University of Freiburg
Department of International Economic Policy
Discussion Paper Series
Nr. 45

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February 2024

ISSN 1866-4113

University of Freiburg
Department of International Economic Policy
Discussion Paper Series

The Discussion Papers are edited by:
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University of Freiburg
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Editor:
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ISSN: *1866-4113*
Electronically published: 16.1.2024

The Stock Market Effects of Islamist versus Non-Islamist Terror*

by

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February 2024

Abstract

We are the first to analyze the effect of terror on stock markets by terror ideology. Surprisingly, we find that Islamist terror attacks created significant negative abnormal returns in American and European markets, but the stock market effects of other terror attacks were almost nil. For our sample of all 124 terrorist attacks in the US and Europe in the period 1994 to 2018 that caused at least five fatalities or ten injured people, we show that Islamist terror attacks are given significantly more air time (also after controlling for attack characteristics and the media pressure of competing news stories). This, however, explains only part of the differential effect of Islamist attacks on the stock markets.

JEL Codes: D74, F52, G10, G40, H56

Keywords: Terror, stock market, event studies, Islamist terror, media

* We are grateful to seminar participants at the University of Freiburg, the WEAI meetings, the European Public Choice Society Meeting (Braga) and Luis Martinez for helpful comments. All error are ours.

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1. Introduction

Terrorism has manifold effects on the economy, the polity, and the society. Of course, it causes death, physical and mental impairments (Arce 2019), and the destruction of capital and infrastructure. Even if the direct costs are small in comparison (Becker and Murphy 2001, Arce 2019), indirect effects may be sizeable. Terrorism reduces private consumption and private investment (Llussá and Tavares 2011), deteriorates consumer sentiment and reduces employment and earnings (Brodeur 2018), undermines government stability (Gassebner et al. 2008), erodes tax revenues, diverts public spending to less productive uses (Cevik and Ricco 2020), reduces social cohesion and trust (Arvanitidis et al. 2016, Bloomberg et al. 2011) and through this channel long-run growth prospects (Bjørnskov 2012). Terror may lead to outward migration especially of high-skilled people (Dreher et al. 2011) [1] and to large reallocations of foreign capital. Abadie and Gardeazabal (2008) estimate that a one standard deviation increase in terrorism risk leads to a decline of the net FDI position of five percent of GDP. All of these negative effects should affect firms' expected future income streams negatively, which in efficient capital markets should lead to an instantaneous decline in stock prices.

And yet, the decline in stock market prices in response to terror attacks is far from being an established empirical regularity. Chesney et al. (2011) find that two-thirds of the studied 77 terror attacks in 25 countries and the period 1994 to 2005 had a significant negative impact on at least one of the considered stock markets; Nikkinen and Vähämaa (2010) show that the 9/11 attacks in 2001 in NYC and Washington, the 2004 attacks in Madrid and the 2005 London attacks had significant adverse impacts on investors' sentiments at the London stock exchange. Other examples of negative stock market reactions include Chen and Siems (2004), Arin et al. (2008), Drakos (2010), and Melnik and Eldor (2010). In contrast, Brounrn and Derwall (2010) study 31 attacks involving major economies in the period 1990 to 2005 and find that, after excluding 9/11, stock market reactions are mild and limited to the event day. Goel et al. (2017) analyze all attacks with damage exceeding 1 million USD in the period 1994 to 2004 and conclude, "Overall, our results lead us to argue against a causal relationship between terrorist events and movements in financial and asset markets." (p. 132).

This divergence in results warrants to take a fresh look at this still under-researched issue. How can these contradictory results be explained? We argue that the misprison of considering the underlying terror ideology and the focus on specific, exceptional events or countries are important reasons for widely different results.

Three observations guide our empirical approach: First, investors may revise their expectations about future earnings not only on the basis of observed attack characteristics such as casualties or physical damage but also on the terror ideology as it may be decisive for the fear created and thus the extent of behavioral response and economic damage. We therefore distinguish between Islamist and non-Islamist terror. (In our robustness checks, we differentiate terror ideologies further.) Second, the media presence of terror is crucial for spreading fear (Becker and Rubinstein 2011, Akay et al. 2020) and creating the stock market reactions in response to expected behavioral changes (Melnick and Eldor 2010), in particular, because a larger media presence increases the probability of future attacks (Jetter 2017). We thus control for media presence and investigate whether Islamist terror enjoys a differentially larger media presence at the same time. Our paper thus examines whether Islamist terror attacks create larger stock market

[1] Cf. Krueger and Lindahl (2001) on the effect of education on growth.

reactions and whether part of a differential effect is explained by larger media presence. As media presence of terror attacks depends on competing news on the event day we instrument media presence by media pressure, a measure for competition for airtime on the event day (Eisensee and Strömberg 2007, Durante and Zhuravskaya 2018). Third, it makes little sense to relate terror attacks in the developing world (such as the 2008 Mumbai attack or the 2002 Bali attack) to stocks traded in London or NYC as the majority of the listed firms would not operate in the attacked country and would thus be unaffected. To include all attacks of a certain severity irrespective of their location would create a downward bias in the estimates. We therefore focus on terror responses in the major stock markets in the Western hemisphere and we include only attacks in that hemisphere.[2] In particular, we first calculate the cumulative abnormal returns (CAR) for three indexes in the US (DJIA, NYSE, S&P500) and three indexes in Europe (FTSE100, DAX, CAC40) in response to all 124 terror attacks in the period 1994 to 2018 in Europe or the US that killed at least five or injured at least ten people. We then relate the CAR to the terror ideology, attack characteristics including casualties, attack mode, suicide attacks, location, and target as well as to the media presence that these attacks received.

We find that terror affects stock markets significantly negatively and that this effect is driven by Islamist attacks. Non-Islamist attacks do not affect stock markets in any significant way. We further show that Islamist attacks receive larger media attention (after controlling for attack characteristics); yet, this larger media presence can only partly explain the differential effect that Islamist terror has on stock markets. All our results continue to hold if we exclude outlier events such as the 9/11 attacks and they are robust in a large number of other dimensions.

We make three contributions to the literature. First, we add to the literature on the effects of terror on asset markets by using an up-to-date and much larger sample of terror events than the previous cross-country analyses and by focusing on terrorism and its effects in the Western hemisphere, which makes the affected market area congruent to the area affected by terror.[3] Second, we are the first to study the differential effect of Islamist terror on economic outcomes. Thus far, terror consequences have either been studied in contexts in which the ideology behind terrorism was rather uniform (e.g. in Israel, the Basque country, etc.) or ideological differences of terror have been disregarded. By showing that this omission affects the results on the effect of terror on stock markets, our analysis links to the literature on behavioral finance and analyzes market reactions in the terror context, which with the exception of Drakos (2010) has not been studied at all. Third, our paper speaks to the political-economic literature on media by showing that Islamist terror enjoys a larger media presence than other terror, which cannot be explained by its higher lethality or the more frequent use of suicide missions. The emerging literature on terror and media has focused on the effect of media presence on future terror attacks (Jetter 2017) and on the terror group's reputation and ability to recruit (Jetter 2019a). We are the first to take the converse perspective and show that certain terror ideologies have easier access to the media. We demonstrate a differentially larger effect of Islamist terror ideology on media presence (also after controlling for attack characteristics).

[2] Our estimates would constitute a lower bound of world markets' reactions to terror, as emerging and less capitalized markets react more strongly to terror than developed capital markets (Arin et al. 2008, Kollias et al. 2011a,b) with the US market being the most resilient one (Chesney et al. 2011).

[3] Previous studies either have a narrower focus on specific attacks, countries or industries, or they relate stock market effects to all terror events worldwide of a certain severity or have a significantly smaller coverage.

Our paper proceeds as follows. Section 2 discusses why attacks motivated by different terror ideologies may have different effects on stock markets. Section 3 presents our data, Section 4 contains the event study analysis, Section 5 presents the multivariate analysis explaining, first, the CAR by attack characteristics, media presence, and Islamist ideology, and, second, media presence by Islamist ideology and attack characteristics. Third, the instrumental variable analysis for media presence is presented. Section 6 reports extensions and robustness checks, Section 7 concludes.

2. Theoretical Considerations and Relevant Literature

2.1 The terror angst

Declines in stock prices in the aftermath of terror attacks reflect the deteriorated expectations of future income of the listed firms. This economic damage is brought about by a number of behavioral changes: consumer sentiment may become gloomier, unemployment rates may increase and earnings decrease (Brodeur 2018), private consumption and private investment may decline (Llussá and Tavares 2011); terror may also deter further foreign direct investment (Abadie and Gardezabal 2008) and divert public spending towards - often economically less productive - security purposes (Cevik and Ricco 2020, Drakos and Konstantinou 2014). Terror attacks may undercut political stability (Gassebner et al. 2008), substantially change voting behavior (Montalvo 2011, Getmansky and Zeitzoff 2014), reduce civil liberties (Dreher et al. 2010), lead to out-migration, especially of high-skilled individuals (Dreher et al. 2011) and compromise social cohesion and integration efforts (Shayo and Zussman 2011, Gold and Klor 2014). These changes in behavior (and in attitudes, cf. Bozzoli and Müller 2011) are multi-dimensional and involve different sets of actors (consumers, voters, investors, government officials, etc.); they have the potential to significantly reduce the attractiveness of a country as a business location and to diminish corporate profits.

How severe these effects are depends crucially on how serious and threatening individuals *perceive* the terror attacks to be. Becker and Rubinstein (2011) argue that while the chance of being hit by a terror attack is very small, the fear that terror attacks instill can be intense and can lead to large behavioral changes. These responses differ across types of individuals and depend on media coverage and the type of the attack, e.g., suicide versus non-suicide attacks (Becker and Rubinstein 2011). A substantial body of literature shows that fears of falling victim to a terror attack are vastly exaggerated. Almost two thirds of the respondents of the World Value Survey (6th wave) from countries with Christian heritage worry "a great deal" or "very much" about terror attacks (Leite et al. 2019), even if the risk of being killed by terror attacks is miniscule in comparison.[4] For 29 OECD countries, the annual death toll from road accidents is 390 times the death toll from terror (Wilson and Thompsen 2008). Arce (2019) shows that if terror were considered a disease it would rank in the lowest decile of all 291 diseases. Relatedly, Viscusi (2009) shows that individuals value preventing deaths from terror twice as highly as preventing deaths from natural disasters. Sunstein (2003) argues that when strong emotions are involved, individuals are inclined to assess threats by their catastrophic outcomes only, disregarding the probability distribution of their occurrence. This probability neglect gives rise to overconcern and overreaction to the threat.

If, however, the terror angst – and thus the behavioral response to it – was not based on a rational risk assessment, it could well be that some terror ideologies instilled more fear than others. Islamist terror could be perceived as more menacing than other forms of terror, for instance, as it was regarded as more

[4] Almost half of the US population was worried that they or their families would be terror victims (PRRI 2015); similar evidence is provided by Haner et al. (2019).

alien than, say, left-wing or nationalistic terror. I it could instill more fear because it is driven by a relative new terror ideology compared to left or right extremist terror, which has proven to be largely ineffective in overthrowing Western governments and democracies.[5] Islamist terror could thus be perceived to pose a more systemic threat to democracy and Western values than for instance separatist, anti-abortion or white supremacy terror. Lastly, Islamist terror is more indiscriminate in its choice of targets fighting against “Western infidels” than other forms of terror that have targeted predominantly security forces and high-ranking government or industry leaders. Relatedly, terror attacks may affect investors’ sentiments beyond the rationally expected changes in future income streams and these ‘mood changes’ (Drakos 2010, Hirshleifer 2001, Shiller 2003) may depend on characteristics beyond measurable attack characteristics such as casualties, attack mode, or property damage, with the underlying ideology being the most prominent factor.

We hypothesize that *Islamist* terror attacks are more menacing in the Western hemisphere than other terror attacks and thus create larger stock market reactions. Just as terror ideology has been shown to matter for the specific grievances terror responds to (Kis-Katos et al. 2014), the *perception* of terror may depend on the underlying terror ideology as well. The omission to include terror ideology as a determining factor for the stock market reaction to terror may explain diverging results as the composition of terror by ideology has changed over time and differs across space (Kis-Katos et al. 2014).

2.2 The attacks analyzed

A second reason for diverging results may be that many of the studies focus on very few high-profile attacks, the attacks on September 11th 2001 in particular, while others consider a broad range of attacks. Chen and Siems (2004) analyze the stock market reactions to nine terrorist attacks and 5 military interventions from 1915 to 2011 and find that the US market has become more resilient over time and recovers faster than other financial markets. Maillet and Michel (2005) analyze the impact of the 9/11 attacks on the French and US stock markets using an index of market shocks (IMS) and demonstrate their long-lasting effects. This is corroborated by Charles and Darné (2006), who analyze the effect of the 9/11 attacks on 10 stock market indexes.

Other studies have focused on particularly terror-stricken countries. Abadie and Gardeazabal (2003) construct buy-and-hold portfolios for Basque and for Non-Basque firms traded on the Madrid stock exchange and show that the Basque portfolio significantly outperformed the non-Basque portfolio by ten percent during the period when the announced ETA truce became credible while the compounded abnormal returns for the Basque portfolio yielded minus 11 percent compared to the non-Basque portfolio when the ceasefire was recalled 14 months later. Eldor and Melnick (2004) find that the Tel Aviv stock market index declined substantially in response to terror in Israel from 1990 to 2003. Berrebi and Klor (2010) apply a matching procedure of Israeli and US defense companies and show that while terrorism had an adverse impact of five percent on non-defense firms’ stock prices, defense-related firms’ stocks increased by seven percent in the period January 1st 1998 to September 10th 2001. A third group of studies look at the impact of terror attacks on stocks for specific industries and finds inter alia significant negative

[5] Boumans et al. (2017) show that people more exposed to terror assess terror consequences as less severe than people with less experience. This rationale could carry over to different terror ideologies as Islamist terror is a relative recent phenomenon and their consequences were thus less known in our observation period.

repercussions for airline stocks (Drakos 2004, Kolaric and Schiereck 2018) and positive effects for the defense industry (Berrebi and Klor 2010, Apergis and Apergis 2016).

It may not be surprising that stocks of heavily affected countries and industries react negatively to terror and that selected high-profile terror attacks such as in NYC and Washington 2001 and Madrid 2004 create negative abnormal returns; yet, which picture emerges if the focus is somewhat less narrow? Does terror affect stock markets in general or only in very exceptional cases such as 9/11, Israel, or the travel industry? This is the concern of this paper. We seek to analyze whether Islamist terror gives rise to a stronger stock market reaction and whether this is (partially?) explained by the larger attention it receives in the media.

The paper closest to ours is Melnick and Eldor (2010), who show that the effect of terror on the stock market runs only through media presence.[6] As they study the Tel Aviv stock market index for 2002 only, they cannot investigate a differential effect of Islamist terror. Moreover, we find that (differential) media presence can explain only part of the (differential) effect on stock markets, and that attack characteristics and ideology affect stock market reactions beyond their effect on media presence.

3. Data

3.1 Stock Market Data

We use the world's leading stock indexes to measure stock performance in the US and Europe. Specifically, we use Dow Jones Industrial Average (DJIA), New York Stock Exchange Composite (NYSE), and S&P 500 to measure the performance of the American stock market, and DAX (Germany), CAC 40 (France), and FTSE 100 (UK) to examine the stock markets in Europe. Daily returns for each stock index between 1994 and 2018 are taken from Yahoo Finance.[7]

3.2 Terror Attacks

The data on terror attacks are obtained from Global Terror Database (GTD).[8] GTD systematically records more than 190,000 terrorist events from 1970 to 2018 and is the largest data set on terrorism that is publicly available. As GTD records a large variety of terror attacks ranging from throwing stones to the 9/11 attacks (Kis-Katos et al. 2014), we restrict our analysis to terror attacks that can reasonably be expected to affect investor sentiments. Moreover, we focus on the European and American stock markets and therefore include only terror attacks in these theaters. We thus include the universe of all attacks that satisfy the following criteria:

(1) They took place between January 1st 1994 and December 31st 2018,
(2) They occurred in the US, Western European countries, and Eastern European countries that are part of the European Union,[9]

[6] They also show that terror groups enjoy media presence for free, which has a value double the size of Proctor & Gamble's advertisement budget, the company with the world's largest advertisement budget at that time.

[7] For terror events that occurred on 01. Jan. 1994, we also collect data for 1993 to calculate the expected returns when applying event study analysis.

[8] https://www.start.umd.edu/gtd/ see also LaFree and Dugan (2007).

[9] Western European countries included in our sample are: Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom. Eastern European EU member countries included in our sample are Bulgaria, Czech Republic, Estonia, and Latvia. We thus exclude Russia and the countries in Caucasus, which are sometimes classified as European. Countries that fulfil the geographic requirement but do not have any terror attack that fulfil requirements (1) and (3) are: Austria, Cyprus, Denmark, Iceland, Ireland,

(3) They caused at least five deaths *or* at least ten injuries.

GTD records each attack as a separate terror incident even if attacks are part of an orchestrated effort to terrorize. For instance, the four 9/11 attacks – two attacks on the WTC towers, one on the Pentagon in Washington, and one leading to the airliner crash near Shanksville – are recorded as four separate attacks. While the logic for this is clear, in our context it makes sense to amalgamate these related attacks into one incident and apply the above selection criteria to this combined incident.[10] The Pittsburgh shooting on May 28, 2000, for example, was recorded as six different attacks which jointly caused five deaths; the incident is thus included in our sample. Finally, we manually examined each individual attack and adjusted false entries in the GTD such as deleting duplications and correcting the date of the attack. This results in a data set of 124 terror events. All events are listed in Table A1 in the appendix.

To estimate the effect of terror events on stock indexes, we manually match each terror event to a trading day in the different stock markets. Specifically, we first translate the local time of a terror event to the time zones of New York (GMT-5), London (GMT), and central Europe (CET). Then, we assign the terror event *i* to day *t* for market *m* if the translated time is at least one hour before the market *m* closed on day *t;*[11] otherwise, we assign the event *i* to the next trading day. If an attack occurred on weekends or bank holidays, we assign that attack to the next available trading day.[12] This exercise yields 117 unique trading days that were affected by terrorism.

We differentiate between Islamist and differently motivated terror attacks. To identify whether an attack has an Islamist background, we rely on the GTD variables such as the name of the terror group, the summary of the event, and the motivation. We label 37 terror attacks as Islamist attacks, including those carried out by well-known Islamist terror organizations such Al-Qaida and ISIL, as well as attacks conducted by unaffiliated individuals who pledged allegiance to an Islamist terror group. The classification turned out to be unambiguous in practice.

In our regression analysis, we further control for a variety of terror characteristics in addition to time period and location, which include:

(1) *Number of casualties.* Stock markets may react to the severity of a terror attack, and we thus control for the sum of death and injuries of each attack reported by the GTD. Alternatively, we used the death toll of the attack (excluding the perpetrators).
(2) *Suicide.* We include a dummy variable indicating whether an attack is a suicide attack. Suicide attacks are frequently used to attack hardened targets (Berman and Latin 2008, Piazza 2018); they are on average deadlier and demonstrate the resolve and effectiveness of terror groups (Bloom 2005) and thus might cause a larger stock market reaction.
(3) *Capital city*: Stock markets might react more strongly to attacks that targeted a capital city as they show that terrorists can hit in the political center of a country. We thus include a dummy equal to one if an attack occurred in a capital city.

Luxembourg, and Malta. However, all 25 countries that fulfil the geographical requirement (2) are studied in Section 5.7. when we analyze the Google search index.

[10] We base our amalgamation on the "related" variable in the GTD dataset. The GTD codebook describes related incidents as attacks that are part of a "coordinated, multi-part incident".

[11] We assume that if a terror attack occurred only within an hour before the market closes, investors are unlikely to fully respond to the information, and the market reaction shows only on the next trading days.

[12] This implies that one terror attack may be assigned to different trading days across the US, Germany, France, and UK.

(4) *Target gov.* The effect of terror on stock markets may depend on the target type; attacks that target the government may indicate instability of the regime, and may thus negatively affect confidence and drive away investment. GTD lists at most four different target types for each attack. In this paper, we consider attacks as targeting the government if any of the listed target types is governmental officials, diplomats, police, or military.

(5) *Target citizen*. Attacks that primarily target civilians in a public space such as mass shootings and massacres can cause massive fear and panic, reducing confidence in national security and life satisfaction. We include a dummy *Target citizen* which is one if an attack is labeled as targeting citizens and/or private property by the GTD.[13]

(6) *Target business*. Attacks that target businesses and commercial facilities including supermarkets or hotels may affect investors' perceptions about future income streams more than other terror attacks and thus cause stronger stock market reactions. This notion is inspired by Powers and Choi (2012) who find, for a panel of 123 countries from 1980 to 2008, that terror attacks reduce FDI, but only if they target business interests. We thus include a dummy variable for whether a terror attack targeted businesses, as coded by the GTD database.

(7) *Lone actor*. Lone actors may be considered particularly threatening as there is no group activity to be observed and no organization to be infiltrated and thus counterterrorism activities may find fewer entry points (although most lone actor terrorists do not come out of the blue, cf. Gill 2015). Thus, the reaction of investors may be more pronounced. We coded a dummy variable that is one if we find clear evidence that the perpetrator had no accomplices, zero otherwise. To that end, we manually checked each individual attack with the information in various news reports and internet sites such as Le Figaro, The New York Times, BBC, and The Guardian. We find 35 confirmed lone-actor attacks, of which 11 are Islamist attacks.

(8) *Attack types*. We control for different types of attacks as they may affect stock markets or attract media attention differently. For example, bombing attacks may cause more casualties (which we control for) and larger property damage (which we cannot control for) compared to other types of terror attacks; hostage-takings might attract higher media attention due to the negotiation between governments and terrorists. We code the type of attack by its primary type as labeled by the GTD.[14] If an attack includes multiple incidents, we code its type by the primary type of the incident that caused the highest number of casualties.[15]

3.3 Media Coverage and Media Pressure

For the audience to change their behavior the terrorist message needs to be reported by the media. This is why terrorists seek media attention for their attacks (Jetter 2017). We hypothesize that the more comprehensive the media reporting on the terror attack is, the more likely investors are to consider the

[13] According to GTD, this category includes "attacks on individuals, the public in general or attacks in public areas including markets, commercial streets, busy intersections and pedestrian malls". Attacks that caused casualties of passengers (labelled as target transportation or target air crafts/airports), students and teachers in schools (labelled as target educational facilities), and civilians in businesses (labelled as target business) are not included in this category.

[14] These types are: armed assault, assassination, bombing/explosion, sabotage (labelled in GTD as Facility/infrastructure attack), hijacking, hostage-taking, and unarmed assault.

[15] For example, the Breivik attack on July 22nd 2011 includes a bombing attack (in Oslo, with 23 casualties) and an armed assault (in Utoya, with 129 casualties); we thus code the main type of this combined attack as armed assault.

attack as a serious threat to business operations and thus the larger is the stock market reaction to the terror attack.

To account for this, we include a variable measuring the extent to which a terror attack was reported by the media using data from the Vanderbilt Television News Archive (VTNA). VTNA stores more than 1,200,000 news records from ABC, CBS, and NBC since 1968, CNN since 1995, and Fox News since 2004. In this paper, we use evening news stories broadcasted by ABC, CBS, and NBC; all three networks feature a 30-minute time evening news program. [16]

We measure the media coverage of an attack by the length of news stories devoted to that attack. For each TV network and for each day of the attack and one day after the attack we collected the full information of the evening news broadcast including the order of all news stories, the summary of the story, and the report length (in seconds). Next, we manually coded each news story for whether it reported the underlying terror event. We choose the day that had the longer report on the terror attack as the terror reporting day. The reason is that the terror attack could have occurred after the prime time news or if it occurred before the news, that the event was still unfolding and thus the footage was not yet reflecting the newsworthiness of the event. We then standardize the time devoted to reporting the terror attack on the reporting day by the time of news broadcast on that day.[17] Finally, we compute the average of the standardized report lengths on terror across the three TV networks. The resulting variable *TV Report* is used to measure the media coverage of each terror attack. Our results are robust to using the median of report lengths.

As an alternative measure, we record the rank order of the news story that reported the terror attacks in the prime time news because an earlier report may signal a more severe attack and may thus affect stock markets more strongly. In particular, we first compute the median rank of terror report for each terror attack across the three networks, and then generate the following categories based on whether the median rank (1) equals one, (2) equals two, (3) is equal to, or larger than three, and (4) does not exist, in which case the attack was not reported at all. We also code a dummy variable that is one if the terror attack made the lead news story of all three broadcasts.

One possible concern with our variable *TV Report* is that the actual air time devoted to the terror attacks is not only determined by the newsworthiness of the event, but also by competing events that may crowd out reports on terror events. This would be a concern if investors based their (revised) expectations on the true newsworthiness of the event, not the actual airtime devoted to the event, and that the difference between these two magnitudes would be systematic (i.e. correlated with other variables).

To account for such a possibility, we use the importance of other newsworthy events on the terror reporting day to instrument for *TV Report.* Specifically, we follow Eisensee and Strömberg (2007) and Durante and Zhurasvskaya (2018) and compute the variable *media pressure* for each reporting day and for each TV network. Premised on the notion that the allocation of airtime to newsworthy stories within a 30-minute program is a highly competitive process, the *media pressure* on the report day should negatively predict the report length on terror. To calculate *media pressure*, we divide the total report length of the top three news stories that were unrelated to the underlying terror attack by the total time of the news

[16] We refrain from using CNN data as it is a pure news channel, and Fox News since they have started operating only during our observation period.

[17] This accounts for the possibility that the actual time of evening news varies. This is particularly the case for terror report days. On September 11th 2001, for example, the evening news of NBC lasted more than 90 minutes.

broadcast on that day. Similar to the *TV Report* variable, we use the average of media pressure across the three TV networks as our preferred measurement; switching to the median, however, does not affect our results.

Table 1 reports the descriptive statistics, broken down into Islamist and other terror events. As 9/11 is an exceptional event, we provide the statistics for Islamist terror also excluding 9/11. Marked differences are apparent: Islamist terror attacks are on average more harmful than non-Islamist attacks, as measured by the sum of deaths and injuries. Although excluding the 9/11 attacks substantially decreases the difference in casualties, the difference is still significant at the five percent level. Additionally, Islamist attacks are more likely to be suicidal, more likely to target capitals (although the difference is insignificant after dropping the 9/11 attacks), and last but not least, receive higher media attention.

4. Event Study Approach

4.1. Selected terror attacks and their effects on the stock market

We first provide anecdotal evidence on stock market reactions to four notorious terror attacks in history, two Islamist and two non-Islamist, the 9/11 attacks, the 2005 London train bombing, the 2011 Breivik attacks in Norway, and the Oklahoma City bombing in 1995. The latter two are the deadliest non-Islamist attacks in our sample (77 and 168 deaths respectively). For comparability, the three stock indexes NYSE, CAC, and FTSE are normalized to 100 on the day preceding the attacks.

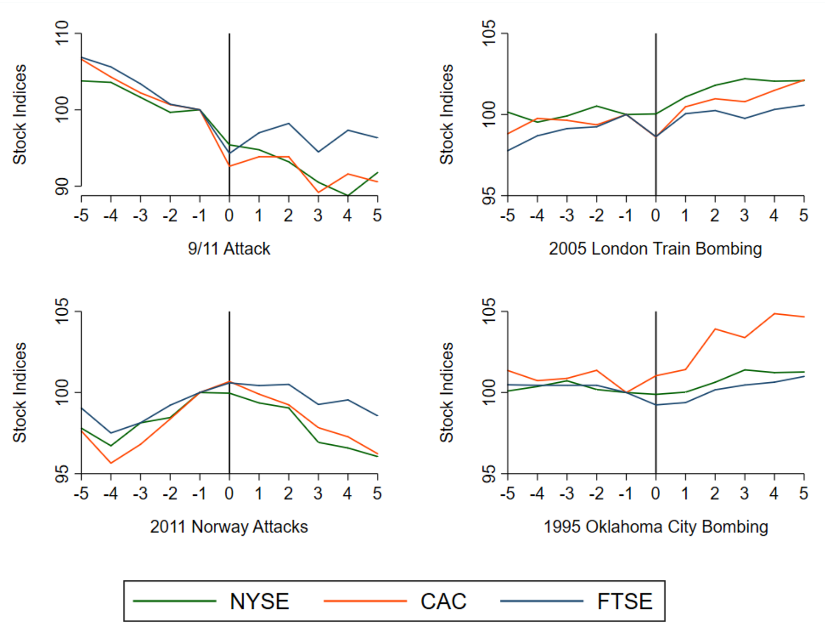
The dichotomous reactions of stock markets to the selected Islamist and non-Islamist attacks are apparent, as shown in Figure 1. Specifically, after the 9/11 attacks, NYSE, CAC, and FTSE fell dramatically by four to seven percent. The European markets responded negatively also to the London train bombing, but the American market remained almost stable. In contrast, we observe no sharp decrease in stock indexes after the Breivik and Oklahoma attacks. The NY market did not react and some European stock indexes actually increased on the day of the attack (CAC and FTSE after the Norway attack, and CAC after the Oklahoma bombing). Are stock market reactions to Islamist attacks different in general, and if so, why? This is explained in the following analyses.

Table 1 Descriptive Statistics

Variables	Mean			Mean Difference	
	Islamist attack		non-Islamist attacks		
	Full events	Exclude 9/11		Full events	Exclude 9/11
Casualties	825.162	157.111	51.345	773.817*	105.766**
	(4079.305)	(362.728)	(132.074)	[435.463]	[44.514]
Suicide	0.189	0.167	0.069	0.120**	0.098*
	(0.397)	(0.378)	(0.255)	[0.060]	[0.059]
Lone actor	0.297	0.306	0.276	0.021	0.030
	(0.463)	(0.467)	(0.450)	[0.089]	[0.090]
Capital city	0.486	0.472	0.322	0.164*	0.150
	(0.507)	(0.506)	(0.470)	[0.094]	[0.095]
Target gov.	0.270	0.250	0.402	-0.132	-0.152
	(0.450)	(0.439)	(0.493)	[0.094]	[0.095]
Target citizen	0.486	0.472	0.437	0.050	0.035
	(0.507)	(0.506)	(0.499)	[0.098]	[0.099]
Target business	0.216	0.194	0.149	0.067	0.045
	(0.417)	(0.401)	(0.359)	[0.074]	[0.074]
TV report	0.296	0.277	0.085	0.211***	0.193***
	(0.253)	(0.229)	(0.167)	[0.039]	[0.037]
Europe	0.676	0.694	0.770	-0.094	-0.076
	(0.475)	(0.467)	(0.423)	[0.086]	[0.086]
Obs.	37	36	87	124	123

Notes: Standard deviations are reported in parentheses while standard errors of estimated mean differences are reported in brackets.

*** p<0.01, ** p<0.05, * p<0.1



Notes: These figures show the changes of stock indices (NYSE, CAC40, and FTSE10) after each of the two Islamist (the 9/11 attack and 2005 London train bombing) and two non-Islamist (1995 Oklahoma City bombing and 2011 attack in Norway) terror attacks. The abscissa represents the number of days before and after the attack, and the ordinate represents the value of the stock index normalized to 100 on the day preceding the attacks.

Figure 1 Stock Market Effects of Selected Attacks

4.2. Methodology

First, we analyze all attacks as single events and calculate the (cumulative) abnormal returns following the terror attack. Figure 2 shows the timeline of the event study approach used in this paper.

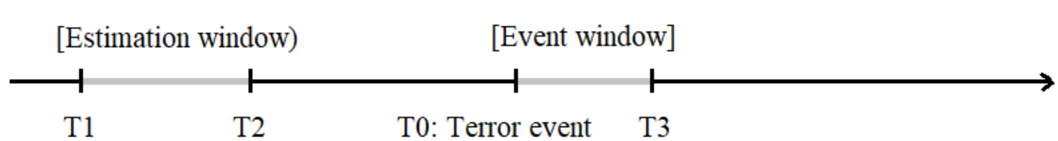


Figure 2 Event Study Timeline

We calculate daily abnormal returns for the terror event *i* at day *t*, including the following days, using the mean-adjusted model:

$$AR_{imt} = R_{imt} - \overline{R_m}$$

where AR_{imt} is the abnormal return for stock index *m* at time *t*, R_{imt} is the actual rate of return for index *m* at time t. $\overline{R_m}$ is the expected return of market m, which is the mean of returns in the estimation window from T1 = *t* - 60 to T2 = *t* -11 relative to the terror date.[18] Specifically, it is calculated as:

$$\overline{R_m} = \frac{1}{50} \sum_{T1=-60}^{T2=-11} R_{mt}$$

To examine how the market reacts to terror over a longer period of time, we set up event windows from T0, i.e. the date at which a terror event took place, to τ (τ ∈ (T0,T3]), and calculate the cumulative abnormal returns and their variances:

$$CAR_{im}(T0, \tau) = \sum_{t=T0}^{\tau} AR_{imt}$$

$$\sigma^2(CAR_{im}(T0, \tau)) = (\tau - T0 + 1)\sigma_m^2$$

where σ^2_m is the variance of historical average returns, i.e. the variance of returns during the estimation window. $\tau - T0 + 1$ denotes the period of aggregation.

Finally, we calculate the average effect across all Islamist and non-Islamist terror events for each of the six stock indices. The average cumulative abnormal return, $\widehat{CAR(T0, \tau)}$, and its variance are given by:

$$CAR\widehat{_{im}(T}0, \tau) = \frac{1}{N} \sum_{i=1}^{N} CAR_{im}(T0, \tau)$$

$$\sigma^2(CAR\widehat{_{im}(T}0, \tau)) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma^2(CAR_{im}(T0, \tau))$$

where *N* denotes the number of Islamist or non-Islamist attacks. Under the assumption of a normal distribution of stock returns, we can test the statistical significance of average cumulative abnormal returns following a normal distribution of mean 0 and variance σ^2.

4.3. Event study results

Table 2 shows the average cumulative abnormal returns for three event windows (τ equals 0, 3, and 6, respectively) in US and European markets. We find that Islamist terror attacks overall created significantly negative abnormal returns. For example, the Dow Jones Industrial Average index shows an abnormal return of -0.4 percentage points immediately after an Islamist attack occurred, which is significant at the one percent level. The effect increases in absolute value to -0.6 percentage points three days and to -0.7 percentage points six days after the attack. European markets show a similar pattern; the effects are initially larger but become less statistically significant when using longer event windows. Specifically, none of the European stock markets reports significant average cumulative abnormal returns during the six-day event window; in the UK, Islamist attacks had an impact only on the event day.

[18] Days used in our event study are always defined as trading days.

In contrast, after non-Islamist attacks, the average cumulative abnormal returns have almost all positive signs, and some of the positive abnormal returns are even significantly different from zero. That could be the case if returns continued to accelerate despite the terror attack. In five cases more than one terror event occurred on the same day, which may affect the computation of abnormal returns and standard errors. Thus, we have excluded these ten overlapping terror events in one robustness check (as shown in Table A2), which did not affect the main results.

Table 2 Baseline Event Study Analysis

	Islamist 37 attacks/36 event days			**Non-Islamist** 87 attacks/84 event days		
	MEAN	**SD**	**P-value**	**MEAN**	**SD**	**P-value**
DJIA						
$\widehat{CAR}$ [0,0]	-0.370***	0.126	0.003	-0.010	0.113	0.952
$\widehat{CAR}$ [0,3]	-0.567**	0.251	0.024	0.581***	0.226	0.002
$\widehat{CAR}$ [0,6]	-0.732**	0.332	0.028	0.504**	0.299	0.031
NYSE						
$\widehat{CAR}$ [0,0]	-0.326**	0.128	0.011	-0.018	0.111	0.989
$\widehat{CAR}$ [0,3]	-0.513**	0.257	0.046	0.527***	0.221	0.004
$\widehat{CAR}$ [0,6]	-0.550	0.340	0.106	0.310	0.293	0.124
S&P 500						
$\widehat{CAR}$ [0,0]	-0.300**	0.129	0.020	-0.047	0.118	0.793
$\widehat{CAR}$ [0,3]	-0.506*	0.258	0.050	0.494***	0.235	0.008
$\widehat{CAR}$ [0,6]	-0.647*	0.341	0.058	0.289	0.311	0.139
DAX						
$\widehat{CAR}$ [0,0]	-0.631***	0.183	0.001	0.137	0.150	0.359
$\widehat{CAR}$ [0,3]	-0.733**	0.365	0.045	0.848***	0.299	0.005
$\widehat{CAR}$ [0,6]	-0.689	0.483	0.154	0.632	0.396	0.110
CAC 40						
$\widehat{CAR}$ [0,0]	-0.516***	0.188	0.006	0.104	0.145	0.473
$\widehat{CAR}$ [0,3]	-0.687*	0.375	0.067	0.943***	0.290	0.001
$\widehat{CAR}$ [0,6]	-0.731	0.497	0.141	0.660*	0.384	0.086
FTSE 100						
$\widehat{CAR}$ [0,0]	-0.315**	0.146	0.031	0.019	0.118	0.875
$\widehat{CAR}$ [0,3]	-0.385	0.292	0.187	0.448*	0.237	0.058
$\widehat{CAR}$ [0,6]	-0.427	0.386	0.269	0.179	0.313	0.568

Notes: The total number of event days is 120 (36 Islamist event days and 84 non-Islamist event days). Average cumulative abnormal returns are reported under columns “Mean”, times 100. P-values calculated under the normality assumption are reported under columns “P-value”.

*** p<0.01, ** p<0.05, * p<0.1

Our results thus support the notion that stock markets react very differently to Islamist and non-Islamist terror. However, (some) Islamist attacks could have a negative impact on stock markets as opposed to non-Islamist attacks because they are deadlier or because they use suicide terrorists more often, not because they are Islamist attacks as such. Relatedly, Islamist terror attacks could affect stock markets negatively, not because investors care about the motivation behind the attacks, but because they generate more media attention and thereby affect investors’ sentiments more profoundly. This aspect is investigated next.

5. Multivariate Analysis

5.1. Empirical Strategy

To examine *why* Islamist attacks lead to negative stock market performance, we rely on an OLS estimation using our sample of 124 terror attacks. Intuitively, we compare the cumulative abnormal returns affected by Islamist and non-Islamist terror attacks, controlling for characteristics of each attack. The regression equation is as follows:

$$\widehat{CAR_i(T0,\tau)} = \alpha + \beta_1 * Islamist_i + \beta_2 TV\ report_i + \boldsymbol{X'}_i\delta + \gamma_t + Euro_i + Type_i + \varepsilon_{it} \qquad (1)$$

where $\widehat{CAR_i}$ denotes the average cumulative abnormal returns across six markets on the event day of attack *i* or during the event window. *Islamist* is the independent variable of interest, which equals one if the attack *i* is an Islamist attack and zero otherwise; the coefficient of interest, β_1, thus captures the difference of $\widehat{CAR}$s between Islamist and non-Islamist attacks after controlling for different characteristics of the attack. To account for the effect of media coverage on investor perceptions, we include the report length of every attack, denoted by *TV report*. Terror event characteristics reported in Section 2 are included in $\boldsymbol{X}_{i,}$. Finally, γ_t is the 5-year interval time fixed effects, *Type* is the full set of dummy variables denoting the main type of an attack, and *Euro* is a dummy variable indicating if an attack occurred in Europe.

A differential effect of Islamist terror on stock market performance could be caused by biased media coverage that reports more extensively on Islamist terror than on other terror (after controlling for different attack characteristics). However, apart from investigating a potential channel for a dichotomous stock market reaction, a media bias in favor of Islamist terror would be interesting in itself, not only because it is a variant of the media bias not analyzed hitherto.[19] Media bias has been analyzed in the context of political competition; one instrument of the media is the amount of coverage devoted to an issue, which is intended to influence the importance viewers ascribe to the issue. In our case, the dimension of political competition is less obvious even though terror has been shown to affect voting behavior (e.g., Berrebi and Klor 2008, Montalvo 2011), but a differential coverage of Islamist terror may

[19] Gentzkow et al. (2015) survey the theoretical literature, Puglisi and Snyder (2015) survey the empirical analyses on media bias.

likewise affect the perceived importance of Islamist terror attacks as compared to attacks motivated by other ideologies. We are the first to study this differential effect.

Moreover, a larger media coverage of Islamist terror would fuel future Islamist terror attacks disproportionally and thereby make this terror more effective than other terror. Jetter (2017, 2019a) shows that large media coverage leads to more attacks and higher online popularity of the terror group. A differential effect of Islamist versus non-Islamist terror attacks on media coverage adds to our understanding of the intricate relationship between terror groups and the media and contributes to an emerging literature on that topic (Melnick and Eldor 2010, Jetter 2017, 2019a).

To investigate a possible media bias in favor of Islamist terror attacks we run the following regression model:

$$TV\ report_i = \vartheta_1 + \vartheta_2 * Islamist_i + \boldsymbol{X'}_i\mu + \gamma_t + Euro_i + Type_i + \varepsilon_{it} \qquad (2)$$

We control for attack characteristics because Islamist terror is more deadly (Kis-Katos et al. 2014) and uses suicide terror more often (see also Table 1), which has been shown to generate more news coverage (Jetter 2019b). The parameter estimate of interest is ϑ_2.

As the extent of media reporting depends on competing newsworthy events (see Section 2), we instrument *TV report* by media pressure and estimate the following first-stage regression:

$$TV\ report_i = \theta_1 + \theta_2 * Media\ pressure_i + \theta_3 * Islamist_i + \boldsymbol{X'}_i\pi + \gamma_t + Euro_i + Type_i + \varepsilon_{it} \qquad (3)$$

This will give us the TV report length after accounting for the intensity of media pressure. If investors changed their expectation not based on the actual coverage, but on what it would be with an average media pressure, i.e. based on the 'true newsworthiness', the instrumental variable approach would provide us with a better measure of media presence.

5.2. Stock Market Results

The main results of the OLS analysis are reported in Table 3. Column (1) shows that Islamist terror attacks are associated with a 0.6 percentage point negative abnormal return on the event day, which is statistically significant at the one percent level. Once *casualties* (measured in 100 casualties in the OLS regressions) is controlled for, the estimated coefficient drops to 0.4 percentage points, echoing the evidence in Table 1 that Islamist terror attacks are deadlier (column 2).

Casualties are negatively and significantly associated with abnormal returns - 100 more deaths or injuries lead to a decrease of the average abnormal return by 0.03 percentage points on the event day. This result suggests that deadlier attacks affect investors' sentiments more negatively. In column (3), we include the full set of controls –the effect of Islamist attacks remains highly significant and even increases in (absolute) magnitude to -0.5. The same is true for the effect of the number of casualties. All other attack characteristics do not affect the stock index in any significant way (except for *capital city*, which seems to be positively related to abnormal returns in this specification). In particular, media coverage does not influence the event day abnormal return at usual significance levels.

Table 3: Baseline Results

Dependent variable: Cumulative average abnormal returns across all markets *100									
	CAAR[0,0]			CAAR[0,3]			CAAR[0,6]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Islamist	-0.557***	-0.381**	-0.452***	-1.444***	-1.139**	-1.280***	-1.097**	-0.814	-1.162**
	(0.205)	(0.171)	(0.169)	(0.484)	(0.454)	(0.425)	(0.543)	(0.536)	(0.526)
Casualties		-0.026***	-0.023***		-0.045***	-0.040***		-0.041***	-0.042***
		(0.001)	(0.003)		(0.005)	(0.009)		(0.007)	(0.009)
TV report			-0.648			1.590			3.056*
			(0.518)			(1.331)			(1.757)
Suicide			0.366			-0.366			-0.081
			(0.321)			(0.789)			(0.664)
Lone actor			0.069			0.222			0.277
			(0.167)			(0.462)			(0.572)
Capital city			0.343*			-0.421			-0.206
			(0.193)			(0.473)			(0.592)
Target gov.			-0.204			-0.149			-0.132
			(0.204)			(0.482)			(0.543)
Target citizen			-0.260			-0.871*			-0.679
			(0.200)			(0.514)			(0.588)
Target business			-0.396			-0.572			-0.849
			(0.266)			(0.617)			(0.716)
Observations	124	124	124	124	124	124	124	124	124
R-squared	0.206	0.402	0.461	0.153	0.273	0.311	0.154	0.230	0.270
Type dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Europe dummy.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions with robust standard errors reported in parentheses. Dependent variables are average cumulative abnormal returns in the event windows [0,0] (columns (1)-(3)), [0,3] (columns (4)-(6)), [0,6] (columns (7)-(9)).

*** p<0.01, ** p<0.05, * p<0.1

5.3 Terror and Media

We estimate equation 2 on the determinants of media reporting of major terror attacks in the European and North American theaters. In columns (1) – (7) of Table 4, we regress *TV Report* on each of our control variables in addition to the Islamist dummy. Consistent with the descriptive evidence in Table 1, we find that Islamist attacks are covered more extensively, and that the difference is economically and statistically significant. In column (1), Islamist attacks are reported one-half of a standard deviation longer. The number of c*asualties* likewise increases airtime significantly, but the magnitude is relatively small. Suicide attacks attract significantly higher media attention, which is in line with findings by Jetter (2019b). The magnitude is even slightly larger than the Islamist effect. Lastly, the European dummy is always negative and significant (not reported in the table), which is not surprising because terror attacks on American soil are likely to be reported more extensively by the US media.

When we control for all attack characteristics simultaneously, the estimated coefficient of the Islamist dummy drops slightly to 0.1 but remains significant at the one percent level. Our results for media presence thus parallel those for the stock markets in Table 3: Islamist attacks receive higher media coverage for reasons not fully explained by the characteristics of attacks.

As discussed in Section 2.3., the effect of media coverage on stock markets can be biased if investors evaluate the influence of a terror attack based on the true newsworthiness of the event, taking into account that other competing news might reduce the report length of terror. It is quite plausible that rational investors would see through the rationale of TV networks' newsrooms.

To account for this, we use media pressure of the terror report day to instrument the report length of terror events (equation 3). We use both the average and the median measure of media pressure to ensure that the results are not driven by a specific measurement concept (or outliers).

In the first-stage regressions reported in Table 5, we show that media pressure, regardless of whether we use mean or median measurement, negatively affects the report length on the terror event on the report day (columns 1 and 3). This result supports our hypothesis that the allocation of terror-related news depends highly on the newsworthiness of other unrelated news (also if the characteristics of terror attacks are controlled for).

Columns (2) and (4) report second-stage results. The effect of media coverage turns out significant at the ten percent level and increases in absolute value to 1.7 (column 2), which is more than double the baseline effect; a one-standard-deviation increase of normalized media coverage (which is approximately 22% increase of coverage in a broadcast) decreases the abnormal return by 0.3 standard deviations. Using median report length yields quantitatively similar results. The coefficient of the Islamist dummy remains significant at the five percent level and reduces somewhat in magnitude to -0.35. When taking into account that media coverage depends on news pressure, we show that larger media coverage of Islamist attacks partly explains why Islamist terror has a negative effect on stock markets; yet our result is confirmed that even after accounting for the differentially larger media coverage of Islamist terror and their different attack characteristics Islamist terror reduces stock market values even more than 'other' terror.

Table 4 Islamist Attacks and Media Coverage

Dependent variable: TV Report (Mean:0.148, Std.Dev: 0.219)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Islamist	0.108***	0.117***	0.122***	0.117***	0.125***	0.128***	0.125***	0.099***
	(0.037)	(0.037)	(0.039)	(0.040)	(0.039)	(0.039)	(0.039)	(0.037)
Casualties	0.003***							0.002***
	(0.001)							(0.001)
Suicide		0.126*						0.086
		(0.065)						(0.065)
Lone actor			-0.036					-0.025
			(0.041)					(0.036)
Capital city				0.032				0.021
				(0.022)				(0.020)
Target gov.					-0.008			-0.009
					(0.027)			(0.028)
Target citizen						0.045		0.030
						(0.028)		(0.032)
Target business							-0.018	-0.035
							(0.043)	(0.042)
Observations	124	124	124	124	124	124	124	124
R-squared	0.665	0.650	0.628	0.628	0.625	0.633	0.625	0.689
Type dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Europe dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions with robust standard errors reported in the parentheses. Dependent variable is *TV Report*, measured by the average report length of terror events across ABC, NBC, and CBS, normalized by the total length of the broadcast.

*** p<0.01, ** p<0.05, * p<0.1

Table 5 Instrumenting Media Coverage

Instruments:	Mean media pressure		Median media pressure	
	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)
Media pressure	-0.876***		-0.839***	
	(0.141)		(0.136)	
Islamist	0.069**	-0.352**	0.066**	-0.341**
	(0.028)	(0.172)	(0.029)	(0.171)
TV report		-1.651*		-1.766*
		(0.924)		(0.983)
F-statistics	38.654		37.982	
Observations	124	124	124	124
R-squared	0.795	0.446	0.793	0.443
Controls	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Europe dummy	Yes	Yes	Yes	Yes

Notes: 1st stage regressions are reported in columns (1) and (3), where the outcome variable is *TV Report*. "F-statistics" is the Kleibergen-Paap rk Wald F statistic for weak identification test. 2nd stage regressions reported in columns (2) and (4), where the dependent variable is average abnormal return on day 0. *TV report* is instrumented by *Media pressure*. *Controls* refer to *casualties, suicide, lone actor, capital city, target gov., target citizen,* and *target business*. Robust standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

6. Robustness Checks and Extensions

We now demonstrate the robustness of our two central results on stock markets' response to and media attention to Islamist versus non-Islamist terror.

6.1. Islamist Attacks and Media Measurements

First, we investigate whether the use of alternative media measurements affects our results on stock markets. Results are reported in Panel A of Table 6. Specifically, we use a dummy variable that equals one if a terror event was reported by any of the three networks (TV report_dummy, column 1), the median measurement of TV report (column 2), the rank of terror report in the news (column 3) and the dummy indicating that the terror event made the lead news (column 4). Consistent with the baseline results in Table 3, our findings in Panel A show a negative sign and a similar magnitude of various measures for media presence, which do not reach usual significance levels either. Results on the Islamist dummy remain unaffected in sign, significance, and magnitude by the use of alternative media measures.

In Panel B, we regress various media variables on the Islamist dummy and the other controls and find that Islamist attacks are more likely to be reported (column 5), and are reported with longer airtime as measured by the median report length (column 6). Using an ordered logit regression in column (7) in which the dependent variable is the rank of terror report, we find that Islamist attacks are more likely to be reported by an earlier news segment, although the effect is not significant at usual levels. Finally, we show that Islamist attacks are significantly more likely to be reported as the lead news (column 8).

5.2. Islamist Attacks and Casualties Measurements

Our evidence suggests that the number of casualties can have a significant effect on stock markets and media coverage. This subsection further extends our measurements of casualties. In panel A of Table 7, we show that alternative measurements of casualties do not change our results on the stock market effects of Islamist attacks. Specifically, column (1) controls for the number of deaths (rather than casualties), column (2) repeats column (1) but excludes killed terrorists from the fatalities, column (3) controls for the number of injuries, and column (4) controls for both fatalities and injuries. The coefficient of the Islamist dummy varies only slightly and remains significant at the five percent level. As reported in panel B, the 1st stage results show that Islamist attacks attract higher media attention regardless of the choice of casualty measurements in the regression model.

Table 6: Robustness on media

Panel A, DV: Average abnormal return on day 0				
	(1)	(2)	(3)	(4)
Islamist	-0.497***	-0.437**	-0.500***	-0.447***
	(0.178)	(0.169)	(0.182)	(0.168)
TV report_dummy	-0.053			
	(0.206)			
TV report_median		-0.801		
		(0.516)		
1st rank report			-0.149	
			(0.247)	
2nd rank report			0.130	
			(0.268)	
3rd rank report			-0.059	
			(0.277)	
Lead news				-0.314
				(0.244)
Observations	124	124	124	124
R-squared	0.455	0.465	0.460	0.462
Panel B: Islamist terror and media				
	(5)	(6)	(7)	(8)
DV:	TV Report dummy	TV Report median	Rank	Lead news
	(5)	(6)	(7)	(8)

Islamist	0.378***	0.100**	-1.398	0.218**
	(0.096)	(0.040)	(0.879)	(0.087)
Observations	124	124	124	124
R-squared	0.516	0.666	0.401	0.583
Controls	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Europe dummy	Yes	Yes	Yes	Yes

Notes: OLS regressions with robust standard errors reported in the parentheses (except for column (7)). The dependent variable in panel A is the average abnormal return on day 0, while in Panel B the dependent variables are alternative measurements of media coverage. In particular, column (7) reports results using an ordered logistic regression where regression coefficients and a pseudo R^2 are reported. *Controls* refer to *casualties, suicide, lone actor, capital city, target gov., target citizen,* and *target business*.

*** p<0.01, ** p<0.05, * p<0.1

Table 7 Robustness on Casualties

Panel A: Second-stage of IV regressions, DV: Average abnormal return on day 0				
	(1)	(2)	(3)	(4)
Islamist	-0.356**	-0.356**	-0.352**	-0.345**
	(0.173)	(0.173)	(0.172)	(0.174)
TV Report	-1.671*	-1.674*	-1.648*	-1.597*
	(0.923)	(0.923)	(0.924)	(0.924)
#Deaths	-0.170***			0.703
	(0.034)			(0.580)
#Deaths of victims		-0.171***		
		(0.034)		
#Injuries			-0.024***	-0.120
			(0.005)	(0.078)
Observations	124	124	124	124
R-squared	0.441	0.441	0.447	0.459
Panel B: First-stage regressions, DV: TV Report				
	(5)	(6)	(7)	(8)
Islamist	0.068**	0.068**	0.069**	0.071**
	(0.028)	(0.028)	(0.028)	(0.029)
Media pressure	-0.875***	-0.876***	-0.876***	-0.885***
	(0.141)	(0.141)	(0.141)	(0.144)

Observations	124	124	124	124
R-squared	0.797	0.797	0.795	0.804
Controls	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Europe dummy	Yes	Yes	Yes	Yes

Notes: 2nd stage results of IV regressions are reported in panel A while 1st stage results are reported in panel B. *TV report* is instrumented by *Media pressure. Controls* refer to *suicide, lone actor, capital city, target gov., target citizen,* and *target business.* Column (1) controls for the number of deaths caused by a terror attack. Column (2) controls for the total deaths excluding the number of killed terrorists. Column (3) controls for the number of injuries, columns (4) controls for both fatalities and injuries. All casualty measures are divided by 100. Robust standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

6.3 Outliers

As discussed in Section 3, the average effect of Islamist attacks on abnormal returns may be driven by certain "high-profile" Islamist terror attacks. To test this possibility, estimations reported in Table 8 drop each of such attacks individually (columns (1)-(4)).

We start by excluding the 9/11 attacks in column (1). The effect of Islamist attacks remains almost unchanged, suggesting that our baseline results are not driven by the deadliest terror attack in history. Columns (2) – (4) further drop the Madrid train bombing, the London train bombing, and the Boston Marathon bombing, which caused a total number of casualties of 1991, 840, and 267, respectively. The effect of Islamist attacks varies from -0.312 to -0.357 and still remains significant.

The 1st stage results in panel B show that Islamist attacks continue to receive higher media attention regardless of the severity of the attacks, but higher media attention cannot fully explain the stock market effect of Islamist attacks.

6.4 Propensity score matching

To what extent can the effect of terror on stock markets be explained by the Islamist background as such, rather than characteristics associated with Islamist attacks? For example, one concern might be that the Islamist attacks negatively affect stock markets because they are deadlier and more often reported by the media (which they are, see Table 1), not because of the religious motivation of the attacks. To address this concern in a different way than before, in this section we use propensity score matching (PSM) to compare the outcome for terror attacks that are highly similar and differ only in the Islamist ideology.

Specifically, we match Islamist and non-Islamist terror attacks using a set of matching variables. This includes *casualties* and *suicide* because Islamist attacks are reported to be more deadly and suicidal. To ensure that the difference in media reporting between Islamist and non-Islamist attacks is not driven by a systematic difference in media pressure associated with the two types of terror, we add media pressure to the set of matching variables. Finally, we include the Europe dummy and year period dummies, which enables us to compare events within the same period and theater. We perform both radius and kernel matching techniques and make use of the common support condition to improve the quality of the matching.

As reported in Table A.3, the PSM provides a highly balanced sample of terror attacks. Compared to the unmatched sample reported in Table 1, the differences in casualties, suicide attacks, and media pressure between Islamist and non-Islamist attacks reduce dramatically and become insignificant for both matching techniques.

Combining the PSM and IV technique, column (2) of Table 9 shows that the stock market effect of Islamist attacks reduces to -0.298, which is significant at the ten percent level. The effect of media coverage, on the other hand, increases to -1.845 and becomes significant at the five percent level. 1st stage results (columns 1 and 3) are consistent with previous findings: Islamist attacks are associated with higher media attention. Finally, the two matching techniques yield qualitatively similar results.

To show that the results persist when using alternative matching methods, we provide results with Coarsened Exact Matching (CEM). Instead of relying on a logistic regression estimation that predict the treatment in PSM, CEM coarsens continuous variables and therefore ensures exact matching based on the selected matching variables. In columns (1) and (2) of Table A4, we report the first and second stage of regression results using CEM based on the same set of matching variables used in our PSM estimations. Columns (3) and (4) present results using year instead of period as a matching variable, allowing for a more accurate matching regarding the time of attacks. The CEM results reported in Table A4 are consistent with our baseline findings, even though this more accurate matching approach largely reduces the total number of attacks to around 60.

Table 8: Excluding Outlier Events

Drop outliers:	9/11 attacks	Madrid train bombing	London train bombing	Boston Bombing
Panel A: 2nd stage of IV regressions, DV: Average abnormal return on day 0				
	(1)	(2)	(3)	(4)
Islamist	-0.357**	-0.312*	-0.357**	-0.332**
	(0.169)	(0.168)	(0.172)	(0.168)
TV Report	-1.767*	-1.614*	-1.770*	-1.471
	(1.062)	(0.908)	(1.015)	(0.937)
Observations	123	123	123	123
R-squared	0.206	0.437	0.443	0.451
Panel B: 1st stage regressions, DV: TV Report				
	(5)	(6)	(7)	(8)
Islamist	0.056**	0.067**	0.061**	0.067**
	(0.026)	(0.029)	(0.028)	(0.029)
Media pressure	-0.778***	-0.874***	-0.819***	-0.867***
	(0.137)	(0.142)	(0.135)	(0.145)

Observations	123	123	123	123
R-squared	0.796	0.795	0.799	0.786
Controls	Yes	Yes	Yes	Yes
Period dummies.	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Europe dummy.	Yes	Yes	Yes	Yes

Notes: 2nd stage results of IV regressions are reported in panel A while 1st stage results are reported in panel B. *TV report* is instrumented by *Media pressure. Controls* refer to *casualties, suicide, lone actor, capital city, target gov., target citizen,* and *target business*. Columns (1)-(4) exclude the observation of 9/11 attacks, Madrid train bombing, London train bombing, and Boston marathon bombing, respectively. Robust standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.

Table 9 Using Propensity Score Matching

Matching:	Kernel		Radius	
	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)
ISLAMIST	0.068***	-0.298*	0.066***	-0.313*
	(0.024)	(0.175)	(0.024)	(0.174)
TV report		-1.845**		-1.826**
		(0.874)		(0.876)
Media pressure	-1.207***		-1.205***	
	(0.155)		(0.158)	
Observations	121	121	97	97
R-squared	0.850	0.370	0.850	0.373
Controls	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Europe dummy	Yes	Yes	Yes	Yes

Notes: IV regression results using propensity score matching with the common support condition. Kernel matching is used in columns (1) and (2), whereas radius marching is used in columns (3) and (4). Matching variables are *casualties,* *suicide, Europe, media pressure*, and *period. TV report* is instrumented by *Media pressure.* Columns (1) and (3) are 1st stage regressions where the dependent variable is TV report. Columns (2) and (4) are 2nd stage regressions where the dependent variable is average abnormal return on day 0. *Controls* refer to *casualties, suicide, lone actor, capital city, target gov., target citizen,* and *target business*. Robust standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

6.5. Placebo Analysis

Although it is very unlikely that investors predicted an Islamist terror attack and adjusted their behavior accordingly, Islamist groups might have timed their attack during economic downturns (but the other terror groups might have not). If that were the case, our benchmark results might capture a spurious relationship between Islamist terrorism and a negative stock market performance.

To show that this is not a concern in our study, we use a placebo event study which resets the event date of each terror attack ten days prior to the actual date. If a significant and negative abnormal return after a "placebo Islamist attack" is still present in the placebo design, we could no longer distinguish the Islamist effect from other unobserved factors in the stock market. Table A4, however, shows no negative abnormal returns ten days before an Islamist terror attack, suggesting a genuine stock market effect of Islamist terrorism.

Furthermore, we re-estimate the OLS and IV models using the abnormal returns calculated in the placebo exercise as the dependent variable. As shown in Table 10, the abnormal returns ten days before Islamist and non-Islamist terror attacks are not statistically different from zero (columns (1) and (2)). The IV result in column (3) shows that the difference is not only insignificant but also quantitatively very small (-0.009), which once again confirms our expectation.

Table 10 Placebo Analysis

DV: Average abnormal return 10 days prior to the terror attack			
	(1)	(2)	(3)
Islamist	0.029	0.057	-0.009
	(0.199)	(0.191)	(0.177)
TV report		-0.279	0.380
		(0.589)	(0.823)
Observations	124	124	124
R-squared	0.179	0.180	0.172
Controls	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes
Europe dummy	Yes	Yes	Yes

Notes: Abnormal return in this table is calculated based on the placebo event day, which is 10 days prior to the terror attack. Columns (1) and (2) report OLS estimations while columns (3) reports the IV estimation,

such that *TV report* is instrumented by *media pressure*. *Controls* refer to *casualties, suicide, lone actor, capital city, target gov., target citizen*, and *target business*. Robust standard errors are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

6.6. Google Trends and Public Attention

To present an additional insight on why Islamist attacks negatively affect stock markets, this section shows that Islamist attacks were more capable of attracting public attention than non-Islamist attacks, with ensuing effects on the sentiments of investors. In practice, we measure the public attention on terrorism with the frequency of Google searches of terror-related keywords. Google is the leading search engine provider with more than 80% of the market share,[20] and the Google search frequency index has been used in many related studies to measure public attention on certain topics and events (e.g., Gentzkow et al. 2019, Jetter, 2019b, Stephens-Davidowitz, 2014).

We collect the Google search index during the period 2004 - 2018 in all 25 countries including the US, Western European countries, and Eastern European EU member countries, regardless of whether a terror attack in our baseline sample took place in any of those countries. The search frequency obtained from Google is a relative measure at the monthly level ranging from 0 to 100; the month of the highest search frequency between 2004 and 2018 is coded as 100 and the other months are coded in relative terms to that month.

We search for three keywords for their frequency: "terror", "terrorism", and "terrorist". Considering that multiple languages are spoken in European countries and plausibly in the US, we additionally obtain the search frequencies of the keywords in German ("terror", "terrorismus", "terrorist"), French ("terreur", "terrorisme", "terroriste"), and Spanish ("terror", "terrorismo", "terrorista") for each country, resulting in 300 combinations of data downloading.[21]

First, to examine whether Islamist attacks received higher public attention, the following time series regression is estimated for a selection of terror-stricken countries:

$$Google_{mt} = \rho_1 + \rho_2 * Terror_{mt} + \rho_3 * Islamist_{mt} + \rho_4 * Casualties_{mt} + Year_t + Month_m + \varepsilon_{mt} \qquad (4)$$

where $Google_{mt}$ is the search frequency in month *m* and year *t*. $Terror_{mt}$ equals one if any terror attack in our baseline sample took place in month *m* and year *t*. $Islamist_{mt}$ equals one if at least one Islamist terror attack in our sample happened in month *m* and year *t*. By including *Terror* and *Islamist* in the equation at the same time, ρ_2 captures the effect of non-Islamist terror attacks and ρ_2 the difference in the extent to which terror attracts public attention between Islamist and non-Islamist terror attacks; $\rho_2 + \rho_3$ thus captures the overall effect of Islamist terror attacks. As the number of casualties is positively and significantly associated with media attention (as reported in Table 4), we include *Casualties* as a control variable. It is calculated as the total number of deaths and injuries caused by the terror attacks in our

[20] https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/
[21] In particular, that is 25 countries times three keywords times four languages. However, the actual number of searches is smaller than 300 because: (1) the keywords are the same in certain languages (e.g. terror is both an English and a German word.) and Google cannot distinguish the language for the same word. (2) for a given language in a given country, the search frequency can be too low such that Google simply returns a result of zero searches.

sample that happened in a given month-year cell. Finally, $Year_t$ and $Month_m$ are the year and month fixed effects.

Table 11 reports the time series analysis for five terror-stricken countries in the West: the US, UK, France, Germany, and Spain. Specifically, panel A shows the results using the average search frequencies across all four languages and keywords in a given month and year as the dependent variable, and we find that the coefficient of *Islamist* is significantly positive (with the exception of Germany in column (2)). The frequency of searching for terror-related keywords following an Islamist attack is 23%-51% higher than the frequency after a non-Islamist attack, which is a sizable difference. Non-Islamist attacks, however, do not have any effect on the search frequency, as indicated by the insignificant (and in one case even significantly negative) ρ_2 coefficient. We also find that the search frequency increases with the total number of terror-related casualties, which is not surprising. In Panel B, we restrict the keywords to those written in the official language of each country[22] and find qualitatively similar and quantitatively more pronounced results.

Table 11 Time Series Analysis of Google Trends

Panel A: DV: average search frequency across all keywords and languages					
Countries	US	Germany	France	UK	Spain
	(1)	(2)	(3)	(4)	(5)
Islamist	5.448**	1.966	3.767**	6.837***	4.612**
	(2.127)	(2.822)	(1.804)	(1.894)	(1.796)
Terror	-0.417	1.167	-0.615	-1.530**	-0.930
	(0.867)	(1.882)	(0.909)	(0.771)	(0.604)
Casualties	0.391	1.477***	1.770***	1.081**	1.392***
	(0.635)	(0.491)	(0.342)	(0.427)	(0.382)
Mean(non-Islamist)	16.282	14.810	13.773	9.792	10.306
Observations	180	180	180	180	180
R-squared	0.602	0.563	0.606	0.578	0.587
Year dummies	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes

Panel B: DV: average search frequency of three keywords in the official language					
Countries	US	Germany	France	UK	Spain
	(6)	(7)	(8)	(9)	(10)
Islamist	8.920***	4.366*	7.046***	10.839***	1.435
	(2.505)	(2.464)	(2.622)	(3.798)	(1.533)
Terror	0.502	-1.590**	-1.635*	-1.088	-0.918
	(0.962)	(0.773)	(0.896)	(1.173)	(0.574)
Casualties	0.262	1.417**	0.933	1.028	1.854***
	(0.720)	(0.555)	(0.570)	(0.708)	(0.469)

[22] In particular, we use English searches for the US and the UK, French for France, German for Germany, and Spanish for Spain.

Mean(non-Islamist)	28.736	16.653	15.056	16.056	20.653
Observations	180	180	180	180	180
R-squared	0.778	0.572	0.490	0.499	0.662
Year dummies	Yes	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes	Yes

Notes: Time series analysis based on the Google search frequency at the monthly level, from 2004 to 2018. Keywords used are "terror", "terrorism", and "terrorist". We also search in German ("terror", "terrorismus", "terrorist"), French ("terreur", "terrorisme", "terroriste"), and Spanish ("terror", "terrorismo", "terrorista"). In panel A, the dependent variable is the average search frequency across all four languages and all keywords. In panel B, the dependent variable is the average search frequency of three keywords in the official language of each country (English for the US and UK, German for Germany, French for France, and Spanish for Spain). *Casualties* is the total number of deaths and injuries caused by the terror attacks in our sample that happened in a given month-year cell, divided by 100. *Mean(non-Islamist)* stands for the mean of search frequency of terror-related keywords during the month in which only non-Islamist terror attacks took place. Robust standard errors are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Next, we utilize the large dataset of the Google search frequency and construct a balanced panel dataset at the month-year-country level. In the following panel regression analysis, we additionally control for country fixed effects and country-specific year trends. The results presented in Table 12 are consistent with our findings in the time series analysis. In particular, column (1) shows that Islamist attacks attracted significantly more public attention than non-Islamist attacks; columns (2)-(5) show that the results are robust to the languages in which the keywords are used. The number of casualties remains positively and significantly associated with the search frequency, regardless of the language used for the search. Finally, we do not find that non-Islamist terror attacks shifted public attention towards terror in any significant pattern.

Table 12 Panel Analysis of Google Trends

Dependent variable: Google search frequency in all/specific languages					
Language	All	English	German	French	Spanish
	(1)	(2)	(3)	(4)	(5)
Islamist	4.377***	5.455***	4.193***	4.724***	4.898***
	(0.358)	(0.602)	(0.384)	(0.461)	(0.568)
Terror	-0.224	-0.156	-0.362	-0.216	-0.460
	(0.205)	(0.295)	(0.305)	(0.280)	(0.301)
Casualties	0.649***	0.778***	0.699***	0.353**	0.761***
	(0.115)	(0.185)	(0.166)	(0.131)	(0.168)
Observations	4,500	4,500	4,500	4,500	4,500
R-squared	0.435	0.392	0.354	0.281	0.382
# countries	25	25	25	25	25
Year dummies	Yes	Yes	Yes	Yes	Yes

Month dummies	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Country-year trend	Yes	Yes	Yes	Yes	Yes

Notes: Panel analysis based on the Google search frequency at the country-month level from 2004 to 2018. Keywords used are "terror", "terrorism", and "terrorist". We also search in German ("terror", "terrorismus", "terrorist"), French ("terreur", "terrorisme", "terroriste"), and Spanish ("terror", "terrorismo", "terrorista"). In column (1), the dependent variable is the average search frequency across all four languages and all keywords. In columns (2) – (5), the dependent variable is the average search frequency of three keywords in a specific language; we use English in column (2), German in column (3), French in column (4), and Spanish in column (5). *Casualties* is the total number of deaths and injuries caused by the terror attacks in our sample that happened in a given month-year cell, divided by 100. Robust standard errors clustered at the country level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

6.8. Other Sensitivity Checks

We include additional fixed effects in our analysis. First, we follow the empirical finance literature and control for the month and the weekday of the attack. Next, we include the interaction of the Europe dummy and period dummies to capture the difference in the trend of stock market performance between the US and European countries. Reported in columns (1) and (2) of Table 13, the Islamist effect almost doubled compared to the benchmark IV regression in Table 5, and it remains significant at the one percent level.

Furthermore, we distinguish between domestic and international terror. Since we concentrate on larger terror events in Europe and the US, one would expect that in almost all cases foreigners or foreign assets were affected, making almost all attacks international. Yet, there are a number of terror attacks that cannot be identified as international or domestic by GTD. We, therefore, include a dummy variable indicating that an attack is an identified international terror, considering the unknown cases as domestic attacks. As shown in column (3), the Islamist effect remains significant.

Finally, we control for the ideological orientation of the non-Islamist terrorists and distinguished left-wing, right-wing, and ethnic-separatist terror following the approach by Kis-Katos et al. (2014). Reported in columns (4)-(6), controlling for additional non-Islamist ideologies does not change our results; the Islamist effect remains significant, all other ideologies were insignificant.

Table 13 Other Sensitivity Checks

DV: Average abnormal return on day 0						
Specification	Fixed Effects		International & ideology			
	(1)	(2)	(3)	(4)	(5)	(6)
Islamist	-0.630***	-0.663***	-0.408**	-0.306*	-0.392**	-0.385**
	(0.189)	(0.193)	(0.200)	(0.183)	(0.187)	(0.175)
TV report	-1.500*	-1.600*	-1.720*	-1.594*	-1.618*	-1.641*
	(0.826)	(0.862)	(0.936)	(0.909)	(0.929)	(0.923)
International			0.117			
			(0.165)			

Left-Wing				0.139		
				(0.216)		
Right-Wing					-0.129	
					(0.174)	
Ethnic-Separatist						-0.094
						(0.189)
Month, days of week	Yes	Yes				
Europe*Period	No	Yes				
Europe dummy	Yes	Yes	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124	124	124	124	124	124
R-squared	0.579	0.586	0.446	0.450	0.449	0.448

Notes: 2nd stage IV estimations reported. *TV report* is instrumented by *Media pressure.* Column (1) controls for the month and day-of-the-week fixed effect. Column (2) additionally controls for the interaction between the *Europe* dummy and period dummies. *Controls* refer to *casualties, suicide, lone actor, capital city, target gov., target citizen,* and *target business*. Robust standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

7. Conclusion

In this paper, we have analyzed the effect of all 124 terror attacks that caused at least 5 deaths or 10 injuries and were staged on the US and European soil between 1994 and 2018 on the major US and European stock markets. We have found that terror leads to significant negative abnormal returns, a result that is driven by Islamist attacks and not by the majority of the "other" attacks. We have also shown that the media report disproportionally on Islamist attacks, even after controlling for attack characteristics and media pressure, which accounts for competing newsworthy events. Yet, even after controlling for differential media coverage, Islamist terror attacks still exert a substantially more detrimental effect on stock markets in the Western hemisphere.

We conclude that Islamist attacks are perceived as more threatening to economic prosperity than other attacks with similar characteristics but are motivated by different ideologies. Our contribution thus complements research that disaggregates terror by its underlying ideology and shows that differently motivated terror is determined by different factors as it answers to different grievances (Kis-Katos et al. 2014). We demonstrate that the ideology behind the terror affects the *perception* of the detrimental effects of terror and thereby the detrimental effect of terror itself.

We therefore show, for the first time, that ideology as such has an economic effect. In our context the effect of ideology on the economy works through multiple channels – a perceived higher newsworthiness of Islamist terror attacks is responsible for part of the differentially negative effect of Islamist attacks on stock markets. Yet, Islamist attacks affect stock markets more negatively than other attacks beyond their larger media presence. The larger media presence, in turn, gives rise to more Islamist terror attacks in the future as Jetter (2017) has shown, which makes Islamist terror even more dreadful. The differential fear thus nurtures itself.

Our research deliberately focuses on a world area with deep capital markets and an established media sector. We surmise that other stock markets may react more strongly to terror attacks given that they are less liquid and that the differential effect of Islamist terror may be even more pronounced. The role of the media may be different in other parts of the world too, especially if they are operating in an autocratic regime. To explore this is left for future research.

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Appendix

Table A1: List of all Terror Attacks in the Sample

Date	Country	City	Islamist	TV Coverage	Deaths	Injuries
1994/01/01	Belgium	Brussels			0	11
1994/01/01	Germany	Bremen			0	22
1994/02/20	Germany	Ulm			0	13
1994/06/18	UK	Loughinisland		✓	6	5
1994/07/26	UK	London		✓	0	14
1994/07/29	UK	Newry			0	28
1994/07/29	Spain	Madrid			3	14
1994/08/26	UK	Downpatrick			0	10
1994/09/19	Greece	Athens			1	10
1995/04/19	Spain	Madrid			0	16
1995/04/19	USA	Oklahoma City		✓	168	650
1995/06/11	Portugal	Lisbon			0	12
1995/07/25	France	Paris	✓	✓	7	86
1995/08/17	Spain	Arnedo		✓	0	40
1995/08/17	France	Paris	✓	✓	0	17
1995/09/07	France	Lyon	✓		0	14
1995/10/06	France	Paris	✓	✓	0	13
1995/10/09	USA	Hyder		✓	1	78
1995/10/17	France	Paris	✓	✓	0	29
1995/12/08	USA	New York City		✓	8	4
1995/12/11	Spain	Madrid			6	12
1996/02/01	Estonia	Johvi			1	10
1996/02/09	UK	London		✓	2	100
1996/06/15	UK	Manchester		✓	0	200
1996/07/14	UK	Enniskillen		✓	0	17
1996/07/21	Spain	Reus		✓	0	35
1996/07/27	USA	Atlanta		✓	1	75
1996/10/07	UK	Lisburn		✓	1	30
1996/12/03	France	Paris	✓	✓	3	91
1997/07/21	Germany	Essen			0	21
1998/02/20	UK	Moira			0	11
1998/08/01	UK	Banbridge		✓	0	12
1998/08/15	UK	Omagh		✓	29	220
1998/10/02	Italy	Naples			0	13
1999/02/17	Germany	Berlin		✓	3	43
1999/04/17	UK	London		✓	0	48
1999/04/20	USA	Littleton		✓	15	24
1999/04/24	UK	London		✓	0	13

1999/04/30	UK	London		✓	3	79
2000/04/28	USA	Pittsburgh		✓	5	1
2000/07/27	Germany	Dusseldorf			0	10
2000/08/08	Spain	Madrid			0	11
2000/08/17	Latvia	Riga			1	34
2000/10/30	Spain	Madrid			3	30
2000/11/11	Spain	Donostia-San Sebastian			0	11
2001/06/28	Spain	Madrid		✓	0	16
2001/07/10	Spain	Madrid			1	12
2001/07/23	France	Borgo			0	14
2001/08/18	Spain	Salou			0	13
2001/09/11	USA	New York City	✓	✓	3004	21871
2001/09/27	Switzerland	Zug		✓	14	18
2001/10/12	Spain	Madrid			0	14
2001/11/06	Spain	Madrid			0	95
2002/05/01	Spain	Madrid			0	17
2002/08/04	Spain	Alicante			2	30
2003/06/04	Belgium	Brussels			0	20
2003/07/19	France	Nice			0	16
2003/07/22	Spain	Alicante			0	13
2003/11/19	Italy	Unknown			0	50
2004/03/11	Spain	Madrid	✓	✓	191	1800
2004/06/09	Germany	Mulheim			0	22
2004/10/08	France	Paris	✓		0	10
2005/02/09	Spain	Madrid			0	43
2005/05/25	Spain	Madrid			0	34
2005/07/07	UK	London	✓	✓	56	784
2006/12/30	Spain	Madrid			2	12
2007/11/07	Finland	Tuusula			9	13
2008/06/28	Czech Republic	Brno			0	20
2008/09/21	Spain	Ondarroa			0	11
2008/10/30	Spain	Pamplona			0	17
2009/03/20	France	Lyon			0	10
2009/04/30	Netherlands	Apeldoorn		✓	7	12
2009/07/29	Spain	Burgos			0	46
2009/11/05	USA	Killeen	✓	✓	13	32
2010/02/18	USA	Austin		✓	2	15
2011/07/22	Norway	Oslo		✓	77	75
2012/07/18	Bulgaria	Burgas	✓	✓	7	30
2012/08/05	USA	Oak Creek		✓	7	4
2013/04/15	USA	Boston	✓	✓	3	264
2013/04/17	USA	West		✓	15	151
2013/04/19	USA	Watertown	✓	✓	2	16
2013/08/09	UK	Belfast			0	56
2014/05/23	USA	Isla Vista		✓	7	13

2014/06/08	USA	Las Vegas		✓	5	0
2014/12/21	France	Dijon			0	11
2015/01/07	France	Paris	✓	✓	12	12
2015/01/09	France	Paris	✓	✓	7	5
2015/06/17	USA	Charleston		✓	9	0
2015/07/16	USA	Chattanooga	✓	✓	6	2
2015/10/01	USA	Roseburg		✓	10	7
2015/11/13	France	Paris	✓	✓	137	413
2015/12/02	USA	San Bernardino	✓	✓	16	17
2015/12/07	Germany	Altenburg			0	10
2015/12/24	Germany	Wallerstein			0	12
2016/03/22	Belgium	Brussels	✓	✓	35	270
2016/06/12	USA	Orlando	✓	✓	50	53
2016/07/07	USA	Dallas		✓	6	9
2016/07/14	France	Nice	✓	✓	87	433
2016/07/22	Germany	Munich		✓	10	27
2016/07/24	Germany	Ansbach	✓	✓	1	15
2016/09/17	USA	New York City	✓	✓	0	29
2016/09/17	USA	St. Cloud	✓	✓	1	10
2016/11/20	France	Paris			0	15
2016/11/28	USA	Columbus	✓	✓	1	11
2016/12/16	France	Paris			1	13
2016/12/19	Germany	Berlin	✓	✓	13	48
2017/01/06	USA	Fort Lauderdale	✓	✓	5	6
2017/02/26	Sweden	Vanersborg			0	15
2017/03/22	UK	London	✓	✓	6	50
2017/04/07	Sweden	Stockholm	✓	✓	5	14
2017/05/22	UK	Manchester	✓	✓	23	119
2017/06/03	UK	London	✓	✓	11	48
2017/06/19	UK	London		✓	1	12
2017/08/04	USA	Kansas City			0	10
2017/08/12	USA	Charlottesville		✓	1	28
2017/08/17	Spain	Barcelona	✓	✓	21	110
2017/09/15	UK	London	✓	✓	0	29
2017/10/01	USA	Las Vegas		✓	59	851
2017/10/31	USA	New York City	✓	✓	8	13
2018/02/14	USA	Parkland		✓	17	17
2018/03/23	France	Trebes	✓	✓	5	15
2018/05/18	USA	Santa Fe		✓	10	14
2018/10/27	USA	Pittsburgh		✓	11	7
2018/12/11	France	Strasbourg	✓	✓	5	11

Source: Global Terrorism Database

Notes: The list contains all attacks with at least 5 fatalities or 10 injuries that took place in the US or Europe (excluding the Caucasus) in 1994-2018.

Table A2: Event Study Results Excluding Overlapping Terror Events

	Islamist 34 attacks/34 event days			**Non-Islamist** 80 attacks/80 event days		
	MEAN	**SD**	**P-value**	**MEAN**	**SD**	**P-value**
DJIA						
$\widehat{CAR}$ [0,0]	-0.380***	0.130	0.003	-0.025	0.118	0.834
$\widehat{CAR}$ [0,3]	-0.607**	0.259	0.019	0.559**	0.236	0.018
$\widehat{CAR}$ [0,6]	-0.727**	0.343	0.034	0.492	0.312	0.114
NYSE						
$\widehat{CAR}$ [0,0]	-0.346***	0.132	0.009	-0.019	0.116	0.866
$\widehat{CAR}$ [0,3]	-0.597**	0.264	0.024	0.529**	0.231	0.022
$\widehat{CAR}$ [0,6]	-0.590*	0.349	0.091	0.300	0.306	0.327
S&P 500						
$\widehat{CAR}$ [0,0]	-0.306**	0.133	0.022	-0.051	0.123	0.678
$\widehat{CAR}$ [0,3]	-0.560**	0.266	0.036	0.495**	0.246	0.044
$\widehat{CAR}$ [0,6]	-0.670*	0.353	0.057	0.278	0.325	0.391
DAX						
$\widehat{CAR}$ [0,0]	-0.701***	0.189	0.000	0.129	0.155	0.406
$\widehat{CAR}$ [0,3]	-0.858**	0.378	0.023	0.858***	0.310	0.006
$\widehat{CAR}$ [0,6]	-0.664	0.500	0.184	0.605	0.410	0.140
CAC 40						
$\widehat{CAR}$ [0,0]	-0.591***	0.194	0.002	0.070	0.150	0.638
$\widehat{CAR}$ [0,3]	-0.815**	0.388	0.036	0.901***	0.300	0.003
$\widehat{CAR}$ [0,6]	-0.675	0.513	0.188	0.579	0.396	0.144
FTSE 100						
$\widehat{CAR}$ [0,0]	-0.405***	0.150	0.007	0.037	0.123	0.763
$\widehat{CAR}$ [0,3]	-0.502*	0.299	0.093	0.439*	0.246	0.074
$\widehat{CAR}$ [0,6]	-0.487	0.396	0.219	0.160	0.325	0.623

Notes: After Excluding terror events with overlapping dates, the total number of event days in this exercise is 114 (34 Islamist event days and 80 non-Islamist event days). Average cumulative abnormal returns are reported under columns "Mean", times 100. "# 10% sig" reports the number of events with a *negative* cumulative abnormal return that is significantly different from 0 at least at the ten percent level. P-values calculated under the normality assumption are reported under columns "P-value".

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Descriptive Statistics after Propensity Score Matching

	Mean		Mean Diff.
	Islamist	Non-Islamist	
	Panel A: Kernel Matching		
Casualty	141.206	77.997	63.209
	(62.093)	(38.785)	[73.517]
suicide	0.118	0.061	0.057
	(0.055)	(0.030)	[0.064]
Media pressure	0.203	0.212	-0.009
	(0.017)	(0.014)	[0.022]
#Observations	34	87	121
Sum of weight			68
	Panel B: Radius Matching		
Casualty	141.206	76.286	64.920
	(62.093)	(37.792)	[73.126]
suicide	0.118	0.059	0.059
	(0.055)	(0.029)	[0.353]
Media pressure	0.203	0.213	-0.010
	(0.017)	(0.014)	[0.022]
#Observations	34	63	97
Sum of weight			68

Notes: Descriptive statistics using propensity scores weighting. Matching variables are *casualties, suicide Europe, media pressure*, and *period.* Standard deviations are reported in parentheses while standard errors of estimated mean differences are reported in brackets. Panel A uses Kernel matching technique while panel B uses radius matching technique (caliper as 0.1).

Table A4: Results with Coarsened Exact Matching

	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)
ISLAMIST	0.061*	-0.458**	0.062*	-0.479**
	(0.031)	(0.201)	(0.034)	(0.218)
TV report		-2.477**		-2.644*
		(1.250)		(1.362)
Media pressure	-1.093***		-1.083***	
	(0.289)		(0.321)	
Observations	60	60	56	56
R-squared	0.863	0.506	0.857	0.505
Controls	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes
Type dummies	Yes	Yes	Yes	Yes
Europe dummy	Yes	Yes	Yes	Yes

Notes: IV regression results using Coarsened Exact Matching. Matching variables for columns (1) and (2) are *casualties, suicide Europe, media pressure*, and *period*. Matching variables for columns (1) and (2) are *casualties, suicide Europe, media pressure*, and *Year.* Columns (1) and (3) are 1st stage regressions where the dependent variable is TV report. Columns (2) and (4) are 2nd stage regressions where the dependent variable is average abnormal return on day 0. *TV report* is instrumented by *Media pressure. Controls* refer to *casualties, suicide, lone actor, capital city, target gov., target citizen,* and *target business*. Robust standard errors are reported in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A5: Placebo Event Study

	Islamist		Non-Islamist	
	MEAN	**SD**	**MEAN**	**SD**
DJIA				
$\widehat{CAR}$ [0,0]	0.170	0.125	0.140	0.109
$\widehat{CAR}$ [0,3]	0.062	0.251	0.161	0.219
$\widehat{CAR}$ [0,6]	-0.376	0.332	0.145	0.289
NYSE				
$\widehat{CAR}$ [0,0]	0.158	0.127	0.090	0.107
$\widehat{CAR}$ [0,3]	0.133	0.254	0.012	0.214
$\widehat{CAR}$ [0,6]	-0.335	0.336	-0.117	0.283
S&P500				
$\widehat{CAR}$ [0,0]	0.146	0.129	0.107	0.115
$\widehat{CAR}$ [0,3]	0.153	0.258	0.065	0.229
$\widehat{CAR}$ [0,6]	-0.352	0.341	-0.149	0.303
DAX				
$\widehat{CAR}$ [0,0]	0.082	0.179	-0.218	0.146
$\widehat{CAR}$ [0,3]	-0.242	0.358	0.073	0.292
$\widehat{CAR}$ [0,6]	-0.175	0.474	-0.004	0.386
CAC40				
$\widehat{CAR}$ [0,0]	0.197	0.186	-0.329**	0.141
$\widehat{CAR}$ [0,3]	-0.132	0.371	-0.203	0.281
$\widehat{CAR}$ [0,6]	-0.237	0.491	-0.531	0.372
FTSE100				
$\widehat{CAR}$ [0,0]	0.101	0.141	-0.168	0.115
$\widehat{CAR}$ [0,3]	-0.046	0.282	-0.036	0.23
$\widehat{CAR}$ [0,6]	-0.123	0.373	-0.080	0.304

Notes: Abnormal return in this table is calculated based on the placebo event day, which is 10 days prior to the terror attack.

*** p<0.01, ** p<0.05, * p<0.1