Pakistan	Lahore	27	200
2.16.08	PAK 13	Pakistan	Parachinar	38	93
12.27.07	PAK 12	Pakistan	Rawalpindi	20	100
12.21.07	PAK 11	Pakistan	Charsadda	72	101
11.18.07	PAK 10	Pakistan	Parachinar	90	150
10.18.07	PAK 9	Pakistan	Karachi	141	250
7.10.07	PAK 8	Pakistan	Islamabad	96	35
7.4.07	PAK 7	Pakistan	Islamabad	7	207
4.11.06	PAK 6	Pakistan	Karachi	57	125
5.27.05	PAK 5	Pakistan	Islamabad	20	100

10.7.04	PAK 4	Pakistan	Multan	41	100
5.7.04	PAK 3	Pakistan	Karachi	18	100
3.2.04	PAK 2	Pakistan	Quetta	44	130
7.4.03	PAK 1	Pakistan	Quetta	53	53
10.19.07	PHL 2	Philippines	Manila Makati	8	130
3.4.03	PHL 1	Philippines	Davao City	24	150
9.1.04	RUS 8	Russia	Beslan	344	727
2.6.04	RUS 7	Russia	Zamoskvorechye	40	122
12.5.03	RUS 6	Russia	Yessentuki	47	170
8.1.03	RUS 5	Russia	Mozdok	40	76
5.12.03	RUS 4	Russia	Znamenskoye	59	197
12.27.02	RUS 3	Russia	Grozny	57	121
5.9.02	RUS 2	Russia	Kaspiysk	43	130
3.24.01	RUS 1	Russia	Mineralnye Vody	18	86
4.20.09	SRI 3	Sri Lanka	Putumattalan	20	200
10.6.08	SRI 2	Sri Lanka	Anuradhapura	29	80
5.16.08	SRI 1	Sri Lanka	Colombo	11	95
3.31.12	THL 1	Thailand	Hat Yai	14	400
7.27.08	TRK 3	Turkey	Istanbul	17	154
11.20.03	TRK 2	Turkey	Istanbul	32	448
11.14.03	TRK 1	Turkey	Istanbul	22	302
9.11.01	USA 3	United States	New York	2997	106
7.27.96	USA 2	United States	Atlanta	1	110
4.19.95	USA 1	United States	Oklahoma City	168	650

APPENDIX B

COUNTRY DUMMIES FOR TABLE 1

Country	(1)	(2)	(3)	(4)	(5)
Argentina	(omitted contrast)				
Egypt	5.820** (2.897)	3.548 (2.651)	5.643* (2.956)	3.598 (2.694)	3.636 (2.627)
Great Britain	6.118** (2.757)	5.023* (2.706)	6.062** (2.814)	5.074* 2.750	5.073* (2.680)
Indonesia	4.670 (2.949)	2.966 (2.718)	4.536 (3.010)	3.050 (2.762)	3.101 (2.681)
Iraq	6.106** (2.911)	4.072 2.598	5.926** (2.971)	4.152 (2.640)	4.225 2.564
Israel	6.227** (2.874)	4.044 2.566	6.061** (2.933)	4.136 (2.607)	4.110 (2.544)
Japan	6.132** (2.946)	4.880* (2.812)	6.866** (2.988)	5.739** (2.825)	4.429 (2.682)
Lebanon	6.043* (3.124)	4.504 (2.960)	5.952* (3.189)	4.618 (3.008)	4.486 (2.937)
Mexico	0.084 (3.002)	0.550 (2.961)	0.231 (3.064)	0.596 (3.009)	0.596 (2.937)
Nigeria	3.533 (2.812)	3.680 (2.708)	3.694 (2.870)	3.754 (2.752)	3.790 (2.681)
Pakistan	6.729** (2.702)	4.833* (2.444)	6.527** (2.757)	4.854* (2.484)	4.921** (2.421)
Philippines	4.432 (3.030)	3.282 (2.961)	4.378 (3.094)	3.358 (3.009)	3.316 (2.937)
Russia	6.804** (2.718)	5.213** (2.564)	6.644** (2.774)	5.218** (2.606)	5.253** (2.543)
Sri Lanka	5.218* (2.970)	3.989 (2.791)	5.091* (3.031)	4.051 (2.837)	4.027 (2.769)
Thailand	6.447* (3.632)	4.112 (3.471)	6.571* (3.708)	4.431 (3.525)	4.307 (3.391)
Turkey	5.859** (2.909)	4.323 (2.798)	5.931** (2.970)	4.502 (2.843)	4.387 (2.769)
United States	6.768** (3.051)	5.343* (2.969)	4.873 (2.989)	3.709 (2.905)	5.438* (2.930)

*** = Statistical significance at 1%
** = Statistical significance at 5%
* = Statistical significance at 10%
For reading convenience, all estimates displayed 10^2 times larger than actual value.
Country dummies were not included in Regression 6.