Does Safety Uncertainty Affect Acquisitions?

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Abstract

Using terrorist attacks as an exogenous shock to *safety* uncertainty, we provide causal evidence that firms located near terrorism-stricken areas receive lower takeover premium. The latter finding is reflected in lower target firm abnormal returns and synergy gains. Additionally, given that firms in terrorism-afflicted areas become less attractive, they are less likely takeover targets for two years after the terrorist attack, and acquirers from such areas are more likely to buy target firms from more distant locations. We attribute our results to human capital which is affected by terrorism induced safety uncertainty, consistent with Abadie and Gardeazabal's (2008) theoretical model.

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Bernanke (1983), Bloom, Bond, and Van Reenen (2007), and Julio and Yook (2012) show that firms become cautious and hold back on investment in the face of uncertainty. Nevertheless, there is limited evidence on how *safety* uncertainty, specifically, affects investments. In this paper we exploit terrorist attacks as a natural experiment and explore the causal effects of safety uncertainty on the most important corporate investment, i.e., mergers and acquisitions (M&As).

As Dai, Rau, Stouraitis, and Tan (2019) state, a terrorist attack allows to draw causal inferences because it is a "clean, sharp, and specific event that forms an unexpected unambiguous" negative change of a certain environment. In particular, unexpected terrorist attacks induce a negative shock to business conditions which causes *safety* uncertainty to economic agents stemming mostly from psychological reasons (Ahern 2018).[1] In a related context, the theoretical model of Abadie and Gardeazabal (2008) explicitly accounts for the relation between terrorism intensity and investments. The authors argue that the main impact of terrorism is intangible as it increases safety uncertainty and fear among economic agents distorting human capital productivity. They also show that terrorism intensity reduces the expected return of investment and increases its expected risk in the terrorism–afflicted areas. Additionally, they suggest that mobility of human capital productive factors is one of the main effects of terrorism in an open economy.

Motivated by the above theoretical model and the associated arguments, we argue that in M&As, terrorism induced safety uncertainty among economic agents can influence human capital in two main ways. First, target firms are likely to lose key risk–averse employees or face the difficulty of employing new staff, especially highly–skilled labor force (see, e.g., BenYishay and Pearlman 2013; Ksoll, Macchiavelloy, and Morjariaz 2018). Additionally, the negative psychological impact of terrorism is likely to reduce job satisfaction, participation, effort, learning, and creativity of the existing employees (Becker and Rubinstein 2011; Ahern 2018).

[1] Terrorist attacks appear to hurt businesses even more than natural disasters regardless of the severity of the event (Oh and Oetzel 2011). Additionally, an article related to a poll prepared by Gallup Analytics (December 14, 2015) reports: "After the deadly terrorist attacks in Paris and San Bernardino, California, Americans are now more likely to name terrorism as the top issue facing the U.S. than to name any other issue -- including those that have typically topped the list recently, such as the economy and the government. About one in six Americans, 16%, now identify terrorism as the most important U.S. problem, up from just 3% in early November". (https://news.gallup.com/poll/187655/americans-name-terrorism-no-problem.aspx).

Consequently, target firm labor productivity is handicapped and the expected return to acquisitions in the terrorism–afflicted areas declines. Second, CEOs (and other board members) of acquiring firms should be most likely reluctant for acquisition investments, at least for the first period after the terrorist incident, which could potentially put their life and safety at stake. For instance, due to safety uncertainty and fear, they should be less inclined to travel to the headquarters of target firms located near terrorist attack scenes.

We therefore argue that firms in terrorism–afflicted areas become less attractive and have lower bargaining power. This leads to our first predictable hypothesis that such firms should receive lower acquisition premium. The latter effect should be reflected in lower target firm announcement stock abnormal returns and synergy gains. Further, given that firms in such areas become less attractive, they should experience lower probability of receiving acquisition bids.

To test our predictions, we use a sample of terrorist attacks in the US between 1995 and 2015, which caused human casualties and were publicly covered by major newspapers. Our measures of terrorism intensity are based on the number of killed and injured individuals in a specific area due to a terrorist attack. We then follow prior studies (e.g., Kang and Kim 2008; Kedia and Rajgopal 2009) and use metropolitan statistical area (MSA) identifiers and physical distance (100 kilometers) as primary measures of firm geographic proximity from the attacked location, and firm headquarters as a proxy for its location (e.g., Acharya, Baghai, and Subramanian 2014).

We begin the analysis with an event study for firms located near terrorist attack scenes. We find that such firms experience an average cumulative abnormal return of –1.05% at the days of the terrorist attack. Additionally, the return difference relative to firms which are not located near terrorism-afflicted areas is -1.01%. This is a first indication that the market assigns lower value to terrorism–affected firms, which should have further implications on acquisition outcomes.

Next, we move to the main tests and examine the value effects of terrorism intensity on M&As. Consistent with the notion that target firms located in terrorism-stricken areas become less attractive having lower bargaining power, we find that if terrorism intensity doubles (for instance, if a terrorist attack causes the death of six people instead of three), acquirers pay 4.78%

lower premium to buy such target firms. The reduction in acquisition premium translates into 3.19% lower target firm stock abnormal returns. In economic terms, this is equal to approximately $180.24 million value destruction for our sample average public target firm. Additionally, synergy gains (measured by the combined firm stock returns) also decline.

We then examine the effect of terrorism intensity on the likelihood of firms located in attacked areas to receive an acquisition bid. Using a probit specification, we find a negative relation at the 1% significance level. In economic terms, if terrorism intensity doubles, there is a 17.36% decrease relative to the sample average unconditional M&A probability. Additionally, we acknowledge that while the timing of a terrorist attack is most likely unexpected, the location of a terrorist attack is not necessarily random as terrorists most likely prefer to attack larger and richer population areas for publicity reasons. Thus, firms located in such areas are likely to differ along several characteristics relative to firms located in non–terrorism stricken areas. If the location choice is indeed correlated with acquisition activity, then we cannot attribute the reduction in acquisition likelihood to terrorist attacks. Therefore, to further validate our findings, we perform a propensity score matching (PSM) analysis to control for characteristics that could potentially lead to selection bias. Our results hold, as we find that firms located in terrorism-stricken areas are less likely to receive a takeover bid.

Additionally, we explore whether terrorism intensity affects *acquiring* firms' geographical flow and distance of the deals they decide to conduct. In particular, we investigate whether terrorism induces acquirers to ignore the advantages of geographic proximity in acquisition deals of in–MSA or closely located target firms, leading them to acquire target firms from different countries and MSAs, or from areas with relatively greater geographical distance. The results confirm our prediction. This finding is the mirror image of the previous results that firms located in areas that are subject to a terrorist attack become less attractive takeover targets.

Further, by performing placebo tests, we show that the negative impact of terrorism intensity on acquisitions is not significant before terrorist attacks. This finding indicates the unexpected nature of terrorist attacks which are hard to predict *ex–ante*. Moreover, confirming the psychological impact of terrorism, we show that the effects of terrorism on acquisitions are rather temporary, since they last for two years after the year of the terrorist incident. In addition, identifying a sharp drop in acquisition likelihood for treated firms after the terrorist attacks, but not before, indicates that there is no reverse causality and the attacks are indeed exogenous.

In the last part of our empirical analysis, we investigate potential economic mechanisms behind the relation between terrorism intensity and acquisitions. Motivated by the theoretical predictions of Abadie and Gardeazabal's (2008) model, we argue that human capital is one plausible candidate. In particular, we offer two non-mutually exclusive findings related to safety uncertainty which affects both target firm labor productivity and acquiring firm CEOs.

Firstly, we show that terrorism intensity leads to lower firm labor productivity. This is consistent with both the theoretical predictions by Abadie and Gardeazabal (2008) and the event study results (i.e., negative stock abnormal returns for treated firms, and lower than control firms, at the days of terrorist attacks). Interestingly, we also find that the negative impact of terrorism intensity on labor productivity lasts for two years, which coincides precisely with the effect on acquisition likelihood; this implies that target firm labor productivity is a plausible channel behind the negative relation between terrorism and acquisitions. Additionally, we examine heterogeneous effects on human capital. We find that the negative impact of terrorism intensity on takeover premium, target firm returns, combined firm returns, and acquisition likelihood is stronger for firms: i) with high labor productivity; ii) operating in high labor intensity industries; and iii) operating in highly–skilled labor industries. These are firms which are primarily dependent on human capital, further reinforcing our argument that human capital is a plausible mechanism for the relations we uncover. Finally, in the last part of our analysis, we show that the number of employees in terrorism-stricken areas also declines. This is in line with Fich, Nguyen, and Petmezas (2019), who examine the impact of uncertainty on corporate innovation using terrorist attacks; they provide evidence that after terrorist attacks inventors move far away from terrorism-stricken areas and also firms reduce hiring new inventors.

Secondly, if acquirer CEO safety uncertainty also drives the negative relation between terrorism intensity and acquisitions, then this effect should be more pronounced in cases where CEOs are more risk averse. Naturally, such CEOs should be more likely to be affected by safety uncertainty. Prior literature suggests that CEOs who are non–overconfident, old, or women are more risk averse relative to CEOs who are overconfident, young, or men (see, e.g., Malmendier and Tate 2005; Yim 2013; Huang and Kisgen 2013; Faccio, Marchica, and Mura 2016). We focus on CEO decisions related to the acquisition premium paid and the location of the target firms they decide to acquire. As expected, we find that the negative (positive) relation between terrorism intensity and: i) acquisition premium; ii) (out-of-MSA-deals); iii) (cross-MSA deals); and iv) (geographical distance between the acquirer and target firm) is amplified when acquiring firms' CEOs are more risk averse.

In this paper we focus on M&As because, apart from being the most important corporate investments, there is recent evidence that target firm human capital is a significant determinant in acquisition investment decisions (e.g., Tate and Yang 2015; Ouimet and Zarutskie 2016; Chen, Gao, and Ma 2017). Hence, terrorism impact is highly relevant in this context. Additionally, whereas most determinants that affect M&As documented in the literature are mostly endogenous, and studies attempt to solve the causality and endogeneity issues in varying ways, it is still econometrically difficult to clearly attribute causality to those factors. In contrast, terrorist attacks constitute a clean, sharp and exogenous negative shock to business conditions, allowing to draw causal inferences on how safety uncertainty affects M&As.

This study offers novel contributions to the terrorism, M&As, and human capital literature. First, it provides comprehensive evidence that *safety* uncertainty affects investments negatively, in line with the literature which suggests that (policy and political) uncertainty adversely affects investment (Bernanke 1983; Bloom et al. 2007; Julio and Yook 2012). This is particularly important as it allows to draw conclusions on whether firms in areas subject to safety uncertainty become indeed less attractive. In particular, if the reduction in share value we find in the event study results reflects the expected loss in the overall value of the terrorism–afflicted firms, then a lower takeover premium offered to these firms would be justified as a compensation for that loss. This would imply that perhaps these firms could become even more attractive, given the lower acquisition premium required. However, the fact that terrorism–afflicted firms are on average less likely to receive a takeover bid implies that acquirer CEOs price such firms differently (i.e., more unfavorably) than the market at the time of the terrorist attack; thus, the lower premium required does not offset the negative impact of safety uncertainty. This unfavorable pricing is actually also confirmed by the lower synergy gains at the acquisition announcements after terrorist attacks. Alternatively, there is a behavioral element (i.e., acquirer CEOs' fear and safety uncertainty) that is most likely not priced by the market which deters them from buying targets from areas that were subject to a terrorist attack despite the lower premium their firms would need to offer.

Second, it lends support to the view that the impact of terrorism is indeed multiple and apart from social, psychological, and political effects, has also real economic effects. Additionally, while prior studies mainly focus on the macroeconomic impact of terrorism, our work contributes to recent studies on its microeconomic impact by providing comprehensive empirical evidence that terrorism has economically significant negative effects on M&As.[2] This answers the call of Czinkota et al. (2010) to provide more empirical evidence on how terrorism exerts impact at firm level. Understanding the dynamics between terrorism and M&As is of first order importance given the prominence of acquisition activity in driving economic growth and, in turn, firm value.

Third, it provides new evidence regarding how risk affects M&As. Terrorism risk is an example of a low–probability event with extreme negative consequences; we show that it has similar effects on M&As. Specifically, it contributes to the literature on the factors that affect M&As by

[2] For instance, terrorism, among others, reduces per capita GDP (Abadie and Gardeazabal 2003), discourages economic growth (Blomberg, Hess, and Orphanides 2004), decreases foreign direct investment (Bandyopadhyay, Sandler, and Younas 2014), leads to lower consumption (Eckstein and Tsiddon 2004), and reduces international trade (Nitsch and Schumacher 2004). However, a rather unexplored issue is the microeconomic impact of terrorism; some rare examples which exploited the exogeneity of terrorist attacks to establish causal relationships between terrorist attacks and various financial microeconomic outcomes are studies on the impact of terrorism on stock prices (Karolyi and Martell 2010) and cost of debt (Procasky and Ujah 2016). Additionally, Antoniou, Kumar, and Maligkris (2016) and (2017) show that terrorist attacks affect analysts' earnings forecasts negatively, and induce corporate managers to reduce R&D expenditure and leverage, and hold more cash. Dai et al. (2019) provide evidence that terrorist attacks lead to an increase of CEO compensation in firms located in terrorism-afflicted areas. Finally, Wang and Young (2019) use mutual fund data and find that terrorism is negatively associated with investor risk preferences.

uncovering a new determinant that has an independent (negative) influence on firm acquisition decisions and shareholders' wealth.

Finally, it contributes to the human capital literature in three main ways by showing that: i) terrorism affects labor productivity negatively; ii) terrorism induced safety uncertainty can influence CEO decisions; and iii) the negative relation between terrorism and acquisitions is conditioned on target firm human capital dependence and acquiring firm CEO risk aversion.[3]

The rest of the paper is organized as follows. Section 1 presents related literature on the link between terrorism and human capital. Section 2 describes our sample, data, terrorism measures, and reports summary statistics. Section 3 presents the empirical results for the impact of safety uncertainty, as measured by terrorism intensity, on acquisitions. Section 4 assesses potential economic mechanisms behind the relation between terrorism intensity and M&As. Section 5 provides further robustness tests and supplementary empirical analysis. Section 6 offers alternative explanations and implications of the findings. Finally, section 7 concludes the study.

1. Related Literature

The theoretical model of Abadie and Gardeazabal (2008) suggests that the main impact of terrorism is intangible as it increases safety uncertainty and fear among economic agents distorting human capital productivity. First, there is a behavioral explanation for the distortive impact of fear and uncertainty on human behavior (Kahneman and Tversky 1973, 1979; Tversky and Kahneman 1974). For instance, Tversky and Kahneman's (1973) "availability heuristic" can explain the possibility that economic agents subject to a terrorist attack might overestimate the probability of a subsequent attack. In addition, Dai et al. (2019) argue that negative events, such as terrorist attacks, adversely affect emotions.

[3] There is a growing literature acknowledging the importance of human capital on corporate financing decisions (Agrawal and Matsa 2013; Chemmanur, Cheng, and Zhang 2013; and Ghaly, Dang, and Stathopoulos 2017). In the M&A literature, Tate and Yang (2015) provide evidence that after acquisitions, diversified firms have higher labor productivity and lower likelihood of labor redeployment. Along similar lines, Ouimet and Zarutskie (2016), and Chen, Gao, and Ma (2017) show that acquiring target firm's human capital is an important motive for M&As. Our work is mostly related to the latter studies. In our study, human capital is not the outcome variable, but a key moderator in the negative relation between terrorism and acquisitions.

Second, the rational explanation is in line with the literature that depicts top managers as risk averse (e.g., Harris and Raviv 1979). Additionally, according to the rational approach of Becker and Rubinstein (2011), terrorism can generate the powerful emotion of fear, where fear is the degree to which subjective beliefs about danger deviate from objective assessments of risk. For example, the increased risk of life hazard would deter individuals to work near terrorism–stricken areas (Abadie and Dermisi 2008; Besley and Mueller 2012). In a similar vein, Ahern (2018) also argues that terrorism has psychological effects on individuals' perceptions of well–being and their own security. In this respect, increased fear and safety uncertainty can reduce job satisfaction, participation, effort, learning, and creativity of the existing employees, thus decreasing their productivity (Becker and Rubinstein 2011; Ahern 2018). Moreover, fear and uncertainty can exacerbate feelings of racism, xenophobia and discrimination related with individuals' ethnic origin, migration status or religion (Birkelund et al. 2019), leaving often certain groups out of the labor market.

The above problems can be further amplified in firms that base their operations on highly–skilled human capital. In fact, highly–skilled employees increase firm productivity; however, they are also more sensitive to the imposed threat of terrorism than lower–skilled employees. Prior research suggests that highly–skilled employees exhibit high geographic mobility, and can find new jobs easily and quickly (Gottschalk 1997; Amior 2015). Furthermore, highly–skilled employees most often require better conditions of life quality and safer work environment; this can trigger a "brain drain" in areas subject to a terrorist attack (Docquier, Lohest, and Marfouk 2007; Dreher, Krieger, and Meierrieks 2011). Overall, prior evidence suggests that terrorist attacks have a distortive impact on human capital.

2. Sample, Data and Measures of Terrorism Intensity

2.1 Sample

Our initial sample consists of all NYSE, Amex, and Nasdaq firms over the period between 1995 and 2015 with financial and stock information available on Compustat and CRSP databases. We use firm headquarters as a proxy for its location (e.g., Acharya et al. 2014). We exclude from our sample all firms without headquarters in the US and with missing ZIP codes. Additionally, to increase the likelihood that production is generated at the headquarter site, we follow Almazan, De Motta, Titman, and Uysal (2010) and use firms with a high percentage of their assets and employees located at the firm's corporate headquarters; we thus exclude from our sample industries like hotels and restaurant chains, and concentrate instead on manufacturing firms. Specifically, we consider firms with primary three–digit SIC between 200 and 399 and firms in SIC 737 (Computer Programming and Data Processing). Our data set also excludes firms in Hawaii and Puerto Rico. The final sample includes 126 industries (based on 3-digit SIC), 21 years, 5,777 firms, and 47,709 firm–year observations. Approximately 81% of our sample belongs to firms classified in SIC 200–399 (manufacturing) and the rest to firms in SIC 737.[4]

Our sample of M&As is obtained from the Thomson Financial SDC Mergers and Acquisitions Database (SDC) and consists of domestic deals that are announced between 1996 and 2016. To be included in the sample, we require the target to be a US public firm with data on its headquarters location available on SDC. We exclude the following transaction types: spinoffs, recapitalizations, exchange offers, repurchases, self–tenders, privatizations, acquisitions of remaining interest, and partial interests or assets. To ensure that the sample includes only meaningful transactions from the acquirer's perspective, we also limit deals with values over $1 million and relative size to the market value of the acquirer (4 weeks prior to the announcement) less than 1%. Finally, given the initial restrictions in the sample, financial firms (SIC 6000-6999) and regulated utilities (SIC 4900-4999) are also excluded. These data filters yield an initial sample of 1,639 acquisition deals with a total deal value of $3.69 trillion. The final sample used in the analysis on acquisition premium, and target and combined firms' announcement returns consists of a pool of 1,388 deals with available data.

[4] Our results hold when we use the entire sample without setting the restrictions as per Almazan et al. (2010). Additionally, as we report in section 5.6, we perform robustness analysis that is based on factory location using the TRI database (though this dataset does not have coverage for all firms), and find similar results.

2.2 Measures of terrorism intensity

To conform to the theoretical model of Abadie and Gardeazabal (2008), we require a variable which captures terrorism *intensity*. Initially, we collect our sample of unexpected terrorist attacks from the Global Terrorism Database (GTD), which is compiled by the National Consortium for the Study of Terrorism and Responses to Terrorism (START). GTD is an open–source database of the University of Maryland with information of more than 170,000 terrorist incidents worldwide. Because the definition of a terrorist attack is debatable, the START establishes the criteria for a terrorist act to be included in the database as follows: "each incident... had to be an intentional act of violence or threat of violence by a non–state actor". In addition, two of the following three criteria also had to be met: i) The violent act was aimed at attaining a political, economic, religious, or social goal; ii) The violent act included evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) other than the immediate victims; and iii) The violent act was outside the precepts of International Humanitarian Law.

Using the GTD, we obtain information of the event date, location, perpetrators, and the number of deaths and injuries due to terrorist attacks in the US over the period between 1995 and 2015. During our sample period there are in total 548 recorded events which resulted in 3,522 deaths and 7,568 injuries. To ensure that the events are sufficiently salient, we restrict our attention to terrorist attacks that cause human casualties.[5] We exclude 9 events in which the only casualty was the perpetrator and no other individual was harmed, as this might have the opposite effects on people's psychology.[6] Additionally, we require the attacks of our sample to be covered in at least one out of six major US newspapers over a 1–week period after the incident to ensure that news regarding the terrorist attacks is publicly known.[7]

The targets which have been attacked are mainly businesses, private citizens, and property. Additionally, there are different classifications of attack. As shown in Table 1, Panel A, the most

[5] In a study on the effects of terrorism on employment and consumer sentiment, Brodeur (2018) documents that terrorist attacks which generate casualties attract more press coverage and are, therefore, more salient, while he does not find similar results for failed terrorist attacks.
[6] For example, the Bank of America plane crash in Tampa, Florida on January 5, 2002.
[7] The list of the six major US newspapers includes the following: The NY Daily News, The NY Post, The NY Times, The Wall Street Journal (abstract), The Washington Post and USA Today.

common types of attack in our sample are armed assault (56.86%) and bombing/explosion (15.69%). Panel B presents the annual distribution of victims (killed and injured individuals) from terrorist attacks. The years with the largest number of victims are 1995, when the number of victims was 898, and, of course, 2001 (which includes the 9/11 attacks),[8] when the number of victims reached a peak of 3,212 killed and 6,123 injured individuals (in total, 9,335 victims).

Prior literature suggests that the impact of terrorist attacks is stronger for individuals closer to the incident's location (e.g., Ahern 2018). Thus, as in Kedia and Rajgopal (2009), we use MSA identifiers as our primary measure of geographic proximity. The US Office of Management and Budget (OMB) defines that an MSA consists of a "core area that contains a substantial population nucleus, together with adjacent communities that have a high degree of social and economic integration with that core". Each MSA must have at least one urbanized area of 50,000 or more inhabitants and includes one or more entire counties.

We then calculate the total number of deaths and injuries due to terrorist attacks for each MSA–year. Since the number of injuries in terrorist incidents is significantly higher than the number of deaths, using the total number of deaths and injuries might not reflect an accurate impact of terrorism intensity on an MSA. We therefore define the measure *terrorism intensity within MSA* as the sum of the number of deaths plus 50% times the number of injuries:

$$Terrorism\ Intensity_t = [Deaths_t + 0.5 * (Injuries_t)] \quad (1)$$

The terrorism intensity measure gives more weight to deaths, which normally attract more attention to the media and public opinion than injuries, thus mitigating potential bias caused by treating these numbers equally.[9] To normalize the distribution of the terrorism intensity variable, which is left-censored at zero and skewed to the right, we create the measure of the natural logarithm of one plus terrorism intensity within MSA (used in the regressions).

[8] As discussed in the robustness check section 5.3, our results are robust if we include a dummy for the 9/11 attacks in our regressions, or exclude the observations affected by the 9/11 incidents.

[9] Note that if we simply use the sum of deaths and injuries, which gives both of them similar weight (i.e., $deaths_t$ + $injuries_t$), does not alter our results. Additionally, as further robustness checks, we used in our formula the weights 0.2 [i.e., $deaths_t$ + 0.2 * ($injuries_t$)] and 0.8 [i.e., $deaths_t$ + 0.8 * ($injuries_t$)] obtaining similar results.

Panel C of Table 1 provides the distribution of victims from terrorist attacks by MSA over the period between 1995 and 2015. New York-Northern New Jersey-Long Island (NY-NJ-PA), Oklahoma City (OK) and Washington-Arlington-Alexandria (DC-VA-MD-WV) rank as the MSAs with the largest number of victims from terrorist attacks.

For robustness, in the spirit of Kang and Kim (2008) and Dai et al. (2019), we also use an alternative measure of geographic proximity which is based on the physical distance between firm headquarters and the location where the terrorist incidents took place. In particular, we define local firms as those which are located within 100 kilometers (km) distance from the place where the incident took place.[10] We match the location data with data from the US Census Bureau's Gazetteers and Zip Code Database to obtain information on the latitude and longitude of the firms and the places where the terrorist incidents took place and use the standard formula for calculating the distance, $d_{i,j}$, between firm i and the location of the terrorist incident j:

$$d_{i,j} = \text{arc}\cos\{\cos(lat_i)\cos(lon_i)\cos(lat_j)\cos(lon_j) + \cos(lat_i)\sin(lon_i)\cos(lat_j)\sin(lon_j) + \sin(lat_i)\sin(lay_j)\}2\pi r/360 \quad (2)$$

where lat and lon are the latitudes and longitudes of the terrorist incident and the firms' areas, respectively, and r denotes the radius of the earth (approximately 6,378 kilometers). We continue to use the sum of the number of deaths plus 50% times the number of injuries to capture the magnitude of attacks and create the measure of the natural logarithm of one plus terrorism intensity within 100 km for those local firms.[11]

In sum, our two measures act as complementary to each other. MSAs are usually within 100 km, but the benefit of the MSA measure is that it allows to capture the impact of urban areas and large business centers; this is important because a statistically larger number of terrorists may be located in larger population centers or because terrorists may target large population and business centers to attract publicity. It also allows to capture fixed differences at location level (by using MSA fixed effects) more precisely. In turn, the 100 km measure allows to separate

[10] Using a distance of 50 or 200 kilometers from the place where the incident took place does not alter our results.
[11] For robustness, in section 5.1 we employ two more measures of terrorism intensity, which are based on news coverage, finding similar results.

treated and control firms in cases that a terrorist attack happens close to the borders of an MSA. In such cases, the MSA terrorism measure should not affect the acquisition likelihood of a firm that is across the borders of a neighbor MSA. However, it should affect the acquisition likelihood of a firm in a different MSA but within a 100 km radius.

It is also worth making a note here. The importance of our two continuous measures is that they capture intensity, which is a necessary requirement in the theoretical model of Abadie and Gardeazabal (2008). In this respect, simply using a dummy variable for a terrorist attack within an MSA/100 km distance from the attacked location in a given year would provide less accurate inferences. In particular, it would give equal weight to any kind of attack, irrespective of the magnitude and consequences it imposed. Nevertheless, we can easily argue that an attack with hundreds of victims and press coverage imposes a substantially stronger psychological affection to people relative to an attack without any victim where not even the press has covered it; this implies that treating all attacks equally would not capture terrorism intensity appropriately.[12]

2.3 Sample descriptive statistics

Table 2 presents descriptive statistics. The definitions of all variables are provided in the Appendix. All variables are winsorized at the 1st and 99th percentiles. Panel A reports statistics for the overall sample and Panel B for the acquisitions sample. Samples similar to ours have been extensively used in previous studies, so we refrain from discussing descriptive statistics but verify that they are in line with prior studies (e.g., Moeller, Schlingemann, and Stulz 2007; Almazan et al. 2010; Golubov, Petmezas, and Travlos 2012; Yim 2013).

3. Empirical Analysis

3.1 Event study at the days of the terrorist attacks

We begin our analysis with an event study at the days of the terrorist attacks. Our premise is that terrorist attacks induce a negative shock to business conditions and therefore the market should

[12] Nevertheless, to be thorough, we have also used a dummy variable taking the value of 1 if there was an attack within firm's MSA or within a 100km distance from firm's location, and 0 otherwise, using the 548 terrorist attacks. We obtain qualitatively similar results.

view firms near terrorist attack scenes as being of lower value. We thus examine market-adjusted stock abnormal returns for terrorism–afflicted firms on day 0 and cumulative abnormal returns (CARs) for a two-day event window (0, +1) with day 0 being the terrorist attack date. We use the CRSP value–weighted market index return as a benchmark to calculate abnormal returns.

Table 3 presents the event study results. We find that when terrorist attacks take place, terrorism–affected firms experience negative market–adjusted stock abnormal returns. In particular, using the MSA measure, they experience a mean (median) abnormal return of –0.49% (–0.53%) on day 0, and a two–day mean (median) CAR of –1.05% (–1.09%), both statistically significant at better than 5% level. The corresponding CARs of non-terrorism affected firms are 0.04% (-0.01%) on day 0, and a two day CAR of -0.04% (-0.019%), with none of these estimates being statistically significant. Interestingly, the two-day mean (median) CAR difference between terrorism-affected firms and non-terrorism affected firms is -1.01% (-1.07%), significant at the 1% level. Similar results are obtained when we use the 100 km distance measure. Overall, these findings suggest that the market assigns a lower value to terrorism–afflicted firms. Additionally, this implies that, among others, there should be further effects on acquisition outcomes, as the valuation of a firm includes its standalone value and the probability that it will receive an acquisition bid (and its implied associated synergies).

3.2 Acquisition premium and shareholders' wealth

In this section we explore how terrorism intensity affects acquisition premium and the quality of M&A deals, as measured by the target and combined firms' stock abnormal returns.

3.2.1 Acquisition premium

We first examine whether terrorism induced safety uncertainty affects the acquisition premium received by target firms in terrorism–afflicted areas. Table 4 reports the results of the OLS analysis. The dependent variable is the 4–week offer premium reported by SDC, which is calculated as the difference between the offer price and the target firm's stock price four weeks before the acquisition announcement divided by the latter for all deals announced in the year after the terrorist attack. To avoid extreme outliers, we follow Officer (2003) and limit the measure to values between 0% and 200%. We classify a firm as treated if the attack occurs within the MSA, or within 100 km, of the firm's headquarters and no other attack occurred within the same MSA, or within 100 km of the same firm, over the prior two years. The control group includes the treatment firms before the attack and after the second year from the attack year, and all remaining firms.[13] This empirical design enables us to study changes in acquisition premium during the year after a terrorist attack for treated firms relative to control firms.

We note that our empirical design is a modified differences-in-differences (DID) approach similar to Dessaint and Matray (2017) who study the effect of hurricanes on cash holdings. As in Dessaint and Matray's (2017) study, following a standard differences-in-differences (DID) approach would be inappropriate. Consider, for instance, a standard differences-in-differences approach when there is a passed law. An event of a passed law creates a permanent effect to treated firms after the year the law was passed, in which a dummy variable is used. This is, however, not the case for a terrorist attack (or a hurricane in the case of Dessaint and Matray 2017); terrorism intensity is a continuous variable and most importantly the effect on treated firms decays. For example, it seems implausible that a terrorist attack which killed one or two people 15 years ago would have any effect on acquisitions today. Thus, in our regressions the value of *terrorism intensity* is greater than zero only for the treated firm and only for the next year after the terrorist attack. For these firms, the value of *terrorism intensity* reverts to zero in all subsequent periods and is only greater than zero if (and when) the same firm is within the same MSA or 100km distance of another attack.

Therefore, our test examines the before–after effect of terrorism intensity in the treated firms affected by terrorist attacks compared to the before–after effect in the control firms. For this purpose we also control for fixed differences between the treatment and control groups via year,

[13] Our empirical design is vulnerable to the common concern that similar attacks that occur at the beginning and at the end of the same calendar year (but occurring in different locations) receive equal consideration in our regressions. In untabulated tests we split attacks according to the semester in which they occur (i.e., first or second half of the year). The results of these tests are analogous to those reported.

industry, and MSA fixed effects. Year fixed effects control for time variation in acquisition premium common to all firms in the sample, whereas industry and MSA fixed effects control for time invariant variables related to industry and location, respectively that might affect acquisition likelihood.[14] The standard errors are adjusted for heteroscedasticity and are double-clustered by firm and year (Bertrand, Duflo, and Mullainathan 2004).

In addition to year, industry, and MSA fixed effects, we also include acquirer and target firm characteristics (*ln (market cap), cash holdings, leverage, market–to–book,* and *run–up*), industry characteristics (*Herfindahl index* and *M&A liquidity)*, and deal characteristics (*diversifying, all cash, hostile, and tender offer)*. In line with our expectation, the coefficients of the two terrorism intensity variables are negative and statistically significant at the 1% level. The magnitude of the estimates for the MSA (100 km) variable is also economically meaningful, suggesting that takeover premium falls by about 4.78% (4.64%) if terrorism intensity doubles, and by about 2.80% (2.72%) if terrorism intensity rises by 50%. In sum, the above findings support the view that target firms in terrorism–afflicted areas become less attractive, thus receiving lower acquisition premium.

3.2.2 Target and combined firms' CARs

Next, we examine whether the results on acquisition premium for target firms near terrorist attack scenes translate also into lower value as expressed in terms of target firm announcement stock abnormal returns and synergy gains (i.e., combined firm announcement stock abnormal returns). The dependent variables are the target and combined firms' market-adjusted cumulative abnormal returns, respectively, over the three–day (–1, +1) window around the acquisition announcement date. The CRSP value–weighted index return is the market return.[15] For the combined firm, we calculate the three–day CAR around the acquisition announcement for

[14] Using firm fixed effects to control for time-invariant omitted variables at firm level leads to qualitatively similar results, as we obtain the same statistical significance but, as expected, lower economic significance due to low within-firm variation in the terrorism intensity variables.

[15] Our results are qualitatively similar when we use: i) a 5-day event window (-2, +2) surrounding the acquisition announcement; or ii) equally-weighted market return as a benchmark.

the value–weighted portfolio of the acquirer and the target firm. Weights are the acquiring and target firms' market values of equity over the combined firm market value of equity four weeks prior to the acquisition announcement.

Specifications (3) through (6) of Table 4 report the results. Specifications (3) and (4) present the results for target firms, and specifications (5) and (6) for combined firms. In specifications (3) and (4) we control for target firm, industry and deal characteristics. The *ln* (*1+terrorism intensity within MSA)* variable carries a negative and statistically significant coefficient at the 1% level. In economic terms, doubling terrorism intensity (increasing terrorism intensity by 50%) leads to 3.19% (1.87%) decrease in target firm CAR, corroborating the results on acquisition premium. To get a sense of such increase in terrorism intensity, this is equivalent to a terrorist attack leading to 8 (6) killed people instead of 4. The economic magnitude of such increase in terrorism intensity translates into approximately $180.24 ($105.66) million value destruction for our sample average public target firm (sample average target firm market value is $5.65 billion). Similar results are obtained with the 100 km terrorism intensity variable. In specifications (5) and (6), for combined firm CAR, we include the same control variables as in specifications (1) and (2). We find that the combined firm CAR has a negative relation with the two terrorism intensity variables, significant at the 5% level in both specifications. This finding suggests that terrorism destroys value overall in acquisitions leaving a "smaller pie" to be distributed.

In sum, the results suggest that, overall, terrorism harms shareholders' wealth leading to lower synergies. Additionally, terrorism–afflicted target firms become, on average, less attractive having lower bargaining power, which leads to lower takeover premium received and, consequently, lower target firm stock abnormal returns.

3.3. Acquisition likelihood – Probit models

Next, we run probit models and examine the effect of terrorism intensity on acquisition likelihood by controlling for a number of determinants that extant literature has shown to affect acquisition propensity. Table 5 reports the results for probit regressions. The dependent variable is an indicator variable which takes the value of one if the firm receives an acquisition bid in a given year, and zero otherwise. All independent variables are lagged by one year. The main independent variables are the *ln* (*1+terrorism intensity within MSA*) in specification (1) and *ln* (*1+terrorism intensity within 100 km*) in specification (2). In addition to year, industry and MSA fixed effects, we also control for firm characteristics including size (*ln (market cap)*, *market–to–book*, *leverage*, *cash holdings*, and *ROA* (return on assets)). We also include the *MSA unemployment rate* and *ln MSA (population)* to control for specific location characteristics that might drive acquisition likelihood. Finally, we control for industry concentration using the *Herfindahl index*, and for industry liquidity of the M&A market (*M&A liquidity*).

We find that the coefficients on both terrorism intensity variables are negative and statistically significant at the 1% level. To get a sense of the economic importance, increasing terrorism intensity by 100% (increasing terrorism intensity by 50%) leads to 0.58% (0.34%) decrease in the likelihood to receive an acquisition bid.[16] This result is economically important as it represents a 17.36% (10.18%) decrease relative to the sample average unconditional M&A probability (that is 3.34%). The estimates of the control variables are also in line with prior studies. The likelihood to receive a bid decreases for larger and low growth opportunities firms, and rises for firms with higher return on assets, and those from less concentrated industries.

3.4. Acquisition likelihood – Propensity score matching (PSM) analysis

Terrorists are not likely to attack areas at random. As Dai et al. (2019) suggest, terrorists prefer to attack larger and richer population areas. Thus, firms located in such areas are more likely to differ along several characteristics relative to firms located in non–terrorism stricken areas. Whereas our main proxy of terrorism intensity is an MSA–based variable and we also employ MSA fixed effects, to further control for potential selection bias, we perform propensity score matching (PSM) analysis.

[16] To estimate the economic magnitude of the terrorism intensity impact on acquisition likelihood, we use marginal effects from the probit regressions which depend on the average value of every other independent variable in the regression. We estimate them to be –0.0083 and –0.0079 for the MSA and 100 km distance variables, respectively.

In particular, we follow the approach of Drucker and Puri (2005), among others, and create a sample of terrorism–afflicted firms (treated) with similar characteristics to non–terrorism–afflicted firms (control), and then use this sample in regression analyses as in our previous tests. As suggested by Rosenbaum and Rubin (1985) and Imbens and Wooldridge (2009), this approach is efficient in eliminating the biases in the estimation of average treatment effects. Specifically, it enables us to make causal inferences from the analysis because it sidesteps the fact that firms' acquisition activity is a function of their own characteristics. To construct the matching sample, we match each treated firm with a control firm. The control firm is a firm located in areas which are not affected by a terrorist attack (i.e., from a different MSA, or with a distance of more than 100 km from the terrorist attack but within the same state), and has the closest propensity score to our treated firm implementing a one–to–one (i.e., nearest neighbor) matching estimator with replacement.[17] The covariate matrix used for the matching is based on the following firm, MSA, and industry–specific characteristics: *ln (market cap), market–to–book, leverage, cash holdings, ROA, MSA unemployment rate, ln (MSA population), Herfindahl index,* and *M&A liquidity*.

Table 5, Panel A, reports parameter estimates from the probit model used to estimate propensity scores for firms in the treatment and control groups. The dependent variable takes the value of one if the firm–year belongs to the treatment group, and zero otherwise. We use the predicted probabilities or propensity scores in columns (1) and (3) to perform nearest neighbor matching obtaining 808 and 1,035 unique pairs of matched firms for MSA and within 100 km distance identifiers, respectively. We then perform several diagnostic tests to ensure that our PSM implementation removes sample selection biases (related to observable firm characteristics) thereby increasing the likelihood that the ATEs are *caused* by an exogenous terrorist attack. First, we re–run the probit model using the 808 matched pairs for the MSA identifier (and 1,035 matched pairs for the within–100 km distance identifier). Columns (2) and (4) of Panel A present the probit estimates. None of the independent variables are statistically significant at

[17] For robustness, we also implement 3-nearest-neighbors and 5-nearest-neighbors matching estimators which yield similar results.

conventional levels while the Pseudo–R^2 drops substantially to 1.2% (1.1%). Second, we examine the differences between the propensity scores of the treatment firms and those of the matched control firms. Panel B shows that the differences are trivial. For example, the maximum distance between the two matched firms' propensity scores is only -0.007 using the within–MSA identifier and 0.027 using the within–100 km distance identifier. Panel C presents univariate comparisons between the treatment and control firms' pre–attack characteristics and their corresponding *t*–statistics. None of the differences are significant, implying that the characteristics of treatment and control firm groups are similar. Overall, the diagnostic tests reported in Panels A through C show that the PSM process appears to remove obvious sample selection biases, increasing the probability that the effects on acquisition likelihood are caused by exogenous terrorist attacks.

Finally, Panel D of Table 5 shows the results for the impact of terrorism intensity on acquisition likelihood for the matched samples using the same control variables and fixed effects as in Table 4. We find robust results. In particular, both terrorism intensity variables are negative and statistically significant at the 5% level. These results are congruent with the baseline results eliminating concerns about selection bias in our sample.[18]

3.5. Geographical flow and distance of acquisition investments

As a further test to examine the impact of terrorism on acquisitions, we explore whether terrorism intensity affects firms' geographical flow and distance of acquisition investments. In particular, we now look at the *acquirer* side and investigate whether terrorism drives acquiring firms to buy targets from different countries, MSAs or from areas with relatively greater geographical distance. If this is the case, then it will strengthen our previous conclusions that firms in areas with a terrorist attack are less attractive becoming less likely takeover targets.

[18] We note that by controlling for location fixed effects (via MSA fixed effects), we control for the greatest factor in the variation in the likelihood of an attack. However, we do not control for time variation in the likelihood of an attack. The threat to our identification strategy is that acquisition likelihood decreased in the same year as the attack because an omitted variable drove both the attack and the reduction in acquisition likelihood at the same time. Though this seems unlikely to be a significant concern, we caution that our methodology is not perfect.

To test this issue, we examine the effects of terrorism intensity on: i) the probability of undertaking out–of–MSA acquisition deals (i.e., acquiring target firms from different countries or MSAs); ii) the probability of cross–MSA acquisition deals; and iii) the geographical distance between acquiring and target firms in domestic acquisition deals. Table 6 reports the results for this analysis. The dependent variable in specifications (1) and (2) is equal to one if an acquisition deal is out–of–MSA, and zero otherwise.[19] The dependent variable in specifications (3) and (4) is equal to one if an acquisition deal is cross–MSA, and zero otherwise. The dependent variable in specifications (5) and (6) is the distance between acquirers and target firms' headquarters measured in kilometers. In all tests, in addition to year, industry, and MSA fixed effects, we also include acquirer characteristics (*ln (market cap), cash holdings, leverage, market–to–book,* and *run–up*), industry characteristics (*Herfindahl index* and *M&A liquidity)*, and deal characteristics (*diversifying, all cash, hostile, and tender offer)* as control variables.

Specifications (1) and (2) show that acquirers have a higher likelihood to undertake out–of–MSA transactions after terrorist attacks (the relation is significant at the 5% level in both specifications), consistent with our prediction for a change in the geographical flow of acquisition investments. In fact, this is the mirror image of the previous findings that target firms located in areas with a terrorist attack are less likely to receive a bid. Similar results are obtained in specifications (3) and (4) for cross–MSA transactions.

Additionally, specifications (5) and (6) show that terrorism–afflicted acquirers prefer to acquire target firms from areas with greater geographical distance.[20] This result is particularly striking if we take into account the fact that acquirers most often prefer to acquire local target firms to take advantage of the geographic proximity.[21] Overall, the results from this analysis

[19] To perform this analysis we added cross-border deals in our sample.
[20] The number of observations in specifications (3) and (4) is smaller than in specifications (5) and (6). That is because some observations drop out in regressions (3) and (4) due to MSA fixed effects which perfectly predict the dependent variable.
[21] For example, Kang and Kim (2008) show that block acquirers prefer to acquire closely located target firms for information advantages and cost savings stemming from monitoring target firm management. Additionally, Uysal, Kedia, and Panchapagesan (2008) also suggest that information advantages of local M&A deals lead acquirer returns to be more than double relative to non-local deals.

suggest that firms located in terrorism–affected areas become less attractive takeover targets.

3.6. Time issues

3.6.1. Placebo tests

In this section, we perform a falsification test using placebo event years of terrorist attacks to examine whether our results are robust or arise mechanically, perhaps due to some methodological flaws. Specifically, we assign a new date (one year (t–1), two years (t–2), three years (t–3), and four years (t–4) before the year of the terrorist incident (i.e., (year t)) to each of the terrorist incident of our sample and construct the variable *ln (1+terrorism intensity within MSA)* in specifications (1) through (4), and *ln (1+terrorism intensity within 100 km)* in specifications (5) through (8). We then run the same regressions as the ones in Table 4. If the placebo tests produce similar results to those in previous analysis, a mis–specification bias could be in place. We present the results in Panel A of Table 7. To conserve space, we report only the coefficients of the main variables of interest. Unlike the results in Table 5, we do not observe any significant impact of terrorism intensity on acquisition likelihood. Specifically, the coefficients on the terrorism intensity variables are statistically insignificant at conventional levels in all eight specifications suggesting that the negative effect of terrorism intensity on acquisition investments occurs only after the terrorist attacks and not before. This finding also highlights the unexpected nature of terrorist attacks which are hard to predict *ex–ante*.

3.6.2. Persistence of terrorism impact on acquisitions

In the previous sections we provide evidence that firms in terrorism–stricken areas are less likely to receive acquisition bids. A natural question that arises is the persistence of terrorism impact and how long it takes to evaporate. We therefore perform an identical analysis to our baseline models in Table 5, but the dependent variable this time is augmented to capture the likelihood of receiving an offer over one, two, three, and four years after the year of the attack.

Table 8, Panel B, reports these results. For space purposes, we report only the coefficients of the main variables of interest. Specifications (1) through (4) present probit regressions for M&A likelihood for the MSA terrorism intensity variable, and specifications (5) through (8) for the within–100 km terrorism intensity variable. Specifications (1) and (5) show the impact of terrorism intensity in year *t* on acquisitions one year after the terrorist incidents (i.e., year *t+1*, these are the identical models (1) and (2) of Table 4), specifications (2) and (6) for two years after the incidents (i.e., year *t*+2), specifications (3) and (7) for three years after the incidents (i.e., year *t*+3), and specifications (4) and (8) for four years after the incidents (i.e., year *t*+4), respectively. We find that the negative effect of terrorism intensity on acquisition likelihood persists for two years (i.e., year *t+1* and year *t+2*) after the year of the incidents, and disappears three and four years after the attacks.[22] Specifically, the terrorism intensity coefficients turn statistically insignificant at conventional levels in specifications (3), (4), (7) and (8) losing also their negative economic magnitude with years.

Figure 1 shows the trends in the relation between terrorism intensity and acquisition likelihood. The *y*-axis plots the estimated coefficients after regressing the acquisition likelihood variable on *ln (1+terrorism intensity within MSA)* in Panel A, and *ln (1+terrorism intensity within 100 km)* in Panel B, as well as on the control variables and fixed effects used in Table 5. The *x*-axis shows the time relative to terrorist attacks for ±4 years around the terrorist attacks. The blue solid line corresponds to the terrorism intensity within MSA and the red solid line to the terrorism intensity within 100 km. The dashed lines correspond to the 95% confidence intervals of the coefficient estimates, where confidence intervals are calculated from standard errors double-clustered by firm and year. The graphs for both MSA and 100 km distance from the terrorist attack show that acquisition likelihood is not statistically different between treated and control firms *before* terrorist attacks. However, there is a sharp drop in acquisition likelihood for treated firms *after* the terrorist attacks which lasts for two years after the incidents, providing confirmation that there is no reverse causality and the attacks are exogenous.

[22] Dai et al. (2019) find that the effect of terrorist attacks on CEO compensation also lasts for up to two years.

In sum, the results suggest that the negative impact of terrorism intensity on acquisition investments is rather temporary implying its psychological nature. There are two main observations here. Firstly, it is rather unlikely that acquirer CEOs know *ex–ante* (i.e., just after a terrorist attack) how long the effects on human capital will last, translated into both their own feelings of safety uncertainty and fear, and target firm labor productivity. This reduces their willingness to acquire terrorism–afflicted firms in the first period after the incident. Additionally, this implies that acquiring firm CEOs, as human beings, have "short memory" and quite easily forget events that might have affected their corporate decisions, at least for a couple of years.[23] Secondly, the results imply that the effect on target firm labor productivity is also temporary, which suggests that employees might also have "short memory" and after some time not be influenced by safety uncertainty and fear; hence, the productivity of existing employees should not be affected anymore and new employees (including highly–skilled ones who are more productive) should be more inclined to find a job in areas that previously experienced a terrorist attack. Indeed, we show in section 4.1.1 that the impact of terrorism intensity on labor productivity also lasts for two years, which coincides with the effect on acquisition likelihood.

4. Mechanisms for the Relation between Terrorism Intensity and Acquisitions

Motivated by the theoretical model by Abadie and Gardeazabal (2008), we argue that there are at least two non-mutually exclusive economic mechanisms for the relation between terrorism and acquisitions, both related with human capital. First, it is likely that terrorism intensity distorts target firm labor productivity. Second, terrorism-induced safety uncertainty and fear are likely to discourage acquiring firms' CEOs to get involved in acquisitions of target firms which are located in terrorism–stricken areas.

[23] There is plenty of anecdotal evidence that individuals have "short memory" on terrorist incidents. For instance, tourists forget quite easily about prior terrorist activity and visit terrorism-affected regions after a while. BBC news on June 29, 2015, reported that: "[...] Short-term, it would put some people off. [...] Longer-term, people have short memories. A lot of people will forget" (https://www.bbc.com/news/magazine-33310217).

4.1 Labor productivity

The theoretical model proposed by Abadie and Gardeazabal (2008) explicitly predicts that terrorism intensity affects labor productivity negatively. In fact, the lower value effects we have already uncovered for treated firms relative to control firms performing event study on: i) stock abnormal returns of terrorism–afflicted firms at the days of the terrorist attacks; ii) target firm returns; and iii) combined firm returns (i.e., synergy gains), as well as the increased likelihood of acquirers from terrorism–stricken areas to prefer target firms from greater geographical distance, are likely to reflect the negative impact of terrorism intensity on labor productivity for firms which are based near terrorist attack locations. We therefore argue that labor productivity is one potential economic mechanism behind the negative relation between terrorism intensity and acquisitions.

We begin with a back–of–the–envelope test and look into the effect of terrorism intensity on the Return–on–Assets (ROA) of the treated firms. If we assume that a firm has five plants, then even if one of the plants is negatively influenced by a terrorist attack, labor productivity will decline, which, in turn, will lead to reduction in operating performance. We therefore run regressions and find negative relation between terrorism intensity and firm ROA at the 1% level for both terrorism intensity measures (not reported in a Table for space purposes).

We then examine the direct effect of terrorism intensity on firm labor productivity and present the results in Table 9. As discussed above, we predict that firms in areas with a terrorist attack should experience lower labor productivity. We therefore regress labor productivity on the two terrorism intensity variables and other control variables.

Specifically, we follow Tate and Yang (2015) and use the ratio of sales to number of employees to proxy for *firm labor productivity*. Specification (1) presents the estimates for the MSA variable and specification (5) reports the estimates for the 100 km variable. We find that the coefficients of both variables are negative and significant at the 5% and 1% levels, respectively. In economic terms, a 100% (50%) increase in terrorism intensity within MSA leads to a –3.05% (–1.78%) decrease in firm labor productivity. The corresponding percentage changes for the 100 km variable are –2.77% (–1.62%). Overall, these findings suggest that terrorism intensity affects labor productivity negatively, consistent with the theoretical predictions of the model proposed by Abadie and Gardeazabal (2008).

4.1.1 Persistence of terrorism impact on labor productivity

The previous section shows that terrorism intensity is negatively related to firm labor productivity. A natural question that arises is whether the effect is persistent. And if it is persistent, how does it relate with the persistence of terrorism impact on acquisition likelihood?

We run the same test as in specifications (1) and (5), but this time the dependent variable is augmented to capture the effect on firm labor productivity over two, three, and four years after the year of the terrorist incidents. Specifications (2) through (4) of Table 9 report the results for *ln (1+terrorism intensity within MSA)* and specifications (6) through (8) for *ln (1+terrorism intensity within 100 km)*. We find that the negative effect of terrorism intensity on labor productivity persists for two years (years *t+1* and *t+2*) after the year of the attacks (year *t*), and disappears three and four years (years *t+3* and *t+4*) after the year of the terrorist incidents. Specifically, the coefficients of terrorism intensity variables turn statistically insignificant at conventional levels in specifications (3), (4), (7) and (8). It is indeed striking that the negative impact of terrorism on labor productivity coincides with the one on acquisitions. This finding provides further support that labor productivity is a potential underlying channel behind the negative relation between terrorism intensity and acquisitions.

Figure 2 presents the above trends in the relation between terrorism intensity and labor productivity. Apart from illustrating the trends for the 4–year period after the terrorist attacks, it also shows the trends prior to the terrorist attacks. In particular, the *y*–axis plots the estimated coefficients after regressing the acquisition probability variable on *ln (1+terrorism intensity within MSA)* in Panel A, and *ln (1+terrorism intensity within 100 km)* in Panel B, as well as on the control variables and fixed effects used in Table 9. The *x*–axis shows the time relative to terrorist attacks for ±4 years around the terrorist attacks. The blue solid line corresponds to the terrorism intensity within MSA and the red solid line to the terrorism intensity within 100 km. The dashed lines correspond to the 95% confidence intervals of the coefficient estimates, where confidence intervals are calculated from standard errors double–clustered by firm and year. The graphs show that firm labor productivity is not statistically different between treated and control firms *before* terrorist attacks. However, there is a sharp decrease in labor productivity for treated firms *after* the attacks which lasts for two years after the incidents, which confirms that there is no reverse causality and the attacks are exogenous.

4.1.2 Heterogeneous effects

In the previous section we provide evidence that terrorism intensity affects labor productivity negatively. In this section we look at the cross sectional variation in human capital variables (including labor productivity) to examine how well human capital can explain the negative relation between terrorism intensity and acquisitions.

We thus condition the impact of terrorism intensity on takeover premium, target firms CARs, combined firm CARs, and acquisition likelihood on variables which capture dependence on human capital. If the decrease in the above acquisition outcomes is due to the negative effects in the human capital of target firms near terrorist attack locations, then firms which are particularly dependent on human capital will suffer more from terrorism, thus being more likely to receive a lower takeover premium, more likely to experience lower target and combined firms' CARs, and less likely to receive a takeover bid. Such firms are most likely to be those with high labor productivity, those operating in industries with high labor intensity, and those operating in industries with highly–skilled employees. Table 10 reports the results of this analysis for terrorism intensity within MSA.

First, we explore the effect on firms that have high labor productivity. High labor productivity indicates the importance of human capital in firms' production function as highly productive employees can adopt more efficient techniques and produce more with less input (Solow 1957; Romer 1986; Lucas 1988). Thus, we predict that if terrorism is distortive, its negative impact should be more important for firms with high labor productivity. As mentioned above, we measure firm labor productivity using the ratio of firm sales to number of employees, and create the *high labor productivity* indicator that equals to one if firms' labor productivity is above the sample median, and zero otherwise. Specifications (1), (4), (7) and (10) report the results of regressions after augmenting the baseline model with *high labor productivity* and its interaction with the terrorism intensity variable*.* We find that the *interaction* of the terrorism intensity variable with *high labor productivity* is negative and significant in all specifications. This suggests that the negative impact of terrorism intensity on acquisition outcomes increases in firms with high labor productivity.

Second, we examine the effect of terrorism intensity on other firms which are highly dependent on human capital, i.e., those with high labor intensity. Following Agrawal and Matsa (2013), we measure labor intensity as the wages–to–sales ratio across all firms in the same 2-digit SIC industry.[24] We create the variable *high labor intensity industry* indicator that equals to one if its value is above the sample median, and zero otherwise. We find in specification (2), (5), (8) and (11) that the *interaction* of *ln (1+terrorism intensity within MSA)* with *high labor intensity industry* is negative and statistically significant. This result suggests again that human capital dependent firms suffer more in M&As after terrorist attacks.

Third, we assess the impact of terrorism on industries in which workforce exhibits variation at the skill level as prior literature documents that highly–skilled employees are more productive (Solow 1957; Romer 1986). However, they are also more mobile than lower–skilled employees; they can move to a safer workplace more easily, seeking for better quality of life or more stable conditions (Docquier et al. 2007). Thus, we predict that firms relying more heavily on highly–skilled employees should suffer more from terrorism. To proxy for employees' skills, we estimate the distribution of skilled employments within an industry. As in Tate and Yang (2015), we use the Standard Occupational Classification (SOC) system from the Bureau of Labor Statistics (BLS)

[24] As in Imrohoroğlu and Tüzel (2013), firms' labor expense (wages) is calculated by multiplying the number of employees from Compustat (EMP) with the average annual wages from the US Social Security Administration.

and define occupations with 2–digit SOC codes less than 29 being the ones of highly–skilled employees. Based on the percentage of skilled employees in 2–digit SIC industries, we create the *high–skill industry* indicator that equals to one if its value is above the sample median, and zero otherwise.[25] Specifications (3), (6), (9), and (12) report the results after including the *high–skill industry* variable and its interaction with *ln (1+terrorism intensity within MSA)*. We find that the coefficient on the *interaction* variable is negative and significant in all specifications. This indicates that firms in highly–skilled industries experience lower takeover premium, target firm CARs, combined firm CARs, and acquisition likelihood after terrorist attacks. Defining local firms with 100 kilometers distance from the attack's location instead of MSAs yields comparable results (not reported for brevity).

Additionally, it is worth noting that both terrorism intensity variables, which capture the unconditional effect, lose their statistical significance in 18 out of 24 models (9 models with the MSA variable and 9 models with the 100 km variable). At the same time, our interaction variables are statistically significant and obtain the expected sign in all models. This finding reinforces our argument that human capital is an important mechanism behind our results.

Overall, the findings of this analysis provide evidence that target firm human capital is one of the channels which can explain the relation between terrorism intensity and acquisitions.

4.2 Acquirer CEO safety uncertainty and fear

Prior literature suggests that terrorism induces safety uncertainty and fear to economic agents (e.g., Ahern 2018). We therefore examine whether safety uncertainty and fear of acquiring firm CEOs is another potential economic mechanism behind the negative relation between terrorism intensity and acquisitions. To do so, we focus on CEOs where we should expect the effect to be more pronounced. In particular, we expect the impact to be more pronounced in cases where CEOs are more risk averse, as naturally such CEOs should be more likely to be affected by safety

[25] We also use the variable LSI, as suggested by Ghaly et al. (2017), to measure firm reliance on skilled labor and find qualitatively similar results.

uncertainty and fear. We therefore include in our analysis the variables non–overconfident CEOs, old CEOs, and female CEOs; prior literature has shown that such CEOs are more risk averse relative to those who are overconfident, young, or men (see, for instance, Malmendier and Tate 2005; Yim 2013; Huang and Kisgen 2013; Faccio et al. 2016). We construct the variable Holder 67 as in Malmendier and Tate (2005) to measure overconfidence. We then create the variable *non–overconfident CEO*, which equals one if a CEO is non–Holder 67, and zero otherwise. We also create: the dummy *old CEO*, which takes the value of one if the age of a CEO belongs to the highest tercile of our sample CEO age distribution, and zero otherwise; and the dummy *female CEO*, which is set to one if a CEO is female, and zero for male CEOs. The main purpose of this test is to examine heterogeneous effects, so we use linear models and interact the three CEO variables with the terrorism intensity variables.

Given that the interaction main variables of interest include acquirer characteristics, we can only assess the impact of acquiring firm CEO safety uncertainty and fear on the acquisition sample. This implies that we cannot examine the effect on acquisition likelihood. We thus focus on the decisions of CEOs regarding the acquisition premium paid and the location of the targets they decide to acquire, i.e., whether they prefer to acquire target firms which are: i) out–of–MSA; ii) cross–MSA; or iii) from a greater geographical distance.

Table 11 reports the results for terrorism intensity within MSA. Specifications (1) through (3) show that the negative impact of terrorism intensity on acquisition premium is driven by risk–averse CEOs as the coefficients on the three interaction variables of terrorism intensity with non–overconfident CEOs, old CEOs, and female CEOs are all negative and statistically significant at conventional levels. Additionally, when terrorist attacks take place risk averse CEOs are more likely to acquire target firms which are out–of–MSA (specifications (4) through (6)), cross–MSA (specifications (7) through (9)), or from a greater geographical distance from the location where the acquiring firm is based (specifications (10) through (12)). Interestingly, in nine out of twelve regressions the unconditional effect of terrorism intensity gets statistically insignificant at conventional levels, implying that risk averse acquirer CEOs drive the relation between terrorism intensity and acquisition decisions. Estimates for terrorism intensity within 100 km lead to analogous inferences (not reported for brevity). Overall, these findings lend support to the view that acquirer CEO uncertainty and fear is another potential economic mechanism – also related to human capital - for the negative relation between terrorism intensity and acquisitions.

5. Further Robustness Tests and Analysis[26]

5.1 Alternative measures of terrorism intensity

For robustness, we also employ two more measures of terrorism intensity which are based on news coverage. They are collected from the Lexis Nexis database and refer to articles related to our sample terrorist attacks published in newspapers within seven days after the terrorist incidents. We use the following six major US newspapers to collect information: The NY Daily News, The NY Post, The NY Times, The Wall Street Journal (abstract), The Washington Post, and USA Today. The keywords for the search are the name and type of the event or the name of the place that the incident occurred. We read all the articles to ensure that their main focus is the event in question. Following this process, we obtain 657 articles, which amounts to an average of 12.88 articles per attack. The first measure is based on the length of the article in the newspapers related to the terrorist incident. In particular, we gather all the articles corresponding to a specific attack and count the number of words in each article. The idea here is that terrorist incidents with higher intensity should be better covered implying that more space should be dedicated in the articles of the newspapers. Therefore, we use the variable "word count" which is defined as the total number of words in the articles in all newspapers.

The second proxy is based on whether news regarding a terrorist incident appears on the first page of the newspapers (in 16 cases more articles than one appear on the first page of the same newspaper). From our total sample of 758 articles, 177 of them are displayed on the first page of the newspaper outlets we consider. Again, the notion is that incidents with higher terrorism intensity are more likely to appear in articles on the first page of newspapers. We thus use the

[26] The robustness tests in this section are not reported in Tables for space purposes but are available upon request.

variable "first page", which is defined as the total number of articles referring to a terrorist incident that are covered on the first page of the newspaper outlets we consider. We find that both variables "word count" and "first page" have significantly negative relation with acquisition premium, target firm CAR, combined firm CAR, and acquisition likelihood.

5.2 Including mass shootings from the Mother Jones database (MJD)

Next, we expand our main sample by including 50 mass shootings from the US Mass Shootings Mother Jones Database (MJD). Most of the events in the MJD do not meet the GTD criteria to be classified as terrorist attacks, thus were not included in the main sample (e.g., the Virginia Tech shooting in April of 2007). We ensure the accuracy of the data related to each event by performing a manual search in US newspapers through Lexis-Nexis. Our results hold after augmenting our sample with the mass shootings events from the MJD.

5.3 Do the 9/11 terrorist attacks drive the results?

To address concerns that our results might be driven by an important outlier, that is the impact of the 9/11 terrorist attacks, we also include in our regressions an indicator variable, the *9/11 attack dummy*. The 9/11 attack dummy takes the value of one for deals including firms from New York, Virginia and Pennsylvania in 2002, and zero otherwise. We find that the coefficients of the terrorism intensity variables remain negative and statistically significant with almost the same economic magnitude. Our patterns do not change either when we remove from the sample observations affected by the 9/11 incidents.

5.4 State*year and region*year fixed effects

We run regressions for all our main tests by using either state*year fixed effects or region*year fixed effects.[27] These tests allow to compare the effects on acquisitions for firms in terrorism–

[27] As in Acharya et al. (2014), we distinguish 4 US regions (Northeast, South, Midwest, and West) following the classification of the US Census Bureau.

afflicted areas relative to firms in non–terrorism–afflicted areas in the same state and year, and the same region and year, respectively. Our results persist.

5.5 Control for several state-level variables

In addition to state*year fixed effects, we also explicitly control for a number of different state-level variables that might be related with acquisitions. Whereas there are no such data at MSA level (for the vast majority of the variables), we can, at least, control for the following characteristics at state level: i) crime rate; ii) natural disasters; iii) right to work laws; iv) political environment (proxied by the red state dummy, which takes the value of one if a Republican presidential candidate received more votes in the state over the period between t–1 and t+2, with year t being the year of elections, and zero otherwise); v) economic freedom; vi) government spending; and vii) business combination, control share acquisition and fair price law. Our results hold when we control for all the above state–level characteristics.

5.6 Factory location

A central argument for the effect of terrorism intensity on acquisitions is that safety uncertainty and fear affect target firm labor productivity. While using a firm's headquarters as a proxy for its location does not alter our conclusions on acquirer CEO uncertainty and fear (as CEOs are based on the headquarters), one could argue that employees might work far from firm headquarters, so the impact of terrorism intensity on labor productivity is only partially captured. Whereas we use the same approach as in Almazan et al. (2010) using a sample which increases the probability that production is generated at the headquarter site, we still conduct an extra test which is based on factories' location as a proxy for firm location. In particular, using the US Environmental Protection Agency's (EPA) toxic release inventory (TRI) database,[28] we consider treated firms to

[28] The TRI database requires firms in manufacturing industries with Standard Industrial Classification (SIC) codes between 2000 and 3999 to report their factories' location as well as their storage, use, and releases of hazardous substances. While our study does not focus on firms' toxic release data, and the database provides coverage for 62.10% of our sample, it still offers us with useful information regarding factories' location. The matching of the datasets is offered by the following link (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/K4KBBR) from the study by Xiong and Png (2019).

be those that have at least one of their factories being located in an attacked MSA (within 100km from the attack location).[29] To avoid losing a significant fraction of observations due to data availability in the TRI database, we keep relying on the location of the headquarters for those firms without factory location data to define whether they are treated firms.

Our main results hold. Terrorism intensity leads to lower takeover premium, target firm CAR, combined firm CAR, acquisition likelihood, and labor productivity. Additionally, the negative relation between terrorism intensity and acquisitions is driven by firms with high labor productivity. Overall, these results eliminate concerns about the sample used to draw conclusions on target firm labor productivity being an economic mechanism behind our results.

5.7 Does the number of employees decline after terrorist attacks?

A further indication that terrorist attacks induce safety uncertainty and fear is whether the number of employees of a given MSA declines in the next year after the terrorist attack. We look into the statistics using data from Compustat and find that 61.35% of firms located in MSAs with terrorist attacks experience a drop in the number of employees in the next year after the year of the terrorist attack relative to a 38.65% decline of firms located in MSAs without a terrorist attack in the same year. Their difference is statistically significant at the 1% level. This finding also sheds further light on reduced human capital productivity after terrorist attacks as existing skilled employees are likely to move to safer places and new skilled employees will be reluctant to get employed in firms located in recently terrorism–afflicted areas.

5.8 Do local markets drive the relation between terrorism intensity and acquisitions?

One could argue that the effect of terrorism intensity on acquisitions should be more pronounced for firms which depend more on local customers and suppliers. Such firms should become less

[29] To eliminate concerns that not all plants are equally important to firms, nor are all plants equally affected by the same terrorist attack, we use the waste produced by each factory, which is available in the TRI database, to proxy for "labor activity" in each factory. Ideally, we would like to calculate the percentage of firm's factories affected by a terrorist attack in a given year by using the contribution of profits or production levels of each plant. Because we do not have such data, we calculate the weight for each factory's waste produced and then estimate the weighted average of terrorism intensity for each firm in a given year. Our main results are not affected.

attractive takeover targets after terrorist attacks, implying that they should experience lower acquisition likelihood, takeover premium, and target and combined firms' CARs. We collect data from the Compustat Segments Customer File. Using manual search procedures, we identify and match US listed customers to their Compustat identifiers (i.e., GVKEY). We then create the variables *local customers* and *local suppliers*. *Local customers* is a dummy variable which takes the value of one if customers are within the same MSA or within 100 km distance from the attack location, and zero otherwise. Accordingly, we create the dummy *local suppliers* that is set to one if suppliers are within the same MSA or within 100 km distance from the location of the attack, and zero otherwise.

We then augment our main regressions using the variables *local customers* and *local suppliers* and also interact them with our two terrorism intensity variables. All interaction variables are statistically insignificant at conventional levels, while the main terrorism intensity variables continue to carry negative coefficients in all specifications. This finding suggests that the negative effect of terrorism intensity on acquisition outcomes is present in firms with both local and non-local customers and suppliers. In addition, this rules out a potential explanation that local markets drive the relations we uncover.

6. Alternative Explanations and Further Implications of the Findings

6.1 Alternative explanations

Our findings on human capital do not rule out other potential explanations. For instance, it is likely that insurance and security costs increase in areas where terrorist attacks take place, suggesting that target firms in such states become more expensive assets to be acquired.[30] Indeed, using state–level data from the Insurance Information Institute over the period 2008–2016, we find that in 100% of attacked states insurance premium for property and casualty increases in the next year of the attack; the insurance premium increase for non–attacked states in the same

[30] From CNN Money: "After Sept. 11, the premiums that insurers could charge suddenly rocketed upward into what's called a "hard market." (https://money.cnn.com/magazines/fortune/fortune_archive/2002/06/10/324523/) (June 10, 2002).

year is 73.21%. Their difference is significant at 5% level. Additionally, it is likely that firms in terrorism–stricken areas will increase their expenditure on security, or even that acquiring firms' CEOs will raise their own expenditure on security when visiting the headquarters of terrorism–afflicted target firms. Hence, increased insurance and security costs could be another potential reason why terrorism–afflicted target firms become less attractive.

In addition, we can also add to the increased operating costs of firms near terrorist attack locations the higher compensation paid to CEOs in such areas. Dai et al. (2019) provide evidence that CEOs of firms close to a terrorist attack receive on average 12% higher compensation after the incident, which lasts up to two years after the terrorist attack.

Furthermore, it is likely that the reputational capital of firms in terrorism–afflicted areas is also affected. The reputational capital should have implications for customers, suppliers and investors as they will be less likely to buy from, sell to, or invest in firms located in areas being hurt by terrorist attacks. This should lower firms' attractiveness as potential acquisition targets providing another explanation for the lower acquisition synergy gains we find. As suggested above, this potential negative impact is not likely to be concentrated in the local markets only.

Finally, it is likely that after terrorist attacks local governments invest less in infrastructure and more in security. This obviously creates a less friendly environment for investments, lowering, in turn, the attractiveness of potential target firms which are located in such areas.

6.2 Further implications of the findings

Our main results suggest that firms near terrorist attack scenes become less attractive due to distortion in human capital and other alternative explanations. This is also implied by the event study results, as we find that at the days of the terrorist attacks, the market assigns lower value to firms with close geographic proximity to terrorism–stricken areas.

There is another implication of the event study results. In particular, they provide another justification for examining the effect of terrorism intensity on acquisitions, because acquisitions are another way to look at the sources of firm value. Terrorist attacks affect valuation, hence, the market naturally puts a lower value to the target firm given that uncertainty regarding its value increases. In fact, each firm has a standalone value and a value which comes from the probability to receive an acquisition (and the associated synergies from the deal). Thus, since the probability of an acquisition is lower, so does the value of the firm, and this is reflected at the days of the terrorist attack.

Additionally, as discussed in section 5.7, the number of employees in treated firms decreases more than in control firms due to terrorism (implying that particularly skilled employees might prefer to move to safer places). This can be a second source of reduction in labor productivity in addition to increased safety uncertainty and fear of the employees who do not relocate. Nevertheless, this might also imply that firms could experience potential labor cost savings from consolidation. In other words, firms in terrorism–stricken areas can become more attractive acquisition targets, because they offer higher potential for economies of scale due to job cuts. However, this argument is refuted, collectively, from our results. Firms affected by terrorism: i) experience lower stock returns at the terrorist attack days implying lower value; ii) are less likely to receive a takeover bid; iii) receive lower (not higher) acquisition premium; and iv) experience lower target and combined firms' CARs, which suggests that they become indeed less attractive – not more attractive. Additionally, those executives who remain in firms in terrorism–afflicted areas might negotiate for higher compensation (Dai et al. 2019), increasing labor costs further.

Finally, the two-year impact of terrorist attacks, which is rather temporary, has two main implications. Either the effect is completely psychological, so that after a while safety uncertainty and fear of economic agents disappear, or government and firm interventions toward security and protection alleviate concerns regarding further terrorist attacks at the same location.

7. Conclusions

This paper provides novel evidence on the impact of safety uncertainty, measured by terrorism intensity, on acquisitions. We argue and provide empirical evidence that firms located near terrorist attack scenes become less attractive to potential acquirers. This is initially reflected by the event study results which show that firms in terrorism–afflicted areas experience negative stock abnormal returns at the days of the attack, and lower than firms located elsewhere, implying that the market assigns lower value to these firms.

Being less attractive to potential acquirers has several consequences in M&As. In particular, we find that firms in terrorism–stricken areas receive lower acquisition premium, reflecting their lower bargaining power. This also translates in lower target firm stock returns and lower overall acquisition synergies.

Furthermore, we investigate the effect of terrorism intensity on acquisition likelihood. We find that target firms in terrorism–afflicted areas are less likely to receive an acquisition bid. Moreover, we show that the terrorism impact is rather temporary and lasts for two years after the year of the terrorist attack. We also provide evidence that terrorism intensity distorts acquiring firms' geographical flow and distance of acquisition investments, further supporting the argument that target firms located in areas subject to a terrorist attack become less attractive.

Finally, consistent with the theoretical predictions of the model by Abadie and Gardeazabal (2008), we argue that human capital is one plausible economic mechanism that lies behind the relationship between terrorism and acquisitions. We initially show that terrorism intensity leads to decrease in firm labor productivity. Interestingly, when we investigate the persistence of the effect, we find that the negative impact of terrorism on labor productivity coincides with the one on acquisitions as it lasts for two years after the year of the terrorist attack. This finding reinforces our argument that target firm labor productivity offers a plausible explanation for the relation between terrorism and acquisitions. Additionally, providing further evidence of human capital being an important mechanism for our results, we examine heterogeneous effects; we show that the negative impact of terrorism intensity on takeover premium, target and combined firms' stock abnormal returns, and acquisition likelihood is more pronounced for firms which are highly dependent on human capital.

Moreover, our results suggest that safety uncertainty is likely to induce acquirer CEOs to avoid acquisitions of target firms near terrorist attack locations. We find that the negative (positive) relation between terrorism intensity and acquisition premium offered (the decision to acquire target firms which are out–of–MSA, cross–MSA, or from greater geographical distance from the location of the acquirer), is more pronounced when the acquirer CEOs are more risk averse, thus being more likely to be affected by safety uncertainty and fear.

Overall, our findings have important implications for academics, policy makers and practitioners. Specifically, our results reveal that safety uncertainty affects corporate investments and value creation, indicating that it has real economic effects. Additionally, our results highlight the significance of the M&A setting as a mechanism to examine the valuation implications of safety uncertainty. Our results have also important policy implications. Particularly, apart from the greater expenditures on security and police protection identified, local government spending should be shifted toward more investment–oriented aims. As highlighted above, human capital reduces after terrorist attacks; thus, investing more in infrastructure and creating a more investment–friendly environment will have further implications on retaining and attracting skilled human capital. Furthermore, our findings suggest that target firms located near terrorism-stricken areas receive lower acquisition premium, which negatively affects their shareholders' value. Managers and financial advisors should therefore take this information into account when engaging into M&A deals. Finally, our evidence can trigger a lot of follow–up discussions regarding unexplored research questions related to firms that are affected by safety uncertainty. For instance, does safety uncertainty have an impact on other corporate decisions? If so, what is the underlying mechanism? We hope future research will shed light on these and other questions related to the effects of safety uncertainty in the corporate world.

References

Abadie, A., and S. Dermisi. 2008. Is Terrorism Eroding Agglomeration Economies in Central Business Districts? Lessons from the Office Real Estate Market in Downtown Chicago. *Journal of Urban Economics* 64: 451–463.

Abadie, A., and J. Gardeazabal. 2003. The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review* 93: 113–132.

Abadie, A., and J. Gardeazabal. 2008. Terrorism and the World Economy. *European Economic Review* 52: 1–27.

Acharya, V., R.P. Baghai, and K.V. Subramanian. 2014. Wrongful Discharge Laws and Innovation. *Review of Financial Studies* 27: 301–346.

Agrawal, A., and D. Matsa. 2013. Labor Unemployment Risk and Corporate Financing Decisions. *Journal of Financial Economics* 108: 449–470.

Ahern, K.R. 2018. The Importance of Psychology in Economic Activity: Evidence from Terrorist Attacks. Working Paper, University of Southern California.

Almazan, A., A. De Motta, S. Titman, and V. Uysal. 2010. Financial Structure, Acquisition Opportunities, and Firm Locations. *Journal of Finance* 65: 529–563.

Amior, M. 2015. Why Are Higher Skilled Workers More Mobile Geographically? The Role of the Job Surplus. CEP Discussion Papers, Centre for Economic Performance, LSE.

Antoniou, C., A. Kumar, and A. Maligkris. 2016. Terrorist Attacks, Sentiment, and Corporate Policies. Working Paper, Warwick Business School.

Antoniou, C., A. Kumar, and A. Maligkris. 2017. Terrorist attacks, Analyst Sentiment, and Earnings Forecasts. Working Paper, Warwick Business School.

Atanassov, J. 2013. Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting. *Journal of Finance* 68: 1097–1131.

Bandyopadhyay, S., T. Sandler, and J. Younas. 2014. Foreign Direct Investment, Aid, and Terrorism. *Oxford Economic Papers* 66: 25–50.

Becker, G., and Y. Rubinstein. 2011. Fear and the Response to Terrorism: An Economic Analysis. CEP Discussion Papers, Centre for Economic Performance, LSE.

BenYishay, A., and S. Pearlman. 2013. Homicide and Work: The Impact of Mexico's Drug War on Labor Market Participation. Working Paper, University of New South Wales.

Bernanke, B.S. 1983. Irreversibility, Uncertainty, and Cyclical Investment. *Quarterly Journal of Economics* 98: 85–106.

Berrebi, C., and J. Ostwald. 2016. Terrorism and the Labor Force: Evidence of an Effect on Female Labor Force Participation and the Labor Gender Gap. *Journal of Conflict Resolution* 60: 32–60.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. How Much Should we Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics* 119: 249–275.

Besley, T., and H. Mueller. 2012. Estimating the Peace Dividend: The Impact of Violence on House Prices in Northern Ireland. *American Economic Review* 102: 810–833.

Birkelund, G.E., T.W. Chan, E. Ugreninov, A.H. Midtbøen and J. Rogstad. 2019. Do Terrorist Attacks Affect Ethnic Discrimination in the Labour Market? Evidence from Two Randomized Field Experiments. *British Journal of Sociology* 70: 241–260.

Blomberg, S.B., G.D. Hess, and A. Orphanides. 2004. The Macroeconomic Consequences of Terrorism. *Journal of Monetary Economics* 51: 1007–1032.

Bloom, N., S. Bond, and J. Van Reenen. 2007. Uncertainty and Investment Dynamics. *Review of Economic Studies* 74: 391–415.

Brodeur, A. 2018. The Effect of Terrorism on Employment and Consumer Sentiment: Evidence from Successful and Failed Terror Attacks. *American Economic Journal: Applied Economics* 10: 246-282.

Chen, D., H. Gao, and Y. Ma. 2017. Human Capital Driven Acquisition: Evidence from the Inevitable Disclosure Doctrine. Working Paper, Kelley School of Business.

Chemmanur, T.J., Y. Cheng, and T. Zhang. 2013. Human Capital, Capital Structure, and Employee pay: An empirical Analysis. *Journal of Financial Economics* 110: 478–502.

Czinkota, M.R., G. Knight, P.W. Liesch, and J. Steen. 2010. Terrorism and International Business: A Research Agenda. *Journal of International Business Studies* 41: 826–843.

Dai, Y., R.P. Rau, A. Stouraitis, and W. Tan. 2019. An Ill Wind? Terrorist Attacks and CEO Compensation. *Journal of Financial Economics*, Forthcoming.

Dessaint, O., and A. Matray. 2017. Do Managers Overreact to Salient Risks? Evidence from Hurricane Strikes. *Journal of Financial Economics* 126: 97–121.

Docquier, F., O. Lohest, and A. Marfouk. 2007. Brain Drain in Developing Countries. *World Bank Economic Review* 21: 193–218.

Dreher, A., T. Krieger, and D. Meierrieks. 2011. Hit and (They Will) Run: The Impact of Terrorism on Migration. *Economics Letters* 113: 42–46.

Drucker, S., and M. Puri. 2005. On the Benefits of Concurrent Lending and Underwriting. *Journal of Finance* 60: 2763–2799.

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

Faccio, M., M.-T. Marchica, and R. Mura. 2016. CEO Gender, Corporate Risk–Taking, and the Efficiency of Capital Allocation. *Journal of Corporate Finance* 39: 193–209.

Fich, E., T.D. Nguyen, and D. Petmezas. 2019. Uncertainty and Corporate Innovation: Evidence from Terrorist Attacks. Working Paper, Drexel University and University of Surrey.

Getmansky, A., and T. Zeitzoff. 2014. Terrorism and Voting: The Effect of Rocket Threat on Voting in Israeli Elections. *American Political Science Review* 108: 588–604.

Ghaly, M., V.A. Dang, and K. Stathopoulos. 2017. Cash Holdings and Labor Heterogeneity: The Role of Skilled Labor. *Review of Financial Studies* 30: 3636–3668.

Golubov, A., D. Petmezas, and N.G. Travlos. 2012. When It Pays to Pay Your Investment Banker: New Evidence on the Role of Financial Advisors in M&As. *Journal of Finance* 67: 271–312.

Gottschalk, P. 1997. Inequality, Income Growth, and Mobility: The basic Facts. *Journal of Economic Perspectives* 11: 21–40.

Harris, M., and A. Raviv. 1979. Optimal Incentive Contracts with Imperfect Information. *Journal of Economic Theory* 20: 231–259.

Huang, J., and D.J. Kisgen. 2013. Gender and Corporate Finance: Are Male Executives Overconfident Relative to Female Executives? *Journal of Financial Economics* 108: 822–839.

Imbens, G.W., and J.M. Wooldridge. 2009. Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature* 47: 5–86.

Imrohoroğlu, A., and S. Tüzel. 2014. Firm-Level Productivity, Risk, and Return. *Management Science* 60: 2073–2090.

Julio, B., and Y. Yook. 2012. Political Uncertainty and Corporate Investment Cycles. *Journal of Finance* 67: 45–83.

Kahneman, D., and A. Tversky. 1973. On the Psychology of Prediction. *Psychological Review* 80: 237–251.

Kahneman, D., and A. Tversky. 1979. Prospect Theory: An Analysis of Decision Under Risk. *Econometrica* 47: 263–292.

Kang, J.-K., and J.-M. Kim. 2008. The Geography of Block Acquisitions. *Journal of Finance* 63: 2817–2858.

Karolyi, A., and R. Martell. 2010. Terrorism and the Stock Market. *International Review of Applied Finance Issues and Economics* 2: 285–314.

Kedia, S., and S. Rajgopal. 2009. Neighborhood matters: The Impact of Location on Broad Based Stock Option Plans. *Journal of Financial Economics* 92: 109–127.

Ksoll, C., R. Macchiavello, and A. Morjaria. 2018. Guns and Roses: Flower Exports and Electoral Violence in Kenya. Working paper, University of Oxford.

Lucas, R.E. 1988. On the Mechanics of Economic Development. *Journal of Monetary Economics* 22: 3–42.

Malmendier, U., and G. Tate. 2005. CEO Overconfidence and Corporate Investment. *Journal of Finance* 60: 2661–2700.

Moeller, S.B., F.P. Schlingemann, and R.M. Stulz. 2007. How do Diversity of Opinion and Information Asymmetry Affect Acquirer Returns? *Review of Financial Studies* 20: 2047–2078.

Moghaddam, F.M. 2005. The Staircase to Terrorism: A psychological Exploration. *American Psychologist* 60: 161–169.

Nitsch, V., and D. Schumacher. 2004. Terrorism and International Trade: An Empirical Investigation. *European Journal of Political Economy* 20: 423–433.

Officer, M.S. 2003. Termination Fees in Mergers and Acquisitions. *Journal of Financial Economics* 69: 431–467.

Oh, C.H., and J. Oetzel. 2011. Multinationals' Response to Major Disasters: How Does Subsidiary Investment Vary in Response to the Type of Disaster and the Quality of Country Governance? *Strategic Management Journal* 32: 658–681.

Ouimet, P., and R. Zarutskie. 2016. Acquiring Labor. Working paper, University of North Carolina at Chapel Hill.

Procasky, W., and N.U. Ujah. 2016. Terrorism and its Impact on the Cost of Debt. *Journal of International Money and Finance* 60: 253–266.

Romer, P.M. 1986. Increasing Returns and Long-Run Growth. *Journal of Political Economy* 94: 1002–1037.

Rosenbaum, P.R., and D.B. Rubin. 1985. Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *American Statistician* 39: 33–38.

Solow, R.M. 1957. Technical Change and the Aggregate Production Function. *Review of Economics and Statistics* 39: 312–320.

Tate, G., and L. Yang. 2015. The Bright Side of Corporate Diversification: Evidence from Internal Labor Markets. *Review of Financial Studies* 28: 2203–2249.

Tversky, A., and D. Kahneman. 1973. Availability: A Heuristic for Judging Frequency and Probability. *Cognitive Psychology* 4: 207-232.

Tversky, A., and D. Kahneman. 1974. Judgment Under Uncertainty: Heuristics and Biases. *Science* 185: 1124–1131.

Uysal, V.B., S. Kedia, and V. Panchapagesan. 2008. Geography and Acquirer Returns. *Journal of Financial Intermediation* 17: 256–275.

Wang, A., and M. Young. 2019. Terrorist Attacks and Investor Risk Preference: Evidence from Mutual Fund Flows. *Journal of Financial Economics,* Forthcoming.

Xiong, X., and I.P.L. Png. 2019. Location of U.S. Manufacturing, 1987-2014: A New Dataset. Working Paper.

Yim, S. 2013. The Acquisitiveness of Youth: CEO Age and Acquisition Behavior. *Journal of Financial Economics* 108: 250–273.

Appendix – Variable Definitions

Dependent variables

- **Acquisition Premium:** The difference between the offer price and the target firm's stock price four weeks before the acquisition announcement divided by the latter, as reported by Thomson Financial SDC. The values are limited between 0% and 200%.
- **Target Firm CAR (–1, +1):** Target firm's market-adjusted cumulative abnormal return over the three–day window around the acquisition announcement date. The CRSP value–weighted index return is the market return.
- **Combined Firm CAR (–1, +1):** Market-adjusted cumulative abnormal return for the value–weighted portfolio of the acquirer and the target firm over the three–day window around the acquisition announcement date. Weights are acquirer and target firm market value of equity over combined market value of equity four weeks prior to the acquisition announcement. The CRSP value–weighted index return is the market return.
- **Receiving a Bid:** Dummy variable that takes the value of one if the firm announced at least one acquisition in year *t+1*, and zero otherwise. The variable is created using data from Thomson Financial SDC.
- **Out–of–MSA Deals:** Dummy variable that takes the value of one for acquiring firms undertaking out–of–MSA (i.e., cross–border or cross–MSA) acquisition deals, and zero otherwise. This variable is created using data from Thomson Financial SDC.
- **Cross–MSA Deals:** Dummy variable that takes the value of one for acquiring firms undertaking cross–MSA acquisition deals, and zero otherwise. This variable is created using data from Thomson Financial SDC.
- **Geographical Distance:** The natural logarithm of the geographical distance between acquiring and target firm headquarters measured in kilometers**.** This variable is created using data from Thomson Financial SDC.
- **Labor Productivity:** The ratio of firm sales (SALE) to employment (EMP). This variable is created using data from Compustat.

Terrorism Intensity Variables

- **Ln (1+Terrorism Intensity within MSA):** The natural logarithm of one plus the sum of the number of deaths and 50% times the number of injuries [i.e., number of deaths + 0.5 * (injuries)] due to terrorist attacks in a given year within the same metropolitan statistical area (MSA).
- **Ln (1+Terrorism Intensity within 100 km):** The natural logarithm of one plus the sum of the number of deaths and 50% times the number of injuries [i.e., number of deaths + 0.5 * (injuries)] due to terrorist attacks in a given year within 100 kilometers from the place where the terrorist incident took place. Additionally, data obtained from the U.S. Census Bureau's Gazetteers and Zip Code Database to obtain information on the latitude and longitude of the firms and the places where the terrorism incidents took place. We then used the standard formula for calculating the distance, $d_{i,j}$, between the firm *i* and the location of the terrorism incident *j*: $d_{i,j} = \arccos\{\cos(lat_i)\cos(lon_i)\cos(lat_j)\cos(lon_j) + \cos(lat_i)\sin(lon_i)\cos(lat_j)\sin(lon_j) + \sin(lat_i)\sin(lay_j)\}2\pi r/360$, where *lat* and *lon* are the latitudes and longitudes of the terrorism incident and the firms' locations, respectively, and *r* denotes the radius of the earth (approximately 6,378 kilometers).

Firm Variables

- **Ln (Market Cap):** The natural logarithm of the market capitalization. The market capitalization is calculated by multiplying the common number of shares outstanding (Compustat item CSHO) by the share price (PRCC_F). This variable is created using data from Compustat.
- **Market–to–Book:** The market value of equity divided by the book value of equity, where book value of equity is shareholders' equity (CEQ) minus book value of preferred stock

(in the following order: PSTKRV or PSTKL or PSTK) plus deferred taxes and investment tax credit (TXDITC). The market value of equity is calculated by multiplying the common number of shares outstanding (CSHO) by the share price (PRCC_F). This variable is created using data from Compustat.

- **Leverage:** The sum of long term debt (DLTT) and debt in current liabilities (DLC) scaled by total assets (AT). This variable is created using data from Compustat.
- **Cash Holdings:** Cash and short–term investments (CHE) scaled by total assets (AT). This variable is created using data from Compustat.
- **ROA:** Return on assets, measured as operating income before depreciation (OIBDP) divided by total assets scaled by the book value of total assets (AT). This variable is created using data from Compustat.
- **Run–Up:** The market–adjusted buy–and–hold abnormal return over the period starting 240 days and ending 41 days prior to the merger announcement. This variable is created using data from CRSP.

MSA Variables

- **MSA Unemployment Rate:** The unemployment rate in the target MSA. (Source: The Bureau of Labor Statistics (BLS)).

- **Ln (MSA Population):** The natural logarithm of MSA population of the target MSA. (Source: The US Census Bureau).

Industry Variables

- **Herfindahl Index:** The sum of squares of the market shares of all firms in a given year and three–digit SIC code, where market share is defined as sales of the firm divided by the sum of the sales in the industry. This variable is created using data from Compustat.
- **M&A Liquidity:** The sum of deal values in a given year and three–digit SIC code, divided by the sum of total assets of all firms in COMPUSTAT with the same 3–digit SIC code.

Deal Variables

- **Diversifying:** Dummy variable that equals to one for cross-industry transactions, and zero for same industry transactions. Industries are defined at the three-digit SIC level. (Source: Thomson Financial SDC).
- **All Cash:** Dummy variable that equals to one for deals where the method of payment is 100% cash, and zero otherwise. (Source: Thomson Financial SDC).
- **Hostile:** Dummy variable that equals to one for deals classified as hostile or unsolicited, and zero otherwise. (Source: Thomson Financial SDC).
- **Tender Offer:** Dummy variable that equals to one for deals defined as tender offers, and zero otherwise. (Source: Thomson Financial SDC).

Human Capital Variables

- **High Labor Productivity:** An indicator variable that equals to one if the firm labor productivity (measured as firm sales to number of employees) is above the sample median, and zero otherwise. The variable is created using data from Compustat.
- **High Labor Intensity Industry:** An indicator variable that equals to one if the ratio of employees' wages to sales (from Compustat) across all firms in the same 2–digit SIC industry is above the sample median, and zero otherwise. Wages are calculated by multiplying the number of employees from Compustat (EMP) with the average annual wages from the US Social Security Administration.
- **High–Skill Industry:** An indicator variable that equals to one if the proportion of highly skilled employments in firms with the same 2–digit SIC industry is above the sample median, and zero otherwise. As in Tate and Yang (2015), to calculate the distribution of skilled employments within an industry, we use the Standard Occupational Classification

(SOC) system from the Bureau of Labor Statistics (BLS) and define occupations with 2–digit SOC codes less than 29 being the ones of highly skilled employees. Based on the percentage of skilled employees in 2–digit SIC industries, we create the high–skill industry indicator.

CEO Variables

- **Non–Overconfident CEO:** Dummy variable that equals to one if a CEO is identified as non–overconfident, and zero otherwise. A CEO is non–overconfident if she exercises vested options that are at least 67% in–the–money (i.e., Non–Holder 67). (Source: ExecuComp and CRSP).
- **Old CEO:** Dummy variable that equals to one if the age of a CEO belongs to the highest tercile of the sample CEO age distribution, and zero otherwise. (Source: ExecuComp).
- **Female CEO:** Dummy variable that equals to one if a CEO is female, and zero for male CEOs. (Source: ExecuComp).

Figure 1

Trends in the Relation Between Terrorism Intensity and Acquisition Likelihood

This figure shows the trends in the relation between terrorism intensity and acquisition likelihood over the 4–year period before and 4–year period after the terrorist attacks. The *y*–axis plots the estimated coefficients after regressing acquisition likelihood on ln (1+terrorism intensity within MSA) in Panel A, and ln (1+terrorism intensity within 100 km) in Panel B, as well as on the control variables and fixed effects used in Table 5. The *x*–axis shows the time relative to terrorist attacks for ±4 years around the terrorist attacks. The blue solid line corresponds to the terrorism intensity within MSA and the red solid line to the terrorism intensity within 100 km. The dashed lines correspond to the 95% confidence intervals of the coefficient estimates. Confidence intervals are calculated from standard errors double-clustered by firm and year. The symbols *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

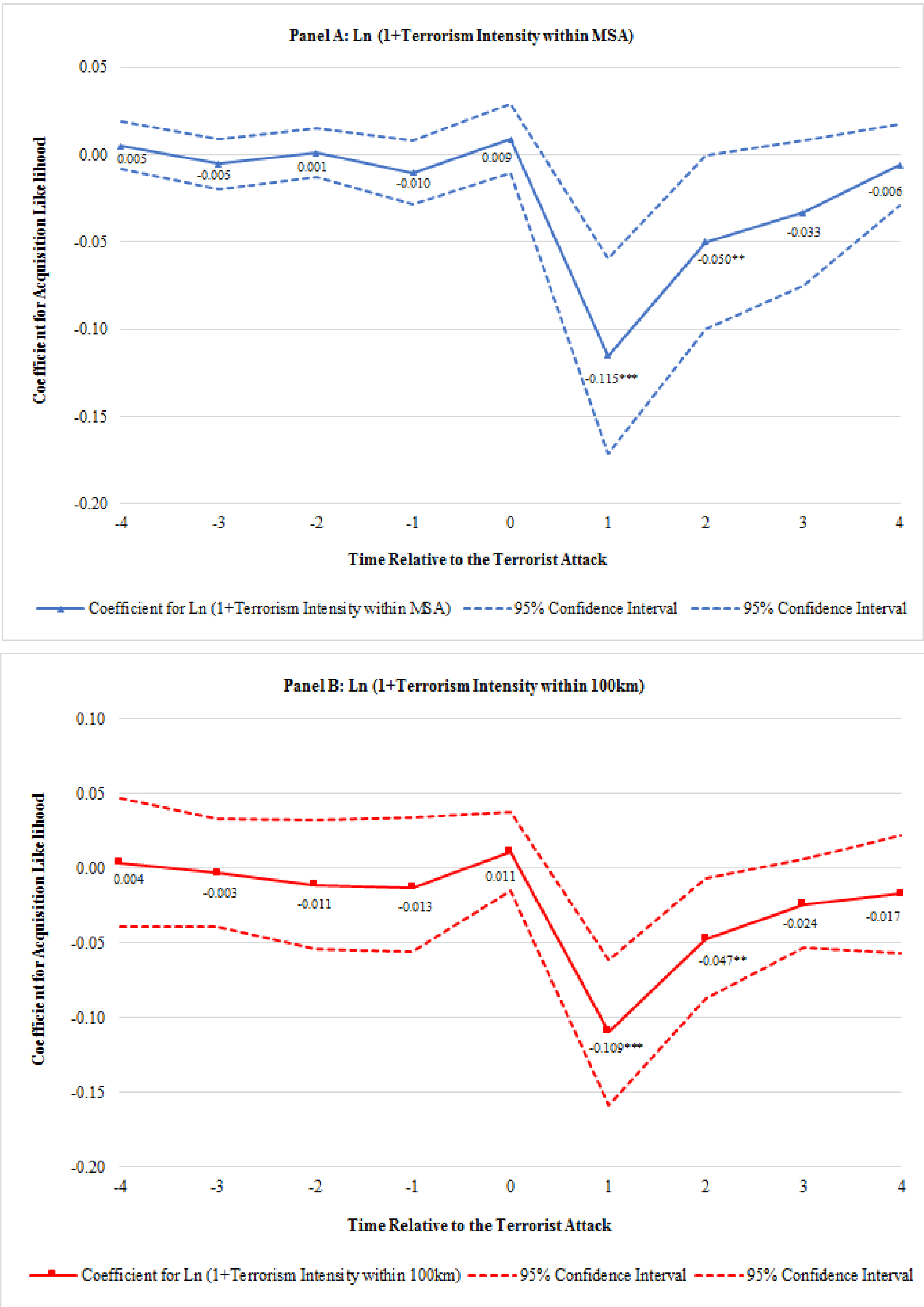
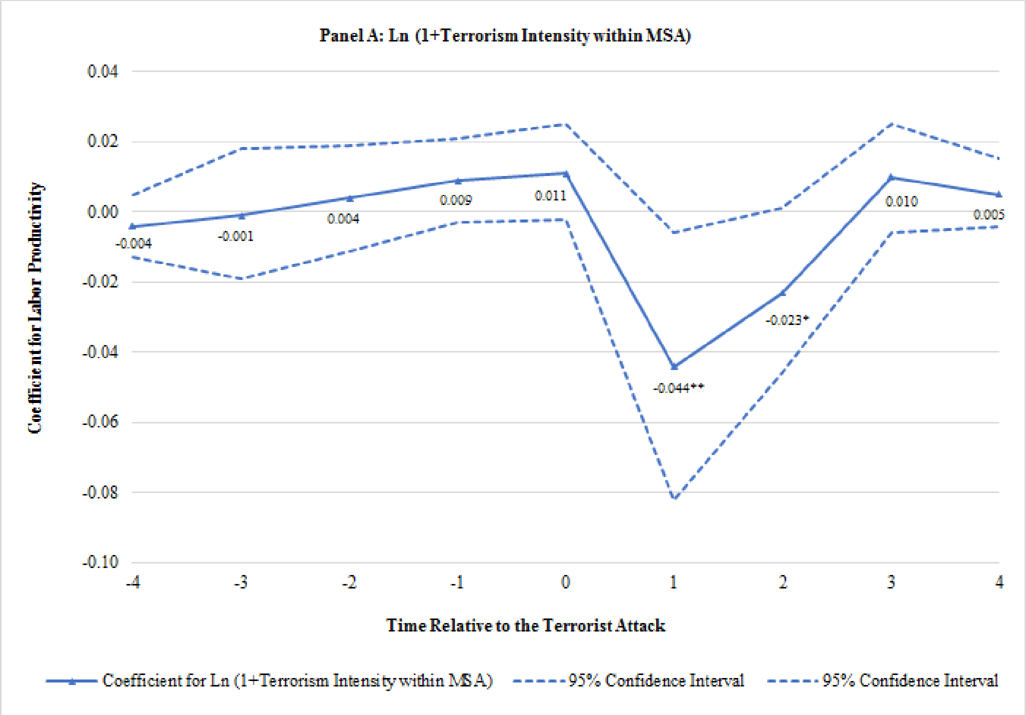


Figure 2

Trends in the Relation Between Terrorism Intensity and Labor Productivity

This figure shows the trends in the relation between terrorism intensity and labor productivity over the 4–year period before and 4–year period after the terrorist attacks. The *y*–axis plots the estimated coefficients after regressing labor productivity on ln (1+terrorism intensity within MSA) in Panel A, and ln (1+terrorism intensity within 100 km) in Panel B, as well as on the control variables and fixed effects used in Table 9. The *x*–axis shows the time relative to terrorist attacks for ±4 years around the terrorist attacks. The blue solid line corresponds to the terrorism intensity within MSA and the red solid line to the terrorism intensity within 100 km. The dashed lines correspond to the 95% confidence intervals of the coefficient estimates. Confidence intervals are calculated from standard errors double-clustered by firm and year.The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.



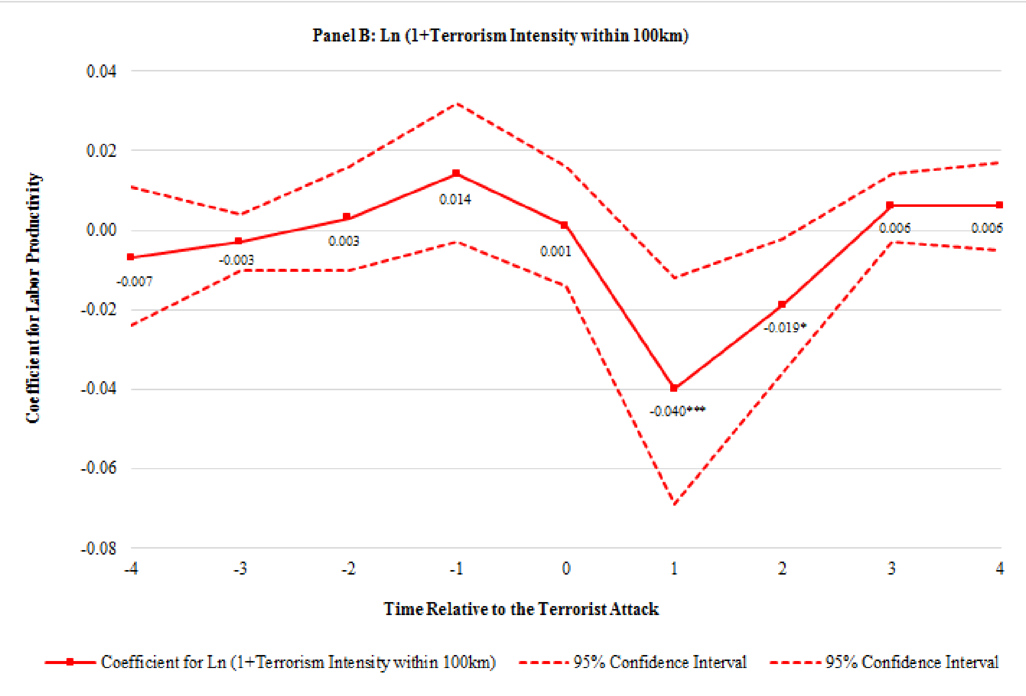


Table 1
Terrorist Attacks Statistics

This table presents descriptive statistics on terrorist attacks. Panel A presents the percentage distribution by attack type, Panel B presents the distribution of victims (i.e., deaths and injuries) from terrorist attacks by year, and Panel C presents the distribution of victims from terrorist attacks by MSA.

Panel A: Distribution of Terrorist Attacks by Attack Type

Attack type	Percentage
Armed Assault	56.86%
Bombing/Explosion	15.69%
Facility/Infrastructure Attack	5.88%
Hijacking	7.85%
Hostage Taking	5.88%
Unarmed Assault	7.84%

Panel B: Distribution of Victims from Terrorist Attacks by Year

Year	Deaths	Injuries	Year	Deaths	Injuries
1995	170	728	2008	2	7
1996	2	111	2009	16	32
1997	2	6	2010	1	15
1998	5	2	2012	6	4
1999	20	38	2013	22	434
2001	3,212	6,123	2014	16	15
2002	2	4	2015	45	44
2006	1	5			

Panel C: Distribution of Victims from Terrorist Attacks by MSA

MSA	Deaths	Injuries	MSA	Deaths	Injuries
Atlanta-Sandy Springs-Marietta, GA	1	110	Los Angeles-Long Beach-Santa Ana, CA	4	12
Austin-Round Rock, TX	1	15	Miami-Fort Lauderdale-Pompano Beach, FL	2	5
Birmingham-Hoover, AL	1	1	Milwaukee-Waukesha-West Allis, WI	6	4
Bloomington, IN	1	0	New Haven-Milford, CT	1	0
Boston-Cambridge-Quincy, MA-NH	5	279	New York-Northern New Jersey-Long Island, NY-NJ-PA	2,982	6,006
Buffalo-Niagara Falls, NY	1	0	Oklahoma City, OK	168	650
Charleston-North Charleston, SC	9	0	OR Nonmetropolitan area	9	7
Chattanooga, TN-GA	5	2	PA Nonmetropolitan area	41	1
Chicago-Naperville-Joliet, IL-IN-WI	1	9	Redding, CA	2	0
Colorado Springs, CO	3	9	Riverside-San Bernardino-Ontario, CA	15	18
Danville, IL	1	0	Sacramento-Arden-Arcade-Roseville, CA	1	0
Denver-Aurora, CO	15	24	Santa Barbara-Santa Maria-Goleta, CA	6	14
Durham, NC	3	0	Seattle-Tacoma-Bellevue, WA	1	5
Kansas City, MO-KS	3	0	TX Nonmetropolitan area	1	0
Killeen-Temple-Fort Hood, TX	13	31	Waco, TX	15	151
Knoxville, TN	2	7	Washington-Arlington-Alexandria, DC-VA-MD-WV	195	120
Lafayette, LA	2	9	Wichita, KS	1	0
Las Vegas-Paradise, NV	3	0	Yuma, AZ	1	78
Little Rock-North Little Rock-Conway, AR	1	1	**Total**	**3,522**	**7,568**

Table 2
Sample Descriptive Statistics

This table presents summary statistics for a sample of US publicly listed firms with data available on CRSP and Compustat over the period 1995-2015, and for a sample of US domestic public acquisitions announced over the period 1996-2016. Specifically, it reports the mean, median, standard deviation, and number of observations for the overall sample (Panel A), and for the acquisition sample (Panel B). The definitions of all variables are provided in the Appendix.

	Mean	Median	Standard Deviation	Observations
Panel A: Overall Sample				
Dependent Variable				
Acquisition Likelihood	0.033	-	0.180	47,709
Firm Variables				
Terrorism Intensity within MSA	0.126	0.000	0.796	47,709
Terrorism Intensity within 100km	0.149	0.000	0.857	47,709
Ln (Market Cap)	1.706	0.210	2.056	47,709
Market-to-Book	3.315	2.177	4.356	47,709
Leverage	0.172	0.110	0.192	47,709
Cash Holdings	0.277	0.187	0.267	47,709
ROA	-0.009	0.088	0.290	47,709
MSA Variables				
MSA Unemployment Rate	5.498	5.083	1.996	47,709
Ln (MSA Population)	15.015	15.206	1.095	47,709
Industry Variables				
Herfindahl Index	0.184	0.113	0.154	47,709
M&A Liquidity	0.008	0.005	0.016	47,709
Panel B: Acquisition Sample				
Dependent Variables				
Acquisition Premium	0.491	0.406	0.405	1,007
Target Firm CAR (-1,+1)	0.244	0.201	0.326	1,388
Combined Firm CAR (-1,+1)	0.075	0.083	0.116	1,007
Acquirer Characteristics				
Ln (Market Cap)	1.974	2.015	0.302	1,007
Cash Holdings	0.234	0.163	0.217	1,007
Leverage	0.181	0.145	0.187	1,007
Market-to-Book	4.227	2.813	5.015	1,007
Run-Up	-0.100	-0.068	0.289	1,007
Target Firm Characteristics				
Terrorism Intensity within MSA	0.031	0.000	0.294	1,007
Terrorism Intensity within 100km	0.032	0.000	0.293	1,007
Ln (Market Cap)	1.671	1.719	0.370	1,388
Cash Holdings	0.294	0.227	0.254	1,388
Leverage	0.160	0.082	0.198	1,388
Market-to-Book	3.398	2.265	3.859	1,388
Run-Up	-0.187	-0.119	0.391	1,388
Industry Characteristics				
Herfindahl Index	0.156	0.097	0.131	1,388
M&A Liquidity	0.009	0.005	0.025	1,388
Deal Characteristics				
Diversifying	0.561	-	0.496	1,388
All Cash	0.403	-	0.491	1,388
Hostile	0.070	-	0.255	1,388
Tender Offer	0.247	-	0.431	1,388

Table 3
Event Study at the Days of the Terrorist Attacks

This table presents event study results for the market reaction at the day(s) of the terrorist attacks for treated and control firms within and outside the MSA of the terrorist attack, and within and outside 100 km distance from the terrorist attack on day 0, and over a 2-day event window (0, +1) with day 0 being the day of the terrorist attack. Column (1) presents the event day (window) of the terrorist attack. Columns (2) and (3) present the mean (median) market-adjusted stock abnormal return for treated firms on day 0 and cumulative abnormal return (CAR) for the event window (0, +1). Columns (4) and (5) present the corresponding mean (median) market-adjusted stock abnormal return for control firms on day 0 and cumulative abnormal return (CAR) for the event window (0, +1). The CRSP value–weighted market index return is used to calculate abnormal returns. Columns (6) and (7) present the *p*-value differences for means and equality of medians, respectively between within MSA firms and outside MSA firms, and between within 100 km distance firms and outside 100km distance from the terrorist attack. The symbols *** and ** indicate statistical significance at the 1% and 5% levels, respectively. N denotes the number of observations.

Day(s)	Treated Firms		Control Firms		Differences	
	Mean	Median	Mean	Median	*p*-value (Mean)	*p*-value (Median)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Within MSA						
0	-0.490%**	-0.532%***	0.040%	-0.010%	-0.530%***	-0.522%**
(0, +1)	(-1.051%***)	(-1.091%***)	(-0.040%)	(-0.019%)	(-1.011%***)	(-1.072%***)
N	1,152	1,152	1,210,589	1,210,589		
Panel B: Within 100 km Distance						
0	-0.454%**	-0.651%***	-0.103%	-0.161%	-0.351%***	-0.490%***
(0, +1)	(-1.320%***)	(-0.961%***)	(0.036%)	(-0.022%)	(-1.356%***)	(-0.939%***)
N	1,849	1,849	1,209,892	1,209,892		

Table 4
Acquisition Premium and CARs

This table reports OLS regressions of the effect of terrorism intensity on the acquisition premium and announcement abnormal returns. The dependent variable in specifications (1) and (2) is the 4-week offer premium reported by SDC, which is calculated as the difference between the offer price and the target firm's stock price four weeks before the acquisition announcement divided by the latter. The dependent variable in specifications (3) and (4) is the target firm market-adjusted cumulative abnormal return (CAR) over a 3-day event window (1, +1) around the acquisition announcement. The dependent variable in specifications (5) and (6) is the combined firm CAR over a 3-day event window (1, +1) around the acquisition announcement. The CRSP value–weighted market index return is used to calculate abnormal returns. The definitions of all variables are provided in the Appendix. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The *t*-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Acquisition Premium		**Target Firm CAR (-1,+1)**		**Combined Firm CAR (-1,+1)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (1+Terrorism Intensity within MSA)	-0.069***		-0.046***		-0.020**	
	(-2.86)		(-4.05)		(-2.25)	
Ln (1+Terrorism Intensity within 100 km)		-0.067***				
		(-2.58)		-0.053***		-0.020***
Acquirer Characteristics				(-6.66)		(-2.62)
Ln (Market Cap)	0.034***	0.034***			0.008**	0.008**
	(3.09)	(3.05)			(2.09)	(2.08)
Cash Holdings	0.082	0.082			0.004	0.004
	(1.00)	(1.00)			(0.16)	(0.16)
Leverage	-0.096	-0.096			-0.004	-0.004
	(-1.12)	(-1.13)			(-0.18)	(-0.18)
Market-to-Book	0.004	0.004			-0.001	-0.001
	(1.43)	(1.44)			(-0.86)	(-0.85)
Run-Up	0.119**	0.119**			-0.012	-0.012
	(2.38)	(2.37)			(-0.60)	(-0.60)
Target Firm Characteristics						
Ln (Market Cap)	-0.061***	-0.061***	-0.030***	-0.030***	-0.013***	-0.013***
	(-5.65)	(-5.61)	(-3.34)	(-3.35)	(-3.14)	(-3.11)
Cash Holdings	-0.151**	-0.150**	0.010	0.011	-0.046*	-0.045*
	(-2.00)	(-1.98)	(0.12)	(0.13)	(-1.76)	(-1.75)
Leverage	-0.105	-0.104	0.027	0.026	-0.006	-0.006
	(-1.05)	(-1.04)	(0.49)	(0.46)	(-0.22)	(-0.21)
Market-to-Book	-0.000	-0.001	-0.003	-0.003	-0.002	-0.002
	(-0.16)	(-0.18)	(-1.38)	(-1.39)	(-1.42)	(-1.44)
Run-Up	-0.035	-0.035	0.022	0.022	0.001	0.001
	(-0.87)	(-0.88)	(0.53)	(0.53)	(0.01)	(0.01)
Industry Characteristics						
Herfindahl Index	0.218*	0.219*	0.076	0.078	0.107***	0.108***
	(1.75)	(1.75)	(0.92)	(0.94)	(3.72)	(3.71)
M&A Liquidity	-0.279	-0.279	0.165	0.165	-0.080	-0.080
	(-1.17)	(-1.16)	(0.60)	(0.60)	(-1.25)	(-1.26)
Deal Characteristics						
Diversifying	0.059**	0.058**	0.005	0.005	0.009	0.009
	(2.07)	(2.06)	(0.28)	(0.27)	(1.34)	(1.33)
All Cash	0.018	0.017	0.006	0.006	0.028***	0.028***
	(0.65)	(0.65)	(0.17)	(0.16)	(3.56)	(3.56)
Hostile	-0.016	-0.016	-0.021	-0.019	0.015	0.015
	(-0.35)	(-0.35)	(-0.98)	(-0.88)	(0.82)	(0.83)
Tender Offer	0.031	0.031	0.098***	0.098***	0.017**	0.017**
	(0.94)	(0.94)	(2.65)	(2.66)	(2.00)	(1.99)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	1,007	1,007	1,388	1,388	1,007	1,007
Adjusted R^2	0.291	0.291	0.185	0.186	0.306	0.305

Table 5
Terrorism Intensity and Acquisition Likelihood

This table presents coefficients from probit regressions for the effect of terrorism intensity on acquisition likelihood over the period between 1996 and 2016 for a sample of US publicly listed firms. The dependent variable takes the value of 1 if the firm receives at least one acquisition bid in year *t+1*, and 0 otherwise. The treatment group includes all firms that are affected by the attacks that have occurred at time *t*: these are firms that are headquartered within the MSA of the terrorist events (column (1)) or within 100 km of the location of the terrorist events (column (2)), and at least two years have elapsed since the last attack. The control group includes the treatment firms before time *t* and all remaining firms. The definitions of all variables are provided in the Appendix. All control variables are lagged by one year. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The *z*-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: Receiving a Bid		
	(1)	**(2)**
Ln (1+Terrorism Intensity within MSA)	-0.115***	
	(-4.01)	
Ln (1+Terrorism Intensity within 100 km)		-0.109***
		(-4.41)
Ln (Market Cap)	-0.018**	-0.017**
	(-2.16)	(-2.16)
Market-to-Book	-0.005*	-0.005*
	(-1.73)	(-1.75)
Leverage	0.030	0.030
	(0.35)	(0.35)
Cash Holdings	0.021	0.022
	(0.38)	(0.40)
ROA	0.370***	0.369***
	(4.91)	(4.90)
MSA Unemployment Rate	-0.010	-0.011
	(-0.54)	(-0.58)
Ln (MSA Population)	0.054	0.070*
	(1.36)	(1.82)
Herfindahl Index	-0.274**	-0.274**
	(-2.43)	(-2.42)
M&A Liquidity	0.606	0.591
	(0.88)	(0.86)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
MSA Fixed Effects	Yes	Yes
No. of Obs.	47,709	47,709
Pseudo R^2	0.039	0.039

Table 6
Terrorism Intensity and Acquisition Likelihood: Propensity Score Matching (PSM) Analysis

This table presents results of propensity score matching (PSM) analysis of the effect of terrorism intensity on acquisition likelihood over the period between 1996 and 2016 for a sample of US publicly listed firms. The treatment group consists of firms affected by the attack, as defined in Table 5, while the control group consists of firms in the same state but not affected by the attacks. We match firms using one-to-one nearest neighbor propensity score matching with replacement. Panel A presents parameter estimates from the probit model used to estimate propensity scores for firms in the treatment and control groups. The dependent variable is one if the firm-year belongs to the treatment group, and zero otherwise. Industry fixed effects are included in all columns in Panel A. Panel B reports the distribution of estimated propensity scores for the treatment firms, control firms, and the difference in estimated post-matched propensity scores. Panel C reports univariate comparisons between the treatment and control firms' characteristics and their corresponding t-statistics. Panel D reports coefficients from probit regressions. The definitions of all variables are provided in the Appendix. All control variables are lagged by one year. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The z-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Pre-Match Propensity Score Regressions and Post-Match Diagnostic Regressions

	Dummy = 1 if in Treatment Group; 0 if in Control Group			
	Within MSA		Within 100 km Distance	
	(1) Pre-match	(2) Post-match	(3) Pre-match	(4) Post-match
Ln (Market Cap)	0.041***	-0.016	0.027***	-0.006
	(4.32)	(-0.88)	(3.27)	(-0.39)
Market-to-Book	0.001	0.002	0.003	-0.005
	(0.24)	(0.26)	(0.87)	(-0.76)
Leverage	0.079	-0.122	0.098	-0.081
	(0.81)	(-0.67)	(1.16)	(-0.49)
Cash Holdings	-0.506***	-0.093	-0.386***	-0.072
	(-5.94)	(-0.61)	(-5.26)	(-0.53)
ROA	-0.304***	0.047	-0.033	-0.174
	(-4.40)	(0.39)	(-0.56)	(-1.59)
MSA Unemployment Rate	-0.142***	0.010	-0.149***	-0.001
	(-12.47)	(0.46)	(-16.41)	(-0.04)
Ln (MSA Population)	0.557***	-0.020	0.339***	-0.035
	(28.73)	(-0.56)	(22.71)	(-1.36)
Herfindahl Index	0.128	-0.167	0.057	-0.253
	(0.77)	(-0.53)	(0.41)	(-1.02)
M&A Liquidity	-11.567***	4.020	-9.054***	3.889
	(-5.93)	(1.18)	(-5.73)	(1.38)
Industry Fixed Effects	Yes	Yes	Yes	Yes
No. of Obs.	7,230	1,613	9,492	2,069
Pseudo R^2	0.164	0.012	0.108	0.011

Panel B: Estimated Propensity Score Distributions

Propensity Score	No. of Obs.	Min	P5	P50	Mean	SD	P95	Max
Within MSA								
Treatment	808	0.014	0.064	0.375	0.355	0.146	0.552	0.710
Control	808	0.017	0.055	0.396	0.366	0.161	0.590	0.717
Difference		-0.003	0.009	-0.021	-0.011	-0.015	-0.038	-0.007
Within 100 km Distance								
Treatment	1,035	0.013	0.077	0.305	0.288	0.125	0.483	0.674
Control	1,035	0.013	0.078	0.317	0.298	0.129	0.481	0.647
Difference		0.000	-0.001	-0.012	-0.010	-0.004	0.002	0.027

Table 6 (Continued)

Panel C: Comparison of Means across Matched Samples in Year *t-1*								
Variable	**Matched Samples based on MSA**				**Matched Samples based on 100 km Distance**			
	Treatment	**Control**	**Difference**	***t*-statistic**	**Treatment**	**Control**	**Difference**	***t*-statistic**
Ln (Market Cap)	4.791	4.901	-0.110	1.06	5.039	5.164	-0.125	1.31
Market-to-Book	3.489	3.620	-0.131	0.51	3.492	3.743	-0.251	1.11
Leverage	0.166	0.168	-0.002	0.22	0.164	0.166	-0.002	0.27
Cash Holdings	0.289	0.310	-0.021	1.52	0.296	0.303	-0.007	0.56
ROA	-0.036	-0.054	0.018	-1.14	-0.045	-0.026	-0.019	1.38
MSA Unemployment Rate	5.328	5.313	0.015	-0.19	5.443	5.499	-0.056	0.78
Ln (MSA Population)	15.953	15.939	0.014	-0.28	15.604	15.662	-0.058	1.15
Herfindahl Index	0.179	0.171	0.008	-1.02	0.178	0.181	-0.003	0.34
M&A Liquidity	0.008	0.008	0.000	-0.52	0.008	0.008	0.000	-0.52

Panel D: Probit Regressions with PSM Matched Samples		
	Dependent Variable: Receiving a Bid	
	(1)	**(2)**
Ln (1+Terrorism Intensity within MSA)	-0.176**	
	(-2.02)	
Ln (1+Terrorism Intensity within 100 km)		-0.156**
		(-2.08)
Ln (Market Cap)	0.030**	-0.012
	(2.08)	(-0.82)
Market-to-Book	-0.012*	-0.010
	(-1.83)	(-1.21)
Leverage	0.347**	0.200
	(2.33)	(1.44)
Cash Holdings	-0.089	-0.097
	(-0.59)	(-0.82)
ROA	0.386**	0.480***
	(2.44)	(3.25)
MSA Unemployment Rate	0.093**	0.033
	(1.99)	(1.04)
Ln (MSA Population)	0.152***	0.162***
	(2.62)	(3.05)
Herfindahl Index	-0.434**	-0.497**
	(-2.35)	(-2.18)
M&A Liquidity	1.383	1.750*
	(1.64)	(1.83)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
MSA Fixed Effects	Yes	Yes
No. of Obs.	10,594	14,377
Pseudo R^2	0.089	0.084

Table 7
Geographical Flow and Distance of Acquisition Investments

This table presents the effects of terrorism intensity on the geographical flow of acquisition investments for *acquiring* firms and the geographical distance between the acquirer and the target firm. Specifications (1) and (2) present the estimates of probit models where the dependent variable takes the value of 1 for acquiring firms undertaking out-of-MSA (cross-border or cross-MSA) acquisition deals, and 0 otherwise. Specifications (3) and (4) present the estimates of probit models where the dependent variable takes the value of 1 for acquiring firms undertaking cross-MSA acquisition deals, and 0 otherwise. Specifications (5) and (6) present OLS estimates for the effect of terrorism intensity on the geographical distance between acquirer and target firm when involved in acquisition deals. The dependent variable is the natural logarithm of the distance between acquirer and target firm headquarters measured in kilometers. All control variables are lagged by one year. The definitions of all variables are provided in the Appendix. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The *z*-statistics and *t*-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Out-of-MSA Deals		**Cross-MSA Deals**		**Ln (Geographical Distance Between Acquirer and Target Firm)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Ln (1+Terrorism Intensity within MSA)	0.233**		0.377**		0.184*	
	(2.34)		(2.57)		(1.71)	
Ln (1+Terrorism Intensity within 100 km)		0.243**		0.374***		0.178*
		(2.41)		(2.78)		(1.87)
Acquirer Characteristics						
Ln (Market Cap)	-0.051*	-0.050	-0.018	-0.017	0.013	0.012
	(-1.67)	(-1.64)	(-0.52)	(-0.50)	(0.30)	(0.29)
Cash Holdings	0.113	0.115	0.587***	0.579***	0.144	0.144
	(0.58)	(0.59)	(3.15)	(3.13)	(0.32)	(0.32)
Leverage	-0.394	-0.391	-0.048	-0.060	0.199	0.190
	(-1.52)	(-1.51)	(-0.15)	(-0.18)	(0.43)	(0.41)
Market-to-Book	0.011**	0.011**	-0.004	-0.004	0.001	0.001
	(2.07)	(2.07)	(-0.71)	(-0.60)	(0.16)	(0.17)
Run-Up	-0.121	-0.124	-0.033	-0.033	0.079	0.083
	(-0.78)	(-0.81)	(-0.15)	(-0.14)	(0.41)	(0.43)
Industry Characteristics						
Herfindahl Index	1.278**	1.292**	1.866**	1.858**	0.205	0.209
	(2.27)	(2.29)	(2.40)	(2.41)	(0.27)	(0.27)
M&A Liquidity	0.560	0.572	0.628	0.634	0.697	0.708
	(1.34)	(1.36)	(1.49)	(1.50)	(1.18)	(1.18)
Deal Characteristics						
Diversifying	-0.156	-0.158	-0.035	-0.041	0.026	0.018
	(-1.52)	(-1.55)	(-0.29)	(-0.33)	(0.13)	(0.09)
All Cash	0.158**	0.157**	0.087	0.085	0.008	0.005
	(2.08)	(2.06)	(0.79)	(0.76)	(0.04)	(0.03)
Hostile	-0.750***	-0.749***	-0.392	-0.393	-0.268	-0.262
	(-3.03)	(-3.03)	(-1.15)	(-1.16)	(-0.89)	(-0.88)
Tender Offer	-0.154	-0.155	0.397***	0.395***	0.327*	0.329*
	(-1.53)	(-1.54)	(2.77)	(2.79)	(1.88)	(1.90)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	2,520	2,520	851	851	1,181	1,181
Pseudo R^2 (Adjusted R^2)	0.110	0.110	0.119	0.118	0.198	0.198

Table 8
Time Issues

Panel A presents the results of placebo tests related to the results in Table 4, while Panel B presents the results from probit regressions for the persistence of terrorism intensity on acquisition likelihood. In Panel A terrorism intensity variables are constructed one year before the year of the terrorist incident (*t*-1), two years before the terrorist incident (*t*-2), three years before the terrorist incident (*t*-3), and four years before the terrorist incident (*t*-4). In Panel B, the dependent variables take the value of 1 if the firm receives at least one acquisition bid in year *t*+1, year *t*+2, year *t*+3, and year *t*+4, respectively, and 0 otherwise. All control variables are lagged by one year. This table uses the same control variables as in Table 5. The definitions of the variables are provided in the Appendix. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The *z*-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Placebo Tests

	Year (*t-1*)	Year (*t*-2)	Year (*t*-3)	Year (*t*-4)	Year (*t-1*)	Year (*t*-2)	Year (*t*-3)	Year (*t*-4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln (1+Terrorism Intensity within MSA)	-0.010	0.001	-0.005	0.005				
	(-1.11)	(0.17)	(-0.74)	(0.76)				
Ln (1+Terrorism Intensity within 100 km)					-0.013	-0.011	-0.003	0.004
					(-0.35)	(-0.49)	(-0.15)	(0.18)
Control Variables of Table 5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Industry and MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	44,219	42,516	40,879	39,162	44,219	42,516	40,879	39,162
Pseudo R^2	0.039	0.040	0.042	0.044	0.040	0.041	0.042	0.044

Panel B: Persistence of Terrorism Intensity

	Year (*t+1*)	Year (*t*+2)	Year (*t*+3)	Year (*t*+4)	Year (*t+1*)	Year (*t*+2)	Year (*t*+3)	Year (*t*+4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln (1+Terrorism Intensity within MSA)	-0.115***	-0.050*	-0.033	-0.006				
	(-4.01)	(-1.96)	(-1.56)	(-0.47)				
Ln (1+Terrorism Intensity within 100 km)					-0.109***	-0.047**	-0.024	-0.017
					(-4.41)	(-2.29)	(-1.57)	(-0.69)
Control Variables of Table 5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, Industry and MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	47,709	44,784	41,304	37,931	47,709	44,784	41,304	37,931
Pseudo R^2	0.039	0.037	0.036	0.038	0.039	0.037	0.036	0.038

Table 9
Labor Productivity

This table presents the effect of terrorism intensity on labor productivity over the four-year period after the year of the terrorist attack (year *t*). The dependent variable is the ratio of firm sales to number of employees. Specifications (1) through (4) present the results for terrorism intensity within MSA and specifications (5) through (8) present the results for terrorism intensity within 100 km. All control variables are lagged by one year. The definitions of all variables are provided in the Appendix. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The *t*-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Year (*t+1*) (1)	**Year (*t*+2) (2)**	**Year (*t*+3) (3)**	**Year (*t*+4) (4)**	**Year (*t+1*) (5)**	**Year (*t*+2) (6)**	**Year (*t*+3) (7)**	**Year (*t*+4) (8)**
Ln (1+Terrorism Intensity within MSA)	-0.044**	-0.023*	0.010	0.005				
	(0.018)	(0.011)	(0.007)	(0.004)				
Ln (1+Terrorism Intensity within 100 km)					-0.040***	-0.019**	0.006	0.006
					(0.014)	(0.008)	(0.004)	(0.005)
Ln (Market Cap)	0.083***	0.084***	0.085***	0.087***	0.083***	0.084***	0.085***	0.087***
	(0.014)	(0.015)	(0.015)	(0.016)	(0.014)	(0.015)	(0.015)	(0.016)
Market-to-Book	-0.009**	-0.010**	-0.010**	-0.011**	-0.009**	-0.010**	-0.010**	-0.011**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Leverage	0.003	-0.000	-0.025	-0.031	0.004	-0.000	-0.025	-0.031
	(0.117)	(0.121)	(0.122)	(0.128)	(0.117)	(0.121)	(0.122)	(0.128)
Cash Holdings	0.016	0.036	0.066	0.101	0.017	0.036	0.066	0.101
	(0.125)	(0.129)	(0.133)	(0.137)	(0.125)	(0.129)	(0.133)	(0.137)
ROA	1.662***	1.689***	1.743***	1.828***	1.662***	1.689***	1.743***	1.828***
	(0.196)	(0.207)	(0.218)	(0.230)	(0.196)	(0.207)	(0.218)	(0.230)
MSA Unemployment Rate	-0.028	-0.026	-0.023	-0.023	-0.029	-0.026	-0.023	-0.023
	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)
Ln (MSA Population)	0.032	0.038	0.039	0.010	0.041	0.037	0.039	0.010
	(0.049)	(0.052)	(0.051)	(0.055)	(0.050)	(0.052)	(0.051)	(0.055)
Herfindahl Index	0.370	0.375	0.377	0.386	0.371	0.374	0.377	0.386
	(0.250)	(0.258)	(0.264)	(0.270)	(0.250)	(0.258)	(0.264)	(0.270)
M&A Liquidity	0.846	0.859	0.937	0.000	0.843	0.853	0.941	1.160
	(1.019)	(1.011)	(1.027)	(1.049)	(1.021)	(1.009)	(1.027)	(1.049)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	43,827	41,296	38,609	35,728	43,827	41,296	38,609	35,728
Adjusted R^2	0.319	0.319	0.320	0.322	0.319	0.319	0.320	0.322

Table 10
Heterogeneous Effects

This table presents the effects of terrorism intensity on acquisition likelihood, acquisition premium, target firm CAR, and combined firm CAR, conditioning on human capital variables (i.e., high labor productivity, high labor intensity industry, and high-skill industry) for a sample of US publicly listed firms over the period between 1996 and 2016. The dependent variable in specifications (1) through (3) is the 4-week offer premium reported by SDC, which is calculated as the difference between the offer price and the target firm's stock price four weeks before the acquisition announcement divided by the latter. The dependent variable in specifications (4) through (6) is the target firm market-adjusted cumulative abnormal return (CAR) over a 3-day event window (1, +1) around the acquisition announcement. The dependent variable in specifications (7) through (9) is the market-adjusted combined firm CAR over a 3-day event window (1, +1) around the acquisition announcement. The CRSP value–weighted market index return is used to calculate abnormal returns. Specifications (1) through (9) present estimates of OLS regressions employing the control variables used in Table 4. The dependent variable in specifications (10) through (12) takes the value of 1 if the firm receives at least one acquisition bid in year *t+1*, and 0 otherwise. Specifications (10) through (12) present estimates of linear probability models (LPM) employing the control variables used in Table 5. The definitions of all variables are provided in the Appendix. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The *t*-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Acquisition Premium			**Target Firm CAR (-1, +1)**			**Combined Firm CAR (-1,+1)**			**Receiving a Bid**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Ln (1+Terrorism Intensity within MSA)	-0.001	0.006	0.031	-0.024*	-0.018	-0.014	0.001	0.001	0.006	-0.002*	-0.002***	0.001
	(-0.02)	(0.12)	(0.50)	(-1.66)	(-1.11)	(-0.73)	(0.01)	(0.10)	(0.47)	(0.001)	(0.001)	(0.001)
High Labor Productivity	-0.038			-0.039			-0.005			0.005***		
	(-1.42)			(-1.41)			(-0.47)			(0.002)		
Ln (1+Terrorism Intensity within MSA) * High Labor Productivity	-0.103*			-0.044**			-0.030**			-0.002**		
	(-1.86)			(-1.98)			(-2.45)			(0.001)		
High Labor Intensity Industry		0.004			0.008			0.004			0.006	
		(0.08)			(0.26)			(0.29)			(0.004)	
Ln (1+Terrorism Intensity within MSA) * High Labor Intensity Industry		-0.103*			-0.048**			-0.029*			-0.003**	
		(-1.87)			(-2.17)			(-1.85)			(0.001)	
High-Skill Industry			0.047			0.014			0.007			-0.003
			(0.67)			(0.43)			(0.31)			(0.007)
Ln (1+Terrorism Intensity within MSA) * High-Skill Industry			-0.133**			-0.053**			-0.036**			-0.004**
			(-2.04)			(-2.37)			(-2.23)			(0.002)
Control Variables of Table 4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Control Variables of Table 5	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	1,007	1,007	1,007	1,388	1,388	1,388	1,007	1,007	1,007	43,840	47,709	47,709
Adjusted R^2	0.294	0.292	0.293	0.188	0.185	0.185	0.309	0.308	0.308	0.014	0.013	0.013

Table 11
Acquirer CEO Safety Uncertainty and Fear

This table presents linear regressions of the effect of CEO safety uncertainty and fear on the relation between terrorism intensity and acquisitions. The dependent variable in the OLS regressions (1) through (3) is the 4-week offer premium reported by SDC, which is calculated as the difference between the offer price and the target firm's stock price four weeks before the acquisition announcement divided by the latter. The dependent variable in the LPM regressions (4) through (6) takes the value of 1 for acquiring firms undertaking out-of-MSA (cross-border or cross-MSA) acquisition deals, and 0 otherwise. The dependent variable in the LPM regressions (7) through (9) takes the value of 1 for acquiring firms undertaking cross-MSA acquisition deals, and 0 otherwise. The dependent variable in the OLS regressions (10) through (12) is the natural logarithm of the distance between acquirer and target firm headquarters measured in kilometers. Specifications (1) through (3) employ the control variables used in Table 4. Specifications (4) through (12) employ the control variables used in Table 7. All control variables are lagged by one year. The definitions of all variables are provided in the Appendix. Year, industry, and MSA fixed effects, whose coefficients are suppressed, are based on calendar year dummies, Fama-French 48 industries classification dummies, and MSA dummies, respectively. The *t*-statistics reported in parentheses are based on standard errors adjusted for heteroscedasticity and double-clustered by firm and year. The symbols ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Acquisition Premium			**Out-of-MSA Deals**			**Cross-MSA Deals**			**Ln (Geographical Distance Between Acquirer and Target Firm)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Ln (1+Terrorism Intensity within MSA)	0.007	0.006	0.057	0.003	0.003	0.003	0.009	0.010	0.010	0.128**	0.131**	0.135**
	(0.18)	(0.16)	(0.84)	(0.77)	(0.94)	(0.84)	(0.67)	(0.77)	(0.70)	(2.12)	(2.19)	(2.06)
Non–Overconfident CEO	0.012			-0.009		-0.008	-0.016		-0.012	-0.103		-0.093
	(0.36)			(-0.86)		(-0.78)	(-0.46)		(-0.36)	(-0.45)		(-0.41)
Ln (1+Terrorism Intensity within MSA) * Non–Overconfident CEO	-0.100*			0.009**			0.024*			0.146**		
	(-1.92)			(2.45)			(1.68)			(2.45)		
Old CEO		0.021			-0.010			-0.047*			-0.118	
		(0.58)			(-0.87)			(-1.70)			(-0.67)	
Ln (1+Terrorism Intensity within MSA) * Old CEO		-0.100**			0.010***			0.024**			0.169***	
		(-1.97)			(2.85)			(2.04)			(3.23)	
Female CEO			0.284			-0.080			-0.175			-0.285
			(0.99)			(-1.13)			(-1.49)			(-0.45)
Ln (1+Terrorism Intensity within MSA) * Female CEO			-0.236**			0.019*			0.046*			0.194*
			(-2.39)			(1.89)			(1.75)			(1.69)
Control Variables of Table 4	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No
Control Variables of Table 7	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	551	551	551	2,468	2,468	2,468	815	815	815	815	815	815
Adjusted R^2	0.407	0.407	0.417	0.104	0.104	0.105	0.234	0.236	0.238	0.256	0.256	0.256