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WORKING PAPER

FDI, Terrorism and the Availability Heuristic for U.S. Investors before and after 9/11

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Abstract

We record the existence of an availability heuristic that is reflected in disaster myopia of U.S. investors and exists prior to the attacks of 9/11. We argue that this is fueled by an aggregate experience hypothesis effect, resulting in a pronounced increase in the sensitivity of U.S. stock prices to terrorist attacks on foreign soil. After 9/11, stock prices react proportionally to the size of an attack and the share of FDI stock held in the region by the sector in which firms operate. This effect, non-existent prior to 2002, has become increasingly strong in recent years.

JEL classification: F14; G14; G15.

Keywords: Terrorism; Foreign Direct Investment; Availability heuristic; Experience Hypothesis.

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1 Introduction

In an efficient market, equity prices reflect the sum of expected future discounted cash flows. In this paper, we examine events that investors may consider to result in sudden drops in these expected cash flows. However, the events that we study take place on foreign soil, vary greatly in their magnitude and frequency, and assessing their expected impact on cash flows requires knowledge of the capital stocks that generate these cash flows.

The investor who can easily bring to mind relevant adverse instances is more likely to sell, thereby contributing to a drop in equity prices. However, some events are easier to recall than others: the availability heuristic (Tversky and Kahneman, 1973) tells us that these events are often also judged to be more common. At the same time, the experience hypothesis (Malmendier and Nagel, 2011) states that whereas investors may have a short memory, they are much more likely to remember extreme events, and therefore more likely to act on this salient news (Klibanoff et al., 1998; Hirshleifer and Teoh, 2003).

Recently, Berger et al. (2013) have found that U.S. multinational firms benefited from increased exports and share prices (Dube et al., 2011), through covert CIA interventions. Whereas these interventions were extreme in nature, they were generally regarded as positive for the firms involved. In this paper, we investigate whether the reverse holds, and if hostile extreme events lead to a drop in share prices of the firms involved. More specifically, we demonstrate how the experience hypothesis has, for a prolonged time, fueled the effects of the availability heuristic by examining the impact of terrorism on foreign soil on U.S. stock prices. In a fast-moving world with an abundance of news, are investors able to take these events into account? Do equity prices drop as a result? And is the drop proportional to the expected loss in cash flows for U.S. investors?

We show that for the past several years, equity prices indeed drop after a large terrorist attack, and that the drop is commensurate to the capital stock built by U.S. firms in the region where the attack takes place. In sum, we find that nowadays U.S. investors behave as would be expected. But we also

show that in order for investors to act this way, the ‘message’ unfortunately has had to hit home first. The relationship between large terrorist attacks, the stock of foreign direct investment built up by U.S. firms in the region and share prices on the New York Stock Exchange is only significant, both statistically and economically, *after* the tragic events of September 11, 2001.

How different then is the world, since 9/11? We find that the incidence of a terrorist attack in a region did not change materially after 9/11, while media coverage in the U.S. of attacks on foreign soil initially increased, but has since leveled out. Nonetheless, the relationship between terrorist attacks, FDI and share prices remained significant even with reduced coverage of these attacks. We argue therefore that 9/11 was the experience that created awareness among investors about the potential impact of terrorist attacks, and, in line with the experience hypothesis and the salience of terrorism, explains the change in investor behavior afterwards. As a result, we conclude that 9/11 appears to have fueled the availability heuristic, since U.S. investors have become more sensitive to terrorist attacks on foreign soil after 9/11.

We analyze 16,728 terrorist attacks that occurred in 144 countries on 4,009 days between 1998 and 2010. Out of a total of 3,270 trading days on the NYSE in our sample, there are 2,868 days during which information on terrorism can enter the market. Given the abundance of terrorist attacks, we cannot identify abnormal returns using standard event study methods. Instead, we measure abnormal returns using a jump-diffusion model that allows for volatility clustering in stock returns (Maheu and McCurdy, 2004). After establishing that terrorist attacks on foreign soil can have an effect on stock prices, we condition this effect on the share of total foreign FDI stock of the sector that a firm belongs to. Finally, in order to test the aggregate effect of the experience hypothesis, we examine this effect both before (1998-2000) and after (2002-2006) the 9/11 attacks, as well as during the recent crisis (2007-2010).

We observe that the stock market reaction to terrorist attacks is, as expected, highly nonlinear, with only the largest attacks having a material effect. The extent to which these large attacks affect share prices depends on the foreign presence of American firms. Firms build foreign direct invest-

ment stocks in order to enhance productivity and create shareholder value (Harris and Ravenscraft, 1991; Aitken and Harrison, 1999; Javorcik, 2004), and terrorist attacks that occur close to these stocks threaten to destroy part of that value. We find indeed that the stock market effect of terrorist attacks on foreign soil is proportional to the share of investment of a sector on that soil. But we also find that this stock market effect is not apparent prior to 2002 and has become increasingly strong since the 9/11 attacks.

Our paper is related to Abadie and Gardeazabal (2003), who found that stocks of Spanish firms with large parts of their business in the Basque country outperformed their counterparts during a truce period, only to underperform when the truce ended. We also build on Drakos (2010a), who has found that countries with a strong trade relation with Spain and the United Kingdom experienced more pronounced abnormal stock market losses during the attacks in Madrid and London. In this paper, we look at this relationship on a larger scale, taking into account many more instances of terrorism and their connection with FDI in Western Europe, the rest of Europe, Latin America, Africa, the Middle East and Asia, both before and after 9/11.

The rest of the paper is organized as follows. Section 2 provides a brief introduction, while Sections 3 and 4 describe our data and methodology respectively. In Section 5 we present the results of the analysis before concluding briefly in Section 6.

2 Stock Prices, Terrorist Attacks and FDI Stocks

The tragic events on September 11, 2001 were the worst attacks on American soil in 70 years and hit the United States in its financial and political center. The loss of lives and material damage sustained during the attacks displayed the economic consequences of terror, and the ensuing shock waves were felt around the world.

Stock market data, due to their forward looking nature and high frequency, have often been used to assess the economic impact of terrorism. Following 9/11, financial markets in America and around the world showed heavy losses as they incorporated the news of these attacks. Previous research

has shown that stock markets in countries suffering from terrorism exhibit negative abnormal returns as a result of this type of aggression. Findings indicate that stock markets show negative abnormal returns during and after large isolated attacks like the 9/11, Madrid or London attacks (see e.g. Drakos, 2004; Carter and Simkins, 2004; Maillet and Michel, 2005). However, liquid and well diversified markets can absorb these shocks, such that the impact of the effect is instantaneous or in some cases hardly noticeable (Johnston and Nedelescu, 2006; Mende, 2006). When taking into account a larger set of attacks, negative abnormal returns are also found (Drakos, 2010b), accompanied by an increase in stock market variance (Peren Arin et al., 2008). In an increasingly interconnected world, what remains unclear is how terrorism in different geopolitical regions has spilled over to U.S. markets.

Terrorist attacks on foreign soil can affect U.S. stock prices in a number of ways. First, if investors experience higher risk aversion as a result of a terrorist attack, this increases the rate at which they discount future cash flows. In this case we expect to see a uniform price shock occurring across assets/sectors that share a common discount factor. However, there is ample evidence that sectors in the same country (or similar sectors across countries) exhibit different reactions to the same attack (see amongst others Chen and Siems, 2004; Straetmans et al., 2008; Berrebi and Klor, 2010; Chesney et al., 2011), making it unlikely that discount rate changes explain the price shocks we observe after terrorist attacks.

Second, an attack can influence expected future cash flows, either via an increase in expected costs or a decrease in expected revenues. In both cases, the loss in *realized* cash flows depends on the location of an attack, the amount of capital goods present in the location and the level of damage to these productive assets.¹ The damage, in turn, is determined by the magnitude of an attack and specific factors such as population density, building codes and the quality of infrastructure. Do FDI stocks adjust as a result of terrorist attacks? Enders et al. (2006) and Abadie and Gardeazabal

¹These assets can be both physical capital and human capital, although share prices react more to attacks on the latter (Karolyi and Martell, 2010).

(2008) find that in an open economy, country-specific terrorism risk can lead to movements in capital (FDI) to other countries. Others find that terrorism has an impact on determinants of FDI, like growth and consumption (Blomberg et al., 2004; Eckstein and Tsiddon, 2004). Conversely, Enders et al. (2006) find that the presence of U.S. FDI in a country does not lead to increases in terrorist attacks.

There is also the possibility of a third effect, since the *expected* loss as a result of a terrorist attack depends on investors' assessment of the probability of an attack and the losses generated by that attack. Crucial in this assessment is how investors generate expectations: the availability heuristic can make it difficult for investors to properly incorporate all possible outcomes, thereby resulting in biased expectations. The fact that attacks take place on foreign soil does not make things easier: although investors seem remarkably apt at identifying and valuing different forms of FDI (Doukas and Travlos, 1988; Chen et al., 2000), the fact that the cumulative effect of terrorism on the stock of FDI is quite small, totaling less than 1 percent of the total stock (Enders et al., 2006), may make it easy to overlook.

3 Data

To analyze how terrorism on foreign soil affects U.S. stock prices, we combine data from three different sources. We first describe the database on terrorist attacks, followed by data on FDI stocks and stock market data of American multinational companies.

3.1 Terrorist Attacks

We collect data on terrorist attacks from the Global Terrorism Database (GTD), developed and maintained by the University of Maryland. The GTD contains information on over 98,000 international attacks between 1970 and 2010.² For an event to be incorporated in the GTD, it has to be intentional,

²For more information on the GTD see LaFree and Dugan (2007).

violent and carried out by non-state actors.³ We further limit our sample by only including successful attacks, that were considered to be terrorism beyond any doubt by the GTD.⁴ Information on these additional filters is only available from 1998 onwards, leaving us with 16,287 attacks that take place in 144 countries on 4,009 days between 1998 and 2010. Although the number of attacks seems high, it includes both incidents of national and transnational terrorism and is in line with other papers (e.g., Piazza, 2008). Attacks that occur during weekends and holidays are placed on the next available day that the U.S. stock market can react to the attack. Out of a total 3,270 trading days in our sample, there are 2,868 during which information on terrorism can enter the market. We discuss the consequences of this high frequency of events for our analysis in Section 4.

In order to differentiate between the magnitude and geographical location of an act of terror, we construct a daily terrorism intensity index (Eckstein and Tsiddon, 2004; Peren Arin et al., 2008), such that

$$TER_{i,t} = \ln(1 + \# \text{ attacks}_{i,t} + \# \text{ fatalities}_{i,t} + \# \text{ injured}_{i,t}), \quad (1)$$

where i represents the region the attack took place in and t is the day on which the attack is placed. The inputs are the number of attacks, fatalities and injuries as reported by the GTD.⁵ The regions closely follow the grouping

³According to the GTD, terrorist attacks have to be aimed at ‘attaining a political, economic, religious, or social goal,’ there must be ‘evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims,’ and the event must be ‘outside the context of legitimate warfare activities’ (Study of Terrorism and Responses to Terrorism (START), 2011).

⁴Users of the GTD can further govern the parameters of their search results by employing an additional filter. The existence of a ‘Doubt Terrorism Proper?’ field records reservation, in the eyes of GTD analysts, that the incident in question is truly terrorism. Such uncertainty, however, was not deemed to be sufficient to disqualify the incident from inclusion into the GTD. Furthermore, such a determination of doubt is subsequently coded by GTD analysts as conforming to one of four possible alternative designations: 1) Insurgency/Guerilla Action; 2) Internecine Conflict Action; 3) Mass Murder; or 4) Purely Criminal Act. Note that the ‘Doubt Terrorism Proper’ determination was only made for incidents that occurred after 1997.

⁵For the purpose of this paper, including the intensity of media coverage in the U.S. is also a possibility, although unfortunately the GTD reports at most their top 3 sources for the information on the attack.

of outward FDI at our disposal and are Western Europe (comprising the European Union, Norway and Switzerland), the Rest of Europe, Latin America, Africa, the Middle East and Asia & the Pacific.

The terrorism index $TER_{i,t}$ has several attractive features. A trading day on which no terrorist attack occurs has a TER score of 0. Once attacks occur, the TER score is additive in both the number of fatalities/injuries and the number of attacks. For example, 1 attack with 10 injuries will not have the same TER score as 10 separate attacks with 1 injured person each. Whereas the former has a TER score of 2.6, the latter has a score of 3.

One downside of using the number of fatalities and injuries is that these numbers are often not known on the day of the attack itself, but can take weeks or even months to be confirmed. Even though estimated and official death tolls can differ, we assume that the estimated death tolls are at least of a similar magnitude as the official death toll. By using the log transformation, we limit overestimation of the intensity score.⁶

Panel A in Table 1 shows summary statistics of the terrorism intensity in each of the six regions. Asia & the Pacific have experienced the highest intensity of terrorism, with an act of terrorism occurring on 2,086 out of 3,270 trading days in the sample period. This is followed by the Middle East and Africa, which experienced acts of terrorism on 1,522 and 1,101 trading days, respectively. On the contrary, these numbers are much lower for Western Europe and Latin America, where attacks only occur on 640 and 500 trading days respectively. Panel B summarizes the average number of fatalities and wounded per attack, showing that terrorism was most lethal in Africa and the Middle East. By comparison, attacks in Western Europe were the least lethal.

[Insert Table 1 near here]

Important for our analysis is whether the incidence of terrorism has changed since 9/11. In particular, are terrorist attacks more likely and have

⁶For example, in the weeks after the 9/11 attacks the death toll had been estimated to be 6,000 over 4 attacks. This would have lead to a TER score of $\ln(1 + 4 + 6,000) = 8.7$. The official death toll recorded in the GTD is 2,996 (including 19 terrorists), which leads to a TER score of $\ln(1 + 4 + 2,996) = 8.0$.

they increased in severity? To answer these questions, we plot the distribution of the terrorism index for each of the regions, before and after 9/11, in Figure 1. Overall, the distributions have not changed significantly since 9/11. The average value for the index is in fact *lower* in Western Europe, the Rest of Europe, Latin America and Africa after 9/11. On the other hand, the average value of the index is somewhat higher in the Middle East and Asia & Pacific as there were more and larger attacks. However, extreme attacks occur in all regions both before and after 9/11.

[Insert Figure 1 near here]

3.2 FDI Stocks

For the purpose of our analysis, we need accurate information on the assets ‘at stake’: FDI stock built by U.S. firms in different parts of the world. For reasons of confidentiality, such information is typically not available at the firm level. What is available from the U.S. Bureau of Economic Analysis (BEA) is the yearly stock of outward U.S. FDI per region and per industry, published in the ‘Survey of Current Business’. The BEA covers most industries and countries, although not all combinations are reported if the amounts are negligible or if they would threaten to disclose data of individual companies. We use data for the period 1998 to 2010.

Industries are classified by the BEA using either the Standard Industry Classification (SIC) or the North American Industry Classification System (NAICS). In order to link these FDI data to stock market data, we obtain prices of the S&P500 and its sub-sector indices from Datastream. Since the latter are classified using the Global Industry Classification Standard (GICS), we need a mapping from SIC/NAICS to GICS, which to the best of our knowledge does not yet exist. Therefore, we obtain a list of all current and historic S&P500 companies with their SIC/NAICS and GICS codes from Compustat in order to make a conversion table. More details on the data and the conversion are provided in Appendix B. In our analysis, sectors are defined according to the two-digit GICS codes and consist of Energy,

Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Telecommunication Services and Utilities. For the Utilities sector, data on outward FDI were not available after 2002 and it is therefore excluded from the analysis.

Figure 2 shows per sector the average share of U.S. outward FDI that each region received from firms in that sector during the sample period 1998-2010. We see that Western Europe, Latin America and Asia & the Pacific all received large shares of U.S. investments. The main beneficiary of U.S. outward FDI was Western Europe, whose countries received between 50 and 70 percent of all U.S. investments made abroad. The share of Western Europe was lowest in the Energy sector, where investments were more equally distributed between the Middle East, Latin America and Asia & the Pacific. When looking at Asia & the Pacific, we see that they received their highest investment share from the IT and Industrial sectors. Moreover, outside the Energy sector, the shares of Africa and the Rest of Europe were generally quite low and averaged 0.6 percent and 1.5 percent, respectively.

[Insert Figure 2 near here]

4 Methodology

Our analysis consists of three steps. In the first step, we propose a solution for the fact that terrorist attacks occur so often that we cannot make use of a standard event study methodology, since it is very difficult to construct a proper event window. In the second step, we relate share prices to terrorist attacks, allowing for the fact that investors' response may be highly non-linear, as they only respond to attacks that are severe enough to possibly cause (future) cash flow drops. For that reason, we limit ourselves to investors' 'pure' response to terrorism in this step, and do not yet incorporate the role of FDI stocks. After all, an average attack may not have much of an effect, regardless of the FDI stock present. Finally, in the third step, we relate investor responses to large attacks with FDI stocks in different regions,

taking into account the fact that this relationship may vary for reasons other than the share of total FDI each region receives.

4.1 First step: jumps in the price process

To identify the effect of an event like a terrorist attack, we need to separate the normal behavior of returns from abnormal behavior. The abundance of terrorist events around the globe make nearly it impossible to find enough estimation windows with (presumably) normal returns. As this is likely to lead to biased estimates of abnormal returns when using standard event study techniques (see e.g., Craig MacKinlay, 1997), we resort to a different method.

Since terrorist attacks are typically construed to be unexpected events, we expect them to cause jumps in the price process.⁷ For this reason, we rely on a jump-diffusion model to distinguish between attacks that have an impact (i.e., where a jump occurred) compared to those that do not (i.e., no jump observed). Jump-diffusion models hail back to Merton (1976), but while most of them combine a standard Brownian motion with a jump process (see e.g. Naik, 1993), we rely on a simplified GARCH-jump model proposed by Maheu and McCurdy (2004). The main advantage of this approach is that we can capture volatility clusters in a GARCH framework, something that a constant variance Brownian motion cannot do. As a result, large price changes that occur due to volatility clustering are not erroneously classified as a jump. By using this methodology, we assume implicitly that the impact of terrorism abroad will directly impact the share price in the U.S., disregarding any possible contagion effects from foreign markets to home markets (see e.g. Dungey et al., 2005; Bekaert et al., 2011). However, since we deal with many terrorist events, which tend to be absorbed quickly in liquid markets like the U.S. (Johnston and Nedelescu, 2006; Mende, 2006), we choose to look only at event days instead of possible contagion following attacks.

In order to measure jumps, we first define the standard return process. Next, we define jumps and apply a filtering procedure to separate standard

⁷This at least holds for most of the market participants. Insider trading as reported by Poteshman (2006) should not play an important role.

price movements from jumps using a maximum likelihood estimator. Finally, we extract the probability of a jump as well as its (expected) impact on the price.

We start by describing the return process, which is defined as:

$$r_t = \mu + \phi r_{t-1} + \epsilon_t \quad (2a)$$

$$\epsilon_t = \epsilon_{1,t} + \epsilon_{2,t}, \quad (2b)$$

where r_t is the asset return, μ is a constant mean and ϕ an autoregressive component.⁸ The composite error term, ϵ_t , consists of $\epsilon_{1,t}$ and $\epsilon_{2,t}$, innovations by the GARCH and the jump process respectively. What allows us to separate $\epsilon_{1,t}$ from $\epsilon_{2,t}$ is the fact each has a different distribution, as a result of which we can decompose ϵ_t .

We begin with $\epsilon_{1,t}$, which follows a standard GARCH(1,1) process:

$$\epsilon_{1,t} \sim N(0, \sigma_t^2) \quad (3a)$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2. \quad (3b)$$

In contrast, $\epsilon_{2,t}$ represents the impact of jumps in the returns, which is assumed to arrive via a Poisson process with time-varying intensity:

$$\epsilon_{2,t} = J_t - E[J_t | \Phi_{t-1}], \quad (4)$$

where J_t is the actual jump contribution and $E[J_t | \Phi_{t-1}]$ is its expectation conditional on the previous days' returns, $\Phi_{t-1} = \{r_1, \dots, r_{t-1}\}$. The jump contribution J_t is the sum of the stochastic number of jumps, n_t , where the size of each jump $Y_{t,k}$ is assumed to be independently drawn from a normal

⁸Adding more variables to the mean equation is possible, however our explanatory variables are indices and thus already quite broad. For example, it would not make sense to estimate a market model in this case. We have performed robustness tests where the Fama-French HML and SMB (Fama and French, 1992, 1993) factors have been included in the mean equation, but this does not change the results of the analysis. Results are available upon request.

distribution with mean θ and variance δ^2 :

$$J_t = \sum_{k=1}^{n_t} Y_{t,k}, \quad Y_{t,k} \sim N(\theta, \delta^2). \quad (5)$$

Finally, the probability that $n_t = j$ jumps take place on day t given the history of returns Φ_{t-1} is:

$$P(n_t = j | \Phi_{t-1}) = \frac{\exp(-\lambda_t) \lambda_t^j}{j!}, \quad (6)$$

where λ_t is the jump intensity. Maheu and McCurdy (2004) suggest to let the jump intensity follow an AR(1) process, where the expected number of jumps today depend on yesterday's expected number of jumps and the jump intensity residual ξ_{t-1} (the deviation of the number of jumps from its expectation):

$$\lambda_t = E[n_t | \Phi_{t-1}] = \lambda_0 + \rho E[n_{t-1} | \Phi_{t-2}] + \gamma \xi_{t-1} \quad (7)$$

We use the filter procedure proposed by Maheu and McCurdy (2004) and obtain the probability that at least one jump occurred based on the ex post estimation of the number of jumps:

$$P(n_t \geq 1 | \Phi_t) = 1 - P(n_t = 0 | \Phi_t) \quad (8)$$

and the ex-post assessment of the number of jumps that occurred on each trading day:

$$E[n_t | \Phi_t] = \sum_{j=0}^{\infty} j P(n_t = j | \Phi_t) \quad (9)$$

Since the jump sizes are i.i.d and thus unconditional, multiplying the expected number of jumps with the average jump size yields the ex-post expected jump contribution $E[J_t | \Phi_t] = \theta E[n_t | \Phi_t]$. Together, these two elements tell us both how likely it is a jump occurred, as well as its size. Table 2 shows summary statistics for these two variables, based on the estimations in Ta-

ble A.1 in Appendix A.⁹

[Insert Table 2 near here]

The sectors with the highest jump probabilities are Health Care (35.1 percent), Consumer Discretionary (33.8 percent) and Financials (30.2 percent). In contrast, sectors with the lowest average jump probabilities are Utilities (13.5 percent) and Energy (19.2 percent). Panel B summarizes the jump contributions, and shows that while Health Care has the highest average jump probability, its largest jump contribution was only -3.6 percent.¹⁰ The largest contribution of jumps to the Financials sector was -10 percent on August 31st, 1998, the 7th largest one-day loss on the S&P500. Sectors that have experienced both high jump probabilities and high jump contributions are Consumer Discretionary, IT and Financials.

Now that we have a measure for the likelihood and magnitude of jumps, the next question is to what extent terrorist attacks are responsible for these jumps. To investigate the relationship between terrorism, jumps and FDI, we opt for a two-stage analysis. In the first stage, we estimate per sector the relationship between the *TER* index and the likelihood and size of jumps. Using this estimation, we predict the average reaction to a large attack in each of the regions. In a second stage, we regress the predicted jump probabilities and sizes on the share of outward U.S. FDI that regions received in order to test our hypothesis.

While we sacrifice some efficiency in our estimations by opting for this two-stage analysis, there are three important benefits to our approach. First, we consider the possibility that only the largest attacks evoke a reaction on financial markets. A single-stage analysis, with an interaction between the *TER* measure and FDI, would at best capture the effects of an average attack, conditional on the average FDI stock, and may thus fail to capture the conditions under which we expect to see a reaction.

⁹The estimations show that θ is negative for all indices, indicating that jumps are on average negative. Since we multiply the expected number of jumps with the average jump size to obtain the expected jump contributions, this means that these are always negative.

¹⁰This occurred on October 15th, 2008 when the S&P500 lost 9.5 percent for its second biggest one-day loss ever.

Second, we may fail to properly estimate the impact of terrorism conditional on FDI stock if the latter is endogenous. Indeed, Enders et al. (2006) and Abadie and Gardeazabal (2008) find evidence that FDI flows out of a country as a result of terrorism. By identifying the relationship between terrorism, FDI stocks and share prices in two steps, we are able to avoid this problem of endogeneity.

The final reason is related to the measure of outward FDI. The data obtained from the U.S. BEA are recorded in dollar amounts on a historical cost basis, and thus rise on average every year. When FDI in regions grows at more or less the same rate, only the dollar amount invested will be higher, even though the amount invested in each region remains proportionally the same. If large attacks occur later in the sample period, we might (falsely) conclude that more FDI in a region leads to a higher reaction by using dollar amounts. To counter this problem, we propose to calculate shares of outward FDI per region. Unfortunately, regardless of this transformation, a one-step analysis will suffer from severe multicollinearity when using either dollar amounts or relative shares. For instance, when dollar amounts grow every year this implies a positive correlation, whereas the correlation between FDI shares is negative by design: if one region receives a larger share, other regions will lose some of theirs. Splitting up the identification strategy in two steps avoids this problem. We choose to work with relative shares in FDI, since they are more stable over time than the dollar amounts, even though they still exhibit some variability over time. For example 12 percent of the investments made by the Telecom sector in 1998 were located in Asia & the Pacific, while this increased to 26 percent by 2010. Investments made by the Energy sector in Western Europe were 46 percent of the total FDI in 1998, but fell to 22 percent by 2010.

4.2 Second step: nonlinear reactions to terrorist attacks

To assess the impact of terrorist attacks on jump probabilities and jump sizes, we start by estimating:

$$P(n_t \geq 1|\Phi_t) = \alpha + \sum_{k=1}^6 \beta_{1,k}TER_{k,t} + \sum_{k=1}^6 \beta_{2,k}TER_{k,t}^2 + \gamma\text{Month} + \tau\text{DoW} + \nu_t \quad (10a)$$

$$E[J_t|\Phi_t] = \alpha + \sum_{k=1}^6 \beta_{1,k}TER_{k,t} + \sum_{k=1}^6 \beta_{2,k}TER_{k,t}^2 + \gamma\text{Month} + \tau\text{DoW} + \nu_t \quad (10b)$$

where $P(n_t \geq 1|\Phi_t)$ and $E[J_t|\Phi_t]$ are the jump probability and jump contribution respectively, $TER_{k,t}$ is the daily terrorism intensity score in each of the k defined regions and Month and DoW are controls for month and day-of-the-week effects. In order to obtain yearly estimates of the jump probability and jump size due to terrorism, we run this regression separately for each sector i in each year.

Since $P(n_t \geq 1|\Phi_t)$ is a probability and has values in the set $[0, 1]$, we estimate Equation (10a) using a fractional logit approach (Papke and Wooldridge, 1996), obtaining:

$$E [P(n_t \geq 1|\Phi_t) | \mathbf{x}] = \Lambda \left(\alpha + \sum_{k=1}^6 \beta_{1,k}TER_{k,t} + \sum_{k=1}^6 \beta_{2,k}TER_{k,t}^2 + \gamma\text{Month} + \tau\text{DoW} \right), \quad (11)$$

where Λ is the logistic function and Equation (11) is estimated using a Bernoulli log-likelihood function. The fitted probabilities of jumps associated with large terrorist attacks, $\eta_{i,k,t}$ will now be correctly predicted in the $[0, 1]$ range.

Furthermore, as $E[J_t|\Phi_t]$ is always negative, with values ranging between $(-\infty, 0]$, we estimate Equation (10b) using a Tobit model with a censoring from above at 0:

$$E[J_t|\Phi_t] = \begin{cases} E[J_t|\Phi_t]^* & \text{if } E[J_t|\Phi_t]^* < 0 \\ 0 & \text{if } E[J_t|\Phi_t]^* \geq 0 \end{cases}. \quad (12)$$

The fitted values for the jump size now fall correctly in the range $(-\infty, 0]$.

Of course, our objective in the end is to identify investors' reactions to events that may affect (future) cash flows. As a result, we are particularly interested in large attacks that take place in regions where a considerable FDI stock has been built up. But what is a large attack? And are there large attacks in all regions? Do investors react? And is this reaction the same over time?

To answer these questions, we show fitted univariate quadratic plots between the S&P500 jump probabilities and regional *TER* scores in Figure 3. Our objective is to find out whether there is a threshold value beyond which attacks provoke jumps. As expected, most of the patterns displayed in Figure 3 demonstrate a non-linear relationship, where the probability of a jump increases disproportionately with the intensity of a terrorist attack. An exception is the Middle East, where more severe attacks seem to provoke smaller reactions. At first glance this may seem odd, however given the ongoing conflict between Israel and its occupied territories, combined with the invasion and U.S. military presence in Iraq, it could be possible that markets have become desensitized to attacks in this region. Figure A.1 in Appendix A shows the relationship for the Middle East when attacks in these countries are not used to calculate the terrorism intensity score. Compared to Figure 3(e), we see that the relationship between terrorism and stock market sensitivity is less downward sloping and statistically insignificant without these areas.

[Insert Figure 3 near here]

From Table 1 and Figure 3, we observe two things. First, the average maximum *TER* score per region is approximately 7.¹¹ Second, although the confidence intervals are quite wide due to a limited amount of large attacks, a magnitude 7 attack results in a jump probability above 50 in 4 out of the 6 regions. We use this as a threshold value and condition the probability of a jump, in any given year, on the occurrence of a hypothetical attack with magnitude 7, although we use other values as a robustness check. In order

¹¹This corresponds to one large attack with 1,100 injuries and fatalities or for example 10 attacks with an average of 100 injuries and fatalities.

to allow the reaction to this attack to vary over time, we estimate Equations (10a) and (10b) year-by-year. Given each year's and each sector's estimation, the share price reaction for each sector i to a large terrorist attacks is then:

$$\eta_{i,k,t} = E [(P(n_t \geq 1|\Phi_t) | TER_k = 7] \quad (13a)$$

$$\zeta_{i,k,t} = E [E[J_t|\Phi_t]^* | E[J_t|\Phi_t] < 0, TER_k = 7], \quad (13b)$$

where $\eta_{i,k,t}/\zeta_{i,k,t}$ is the estimated probability/size of the jump in the share price of sector i associated with a large terrorist attack in region k in year t . Of course, in years without large attacks, the estimated relationship between terrorism and jump probabilities/sizes is expected to be relatively flat, and predicting the conditional mean given an attack outside of the observed range of actual attacks will likely yield a low jump probability/size.

As a robustness test, we will also estimate Equations (10a) and (10b) on the entire sample instead of yearly subsamples. Since every region suffers from at least one large attack (as can be seen in Figure 3 and Table 1), these estimations have an improved fit. However, this comes at a cost as we have to use average shares of FDI over the entire sample period, thereby ignoring year-to-year changes.

4.3 Third step: linking reactions to large attacks with FDI

Having established what constitute terrorism effectuated jumps, the final step is to analyze to what extent the likelihood and size of these jumps are related to the U.S. FDI stock that has been built up in a region. We therefore estimate:

$$\eta_{i,k,t} = \alpha + \beta FDI_{i,k,t} + \mu_i + \nu Year + v_{i,t} \quad (14a)$$

$$\zeta_{i,k,t} = \alpha + \beta FDI_{i,k,t} + \mu_i + \nu Year + \nu_{i,t}, \quad (14b)$$

where $\eta_{i,k,t}$ and $\zeta_{i,k,t}$ are the predicted jump probability and size of sector i associated with attacks in region k occurring in year t respectively, and

$FDI_{i,k,t}$ is the share of the total FDI stock of sector i that it has invested in region k in year t . Moreover, μ_i and Year are sector and year fixed effects respectively, and are included to control for heterogeneity between sectors and years.¹² If investors take into account the investment position of firms in each sector, we expect β to be positive for $\eta_{i,k,t}$ and negative for $\zeta_{i,k,t}$. In that case, a higher share of FDI in a region will lead to a higher probability of a jump due to a large scale attack and a more negative movement in share prices.

Since $\eta_{i,k,t}$ and $\zeta_{i,k,t}$ are predicted values of $P(n_t \geq 1|\Phi_t)$ and $E[J_t|\Phi_t]$, we again need to take into account their supports. For Equation (14a), we include sector fixed effects and again estimate a fractional logit.¹³ Estimating Equation (14b) using a Tobit approach is less straightforward, as Greene (2004) cautions that adding fixed effects biases the variance of the error term. To still account for unobserved heterogeneity due to the panel nature of the data, we estimate Equation (14b) using a random effects Tobit model with sector-specific random effects (see e.g. Maddala, 1987).

Given the data at our disposal, one side note is in order here. The identification strategy we follow relies on the assumption that terrorism and sector level investment are, more or less, uniformly distributed across countries in the region. Since we lump together the region's investments, we allow prices to be influenced by attacks in other countries, to which a sector might not be exposed to. In this case, unless investors perceive it as a sign of regional instability, we would not expect to see a reaction on the share price as their FDI stock is not 'at stake'. In this scenario, the potential impact would be underestimated, as we compute the average reaction to attacks in the region without being able to make the distinction whether the sector is exposed to only one particular country, or a little bit to all of them. Should we still see a reaction, even though we aggregate on a region and sector level, it would

¹²We do not include region fixed effects as these will absorb the cross-variation of shares between regions that we are interested in.

¹³Papke and Wooldridge (2008) caution adding fixed effects when T is small and N is large. The likelihood ratio test however shows that the unobserved heterogeneity does not play a large role and the estimates are similar to a pooled version of the model. Moreover, similar to Hausman and Leonard (1997), N is fixed in our case, combined with $T = 13$ years.

be indicative of the relative strength of these results.

5 Results

In this section, we retrace the steps we described above. We start by establishing whether investors react to large terrorist attacks. Then we relate these reactions to FDI stocks. Subsequently, we investigate whether investors' reaction to terrorism on foreign soil is proportional to U.S. FDI stocks in the area where the attack takes place, whether the reaction is different *after* 9/11, and if the information that investors receive has changed due to 9/11. We conclude this section with some robustness checks.

5.1 Are investors alert to large terrorist attacks on foreign soil?

Does a large terrorist attack on foreign soil increase the probability of a drop in U.S. share prices? And how large is the expected drop in share prices? In order to answer these questions, Table 3 contains the jump probabilities and jump sizes, conditional on a large attack, as defined by Equations (11) and (12).

[Insert Table 3 near here]

We observe that, during the entire sample, the region where large attacks lead to the highest average predicted jump probability and jump size is Western Europe. On average, the probability that at least one jump occurred in one of the sectors due to a large terrorist attack is 49.90 percent, and the average size of that jump is -2.33 percent. Other regions where attacks lead to noticeable reactions on U.S. stock markets are Latin America and Asia & the Pacific, where the average $\eta_{i,k,t}$ are 38.77 percent and 32.94 percent respectively. The average predicted jump sizes are -1.00 percent for Latin America and -0.76 percent for Asia & the Pacific respectively, and are markedly lower than for Western Europe.

To analyze how much the TER terms add to the prediction, we perform a Shapley decomposition, which is based on the pseudo- R^2 of each regression, and is shown in Table 3. On average, around 10% of the predictive power in the regression comes from the combined TER terms, although for certain year/sector combinations this is as high as 29% for $\eta_{i,t,k}$ and 39% for $\zeta_{i,t,k}$.

Of course, since large terrorist attacks are, fortunately, still rare, share prices are not always expected to jump. For instance, in 2006 our model predicts a jump probability for Western Europe’s Industrials sector equal to 0 percent, whereas in 2009 the jump probability for the same sector was 12.5 percent, although the actual terrorist activity in the region in those years was low and quite similar.¹⁴

5.2 Is investors’ reaction to large attacks proportional to the FDI stock that is ‘at stake’?

Now that we have established investors’ average reaction to large terrorist attacks, the next question is whether this reaction depends on the FDI stock built up by U.S. firms in the region where a large attack takes places. To answer that question, we regress the jump probabilities and jump sizes on FDI stocks. We expect that jump probabilities increase with larger FDI stocks, and we expect to see larger *negative* jumps as FDI stocks increase.

Indeed, this is what we observe from Table 4. The coefficients on the share of received FDI are significant and as expected: higher shares of outward U.S. FDI in a region lead to higher jump probabilities and larger negative jump sizes in response to high TER attacks.¹⁵

¹⁴The highest daily TER scores for Western Europe in 2006 and 2009 are 2.64 and 2.48 respectively.

¹⁵Year and sector fixed effects are included in the fractional logit case, and only year controls in the random effects Tobit case. The sector fixed effects are found to be jointly insignificant in the fractional logit estimation, meaning that the estimates are similar to a pooled version of the model. For the random effects Tobit model, the unobserved heterogeneity in $\zeta_{i,k,t}$ does not play a large role as the random sector effect contributes only 9 percent of total variance. However, a likelihood ratio test comparing the random effects with a pooled version shows that the random effect is significantly different from zero.

[Insert Table 4 near here]

Since the interpretation of the magnitude of the coefficients in Table 4 is not straightforward due to the nonlinear nature of the models, we plot the relationship between FDI stocks and jump probabilities/sizes in Figure 4. We observe that the probability of a jump increases from the unconditional expected value of 30 percent when no investments take place, to 70 percent when a region receives all sector level FDI. The size of the jump due to large terrorist attacks also increases with received FDI, leading to a stock market reaction of -3 percent if a region receives all FDI from that sector. The highest share a region received is found in 2006 when the Telecom sector had 70 percent of its FDI stock invested in Western Europe. Using these estimates, a large attack in that year would have led to a drop of -2.5 percent in its share price, with a 60 percent probability of a jump.

[Insert Figure 4 near here]

These results show that the presence of American firms in regions suffering from terrorism directly affects their share prices. The higher the proportion of investments made in a region, the more the share prices of these sectors react to large terrorist attacks taking place there. This suggests that investors do on average take into account the investment positions of firms belonging to a sector and adjust expectations on cash flows when they are dealt with the negative exposure of terrorism.

5.3 Has 9/11 made investors more alert to what is ‘at stake’?

To what extent do our results so far reflect the post 9/11 state of the world? In order to find out, we split our sample and compare the relationship between investors’ reaction and U.S. FDI stock before and after 9/11, as well during the recent financial crisis.

Table 5 shows the results for each of these periods, relating jump proba-

bilities and jump sizes conditional on large terrorist attacks to FDI stocks.¹⁶ We observe that FDI stocks had no relation to jumps prior to 9/11. After 9/11, higher FDI stocks resulted in higher jump probabilities and more negative jumps, as expected.

[Insert Table 5 near here]

According to the availability heuristic, an explanation of our findings so far would be that 9/11 has made it easier for U.S. investors to bring to mind terrorist attacks, including those that take place on foreign soil. Given the nature of 9/11, it is appealing to interpret our results in this manner. But the lack of comprehensive information on the true impact, in terms of cash flow losses, of the terrorist attacks we study makes it difficult to distinguish this explanation from another one: that investors overreact *after* 9/11 and engage in a blind fire sale after large terrorist attacks on foreign soil.

In Figure 5, we explore two aspects of our results that suggest the latter has not happened. The first aspect concerns the role of what is ‘at stake’: if investors’ reaction post-9/11 is the result of panic, we expect it to be less sensitive to the U.S. FDI stock in a region where an attack takes place. If, however, investors’ reaction post 9/11 reflects the availability heuristic, we expect sensitivity to have increased. Indeed, in Figure 5, we observe that the latter is the case both for jump probabilities (comparing 5(a) and 5(b)) and for jump sizes (comparing 5(d) and 5(e)).

The second aspect concerns whether investors are indeed ‘on alert’ after 9/11: if their reaction post-9/11 is the result of panic, we expect it to decrease over time and become less sensitive to the U.S. FDI stock. Should the investors’ reaction post-9/11 reflect the availability heuristic fueled by the experience of 9/11, we expect sensitivity to increase over time, due to large terrorist attacks in regions where a lot of FDI stock has been built up (e.g., Madrid in 2004 and London in 2005). Indeed, in Figure 5, we observe that the latter is the case both for jump probabilities (comparing 5(b) and 5(c)) and for jump sizes (comparing 5(e) and 5(f)).

¹⁶The jump probability estimates are, however, still based on the entire sample.

[Insert Figure 5 near here]

Between 2002 and 2006, the slope shifts and we see a gradual increase in stock market reaction to attacks in high FDI regions. The effect of FDI becomes even more apparent in the last subsample. In both periods after 9/11, the relationship is statistically significant. In the second subsample, a sector investing all of its FDI in a region under attack experiences on average a jump of -3 percent with a probability of 60 percent. In the last subsample, this same sector would see a near-certain jump of -5.5 percent in its share price.¹⁷

Now that we have shown that investors appear to place more emphasis on what is ‘at stake’, we have not necessarily proven the importance of the experience hypothesis in sustaining the availability heuristic. After all, the world has changed in more ways than one following 9/11. Firstly, Straetmans et al. (2008) find that stock markets have structurally changed after the 9/11 attacks, and point out that this might be caused by the perceived risk of new attacks. Secondly, in the period after 9/11, the U.S. commenced the War-on-Terror and invaded Afghanistan and Iraq, as a response to which terrorists attacked public transportation in Madrid (2004) and London (2005). These experiences showed that Western Europe, beneficiary of the bulk of U.S. FDI, could also be subject to terrorist attacks. Finally, with the developed world suffering from the declining U.S. housing market, more focus was placed on emerging markets as a source of growth and profit. However, while investors and companies shifted more of their investments to regions like Asia and the Middle East, these regions also saw the bulk of terrorist attacks (see Table 1).¹⁸

¹⁷Since year fixed effects are included in Equations (14b) and (14b), we control for the fact that the estimated of jump probabilities and sizes might be higher due to the financial crisis.

¹⁸United Nations Conference on Trade and Development (UNCTAD) (2011) reports that in 2011 52 percent of the world FDI inflows occurred in Developing and Transition Economies, up from 33 percent in 2007. Based on the UNCTAD database on FDI stock, the share of these markets in the total world FDI stock increased from 29 percent in 2007 to 35 percent in 2010.

5.4 Are investors able to assess the probability and frequency of large attacks?

Both arguments given so far in favor of the availability heuristic do not tell the full story. In order to establish that 9/11 has indeed had the effect of waking up investors to the impact of terrorism on foreign soil, then (a) the probability and frequency of large terrorist attacks before 9/11 should not be zero, and (b) investors should have been able to obtain accurate information about these probabilities and frequencies.

In Figure 6(a), we show the frequency of attacks in each region during the sample. Although some regions see an increase (Asia & Pacific and the Middle East), in most regions the annual number of attacks does not change after 9/11. Moreover, the relative frequencies in Figure 6(a) do not change materially once we start excluding smaller attacks. It appears that the events that investors are expected to consider materialize over the entire sample period.

[Insert Figure 6 near here]

In Figure 6(b), we proxy the amount of reporting in the U.S. on terrorism on foreign soil by plotting the yearly number of articles that appeared in the Wall Street Journal for searches on ‘terrorism’ or ‘terrorist’ and each of the regions identified in our analysis. As expected, we see a coverage spike following the 9/11 attacks, driven mainly by articles relating to terrorism and the Europe, Asia and Middle East regions. Prior to 9/11 (1998-2000), there are an average of 3 articles a year on terrorism in these three regions, increasing to 65 articles in the 5 years following the attacks. However, the overall trend is downwards and, with the exception of the Middle East, seems to be leveling out around 2006. Of course, these numbers have to be interpreted with some care: the number of articles depend positively on the occurrence of large attacks, and not every article could give investors accurate information on the probability of a terrorist attack occurring. Nonetheless, based on these figures, we can conclude that the relationship between price jumps, terrorism and FDI stocks remained significant and became stronger, even though the

media coverage of terrorism was lower compared to the years following 9/11. Moreover, as Melnick and Eldor (2010) have shown, the economic impact of terrorist attacks attributable to media coverage diminishes over time, indicating that the news-value for investors at the end of the sample period is potentially lower than right after the attacks. Taken together, we view this as evidence in favor of the experience hypothesis fueling the availability heuristic: the reaction stays significant for a long time after 9/11, even as coverage of terrorism abroad levels out.

5.5 Robustness

In the previous sections we have provided evidence that a terrorist attack at home can act as a wake up call to investors, making them aware of attacks elsewhere and thereby correcting the way they evaluate the frequency and probability of terrorist attacks. Moreover, we have argued that this phenomenon is not driven by an overreaction of investors to attacks, but is rational since it is proportional to the FDI stock ‘at stake’. Here, we examine the robustness of these results.

From Figure 5 we have seen that the relationship between stock market jumps and large terrorist attacks in regions receiving more U.S. FDI has become economically and statistically significant after 9/11. Following attacks in Western Europe, the largest receiver of U.S. FDI, we find that the relationship intensifies even more and is strongest during the last subsample. The fact that large jumps were more prevalent during the financial crisis is controlled for using time fixed effects. Even so, estimating the last subsample without the turbulent year 2008 does not change our results.¹⁹

Another test is to what extent our findings in Figure 5 are the result of the fact that we estimate Equations (10a) and (10b) for each year, rather than for our entire sample. In order to find out, we re-estimate them using the entire sample and adding year fixed effects. As we already concluded from Table 1, all regions have seen at least one large attack and by using these

¹⁹See Table A.2 in Appendix A for the estimations. The coefficients are actually larger in size when estimating without the year 2008.

estimations we therefore avoid having to predict the average reaction to large attacks when they do not occur in a given year. The downside of this strategy is that we are forced to use average shares of outward FDI, disregarding their yearly variability. In Appendix A, Table A.3 shows the estimation results, while Figure A.2 displays the impact of an increase in FDI stock on the jump probabilities and jump sizes for the whole sample. In Figure 7 we show the pooled estimation on each of the subsamples. The results are in line with what we have found so far. In fact, if anything, we find that although the average jumps are somewhat smaller, the changes in jump probabilities after 9/11 are more remarkable, especially in the last subsample. It appears that the impact of 9/11 has indeed lasted for a long time.

[Insert Figure 7 near here]

How relevant is the size of a terrorist attack? Is it the case that the large attacks are what drives investors' reactions? In order to find out, we check whether conditioning the yearly jump forecasts on smaller attacks changes our conclusion. Table A.4 in Appendix A shows the regression results for levels of $TER = 1$, $TER = 3$, $TER = 5$, baseline specification $TER = 7$ and $TER = 9$, while Figure 8 plots the jump probabilities and jump sizes for increasingly large attacks. When terrorist attacks are of a small size, the sector indices do not move and the reaction is very small, even if a sector would make its investments in one single region. As terrorist attacks become increasingly large, the share prices react more to attacks in regions receiving more FDI. For extreme terrorism of $TER = 9$, sectors investing all of their FDI in one region would experience a jump of -5.2 percent with a probability of 72 percent. The exercise shows that this relationship only exists for the largest of observed attacks. In Table 1 we saw that the mean TER scores lie between 0.23 and 1.74. If we had estimated on these mean values, we would be unable to see the reaction both in terms of jump probability and in jump size.

[Insert Figure 8 near here]

Finally, we check whether the results are driven by the large attacks in

London (2004) and Madrid (2005), as Western Europe received the bulk of U.S. outward FDI. Similarly, a country like China receives a lot of FDI, but there are only 21 attack days recorded in the GTD during the sample period. We ran the analysis by excluding the London and Madrid attacks, as well as a separate analysis without China. When excluding the London and Madrid attacks the results become somewhat weaker, whereas they become stronger without China. However, in both cases the relationship between FDI and the reaction to large terrorist attacks is still negative and statistically significant.²⁰

6 Conclusion

We have examined how terrorism in different geopolitical regions of the world has spilled over to U.S. financial markets through the foreign presence of American firms, and how this relationship has changed after 9/11. We document that share prices react negatively to large terrorist attacks on foreign soil, and that this reaction is proportional to the FDI stock of U.S. firms on that soil. However, in order for investors to act this way, the ‘message’ unfortunately has had to hit home first: the relationship is only significant, both statistically and economically, after the tragic events of September 11, 2001, indicating disaster myopia consistent with the availability heuristic. However, given that the frequency of attacks has not changed materially after 9/11, the relationship between share prices, FDI and terrorist attacks abroad has stayed strong even as the media coverage of these attacks has come down from its peak levels post-9/11. Presented with this evidence, we conclude that 9/11 was the experience that created awareness of the potential impact of terrorist attacks among investors, and, in line with the experience hypothesis, explains the change in their behavior afterwards.

The results in this paper are in line with a growing literature (see e.g. Abadie and Gardeazabal, 2003; Drakos, 2010a) that find that the (global) activity of firms and/or sectors leads to sensitivity in their share prices as a

²⁰Results are available on request.

reaction to acts of terrorism. In an increasingly globalized world, this has an impact on both companies and investors. On the one hand, investors need to take into account the geopolitical situation in regions where firms locate their FDI before they invest in this company. On the other hand, multinationals valuing the stability of their share price also need to take this into account before investing in these regions. The documented relationship between foreign presence of firms, terrorism and their share price is likely to become even more important in the coming years: American firms have increasingly built up their presence in Asia and the Middle East, yet these regions have seen the bulk of terrorist attacks since 1998, and are likely to continue to pose a geopolitical risk in the near future. A better understanding of sensitivity to terrorism, preferably using firm level investment positions, is therefore a promising avenue for future research.

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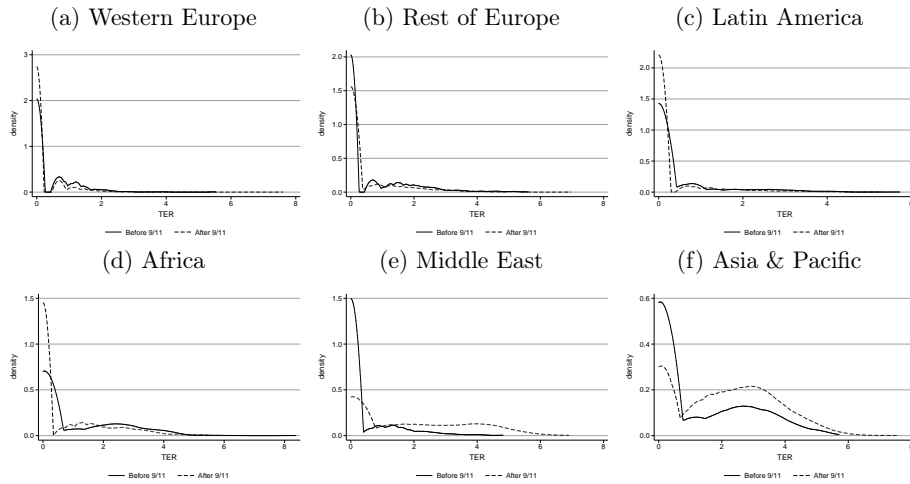
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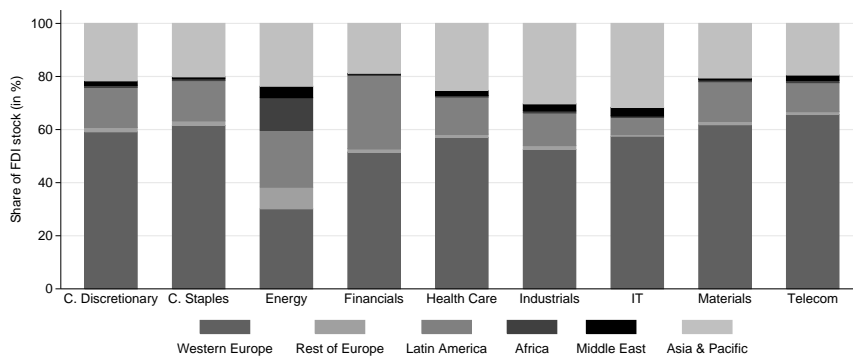
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Figure 1: Terrorism before and after 9/11



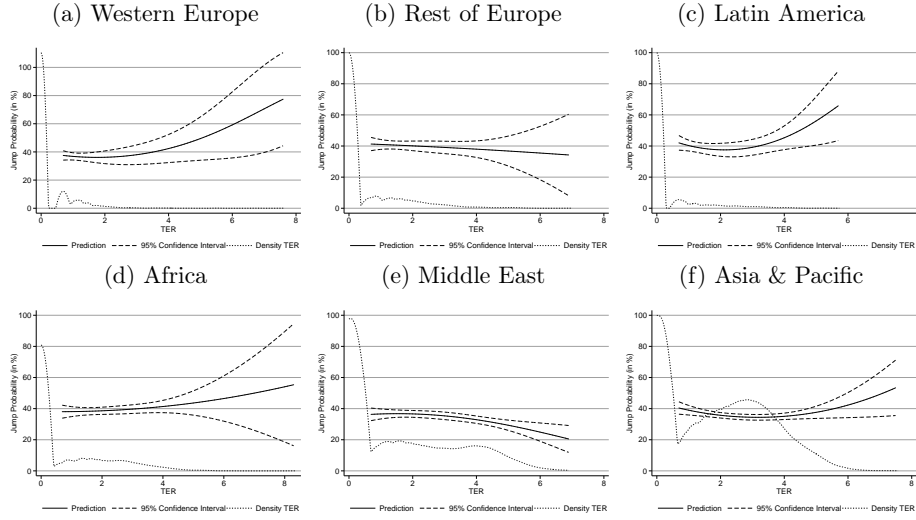
The graphs show the distribution (as a kernel density plot) of the terrorism index, before and after the 9/11 attacks. Kolmogorov-Smirnov tests for differences in the distribution among days on which attacks take place indicate that only for Africa and the Middle East there is a change after 9/11.

Figure 2: U.S. Direct Investment - Sector Distribution Geographical Areas



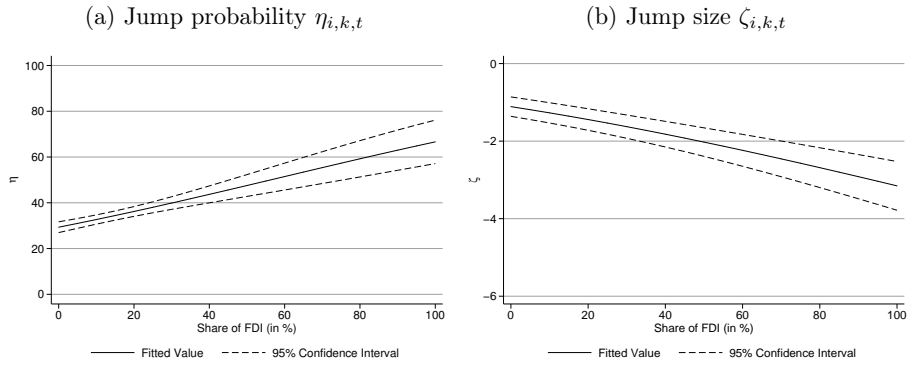
The figure shows the geographical distribution in outward FDI of nine S&P500 sectors. To calculate shares, data from the U.S. Bureau of Economic Analysis are transformed from NAICS/SIC to GICS sectors (see Appendix B) and averaged over the sample period 1998–2010.

Figure 3: S&P500 reaction to terrorism



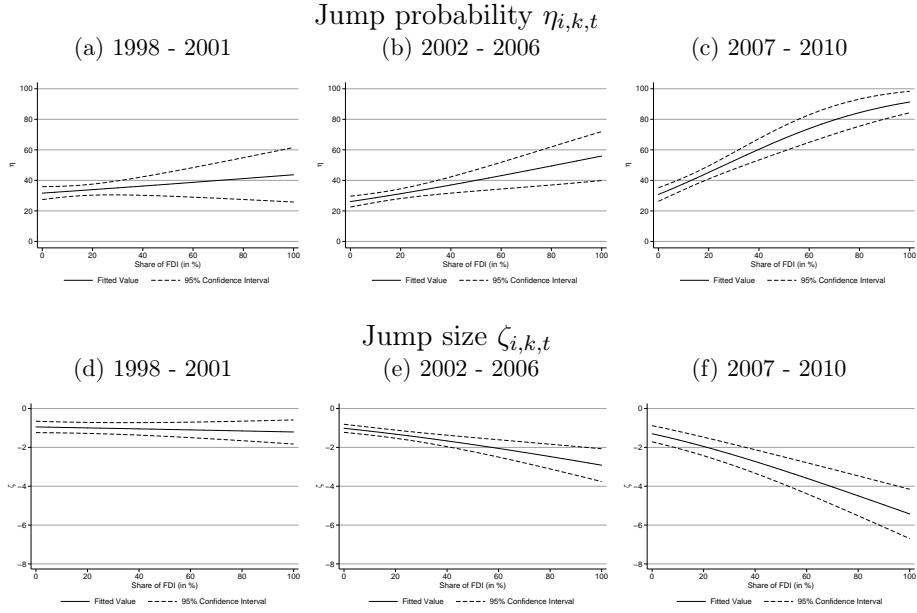
The graphs show the relationship between the intensity of terrorism in different regions of the world and probabilities that the S&P500 experienced a jump on these attack days. Fitted values and their 95 percent confidence intervals are presented, as well as the density of the TER scores.

Figure 4: Are share price reactions proportional to FDI stock ‘at stake’?



The graphs show the jump probability and size in reaction to a large terrorist attack in a region, depending on the share of FDI this region receives. Fitted values and their 95 percent confidence intervals are shown over the response surface for the regressions in Equations (14a) and (14b), and Table 4.

Figure 5: Changes in sensitivity of investors after 9/11



The graphs show for different subsamples the jump probability and size in reaction to a large terrorist attack in a region, depending on the share of FDI this region receives. Fitted values and their 95 percent confidence intervals are shown over the response surface for the regressions in Equations (14a) and (14b) and Table 5.

Figure 6: Exposure to terrorism on foreign soil

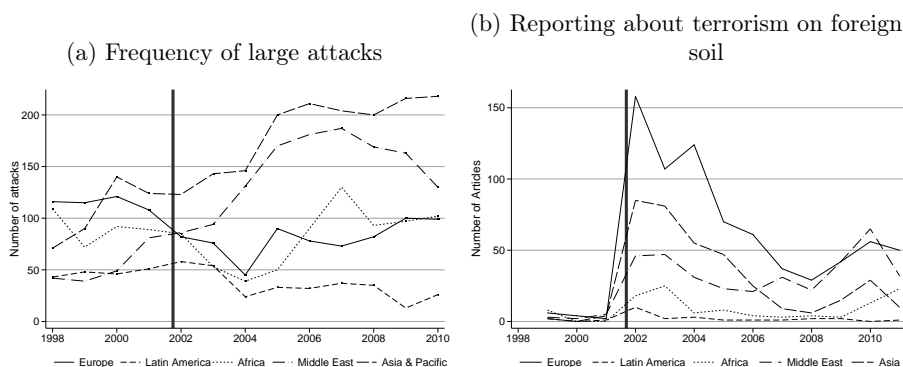


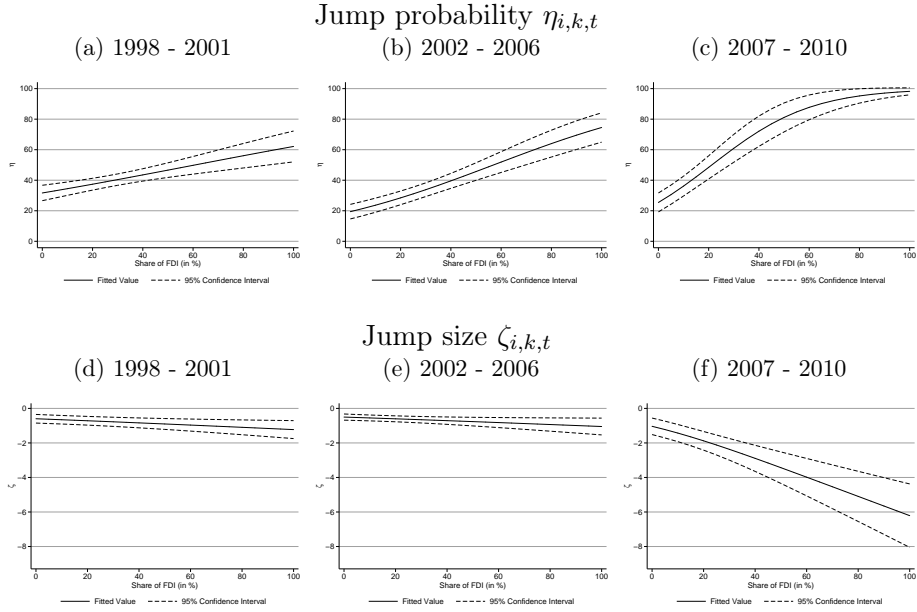
Figure (a) shows the annual frequency of attacks in each of the regions. Figure (b) shows the number of Wall Street Journal articles per year for a Boolean search on ‘(terrorism OR terrorist) AND X’, where X is each of the regions. The search is conducted using the Lexis-Nexis newspaper database. Since the region ‘Rest of Europe’ is not properly defined outside the context of this study, we group it together with ‘Western Europe’ in one large ‘Europe’ region.

Table 1: Summary Statistics of Terrorism

Region	A. <i>TER</i> -scores				B. Attacks	
	Mean	Std. Dev.	Max.	Trading days with attack	Average Deaths	Average Wounded
Western Europe	0.23	0.58	7.60	640	0.43	3.90
Rest of Europe	0.42	0.93	6.98	762	2.43	5.80
Latin America	0.26	0.73	5.73	500	2.44	3.36
Africa	0.74	1.22	8.37	1,101	5.34	7.11
Middle East	1.31	1.72	6.90	1,522	4.66	11.05
Asia & the Pacific	1.74	1.63	7.57	2,086	2.77	6.16

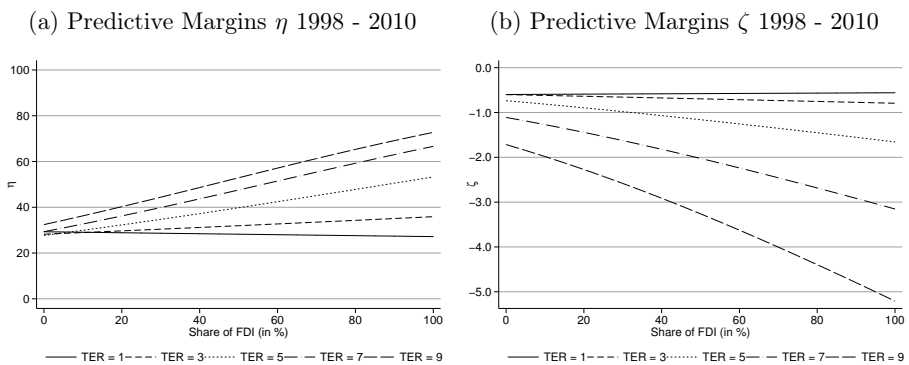
The table displays summary statistics of attacks in different global regions selected from the Global Terrorism Database over the period 1998–2010, spanning a total of 3,270 trading days. Panel A shows the statistics of the *TER* scores calculated from these attacks, where ‘Trading days with attacks’ counts the number of days in the sample where a terrorist attack took place. Panel B shows the average number of fatalities and wounded per attack using the raw data from the Global Terrorism Database. For instance, the Madrid bombings are included as four separate attacks having injured 450 people each.

Figure 7: Reaction to terrorism and share of FDI - Pooled Estimation - Split Sample



The graphs show for a pooled version of the model, the jump probability and size in reaction to a large terrorist attack in a region during different subsamples, depending on the share of FDI this region receives in this subsample. Fitted values and their 95 percent confidence intervals are shown over the response surface for the regressions in Equations 14a and 14b, and Table A.3.

Figure 8: Reaction to terrorism and share of FDI - Variable TER



The graphs show the jump probability and size in reaction to different-sized attacks in each region, depending on the share of FDI this region receives. Fitted values over the response surface of the regressions in Equations (14a) and (14b), and Table A.4 are shown.

Table 2: Summary Statistics (in percent)

	A. Jump probability				B. Jump contribution			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
S&P500	36.9	36.7	0.0	100	-0.7	1.2	-10.0	0.0
C. Discretionary	33.8	34.3	0.0	100	-0.7	1.2	-11.2	0.0
C. Staples	28.7	28.2	1.9	100	-0.2	0.3	-3.3	0.0
Energy	19.2	27.3	0.0	100	-0.5	1.1	-14.3	0.0
Financials	30.2	34.3	0.0	100	-0.7	1.3	-10.8	0.0
Health Care	35.1	29.9	2.8	100	-0.3	0.4	-3.6	0.0
Industrials	28.9	34.3	0.0	100	-0.7	1.3	-11.6	0.0
IT	28.5	34.0	0.0	100	-0.9	1.6	-12.5	0.0
Materials	28.8	28.0	2.3	100	-0.3	0.5	-5.1	0.0
Telecom	27.4	27.8	1.2	100	-0.2	0.3	-2.5	0.0
Utilities	13.5	24.1	0.0	100	-0.3	0.7	-11.6	0.0

The table displays summary statistics of the output from the GARCH-Jump model for the S&P500 and its sectors. Panel A shows the probability that at least one jump occurred on a trading day, $P(n_t \geq 1|\Phi_t)$. Panel B displays the jump contributions, calculated as the expected number of jumps on day t , $E[n_t|\Phi_t]$, multiplied with the average jump size θ .

Table 3: Average reactions to a large terrorist attack

	A. Jump probability $\eta_{i,k,t}$				B. Jump size $\zeta_{i,k,t}$			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Western Europe	49.90	40.99	0.00	100.00	-2.33	4.05	-16.64	0.00
Rest of Europe	30.45	33.39	0.00	100.00	-0.76	1.20	-4.83	0.00
Latin America	38.77	36.13	0.00	100.00	-1.00	1.44	-7.90	0.00
Africa	28.59	22.61	0.08	89.32	-0.48	0.58	-2.97	-0.01
Middle East	30.55	24.58	0.00	96.66	-0.73	1.43	-11.60	0.00
Asia & the Pacific	32.94	22.24	0.04	89.96	-0.67	0.84	-6.68	-0.01
Contribution TER (in %)	10.91	5.69	3.10	29.78	10.22	6.19	2.30	39.81

The table displays summary statistics for the predicted jump probabilities (Panel A) and predicted jump sizes (Panel B) associated with a large attack in each of the regions. The probabilities and sizes are averaged out over year and sector. A large terrorist attack is defined as having a TER score of 7, which corresponds to 1,100 injuries and fatalities. The predictions are obtained by estimating Equations (11) and (12) on a year and sector basis. A Shapley decomposition of McFadden's pseudo- R^2 is performed to determine the contribution of the combined TER terms .

Table 4: Share price reactions and FDI stock

	Jump probability $\eta_{i,k,t}$	Jump size $\zeta_{i,k,t}$
α	-0.917*** (0.229)	-1.235*** (0.307)
$FDI_{i,k,t}$	1.723*** (0.270)	-2.539*** (0.331)
Year FE	Included	Included
Sector FE	Included	
N	696	696
L	-325.27	-1380.07
ρ		0.09
LR Test 1		48.88***
LR Test 2	1.59	

The table shows panel regression results for Equations (14a) and (14b), where reactions of sectors to large terrorist attacks in regions are regressed on the share of FDI they receive. $\eta_{i,k,t}$ is estimated using fractional logit, whereas $\zeta_{i,k,t}$ is estimated using a random effects Tobit model. Standard errors are reported in parentheses, and are robust for $\eta_{i,k,t}$. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. L is the log likelihood value, ρ is the fraction of variance due to the unobserved heterogeneity μ_i and is defined as $\frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\epsilon^2}$. LR Test 1 is a likelihood ratio test of $\sigma_\mu = 0$ in $\zeta_{i,k,t}$. LR Test 2 is a likelihood ratio test for the joint significance of the sector fixed effects in $\eta_{i,k,t}$.

Table 5: The impact of 9/11 on investors' reaction

	A. Jump probability $\eta_{i,k,t}$			B. Jump size $\zeta_{i,k,t}$		
	Before 9/11	After 9/11		Before 9/11	After 9/11	
	1998 - 2001	2002 - 2006	2007 - 2010	1998 - 2001	2002 - 2006	2007 - 2010
mean	0.336	0.306	0.427	-0.742	-0.816	-1.489
(std. dev.)	(0.273)	(0.306)	(0.354)	(1.374)	(2.072)	(2.467)
α	-0.966***	-1.625***	-1.296***	-0.666***	0.120	-0.867**
	(0.294)	(0.343)	(0.301)	(0.257)	(0.276)	(0.411)
FDI $_{i,k,t}$	0.537	1.439***	3.532***	-0.356	-2.449***	-4.745***
	(0.443)	(0.428)	(0.536)	(0.428)	(0.526)	(0.688)
Year FE	Included	Included	Included	Included	Included	Included
Sector FE	Included	Included	Included			
N	210	270	216	210	270	216
L	-99.31	-118.03	-99.77	-348.15	-536.27	-460.52
ρ				0.17	0.04	0.15
LR Test 1				22.51**	3.10***	20.56***
LR Test 2	5.41	1.37	3.40			

The table shows panel regression results of Equations (14a) and (14b) for different subsamples, where reactions of sectors to large terrorist attacks in regions are regressed on the share of FDI they receive. $\eta_{i,k,t}$ is estimated using fractional logit, whereas $\zeta_{i,k,t}$ is estimated using a random effects Tobit model. Standard errors are reported in parentheses, and are robust for $\eta_{i,k,t}$. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. L is the log likelihood value, ρ is the fraction of variance due to the unobserved heterogeneity μ_i and is defined as $\frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\epsilon^2}$. LR Test 1 is a likelihood ratio test of $\sigma_\mu = 0$ in $\zeta_{i,k,t}$. LR Test 2 is a likelihood ratio test for the joint significance of the sector fixed effects in $\eta_{i,k,t}$.

Appendix A

A.1 GARCH-Jump estimates

Estimates of the model for the S&P500 and sector indices are shown in Table A.1. The results show that the estimated average return, μ , is not significantly different from zero and is in line with the actual average return in the sample period. The main coefficients of interest are those that govern the jump dynamics. The autoregressive coefficient in the jump intensity equation, ρ , is close to 1 for all indices, indicating that the jump intensity and jump probabilities advance smoothly over time. It also indicates that, like volatility, jumps exhibit clustering. A likelihood ratio test, testing if $\rho = \gamma = 0$, shows that the null hypothesis that the jump intensity is time-invariant can be rejected.²¹ The average jump size, θ , is negative and significant for all indices ranging between -0.4 percent (Telecom) and -1.7 percent (Energy). The unconditional expected level of jumps, $E\lambda_t$, shows that jumps are more likely to occur during our sample period compared to the more stable indices chosen by Maheu and McCurdy. The difference is due to higher estimates of autoregression in the jump intensity, ρ , and the jump intensity constant, λ_0 . One of the reasons we find a higher expected jump intensity could be that Maheu and McCurdy use an estimation window between 15 and 40 years up to the end of 2001, while our estimation period is thirteen years in which there were three distinct crises (the 1998 crisis, the crash of the internet bubble and the recent financial crisis). Finally, Maheu and McCurdy suggest that the effect of jumps on returns is best measured by the unconditional variance of jump innovations, which is reported in the last row of Table A.1. This average variance due to jumps is highest for the Financials, Energy and IT indices.

²¹The constraint is similar to $\lambda_t = \lambda$.

Table A.1: GARCH-Jump Estimates

$$r_t = \mu + \phi r_{t-1} + \epsilon_{1,t} + \epsilon_{2,t}, \quad \epsilon_{1,t} = \sigma_t z_t, \quad z_t \sim \text{NID}(0, 1),$$

$$\epsilon_{2,t} = \sum_{k=1}^{n_t} Y_{t,k} - \theta \lambda_t, \quad Y_{t,k} \sim N(\theta, \delta^2), \quad \lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \xi_{t-1},$$

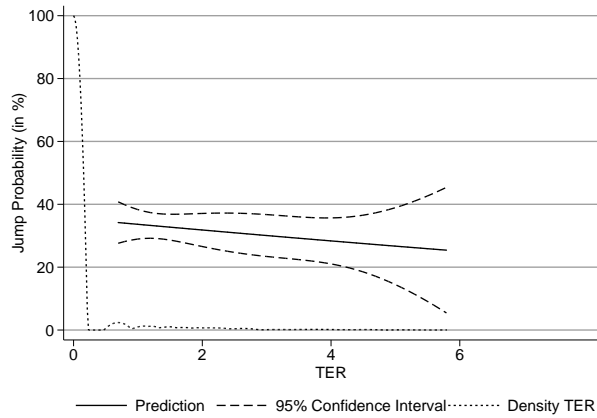
$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \quad \epsilon_{t-1} = \epsilon_{1,t-1} + \epsilon_{2,t-1}.$$

	S&P500	C. Discretionary	C. Staples	Energy	Financials	Health Care	Industrials	IT	Materials	Telecom	Utilities
μ	0.005 (0.016)	0.004 (0.018)	0.016 (0.013)	0.034 (0.024)	0.001 (0.018)	-0.007 (0.017)	0.016 (0.017)	-0.021 (0.024)	0.033 (0.023)	0.015 (0.020)	0.006 (0.017)
ϕ	-0.044** (0.018)	0.032* (0.018)	-0.067*** (0.018)	-0.033* (0.018)	-0.032* (0.018)	-0.010 (0.018)	-0.010 (0.018)	-0.003 (0.018)	0.000 (0.019)	-0.032* (0.018)	0.028 (0.019)
ω	0.004*** (0.001)	0.004** (0.002)	0.003*** (0.001)	0.017*** (0.005)	0.007*** (0.002)	0.005** (0.002)	0.006*** (0.002)	0.009*** (0.002)	0.008*** (0.003)	0.009*** (0.003)	0.016*** (0.004)
α	0.014*** (0.003)	0.022*** (0.005)	0.018*** (0.005)	0.020*** (0.004)	0.035*** (0.006)	0.014** (0.006)	0.014*** (0.004)	0.018*** (0.004)	0.016*** (0.005)	0.016*** (0.006)	0.045*** (0.009)
β	0.968*** (0.006)	0.962*** (0.006)	0.968*** (0.008)	0.964*** (0.007)	0.949*** (0.007)	0.969*** (0.011)	0.971*** (0.007)	0.969*** (0.005)	0.972*** (0.007)	0.969*** (0.008)	0.922*** (0.013)
λ_0	0.020*** (0.005)	0.019*** (0.005)	0.020*** (0.006)	0.011*** (0.004)	0.011*** (0.003)	0.027*** (0.007)	0.013*** (0.004)	0.017*** (0.006)	0.019** (0.008)	0.009** (0.004)	0.015*** (0.005)
ρ	0.974*** (0.005)	0.974*** (0.007)	0.957*** (0.012)	0.970*** (0.008)	0.984*** (0.004)	0.963*** (0.010)	0.975*** (0.005)	0.976*** (0.006)	0.957*** (0.014)	0.978*** (0.008)	0.917*** (0.021)
γ	0.417*** (0.044)	0.468*** (0.067)	0.752*** (0.110)	0.455*** (0.066)	0.541*** (0.090)	0.801*** (0.116)	0.410*** (0.060)	0.564*** (0.073)	0.821*** (0.170)	0.578*** (0.145)	0.485*** (0.107)
θ	-1.051*** (0.098)	-1.149*** (0.115)	-0.421*** (0.076)	-1.700*** (0.192)	-1.256*** (0.169)	-0.470*** (0.088)	-1.290*** (0.137)	-1.564*** (0.187)	-0.636*** (0.197)	-0.402*** (0.148)	-1.572*** (0.250)
δ	0.187 (0.163)	0.084 (0.420)	0.755*** (0.076)	0.007 (0.582)	0.368 (0.244)	0.943*** (0.077)	0.241 (0.217)	0.016 (0.257)	1.161*** (0.148)	1.387*** (0.205)	0.146 (0.708)
L	-4,833.99	-5,373.82	-4,123.81	-5,980.20	-5,874.87	-4,860.22	-5,215.49	-6,238.37	-5,830.54	-5,580.58	-4,869.79
N	3,270	3,270	3,270	3,270	3,270	3,270	3,270	3,270	3,270	3,270	3,270
LR Test	153.99***	94.96***	55.10***	72.72***	79.84***	55.87***	114.88***	68.04***	54.88***	26.93***	56.41***
$E\lambda_t$	0.769	0.731	0.465	0.367	0.687	0.730	0.520	0.708	0.442	0.409	0.181
$E\epsilon_{2,t}^2$	0.891	1.001	0.352	1.071	1.183	0.820	0.919	1.703	0.763	0.816	0.440

The table shows the regression results of the GARCH-Jump model. Standard errors are reported in parentheses. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. The dependent variables are daily returns in percentages, where a 1 percent return is denoted as 1. L is the log likelihood value. LR Test is the Likelihood Ratio test of $\rho = \gamma = 0$, testing for time-varying jump intensity. $E\lambda_t$ is the implied unconditional jump intensity and is calculated as $\frac{\lambda_0}{1-\rho}$. $E\epsilon_{2,t}^2$ is the unconditional variance of jump innovations and is equal to $\frac{(\theta^2 + \delta^2)\lambda_0}{1-\rho}$.

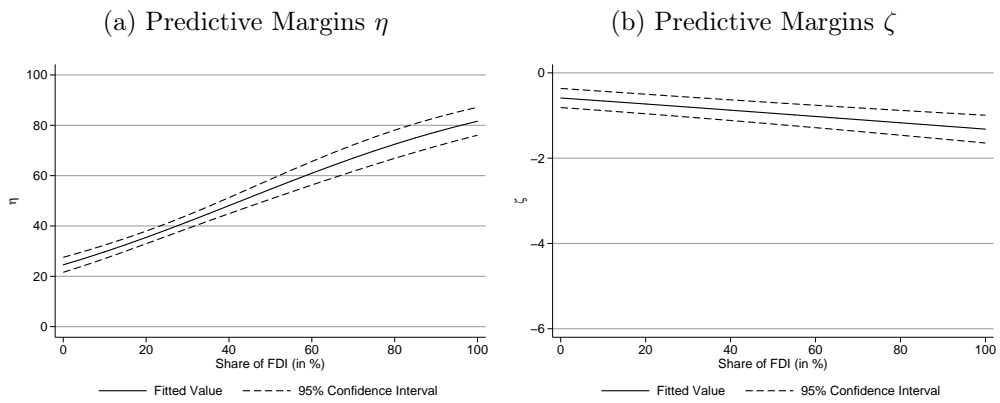
A.2 Additional Figures and Tables

Figure A.1: S&P500 reaction to terrorism in the Middle East - Excluding attacks in Iraq, Israel and occupied territories



The graph shows the relationship between the intensity of terrorism in the Middle-East – excluding Iraq, Israel and the occupied territories – and probabilities that the S&P500 experiences a jump on these attack days. Fitted values and their 95 percent confidence intervals are shown for a univariate quadratic regression of the S&P500 jump probabilities on the *TER* score for days where attacks took place in this region.

Figure A.2: Reaction to terrorism and share of FDI - Pooled Estimation



The graphs show for a pooled version of the model, the jump probability and size in reaction to a large terrorist attack in a region, depending on the share of FDI this region receives. Fitted values and their 95 percent confidence intervals are shown over the response surface for the regressions in Equations (14a) and (14b) and Table A.3.

Table A.2: Investors' reaction conditional on FDI stock in 2006-2010, excluding 2008

	Jump probability $\eta_{i,k,t}$	Jump size $\zeta_{i,k,t}$
mean	0.365	-1.159
(std. dev.)	(0.349)	(2.363)
α	-1.657*** (0.353)	-0.829** (0.358)
FDI $_{i,k,t}$	4.120*** (0.608)	-4.973*** (0.816)
N	162	162
L	-72.20	-345.30
ρ		0.06
LR Test 1		3.53***
LR Test 2	1.45	

The table shows the panel regression of Equations (14a) and (14b) without 2008. Reactions of sectors to large terrorist attacks in regions are regressed on the share of FDI they receive. $\eta_{i,k,t}$ is estimated using fractional logit, whereas $\zeta_{i,k,t}$ is estimated using a random effects Tobit model. Standard errors are reported in parentheses, and are robust for $\eta_{i,k,t}$. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. L is the log likelihood value, ρ is the fraction of variance due to the unobserved heterogeneity μ_i and is defined as $\frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2}$. LR Test 1 is a likelihood ratio test of $\sigma_\mu = 0$ in $\zeta_{i,k,t}$. LR Test 2 is a likelihood ratio test for the joint significance of the sector fixed effects in $\eta_{i,k,t}$.

Table A.3: Regression output - Pooled Estimation

	A. Jump probability $\bar{\eta}_{i,k}$				B. Jump size $\bar{\zeta}_{i,k}$			
	1998 - 2010	1998 - 2001	2002 - 2006	2007 - 2010	1998 - 2010	1998 - 2001	2002 - 2006	2007 - 2010
mean	0.342	0.365	0.277	0.438	-0.699	-0.662	-0.557	-1.556
(std. dev.)	(0.153)	(0.177)	(0.193)	(0.306)	(0.436)	(0.583)	(0.494)	(2.049)
α	-0.931*** (0.145)	-0.796*** (0.220)	-1.152*** (0.428)	-0.988** (0.430)	-0.575*** (0.123)	-0.550*** (0.151)	-0.459*** (0.108)	-0.625* (0.365)
$\overline{FDI}_{i,k}$	2.622*** (0.240)	1.305*** (0.301)	2.524*** (0.349)	5.138*** (0.750)	-0.744*** (0.136)	-0.675** (0.273)	-0.587** (0.278)	-5.587*** (1.058)
Sector FE	Included	Included	Included	Included				
N	54	54	54	54	54	54	54	54
L	-22.31	-23.73	-21.55	-23.29	-2.76	-35.28	-33.46	-103.71
ρ					0.76	0.51	0.26	0.18
LR Test 1					50.48***	20.40**	5.95**	3.18***
LR Test 2	0.18	1.53	0.49	0.00				

The table shows the pooled regression of Equations (14a) and (14b) on different subsamples. Reactions of sectors to large terrorist attacks in regions are regressed on the share of FDI they receive. $\bar{\eta}_{i,k}$ is estimated using fractional logit, whereas $\bar{\zeta}_{i,k}$ is estimated using a random effects Tobit model. Standard errors are in parentheses, and are robust for $\bar{\eta}_{i,k}$. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. L is the log likelihood value, ρ is the fraction of variance due to the unobserved heterogeneity μ_i and is defined as $\frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\epsilon^2}$. LR Test 1 is a likelihood ratio test of $\sigma_\mu = 0$ in $\bar{\zeta}_{i,k}$. LR Test 2 is a likelihood ratio test for the joint significance of the sector fixed effects in $\bar{\eta}_{i,k}$.

Table A.4: Regression output - Variable TER

	A. Jump probability $\eta_{i,k,t}$							B. Jump size $\zeta_{i,k,t}$							
	$TER = 1$	$TER = 3$	$TER = 5$	$TER = 7$	$TER = 9$	$TER = 1$	$TER = 3$	$TER = 5$	$TER = 7$	$TER = 9$	$TER = 1$	$TER = 3$	$TER = 5$	$TER = 7$	$TER = 9$
mean	0.289	0.295	0.317	0.353	0.391	-0.560	-0.587	-0.718	-1.002	-1.460	-0.560	-0.587	-0.718	-1.002	-1.460
(std. dev.)	(0.155)	(0.174)	(0.240)	(0.316)	(0.374)	(0.544)	(0.614)	(1.086)	(2.054)	(3.455)	(0.544)	(0.614)	(1.086)	(2.054)	(3.455)
α	-0.817*** (0.05)	-0.553*** (0.126)	-0.730*** (0.183)	-0.917*** (0.229)	-0.956*** (0.263)	-0.526*** (0.101)	-0.605*** (0.112)	-0.814*** (0.175)	-1.235*** (0.307)	-1.922*** (0.503)	-0.526*** (0.101)	-0.605*** (0.112)	-0.814*** (0.175)	-1.235*** (0.307)	-1.922*** (0.503)
$FDI_{i,k,t}$	-0.115 (0.076)	0.389*** (0.124)	1.203*** (0.202)	1.723*** (0.270)	1.849*** (0.315)	0.046 (0.057)	-0.223*** (0.070)	-1.103*** (0.161)	-2.539*** (0.331)	-4.419*** (0.573)	0.046 (0.057)	-0.223*** (0.070)	-1.103*** (0.161)	-2.539*** (0.331)	-4.419*** (0.573)
Year FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Sector FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
N	696	696	696	696	696	696	696	696	696	696	696	696	696	696	696
L	-264.95	-270.12	-291.66	-325.27	-361.66	-161.85	-312.97	-883.03	-1380.07	-1749.09	-161.85	-312.97	-883.03	-1380.07	-1749.09
ρ						0.46	0.39	0.17	0.09	0.07	0.46	0.39	0.17	0.09	0.07
LR Test 1						391.23***	310.45***	105.61***	48.88***	32.74***	391.23***	310.45***	105.61***	48.88***	32.74***
LR Test 2	7.11	6.04	3.04	1.59	1.50										

The table shows the panel regression of Equations (14a) and (14b) for different levels of TER . $\eta_{i,k,t}$ is estimated using fractional logit, whereas $\zeta_{i,k,t}$ is estimated using a random effects Tobit model. Standard errors are reported in parentheses, and are robust for $\eta_{i,k,t}$. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. L is the log likelihood value, ρ is the fraction of variance due to the unobserved heterogeneity μ_i and is defined as $\frac{\sigma^2}{\sigma_i^2 + \sigma^2}$. LR Test 1 is a likelihood ratio test of $\sigma_\mu = 0$ in $\zeta_{i,k,t}$. LR Test 2 is a likelihood ratio test for the joint significance of the sector fixed effects in $\eta_{i,k,t}$.

Appendix B Industry Classifications and Foreign Direct Investment

The data on the investment position of U.S. sectors were obtained from the website of the U.S. Bureau of Economic Analysis in the section ‘Position on a historical-cost basis, country detail by selected industry’ and include all countries in which there is direct investment.

Industries are classified using the Standard Industrial Classification (SIC) prior to 1999 and according to the North American Industry Classification System (NAICS) thereafter. The industries for which data are publicly available and their respective SIC/NAICS codes are shown in Table B.1.

Table B.1: Industry Classifications

Industry name	SIC	Industry name	NAICS
Oil and gas extraction		Mining	21
+ Petroleum and coal products	13 + 29	Utilities	22
<u>Manufacturing, of which</u>		<u>Manufacturing, of which:</u>	
Food and kindred products	20	Food	311
Chemicals and allied products	28	Chemical	325
Primary and fabricated metal industries	33-34	Primary and fabricated metal products	331-332
Industrial machinery and equipment	35	Machinery	333
Electronic and other electric equipment	36	Computers and electronic products	334
Transportation equipment	37	Electrical equipment, appliances, and components	335
Miscellaneous manufacturing industries	39	Transportation equipment	336
		Miscellaneous	339
Wholesale trade	50-51	Wholesale trade	42
		Information	51
Depository institutions	60	Depository institutions	60
Financial, insurance, and real estate industries	61-67	Finance and insurance	52
Services	70-89	Professional, scientific, and technical services	54
		Holding companies (nonbank)	55
Other	n.a.	Other	n.a.

The table displays the two industry classification available from the U.S. Bureau of Economic Analysis data on outward FDI of U.S. multinational firms. Prior to 1999, the data are classified using SIC, afterwards they are recorded using NAICS.

The BEA also provides a category Other Industries, which combines all remaining industries. Since this category can not be mapped into a series of SIC or NAICS codes we are forced to exclude it. Another exclusion is the Utilities category, as it is only available up until 2002. For regions where

Miscellaneous Manufacturing is missing, we use the provided category Total Manufacturing and subtract all the available separate manufacturing categories.

To match the SIC/NAICS data on investments to the GICS-based stock market indices, we download all current and historic S&P500 companies with their SIC/NAICS and GICS codes from Compustat. We tabulate the SIC/NAICS classifications per 2 digit GICS code and obtain the mapping as shown in Table B.2.

We observe from the mapping that the SIC/NAICS sectors do not correspond one-to-one with their GICS counterparts. For example, firms that are classified as Wholesale Trade appears in Consumer Staples, Health Care and Materials. Another NAICS sector that appears in multiple GICS sectors is Information, mapped into GICS counterparts IT, Telecom and Consumer Discretionary.

Under the SIC classification, this sector was unavailable and therefore we were not able to obtain an estimate of outward U.S. FDI for the Telecom sector in 1998.

Outside of Telecom in 1998 and the non-availability of the Utilities sector, other GICS sectors do not suffer from this problem. Unfortunately however, we do not have more disaggregate data at our disposal to map the SIC/NAICS sectors more accurately to their GICS counterpart. The ‘Holding Companies (nonbank)’ and ‘Other’ categories do not lead to a clear SIC/NAICS mapping and therefore have to be excluded, although they account for 37 percent of yearly U.S. outward FDI on average.

The BEA data is available on region and country level, with the limitations that some country/industry/year combinations are not shown to avoid disclosing data of a specific firm. Since combinations of industry/region/year do not suffer from this limitation, we use the BEA regions Latin America, Middle East, Africa and Asia & the Pacific. The European Union is also reported and takes into account changes in the number of member states. The Rest of Europe is then defined as the value of Europe minus the European Union. Countries in the Rest of Europe are for example Albania, Armenia, Bulgaria, Croatia, Kazakhstan, Moldova, Norway, Russia, Serbia

and Switzerland. Since Norway and Switzerland fit in better with E.U. countries, and outward FDI data is always available for both countries, we place them together with the E.U. countries.

Table B.2: Mapping SIC/NAICS to GICS

GICS	1998 (SIC)	1999-2010 (NAICS)
10. Energy	Oil and gas extraction + Petroleum and coal products (13 + 29) Industrial machinery and equipment (35)	Mining (21), Machinery (333)
15. Materials	Chemicals and allied products (28), Primary and fabricated metal industries (33-34), Wholesale trade (50-51)	Primary and fabricated metal products (331-332), Chemical (325), Wholesale trade (42)
20. Industrials	Primary and fabricated metal industries (33-34), Industrial machinery and equipment (35), Electronic and other electric equipment (36), Transportation equipment (37)	Primary and fabricated metal products (331-332), Machinery (333), Computers and electronic products (334), Electrical equipment, appliances and components (335), Transportation equipment (336)
25. C. Discretionary	Electronic and other electric equipment (36), Transportation equipment (37), Services (70-89)	Transportation equipment (336), Miscellaneous (339), Information (51), Professional, scientific, and technical services (54)
30. C. Staples	Food and kindred products (20), Chemicals and allied products (28), Wholesale Trade (50-51)	Food (311), Chemical (325), Wholesale Trade (42)
35. Health Care	Chemicals and allied products (28), Electronic and other electric equipment (36), Wholesale trade (50-51)	Chemical (325), Computers and electronic products (334), Miscellaneous (339), Wholesale trade (42)
40. Financials	Financial, insurance, and real estate industries (61-67), Depository institutions (60)	Finance and insurance (52), Depository institutions (60)
45. IT	Industrial machinery and equipment (35), Electronic and other electric equipment (36), Services (70-89)	Computers and electronic products (334), Information (51), Professional, scientific, and technical services (54)
50. Telecom		Information (51)

The table displays the mapping of SIC/NAICS sectors to GICS sectors, based on classifications of current and historic S&P500 companies obtained from Compustat.