Accepted Manuscript

The effect of media attention on terrorism

Michael Jetter

PII: S0047-2727(17)30121-4
DOI: doi: 10.1016/j.jpubeco.2017.07.008
Reference: PUBEC 3794

To appear in: *Journal of Public Economics*

Received date: 8 March 2016
Revised date: 29 June 2017
Accepted date: 26 July 2017

Please cite this article as: Jetter, Michael, The effect of media attention on terrorism, *Journal of Public Economics* (2017), doi: 10.1016/j.jpubeco.2017.07.008

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

ACCEPTED MANUSCRIPT

The effect of media attention on terrorism[1]

Michael Jetter[2]

Abstract

This paper tests for a causal connection between media attention devoted to terrorism and subsequent attacks. Analyzing 61,132 attack days in 201 countries produces evidence that increased *New York Times* coverage encourages further attacks in the same country. Using natural disasters in the United States as an exogenous variation diminishing media attention, the link appears causal. One additional article is suggested to produce 1.4 attacks over the following week, equivalent to three casualties on average. This result is robust to numerous alternative estimations and it appears unlikely that attacks are simply postponed. If terrorists do not receive media attention, they will attack less.

Keywords: media attention, terrorism

[1]I am grateful to Hadi Asiaiefard, Susana Berrio Montoya, Alejandra Montoya Agudelo, and Mohammad Sabouri for excellent research assistance. I am thankful for helpful comments and discussions from the handling Editor Brian Knight, two anonymous referees, and seminar participants at the University of Missouri, University of Central Florida, Universidad del Rosario, Universität Heidelberg, Universität Hannover, and the University of Western Australia. All remaining errors are my own.

[2]University of Western Australia, IZA (Bonn), and CESifo (Munich); 35 Stirling Highway, Crawley, WA 6009, Australia. Email: mjetter7@gmail.com.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

The effect of media attention on terrorism[1]

Michael Jetter[2]

Abstract

This paper tests for a causal connection between media attention devoted to terrorism and subsequent attacks. Analyzing 61,132 attack days in 201 countries produces evidence that increased *New York Times* coverage encourages further attacks in the same country. Using natural disasters in the United States as an exogenous variation diminishing media attention, the link appears causal. One additional article is suggested to produce 1.4 attacks over the following week, equivalent to three casualties on average. This result is robust to numerous alternative estimations and it appears unlikely that attacks are simply postponed. If terrorists do not receive media attention, they will attack less.

Keywords: media attention, terrorism

How do you defeat terrorism? Don't be terrorised.
Salman Rushdie, novelist.

1. Introduction

Is media attention devoted to terrorism actively encouraging further terrorist attacks? It has been suggested that terrorist organizations systematically seek media coverage to spread their message, create fear, and recruit followers (Wilkinson, 1997; Pries-Shimsh, 2005; Frey et al., 2007; Walsh, 2010). Most of the time, attacks are not even directly aimed at specific victims but are rather conducted to scare and convey a message (Krueger and Malečková, 2003). Thus, it is possible that once the media is paying attention a terrorist organization may seek to exploit that platform and continue their attacks. The following pages present empirical evidence that supports this hypothesis.

In reality, terrorism has become a popular news topic: media outlets worldwide dedicate TV marathons, front-page headlines, and in-depth portraits to terrorist groups.[3] In fact, the extent of the media coverage terrorist organizations receive (free of charge) has been compared to the "advertising budgets of some of the world's largest corporations" by Melnick and Eldor (2010, p.965). It is possible that people's irrational

[3]In general, media coverage of terrorism (like coverage of other issues) could be demand- and/or supply-driven (Gentzkow et al., 2015; Puglisi and Snyder, 2015), where the demand side relates to consumer preferences and the supply side is commonly associated with the preferences of media owners.

ACCEPTED MANUSCRIPT

fear of terrorism is, at least in part, owed to such media exposure. Half of the US population is worried that they or their family will be a victim of terrorism (PRRI, 2015), even though the odds of dying at the hands of a terrorist are approximately equal to drowning in one's own bathtub (Mueller, 2006; Sandler, 2015). Similarly, according to a World Values Survey study (WVS, 2015), people worldwide worry more about terrorism than losing their job, a war involving their country, or a civil war.

A natural question to ask then is whether media coverage of terrorism carries direct consequences for the behavior of terrorist groups. Once in the spotlight, terrorist groups may choose to exploit this exposure to further spread their message, create fear, and recruit followers. Thus, presumably unintended consequences of covering terrorism may result in encouraging terrorists to continue attacking. If this were the case, society could draw several conclusions. For example, self-imposed restrictions have been powerful drivers in the media industry concerning other topics, such as the sensible and limited coverage of suicides or the coverage of so-called "sucker punches."[4] One could imagine similar arrangements for the coverage of terrorism, raising awareness in the media industry. Other, more drastic options include policies that regulate the coverage of terrorist attacks.

Unfortunately, it has been proven difficult to empirically test the systematic interplay between media attention and terrorism, not to mention studies allowing for a *causal* interpretation. In addition to limited data availability and comparability, persistent endogeneity concerns have plagued such studies.[5] The following pages try to take one step in that direction, studying a sample of 61,132 attack days in 201 countries from 1970 to 2012. First, I derive a measure for the international media attention each attack day receives in the *New York Times* (*NYT*). Then, I use this measure of media coverage as a predictor of upcoming attacks in the same country. To isolate causality, natural disasters in the United States (US) provide an exogenous variation, decreasing media attention devoted to contemporary terrorist attacks in the rest of the world. Such events prove to be a strong predictor of the media coverage terrorist attacks receive in the *NYT*, but are unlikely connected to non-US based terrorist organizations through other meaningful channels.

The findings produce quantitative evidence supporting the hypothesis that media attention devoted to terrorism actively encourages subsequent attacks. The results from instrumental variable estimations reveal a robust positive effect of *NYT* coverage on the number of subsequent attacks in the same country.

---

[4]In the case of suicides, it is recommended to "decide whether to report," "modify or remove information that may increase risk," and "present information about suicide in ways that may be helpful" (see ABC News, 2014, Mindframe, 2014, or `www.reportingonsuicide.org`). Indeed, the media appears to have found a sensible way to report on suicides, usually referring to "incidents" and wisely choosing words that are unlikely to encourage copycats. In the case of "sucker punches" or "king hits", an ample discussion in Australia about labeling sudden knockout punches as an act of cowardice has lead to a change in language by the media (e.g., see ABC News, 2014, or Courier Mail, 2014).

[5]Most notably, Rohner and Frey (2007) suggest positive Granger causality between terrorist attacks and media attention, counting the word "terrorism" in the *New York Times* (*NYT*) with 87 monthly observations.

ACCEPTED MANUSCRIPT

The magnitude of the derived relationship suggests that one additional article increases the number of attacks in the following week by approximately 1.4. This corresponds to about three casualties on average.

These results account for the inclusion of a comprehensive set of control variables, such as the detailed characteristics of the initial attack, country fixed effects, country-specific time trends, and country-year fixed effects for countries most notorious for terrorism, in addition to economic, political, and social aspects. Further, I find no evidence that decreased media attention, because of a natural disaster occurring in the United States, merely postpones attacks. Thus, less press coverage may indeed lead to fewer terrorist attacks overall and not just affect their timing.

The paper aims to contribute to several areas of research. First, it suggests a methodology for systematically collecting data on media coverage of specific terrorist attacks and isolating the causal effect on subsequent actions. In the spirit of Eisensee and Strömberg (2007), who analyze the effect of media coverage on disaster aid, researchers may be able to better investigate the consequences of media coverage. Second, regarding data collection and availability, the paper provides an example of how we can use internet archives to systematically derive data that are readily available for analyzing timely questions.[6]

Third, the paper adds to the growing literature on the consequences of media coverage. In particular, the media has been shown to influence economic and political decision making, such as consumer decisions or voting behavior (e.g., see DellaVigna and Gentzkow, 2010, and Puglisi and Snyder, 2015, for recent summaries). Fourth and final, the paper adds to our understanding of the determinants of terrorism. Although media attention has long been speculated to provide an incentive for terrorists' strategies, this paper provides quantitative evidence using 43 years of data on 61,132 attack days.

The paper proceeds with a discussion of the literature on the media-terrorism link, before introducing the data and methodology. Section 5 presents the main findings, in addition to a number of additional specifications and robustness checks. Finally, section 6 concludes.

2. Background and Literature Review

2.1. The Rise of Terrorism

Figure 1 documents the recent surge of terrorism. In 2012 alone, 15,396 casualties and 25,426 wounded victims were recorded by the Global Terrorism Database (GTD, introduced by LaFree and Dugan, 2007). Beyond the immediate victims, the substantial economic and societal costs of terrorism have been well

[6]Another recent example includes Stephens-Davidowitz (2014), who studies the effect of racial sentiments on presidential elections in the US, using data from Google searches.

ACCEPTED MANUSCRIPT

documented.[7] Further, terrorism is not confined to particular regions, as 201 countries have been affected since 1970. Table 1 displays those economies that have suffered the most, both in absolute terms and relative to their population, accessing GTD data from 1970 to 2012.[8] Although almost half of all incidents have taken place in Asia (46 percent; mostly in India, Iraq, Pakistan, and the Philippines), Latin America (25 percent; e.g., the FARC in Colombia), Europe (15 percent; e.g., the IRA in Northern Ireland and ETA in Spain), and Africa (11 percent; e.g., Boko Haram in Nigeria) have not been spared.

Why do some groups choose violence to promote their agenda, as opposed to pursuing peaceful options? Several potential drivers have been proposed, most notably income levels, democracy, and the absence of civil liberties.[9] Although these factors have received some empirical support, we are far from understanding terrorism completely. In particular, media coverage has received little attention from empirical researchers as a potential driver, even though anecdotal evidence and theoretical considerations may suggest such a link.

2.2. Media Attention on Terrorism

This global surge of terrorism has been accompanied by substantial media attention. International news outlets are extensively covering Al-Qaeda, Boko Haram, and recently the Islamic State of Iraq and the Levant (ISIL). In turn, the media's importance for terrorist organizations has been described in numerous articles (e.g., Wilkinson, 1997, Walsh, 2010). The *Merriam-Webster Dictionary* highlights that "[t]errorism's impact has been magnified by the ... capability of the media to disseminate news of such attacks instantaneously throughout the world." Frey and Luechinger (2003) and Frey et al. (2007) note that terrorists are seeking publicity "in order to make their cause widely known." In sum, the attention of the public seems to be a fundamental objective and potential driver of terrorist activities with the media serving as an indispensable platform.

In practice, why would international media attention encourage terrorist organizations to conduct further attacks in the subsequent days and weeks? If maximizing media exposure is indeed an immediate goal, then terrorist organizations may perceive elevated chances of coverage once the eyes of the world are already on them. This would guarantee a larger audience and opportunity to cause fear, to recruit

[7] See Abadie and Gardeazabal (2003), Blomberg et al. (2004), Eckstein and Tsiddon (2004), Frey et al. (2007), Gaibulloev and Sandler (2009), or Melnick and Eldor (2010) for the economic costs of terrorism. For political and social consequences, one may consider Dreher et al. (2010) or Gassebner et al. (2011).

[8] Note that there are no data available from the GTD for 1993, a problem that is well-known in the literature. Also see Jetter and Stadelmann (2017) for a discussion about measuring terror attacks and victims in absolute terms or in per capita values when comparing terrorism across countries.

[9] Regarding income levels, one may consider Krueger and Malečková (2003), Abadie (2006), or Enders and Hoover (2012). Regarding democracy, Chenoweth (2013) provides a summary on the link to terrorism and Santifort-Jordan and Sandler (2014) find lack of democracy to be associated with terrorism. Krueger and Laitin (2008) find civil liberties to matter, and Gassebner and Luechinger (2011) provide a comprehensive analysis of terrorism determinants.

ACCEPTED MANUSCRIPT

followers, and to promote the group's agenda. If reporters are present and international readers are already familiar with a particular conflict situation, it may also be easier to deliver from a supply-side perspective of media agents. In turn, if an initial attack receives little to no attention on the international stage, it may appear unlikely that a follow-up attack makes headlines. Of course, one could think of other, potentially related narratives. The purpose of this paper is to test whether such a relationship indeed exists and whether we can infer causality.

In related studies, the media has been shown to carry important economic and political consequences. For example, DellaVigna and Gentzkow (2010) summarize the literature on the effects of the media on consumers and voters, whereas Gentzkow and Shapiro (2004) discuss the effects of the media in the Muslim world, focusing on attitudes toward the US. Puglisi and Snyder (2015) provide a recent summary on the power of the media in influencing voters, concluding that the media can have a meaningful impact. However, as Puglisi and Snyder (2015) point out, isolating causality in such analyses has proven difficult, as many times changes in newspapers' behavior (e.g., presidential endorsements) can be endogenous to consumer behavior.

Such concerns have also plagued our understanding of whether and how the media may drive the decisions of terrorist organizations. Most importantly, omitted variables, measurement issues, and reverse causality are likely confounding empirical studies. For instance, Rohner and Frey (2007) find evidence of Granger causality between terrorist attacks and media attention after Nelson and Scott (1992) have not found proof of such a relationship. However, a variety of factors may simultaneously drive media coverage and ensuing terrorist activity, indicating a potential omitted variable bias. For example, some countries may generally be more prone to terrorism at a certain time (say, during political turmoil), which may independently affect media coverage. Econometrically, incorporating attack- and country-specific parameters is likely to produce more reliable results about the media-terrorism link.

In Jetter (2014), I introduce a descriptive overview of terrorist attacks and the corresponding media coverage, also employing data from the *NYT*. The large sample from 1970 – 2012 on the attack day-country level allows for the inclusion of a number of potentially confounding factors, such as attack types, the number of victims from attacks, and country fixed effects. The corresponding findings suggest a positive correlation between media coverage in the *NYT* and subsequent terrorism. A detailed description of the data, which will also be used in this study, is referred to Section 3.

But even after controlling for a comprehensive list of potential terrorism determinants, endogeneity remains a serious concern. In fact, one could think of many examples where both media attention and the occurrence of future attacks are affected by events that are difficult to capture in variables. For instance, consider an attack accompanied by a video message of a terrorist leader, such as Osama bin Laden in the past, announcing further attacks. Media coverage is likely to peak, and if the announcement

ACCEPTED MANUSCRIPT

is of substance, attacks will follow. In this case, both media coverage and attacks are rising, but this correlation is not necessarily causal. Thus, in an ordinary regression analysis the "effect" of media attention on subsequent attacks may be biased upward. In turn, a downward bias could be just as likely if, say, security measures are substantially raised after the terrorists' announcement, thereby decreasing the number of attacks.

As a final example of why a conventional OLS framework may suffer from endogeneity problems, consider reverse causality in the media-terrorism nexus. We wish to test for the causal effect of media coverage on the occurrence of subsequent attacks, but it is possible that the *expectation* of future attacks itself drives media coverage. In sum, considerable hurdles have made it difficult to investigate a potentially causal link between media coverage and terrorism. The present paper aims to take a step in that direction by employing an instrumental variable framework for *NYT* coverage of terrorist attacks around the world. In Jetter (2017), I use a comparable econometric methodology when specifically analyzing the relationship between US television news coverage of Al-Qaeda and the group's subsequent terrorist attacks.

3. Data

The main analysis combines data from three sources. The GTD provides detailed information on terrorist attacks from 1970 to 2012, whereas data on international media attention are derived from the *NYT* archives. (For further details on data collection, I also refer to Jetter, 2014.) Finally, the International Disaster Database (Guha-Sapir et al., 2014) contains information on natural disasters in the US for the same time frame.

3.1. Data on Terrorist Attacks

The richest and most prominent source of data on terrorist attacks to date is collected by the University of Maryland and published as the Global Terrorism Database (GTD). The GTD lists over 113,000 terrorist attacks by day and country from 1970 to 2012 with detailed information on the number of casualties, attack types, targets, and weapons employed. Within the database, several definitions of terrorism are provided, and the upcoming results are robust to applying any of them (see Table AIV).

To prepare these data for an analysis of media attention, I first group terrorist attacks by country and day. The country-day unit constitutes the smallest possible denominator for matching terrorist attacks to their respective international press attention, as explained in detail shortly. This means that the created database could contain a specific day several times, but not for the same country. For example, on March 31, 1970, two countries suffered from terrorist attacks (Japan and Guatemala), thus creating two observations on the country-day level. If a country experienced several attacks on the same day, I

ACCEPTED MANUSCRIPT

sum up all victims. Similarly, variables capturing attack types, targets, and weapon types take on the value of one if at least one attack fulfilled the respective requirement.

Table 2 provides summary statistics for the variables used in the baseline analysis, omitting binary indicators of target and weapon types.[10] The main dependent variable refers to the number of terrorist attacks that have occurred in the same country in the week after an initial attack was recorded by the GTD. Throughout the paper, alternative time frames will be discussed. To illustrate this variable, consider the bombings of a bank in Barakaldo (Spain, close to Bilbao) on June 23, 2000. Until June 30, Spain was subject to three further terrorist attacks (June 25, 26, and 30). Thus, in this case the dependent variable takes on a value of three.

Note that the attack in Spain on June 25 constitutes another data point, and the subsequent attacks on June 26 and 30 enter the respective calculation of future terrorism. Thus, to contain potential issues from serial correlation within countries, errors are clustered at the country level throughout all estimations and immediately preceding terrorist attacks are controlled for. As the data stop on December 31, 2012, the last observation included in the analysis occurred on December 24 of that year to allow the dependent variable to capture the complete seven days following that initial attack. This cutoff is adjusted accordingly when using different time frames.

As displayed in Table 2, we observe an average of five attacks within the upcoming week after an initial attack day, whereas the median observation counts two attacks. The maximum number of 108 attacks has been registered in Iraq after a series of seven attacks on June 2, 2007. In approximately 28 percent of the attacks, the country has not been a victim of another attack within the next seven days. As the variable measuring subsequent attacks contains a small number of outliers (99 percent of all observations count 36 or fewer attacks), I also consider a variety of alternative estimations, such as excluding outliers to various degrees (see appendix Table AIII).

Concerning the victims, an average attack day in a given country produces almost four casualties and 1.8 attacks. The number of victims and attacks is likely to influence media coverage (e.g., Melnick and Eldor, 2010; see Walsh, 2010, for why some attack forms may receive more media coverage than others), as well as predict upcoming terrorism. Further, the number of attacks immediately preceding the current strike can provide a meaningful predictor of upcoming incidents.

[10] Target types are categorized into business, government, police, military, and private. Weapon types include firearms, explosives and bombs, incendiary, chemical, and other weapon types. Other, less common target and weapon types form the respective reference category.

ACCEPTED MANUSCRIPT

3.2. Data on NYT coverage

To measure international media attention devoted to terrorist attacks, I access the *NYT* archives as an internationally representative newspaper. Several reasons speak for the *NYT* as the benchmark media outlet for international press coverage. The *NYT* has been considered the world's highest-quality newspaper by leaders in business, politics, science, and culture (Merrill, 1999; Rohner and Frey, 2007). The international search engine 4imn ranks the *NYT* as number one in their Newspaper Web Ranking (4IMN, 2014). George and Waldfogel (2006, pages 436 and 437) and Rohner and Frey (2007, page 138) provide excellent summaries of why the *NYT* constitutes the most suitable candidate for a representative international daily newspaper. Finally, the previous quantitative analyses on the link between international media attention and terrorism have all used the *NYT* (Nelson and Scott, 1992; Scott, 2001; Rohner and Frey, 2007; Jetter, 2014).[11] Overall, the *NYT* carries a strong intermedia agenda-setting power, driving additional coverage of reported topics on a national and international level.[12]

To derive a proxy for the degree of attention terrorist attacks receive, I first collect the number of *NYT* articles mentioning the name of the attacked country on the day of the respective incidents.[13] To put that number in perspective to the regular *NYT* coverage, I subtract the average daily number of *NYT* articles mentioning the country's name over the entire sample period. The resulting variable constitutes the net excess coverage on the respective attack day and is labelled *NYT* coverage. Country means for both the number of *NYT* articles on attack days and the respective country average are referred to Table AI.

This algorithm extends the methodology used by Rohner and Frey (2007), who count the word "terrorism" within a given month. There are several reasons for capturing a country's name, rather than the word "terrorism." First, it is not clear whether the word "terrorism" would be used in an article mentioning an attack on the same day. Some incidents may only later be identified as terrorism or a number of alternative words could be used (e.g., attack, shooting, strike, bombing).[14] Second, some

---

[11] On a more practical note, the *NYT* permits access to their archive online, allowing the analysis of coverage from the beginning of the GTD database in 1970. Rohner and Frey (2007) also use the *NYT*, and their findings are closely replicated when accessing the Neue Zürcher Zeitung.

[12] Also see Larcinese et al. (2011) or Puglisi (2011) for the agenda-setting power of large media outlets.

[13] *NYT* archives are available under `http://www.nytimes.com/ref/membercenter/nytarchive.html`. As the search term, the country name is used by a computer algorithm in the English language. If the country can be referred to under partial names, such as Bosnia and Herzegovina, the algorithm searches for both terms separately and adds the number of articles, in this case, a search for Bosnia and another for Herzegovina.

[14] In alternative search algorithms, I also tried combinations of the country name with the word "terror." However, this produces only few responses prior to the 9/11 attacks in 2001, which makes the data less comparable in a global panel spanning 43 years. Nevertheless, the correlation between *NYT* coverage and a measure that adds the word "terror" to the search algorithm produces a value of 0.55. Similar problems arise when using combinations of the country name with the respective attack type (e.g., attack, bombing, assault) in the spirit of the methodology employed by Eisensee and Strömberg (2007), who study natural disaster coverage. It is likely that the terminology used to describe such incidents has changed over time.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

incidents may simply be referred to as attacks by a certain group, such as Al-Qaeda or Boko Haram, which would produce an inconsistency in a global sample. Third, it would be difficult to identify coverage of a particular attack in, say, Iraq on a given day by searching for the word "terrorism" if other countries experienced attacks on that same day. Thus, measuring the number of articles mentioning a country's name provides the most general, consistent strategy, producing a comparable measure of media attention across countries and time.[15]

To ensure that *NYT* coverage generally captures attention devoted to terrorist attacks, it serves to compare the mean of that variable with the average *NYT* coverage on days before the attack. If no attack happened the day before, we would expect that there would be less *NYT* coverage. In fact, on such days we only register a value of 0.61 for *NYT* coverage, which is significantly less than on attack days (40 percent less when compared with 1.02; see Table 2). Figure 2 compares the mean *NYT* coverage on the three days before an attack (assuming there was no attack) with *NYT* coverage on the attack day. This provides additional evidence that *NYT* coverage indeed captures media attention devoted to contemporaneous terrorist attacks.

Nevertheless, it is possible that some measurement error remains. Most importantly, an article mentioning "Iraq" may discuss other aspects of the country that are unrelated to terrorist attacks. The main analysis offers four solutions to this concern: subtracting the average *NYT* coverage of the respective country, in addition to including country fixed effects, country-specific time trends, and country-year fixed effects for the countries most notorious for terrorism.[16] In alternative estimations, I also control for national election dates in the respective countries to further isolate coverage dedicated specifically to the respective attack days (see Table 8). Finally, a large sample of over 60,000 observations is likely to cope with white noise, potentially at the cost of inflated standard errors.

Further, the validity of *NYT* coverage rests on the assumption that the *NYT* would mention a country name in a report about the attack. This assumption may be violated in some cases. For example, a terrorist attack in Chicago would not lead the *NYT* to report about the "United States," but rather "Chicago." To cope with this, I exclude attacks in the US. In addition, results are robust to excluding all American and European countries, where country names may not be spelled out necessarily as *NYT* readers may be more familiar with these locations (see Table 7).

Finally, as terrorist attacks and *NYT* coverage are measured on the same day, an inconsistency

[15]Note that this methodology could be specified further when studying particular terrorist groups, such as Al-Qaeda or ISIL. For example, in Jetter (2017), I investigate the link between US television news coverage of Al-Qaeda and subsequent attacks by the group. However, the purpose of the present paper is to analyze a general relationship between the media and terrorism, independent of particular groups.

[16]Note that in the presence of country fixed effects subtracting the average number of *NYT* articles does not change the qualitative interpretation of the derived coefficient, but it does affect quantitative implications. The variable *NYT* coverage captures the excess *NYT* coverage on the attack day, beyond the average country coverage.

ACCEPTED MANUSCRIPT

regarding time zones may arise. For example, an attack in Colombia at 10:00 p.m. is unlikely to result in an *NYT* article on that same day. Note that this problem becomes less severe once attacks move farther to the East. For example, the Middle East is usually six or more hours ahead of the Eastern time zone. Thus, even an evening attack in Iraq may well be reported on the same day by the *NYT* online. In a related paper, Durante and Zhuravskaya (2015) find that terrorist attacks tend to be covered on the same day, analyzing the Israeli-Palestinian conflict. Nevertheless, especially for American countries, lack of time difference with New York could lead to measurement error in *NYT* coverage. In addition to country fixed effects, a robustness check excluding attacks in the Americas is likely to alleviate such concerns, guaranteeing a reasonable time difference. In addition, section 5.4 provides a robustness check where *NYT* coverage of the day after an attack is used for American venues.

3.3. Data on Natural Disasters in the US

To isolate causality in the media-terrorism link, a researcher needs an exogenous variation that influences media coverage devoted to a terrorist attack, but is otherwise unrelated to the respective terrorist group. This paper proposes natural disasters in the US as such an exogenous variation, using data derived from EM-DAT, the Belgian-based International Emergency Disaster Database (Guha-Sapir et al., 2014).

EM-DAT only includes disasters if at least one of the following conditions applies: (*i*) ten or more people reported killed, (*ii*) hundred or more people reported affected, (*iii*) declaration of a state of emergency, or (*iv*) call for international assistance. It is likely that such an event in the US would attract substantial attention, therefore decreasing the coverage of contemporaneous terrorist attacks somewhere else in the world. To minimize the role of potential dynamics between terrorists expecting decreased media coverage, I only use one-day natural disasters, i.e., disasters that have not lasted more than one day.

Overall, 321 one-day natural disasters in the US occurred on days where at least one terrorist attack occurred somewhere else in the world. This corresponds to 1,541 of the attack day-country observations or 2.5 percent of the sample.[17] The advantage of this variable is that it is clearly defined (one-day disasters in the US only, which likely strengthens the impact on *NYT* coverage), whereas the disadvantage comes from the fact that one needs a large sample to capture sufficient statistical variation. With these data in mind, I now move to the empirical strategy.

[17]Note that disasters occur in another country (the US) than terrorist attacks, eliminating the possibility that disasters may make a government vulnerable to domestic terrorism (Berrebi and Ostwald, 2011, 2013).

ACCEPTED MANUSCRIPT

4. Empirical Strategy

4.1. Conventional Regression Framework

As a first step, I consider a conventional OLS regression framework, estimating the number of attacks in the week following an attack day t in country i:

$$\sum_{k=t+1}^{t+7} \big(attacks\big)_{i,k} = \beta_0 + \beta_1 \big(NYT\ coverage\big)_{i,t} + \boldsymbol{x'_{i,t}}\beta_2 + \boldsymbol{z'_t}\beta_3 + \epsilon_{i,t}. \tag{1}$$

The vector $\boldsymbol{x'_{i,t}}$ incorporates the initial attack features, namely binary indicators for the five most common attack, target, and weapon types; variables measuring the number of casualties; the number of attacks in country i on day t; and the number of attacks in country i within the previous seven days. In alternative estimations, I also incorporated the number of wounded people and the number of US victims, but the derived results remain unaffected.

$\boldsymbol{z'_t}$ includes a general time trend on the daily level (as terrorism has increased over time) and fixed effects for months and days of the week. These variables capture the idea that some months and days may be more likely to experience attacks, given seasonal particularities or religious habits. Finally, $\epsilon_{i,t}$ corresponds to the usual error term. In all regressions, error terms are clustered at the country level. Section 5.4 introduces alternative estimation methods and further control variables.

If international media attention were positively related to the occurrence of future attacks, we would expect β_1 to exhibit a positive and statistically relevant coefficient. However, equation 1 likely suffers from severe endogeneity problems, as described in section 2. A priori, β_1 may therefore be biased in either direction and is unlikely to reveal a potentially causal effect of media attention on terrorism.

4.2. Instrumental Variable Strategy

To overcome the latent endogeneity problem of *NYT* coverage in equation 1, I use one-day natural disasters in the US as an instrumental variable. These events can provide a plausible exogenous variation if they are unexpected for terrorists and can directly decrease media attention devoted to any contemporary terrorist attacks around the world.

Intuitively, a major storm in Tennessee is likely to defer *NYT* attention away from a contemporaneous terrorist attack in Iraq, for example. However, it is difficult to construct a scenario in which a storm in Tennessee could be linked to terrorist activities in Iraq through any other channel. Thus, the instrumental variable (IV) strategy uses a two-stage-least-squares framework (2SLS), where the first stage consists of using a binary indicator of a natural disaster in the US on day t to predict $NYT\ coverage_{i,t}$. In econometric

ACCEPTED MANUSCRIPT

terms, the first stage takes on the following form:

$$\left(NYT\ coverage\right)_{i,t} = \gamma_0 + \gamma_1 \left(Natural\ disaster\ in\ US\right)_t + \boldsymbol{x}'_{\boldsymbol{i,t}}\gamma_2 + \boldsymbol{z}'_{\boldsymbol{t}}\gamma_3 + \mu_{i,t}. \tag{2}$$

The estimated value of *NYT* coverage is then used in the second stage to predict the number of attack days in the upcoming week.

4.3. Validity of the IV

If the instrumental variable was valid, *NYT* coverage should be substantially reduced on days where natural disasters in the US occur. Panel A of Figure 3 displays a basic comparison of *NYT* coverage on days with and without a natural disaster in the US. *NYT* coverage averages a value of 1.03 on regular days but only 0.37 on days where the US experienced a natural disaster. The difference in means is strongly significant on any conventional level of statistical importance. Note that using the absolute number of *NYT* articles, unadjusted by average *NYT* coverage, produces the same conclusions (average values of 3.34 and 2.48, respectively).

If media coverage indeed relates to the occurrence of subsequent terrorist attacks, we would expect the number of upcoming attacks to be lower after a natural disaster in the US. Indeed, Panel B of Figure 3 reveals a substantial difference. On days without a natural disaster in the US, a terrorist attack is followed by 5.04 missions in the same country in the upcoming week. However, if a natural disaster strikes the US, that number markedly decreases to 3.84. Once again, the difference between these two values is statistically significant at the one percent level.

Nevertheless, these basic descriptive statistics do not control for potentially confounding factors. For example, it is possible that attacks coinciding with natural disasters in the US happen to occur in less terrorism-prone countries at the time. In general, the initial attack features discussed above or country-specific particularities may influence media coverage and future attacks.

Table 3 presents results from regressing *NYT* coverage and the number of upcoming attacks on these covariates. For both variables, the disaster indicator emerges as a negative predictor. The corresponding coefficient is both statistically significant at the one percent level in the most complete specification and relevant in terms of magnitude. With an average of 1.02, *NYT* coverage reduces by approximately 0.36 articles in the third and most complete estimation. Thus, the occurrence of natural disasters in the US appears to be a strong instrument for *NYT* coverage. Similarly, the number of subsequent attacks is reduced by almost one half of an attack.

ACCEPTED MANUSCRIPT

4.4. Excludability of the IV

Even though the instrument may be statistically powerful in decreasing *NYT* coverage, it is theoretically possible that terrorists anticipate natural disasters in the US. If this were true, terrorists may deliberately postpone attacks, knowing that media attention would be reduced. Thus, the instrument may be directly related to the terrorists' plans and would not be excludable from the main regression.

To test for that possibility, Panel A of Figure 4 compares the number of terrorist attacks on days with and without a natural disaster in the US. There is virtually no difference between the two, indicating that natural disasters in the US are not anticipated or at least terrorists do not adjust their actions accordingly. Similarly, Panel B compares the difference in the number of attacks on a day right before a natural disaster in the US with other, regular attack days. Again, no discernible difference emerges.

Nevertheless, including potentially confounding factors may be important since surrounding characteristics, such as the weekday, month of the year, or a general time trend could influence both the occurrence of natural disasters and the number of terrorist attacks. Table 4 displays results from regressing the number of attacks in country i on the binary indicator for a natural disaster in the US today (columns 1 to 3) or tomorrow (columns 4 to 6), controlling for the respective time variables, the immediate history of attacks in country i, and country fixed effects. If terrorists were indeed aware of natural disasters in the US and planned accordingly, we would expect a negative and statistically significant coefficient for the disaster variables. However, that is not the case.

Further, Panel A of Table 5 presents results from regressing a number of relevant outcome variables taken at day $t-1$ on the binary disaster indicator at day t. If the occurrence of natural disasters was indeed unexpected, the respective country's presence in the *NYT* on the previous day should not be statistically different from any other day. The same logic should apply to terrorist attacks. Controlling for all covariates discussed in equation 1, columns (2) through (7) check whether a natural disaster on day t is a statistically significant predictor of terrorist attacks on day $t-1$, distinguishing between general and international attacks, as well as attacks on business, government, police, and private targets.

Column (8) regresses the average number of sources available for terrorist attacks documented in the GTD. Intuitively, if the number of sources was lower right before natural disasters in the US, this could hint at the GTD missing the documentation of attacks during disasters. Columns (9) through (12) check whether the number of casualties or wounded victims (both in general and US citizens) is significantly different on days before natural disasters. These final regressions employ a negative binomial model, taking account of a substantial number of zeros in the dependent variable.[18] In sum, the corresponding

[18]Please note that the statistical variation in the number of US deaths and wounded victims is not sufficient to estimate a negative binomial model when including all control variables (see columns 11 and 12 in Panel A). However, once control variables are removed, statistically insignificant coefficients are derived for the coefficient associated with natural disasters

ACCEPTED MANUSCRIPT

results in Panel A of Table 5 suggest that natural disasters in the US are indeed not anticipated by the *NYT* (column 1), by terrorist groups, or by the GTD.

Finally, Panels B and C take averages of the respective dependent variables over the previous two and three days. However, I find very little evidence for the hypothesis that these characteristics vary systematically prior to natural disasters in the US. Only when averaging over the previous three days do we find that attacks on business targets are marginally diminished. Further, if anything, the number of deaths and wounded people are marginally *higher* right before a natural disaster, which is difficult to reconcile with the hypothesis that terrorists are anticipating natural disasters in the US and therefore attack less. Overall, these exogeneity tests support the idea that natural disasters do not play a substantial role in the plans of terrorist groups throughout the world.

It may serve to compare these results with those from considering a large global event that is *expected*, such as the soccer World Cup. Taking place in a different country every four years and representing the largest sports event worldwide (John, 2015), dates for the soccer World Cup are planned well in advance. Figure 5 contrasts the number of worldwide attacks on regular days with those on days during the World Cup, using a sample of all days between January 1, 1970, and December 31, 2012 (availability of GTD). In this case, the number of terrorist attacks markedly decreases from 7.9 to 6.4, suggesting that terrorists adjust their actions during this anticipated event.

The following section now turns to the empirical evidence on whether media coverage of terrorism may indeed be causing future terrorist attacks.

5. Empirical Findings

5.1. Conventional Regression Analysis

Starting with a conventional regression framework, Panel A of Table 6 displays results from predicting the number of attacks in the same country within a week after an initial attack. Panels B and C display the findings from IV estimations, which will be discussed shortly, whereas Panel D documents the corresponding control variables included in both the OLS and IV estimations. Column (1) displays results from a univariate regression, only using *NYT* coverage to predict the number of future attacks. The derived coefficient is positive with a value of 0.452 and statistically relevant at the one percent level.

Column (2) adds country fixed effects, and the coefficient of interest drops substantially to approximately 0.1.[19] In addition, the derived coefficient is not distinguishably different from zero, indicating no relationship between *NYT* coverage and future terrorist attacks. Notice that the statistical model

---

in the US.

[19]Hausman tests for fixed versus random effects support the inclusion of fixed effects in all estimations.

ACCEPTED MANUSCRIPT

becomes more precise as the adjusted R^2 increases substantially from 0.058 to 0.336. Thus, country fixed effects alone are able to explain more than one-fourth of the variation in the number of upcoming attacks. Columns (3) to (6) include attack-specific variables, in addition to the recent history of attacks and time-specific parameters. Overall, the most complete OLS specification is able to explain more than half of the upcoming terrorist attacks.

The estimated coefficient associated with *NYT* coverage remains statistically insignificant on conventional levels. But even if it were noticeably different from zero, the quantitative interpretation would be quite modest. In this case, more than 20 additional *NYT* articles would be needed to explain one additional attack. Were we to stop here, the conclusion would state that *NYT* coverage is not predicting future terrorism. However, the obvious endogeneity problems discussed above prevent us from drawing conclusions related to causality. A priori, the derived coefficient could be biased in either direction, which means we are not even able to draw inferences on the sign of a potential relationship.

5.2. Main IV Findings

The results displayed in Panels B and C follow the same sequence of regressions as the OLS regressions presented in Panel A, this time employing a 2SLS framework, where *NYT* coverage is instrumented with a binary indicator for a contemporaneous natural disaster in the US. In the simplest regression, displayed in column (1), the excess number of *NYT* articles produces a firmly positive coefficient with an initial magnitude of 1.819 – a value that is substantially higher than the coefficient produced by a conventional regression framework (0.452).

Columns (2) through (4) then incorporate country fixed effects and the usual attack characteristics. These control variables leave the coefficient of interest virtually unchanged. Similarly, natural disasters in the US remain a strong predictor in the first stage regression. Note that by that time, the OLS results are already firmly insignificant on conventional levels (see Panel A).

Columns (5) and (6) introduce the recent history of attacks in the same country, as well as the usual time parameters. In the most complete specification, the derived coefficient related to media coverage is positive and statistically significant at the one percent level and reaches a magnitude of 1.382. This suggests one additional *NYT* article to be associated with almost 1.4 additional attacks. If we assume these to be "average" attacks, that estimate translates to almost three casualties. Thus, not accounting for the endogeneity of media coverage is suggested to produce a severe downward bias of the relationship between media attention and the occurrence of future terrorist attacks.

Notice that testing for the strength of the instrument confirms its validity. Most notably, the test for weak instruments produces an F-value of 16.33 in the most complete specification, comfortably surpassing the commonly suggested threshold value of ten (Stock et al., 2002; Stock and Watson, 2012). More

ACCEPTED MANUSCRIPT

detailed tests for weak instruments (using the *weakiv* command in Stata, following Magnusson, 2010, for example) provide a lower bound of 0.63 for the estimated coefficient associated with *NYT* coverage – a value that remains comfortably above zero. Similarly, the Kleibergen-Paap test allays concerns about a weak instrument with F-values above ten. Finally, the endogeneity of *NYT* coverage is confirmed by the corresponding test statistics.

The findings from these IV regressions produce a very different picture than the results from conventional OLS regressions, as *NYT* coverage may indeed influence the number of terrorist attacks. I now move to a number of robustness checks that address potential concerns with this analysis, beginning with a focus on the time horizon of subsequent attacks.

5.3. Alternative Time Frames of Future Attacks

One concern about the estimations displayed in Table 6 relates to the potentially arbitrary choice of time frame for future attacks. In reality, our knowledge of the planning horizons of terrorists remains limited. It is likely that large attacks (e.g., 9/11) require a longer planning horizon (see Feinstein et al., 2010, for a theoretical model), yet the vast majority of missions are much smaller in scale, such as armed assaults, kidnappings, or assassinations (approximately 75 percent in the GTD database). It is possible that such plans can form and be conducted within short time periods. For instance, Berrebi and Lakdawalla (2007, page 127, Figure 3) show that the likelihood of subsequent attacks is much higher in the days immediately following an initial attack, focusing on the Israeli-Palestinian conflict.

To allow for more flexibility on the time frame of future attacks, Figure 6 displays the derived coefficient on *NYT* coverage when the dependent variable ranges from three to 20 days. All estimations follow the same structure as the benchmark regression displayed in column (6) of Table 6. In all estimations, *NYT* coverage emerges as a positive and statistically significant predictor. The magnitude of the coefficient increases when larger time frames are considered, but the relationship appears to stabilize about 11 to 14 days after the initial attacks. Thus, increased media coverage may spark future attacks for up to two weeks.

5.4. Robustness Checks

Beyond time frames, I now briefly discuss a number of robustness checks and extensions. Tables 7 and 8 display results from 13 additional regressions, building on the main specification of column (6) in Table 6. Additional robustness checks, such as removing outliers, using alternative definitions of terrorism, identifying terrorist groups following Kis-Katos et al. (2014), and including further economic, social, and political control variables are referred to the appendix.[20]

[20]The GTD distinguishes between domestic and international attacks, in addition to offering three definitions on terrorism and an indicator of whether terrorism has been doubtful. Kis-Katos et al. (2014) categorize terrorist groups along several

ACCEPTED MANUSCRIPT

Columns (1) through (3) of Table 7 include additional covariates, namely, the number of worldwide terrorist attacks on day i, country-specific time trends, and country-year fixed effects for the ten countries with the most terrorist attack days in the sample.[21] Regarding column (1), it is possible that coverage of a terrorist attack changes when many other countries suffer from terrorism on the same day. A priori, we could think of a "media congestion effect," as advocated by Scott (2001), or a cumulative effect ("terrorist attacks occurred in Afghanistan, Iraq, and India today"). Further, the inclusion of country-specific time trends provides a more restrictive econometric framework, acknowledging that some countries may have become the focus of terrorism at certain times. Note especially that those countries with fewer terrorist attacks will display less degrees of freedom in a statistical sense here. Similarly, including country-year fixed effects of the ten most terrorism-prone countries ensures that the result associated with NYT coverage is not driven by specific countries in particular years.

Columns (4) and (5) address the lack of time difference between terrorists operating in the Americas and the *NYT*. For instance, an attack in Colombia at 11:00 p.m. is likely to be reported the following day. This may cause measurement error in media coverage. To alleviate such concerns, I provide two regressions: one using the NYT coverage of the following day for American countries and another excluding American observations. Further, column (6) excludes attacks conducted in Europe to check whether the derived result is driven by Western countries. Throughout all estimations displayed in Table 7, the benchmark result prevails.

Table 8 displays seven additional alternative specifications. Column (1) acknowledges the dispersion of both the dependent variable and the initial number of NYT articles, applying the natural logarithm to both variables. Since both variables can take on the value of zero, I apply $Ln(1 + NYT)$. In addition, I choose the initial number of NYT articles, as opposed to NYT coverage, as the latter can take on negative values. Columns (2) through (5) include additional control variables that may confound the derived media effect: NYT coverage yesterday, election days in the affected country, the political affiliation of the US president and whether the US has been in an election campaign, and the occurrence of large international events.

First, including NYT coverage yesterday further controls for the general media attention the respective country is receiving independent of the current attacks. Second, both the degree of media coverage and

dimensions: by political, separatist, religious, ideological, and organizational status. Additional estimations include the following variables into the analysis: income levels, population size, educational attainment, trade, the role of natural resources in GDP, imports from the US, political regime form, voting affinity with the US in the United Nations, political rights, and civil liberties. Summary statistics of the additional variables are provided in Table AII.

[21]This list includes Afghanistan, Algeria, Colombia, India, Iraq, Northern Ireland, Pakistan, Peru, Philippines, and Spain. Note that the list of countries by attack *days* can differ marginally from the list of countries by total attacks, although the corresponding results are virtually identical. Note that this analysis is restricted to including the ten most prominent countries because including country-year fixed effects for more countries severely limits the explanatory power of natural disasters in the first stage.

ACCEPTED MANUSCRIPT

the number of terrorist attacks may be related to election days. For example, Puglisi (2011) shows that the *NYT* may choose and cover topics differently depending on the political situation, as well as the incumbent president. To test whether the derived media effect is in any way driven by such dynamics, I introduce binary indicators for a Republican sitting president, whether the US is in a presidential election campaign, and an interaction term between the two.[22] Third, large global events may have the potential to affect both media coverage of any country and terrorist activity. I include the following events in that list: the Academy Awards, G8 meetings, Olympic Games, soccer World Cups, and Super Bowls.

Overall, the coefficient associated with *NYT* coverage retains its statistical significance and magnitude in all estimations from column (1) through (5).[23] When country-year fixed effects are included, the estimation becomes less precise – an artifact that is owed to the much stricter econometric framework, leaving less statistical variation for the instrumental variable to operate. Nevertheless, the quantitative effect actually *increases* markedly (column 3), further confirming the role of media attention.

Finally, columns (6) and (7) provide results from two placebo regressions, estimating the number of terrorist attacks in the *previous* days. Intuitively, there is no reason to expect media coverage today to affect terrorism yesterday, and these estimations also test for potential reverse causality concerns. Even though the IV structure is intended to resolve such endogeneity biases, it is comforting to find that *NYT* coverage carries no predictive power for attacks in the past seven or three days in the 2SLS framework.

5.5. The Global Terrorism Database and the Media

In addition to the econometric specification applied, another concern relates to the fact that the GTD is in large part collected from media sources. Specifically, the GTD codebook states that

> "[t]he English-language content from Metabase is supplemented with articles downloaded from the Open Source Center (`www.opensource.gov`), which includes English-language translations of sources from over 160 countries in over 80 languages. This filter isolates an initial pool of potentially relevant articles, approximately 400,000 per month."

Thus, if the GTD is mostly sourced from the media itself, not all terrorist attacks may be captured. If such measurement error were not random with respect to the instrumental variable, then the derived results could be biased.[24] In particular, it is possible that if media outlets focus on covering a natural disaster in the US, then any subsequent terrorist attacks may simply go unnoticed by the GTD. If that

[22]Consistent with Puglisi (2011, p.10), I define the election campaign as taking place between August and October of the respective election year.

[23]Note that the quantitative interpretation changes in column (1) when applying logarithms.

[24]I thank the editor and an anonymous referee for pointing this out.

ACCEPTED MANUSCRIPT

were the case, the results displayed may be spurious, and it would simply be the GTD recording practices that drive the decline in registered subsequent terrorist attacks when a natural disaster occurs in the US.

One intuitive reason why this is unlikely comes from the above citation in the GTD codebook itself. As only terrorist attacks outside the US are considered, and GTD data are derived from over 160 countries, it appears unlikely that a domestic news outlet would not cover a domestic terror attack purely because of a natural disaster in the US. For example, a terrorist attack in India is unlikely to be crowded out of local media coverage because of a storm in Tennessee. Nevertheless, I also consider an empirical test for this hypothesis.

If the GTD were underreporting on days following a natural disaster in the US, then we would expect to see fewer attacks captured for *all* countries in the days following a natural disaster, not just those countries that experienced an attack on that day. To test for this, Tables 9 and 10 display results from several regressions. Columns (1) and (2) of Table 9 introduce a binary variable measuring whether a respective attack occurred on the day before a natural disaster. The dependent variable measures how many attacks occurred on the days $t+2$ until $t+7$ right after the attack. Notice that observations are excluded if another attack happened on day $t+1$, which would coincide with the natural disaster (and therefore test for the original hypothesis). However, I find no evidence that countries experiencing attacks right before a natural disaster in the US also experience fewer attacks in the subsequent days. This holds in a univariate regression framework, but also when adding the usual time parameters.

Further, columns (3) and (4) provide the same test for those attacks occurring right after a natural disaster. In this case, I only choose those country-day observations where the respective country has not experienced an attack on the previous day that coincides with the natural disaster in the US. Here again, the respective coefficient remains far from conventional levels of statistical significance. Thus, GTD reporting appears unaffected for countries experiencing an attack right before or right after a natural disaster in the US.

Columns (5) and (6) then return to employing the full sample of country-day observations with terrorist attacks and borrow the variable *news pressure* from Eisensee and Strömberg (2007). The dependent variable captures the number of attacks experienced in country i and day t. If the GTD indeed listed fewer attacks on days where the news are particularly intense, then we would expect to see a negative and statistically significant coefficient for *news pressure*. However, that is not the case.

Finally, Table 8 takes a broader approach beyond the initial sample of country-day observations that record at least one terror attack in the GTD. Using a sample of all days from January 1, 1970, to December 31, 2012, I regress the daily count of terrorist attacks worldwide on the natural disaster indicator and then also the news pressure variable. Column (1) shows that, if anything, the GTD records *more* attacks on days with a natural disaster in the US. However, that positive correlation becomes

ACCEPTED MANUSCRIPT

statistically meaningless once the usual time variables are incorporated in column (2). Thus, there is no indication that the GTD systematically under-reports on days with a natural disaster in the US.

Columns (3) and (4) then test whether that would be the case if the US experienced a natural disaster yesterday. But, here again, I find no indication. Finally, columns (5) and (6) check whether overall news pressure in the US is associated with fewer GTD entries. Here again, this is not the case.

Overall, I find no indication that countries display fewer entries in the GTD on or after days with a natural disaster in the US. This only affects those countries that also experienced terrorism on the day of the disaster, as highlighted by the main analysis. Similarly, on a global scale, I find no evidence of underreporting in the GTD when a natural disaster happens in the US.

5.6. Are Attacks Simply Postponed?

Finally, a natural question that emerges from the benchmark results relates to the permanency of the effect. A priori, two main explanations are possible. First, terrorists may generally attack less when media coverage of their actions is limited, indicating that media attention carries an overall positive effect on terrorist attacks. Second, terrorists may simply postpone their missions to a future date when the international community is not occupied with a one-day natural disaster in the US. For instance, terrorists may realize on day t or $t+1$ that the international media does not pay attention to their missions and therefore postpone attacks. In this case, there would not be an overall effect of immediate media attention on terrorism, but coverage would merely influence the timing of attacks.

To distinguish between these two explanations, I first return to a reduced form estimation of the baseline sample using the disaster dummy as a predictor for future terrorism. All corresponding control variables from column (6) in Table 6 are included. The estimated coefficient is displayed in Figure 7, once again displaying results from applying several different time frames for future attacks, up to 20 days. Reiterating the benchmark findings, the derived coefficient remains comfortably significant on conventional levels (usually on the one percent level), and the number of upcoming attacks decreases when a natural disaster occurs in the US.

Now, if attacks were merely postponed, *NYT* coverage may not affect terrorism per se, but merely their timing. To test this, I rerun the reduced form estimation, regressing the number of attacks in days 14 to 30 after the initial attack on the disaster dummy, once again providing different time windows in Figure 8. I choose 14 days after the initial attack since the effect of *NYT* coverage seems to flatten out at about that time (see Figures 6 and 7). Nevertheless, the results are closely replicated when choosing similar cutoff times. Finally, the last two coefficients displayed in Figure 8 show the derived coefficient for including up to 45 and 60 days.

If terrorists were indeed postponing their planned attacks to avoid potentially decreased media attention because of a natural disaster in the US, we would expect a positive coefficient on the binary

ACCEPTED MANUSCRIPT

indicator for disasters. However, the derived coefficient never comes close to conventional levels of statistical significance. In fact, the coefficient remains negative, not positive as would be expected if planned attacks were accumulated. Thus, attacks do not appear to be postponed. If anything, we still observe *fewer* attacks for up to 60 days after the natural disaster, although the estimated coefficients remain statistically insignificant on conventional levels.

6. Conclusions

This paper introduces a methodology for evaluating causal links between media attention and subsequent terrorist attacks. Using the *NYT* as a representative international media outlet, I derive a proxy for media coverage devoted to individual attack days, creating 61,132 observations on the country-day level between 1970 and 2012. In a conventional OLS analysis, *NYT* coverage remains a statistically insignificant and quantitatively negligible predictor of future attacks in the same country. However, substantial endogeneity problems are likely contaminating this result as a number of characteristics may influence both terrorism and its media attention in either direction.

To isolate causality, I use natural disasters in the US as an exogenous variation that decreases media attention devoted to contemporaneous terrorist attacks conducted elsewhere in the world. In a 2SLS framework, *NYT* coverage emerges as a positive and sizeable determinant of future attacks – a result that is statistically significant at the one percent level. One additional *NYT* article is suggested to cause 1.4 additional attacks in the upcoming week, which translates to approximately three casualties on average. Thus, providing terrorists with an international media platform may encourage further terrorism. This result is robust to a number of alternative estimations, extensions, and robustness checks. Further, I find no evidence that terrorists merely postpone their missions if coverage is reduced unexpectedly. If anything, the number of attacks remains lower for up to 60 days.

In general, these results provide quantitative evidence that media coverage may encourage further terrorist attacks, a conclusion that advises against elevated media coverage of terrorism. Analyzing a long-term sample of 43 years and 201 countries, this study evaluates the media-terrorism link in its most general form. The disadvantage of this scope is that search terms within the media need to be general and comparable across time and space. Thus, promising future studies may focus on particular conflict zones, allowing for a more refined measure of media attention and the underlying dynamics of terrorism. Similarly, a content analysis of *how* the media reports on terrorism and potential consequences would likely produce fruitful insights.

ACCEPTED MANUSCRIPT

References

4IMN (2014). 2014 newspaper web rankings. 4International Media & Newspapers (online).

Abadie, A. (2006). Poverty, political freedom, and the roots of terrorism. *American Economic Review*, 96(2):50–56.

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

ABC News (2014). Push to refer to king hit attacks as 'coward punches' after teen left in coma. Available under `http://www.abc.net.au/news/2014-01-03/push-to-refer-to-king-hit-attacks-as-coward-punches/5183260`.

Berrebi, C. and Lakdawalla, D. (2007). How does terrorism risk vary across space and time? An analysis based on the Israeli experience. *Defence and Peace Economics*, 18(2):113–131.

Berrebi, C. and Ostwald, J. (2011). Earthquakes, hurricanes, and terrorism: Do natural disasters incite terror? *Public Choice*, 149(3-4):383–403.

Berrebi, C. and Ostwald, J. (2013). Exploiting the chaos: Terrorist target choice following natural disasters. *Southern Economic Journal*, 79(4):793–811.

Blomberg, S. B., Hess, G. D., and Orphanides, A. (2004). The macroeconomic consequences of terrorism. *Journal of Monetary Economics*, 51(5):1007–1032.

Chenoweth, E. (2013). Terrorism and democracy. *Annual Review of Political Science*, 16:355–378.

Courier Mail (2014). NSW cops, pollies, docs call out 'cowards'. Available under `http://www.couriermail.com.au/news/breaking-news/kellys-call-for-tougher-sentencing-laws/story-fnihsfrf-1226794126356?from=public_rss`.

DellaVigna, S. and Gentzkow, M. (2010). Persuasion: Empirical evidence. *Annu. Rev. Econ*, 2:643–69.

Dreher, A., Gassebner, M., and Siemers, L.-H. (2010). Does terrorism threaten human rights? Evidence from panel data. *Journal of Law and Economics*, 53(1):65–93.

Durante, R. and Zhuravskaya, E. (2015). Attack when the world is not watching? International media and the Israeli-Palestinian conflict. *Forthcoming in the Journal of Political Economy.*

Eckstein, Z. and Tsiddon, D. (2004). Macroeconomic consequences of terror: Theory and the case of Israel. *Journal of Monetary Economics*, 51(5):971–1002.

Eisensee, T. and Strömberg, D. (2007). News droughts, news floods, and US disaster relief. *The Quarterly Journal of Economics*, 122(2):693–728.

Enders, W. and Hoover, G. A. (2012). The nonlinear relationship between terrorism and poverty. *American Economic Review*, 102(3):267–272.

Feinstein, J. S., Kaplan, E. H., et al. (2010). Analysis of a strategic terror organization. *Journal of Conflict Resolution*, 54(2):281–302.

Freedom House (2011). Freedom in the world 2011. *Washington, DC.*

Frey, B. S. and Luechinger, S. (2003). How to fight terrorism: Alternatives to deterrence. *Defence and Peace Economics*, 14(4):237–249.

ACCEPTED MANUSCRIPT

Frey, B. S., Luechinger, S., and Stutzer, A. (2007). Calculating tragedy: Assessing the costs of terrorism. *Journal of Economic Surveys*, 21(1):1–24.

Gaibulloev, K. and Sandler, T. (2009). The impact of terrorism and conflicts on growth in Asia. *Economics & Politics*, 21(3):359–383.

Gassebner, M., Jong-A-Pin, R., and Mierau, J. O. (2011). Terrorism and cabinet duration. *International Economic Review*, 52(4):1253–1270.

Gassebner, M. and Luechinger, S. (2011). Lock, stock, and barrel: A comprehensive assessment of the determinants of terror. *Public Choice*, 149(3-4):235–261.

Gentzkow, M., Shapiro, J. M., and Stone, D. F. (2015). Media bias in the marketplace: Theory. *Handbook of Media Economics*, 1B:623–645.

Gentzkow, M. A. and Shapiro, J. M. (2004). Media, education and anti-Americanism in the muslim world. *The Journal of Economic Perspectives*, 18(3):117–133.

George, L. and Waldfogel, J. (2006). The New York Times and the market for local newspapers. *American Economic Review*, 96(1):435–447.

Group, W. B. (2012). *World Development Indicators 2012*. World Bank Publications.

Guha-Sapir, D., Below, R., and Hoyois, P. (2014). *EM-DAT: International Disaster Database*. Université Catholique de Louvain, Brussels, Belgium.

Jetter, M. (2014). Terrorism and the media. *IZA Discussion Paper #8497*.

Jetter, M. (2017). Terrorism and the media: The effect of US television coverage on Al-Qaeda attacks. *IZA Discussion Paper #10708*.

Jetter, M. and Stadelmann, D. (2017). Terror per capita. *CESifo Working Paper #6335*.

John, S. (2015). The world's top 5 most watched sporting events. Top 5 online publication (`http://sports-facts.top5.com/the-worlds-top-5-most-watched-sporting-events/`).

Kis-Katos, K., Liebert, H., and Schulze, G. G. (2014). On the heterogeneity of terror. *European Economic Review*, 68(C):116–136.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133(1):97–126.

Kleibergen, F. and Schaffer, M. E. (2007). Ranktest: Module for testing the rank of a matrix using the Kleibergen-Paap rk statistic. *Statistical software component. Boston College Department of Economics.*

Krueger, A. B. and Laitin, D. D. (2008). Kto kogo?: A cross-country study of the origins and targets of terrorism. *Terrorism, economic development, and political openness*, pages 148–173.

Krueger, A. B. and Malečková, J. (2003). Education, poverty and terrorism: Is there a causal connection? *Journal of Economic Perspectives*, 17(4):119–144.

LaFree, G. and Dugan, L. (2007). Introducing the Global Terrorism Database. *Terrorism and Political Violence*, 19(2):181–204.

Larcinese, V., Puglisi, R., and Snyder, J. M. (2011). Partisan bias in economic news: Evidence on the agenda-setting behavior of US newspapers. *Journal of Public Economics*, 95(9):1178–1189.

Magnusson, L. M. (2010). Inference in limited dependent variable models robust to weak identification. *The Econometrics Journal*, 13(3):S56–S79.

ACCEPTED MANUSCRIPT

Marshall, M. G. and Jaggers, K. (2002). Polity IV project: Political regime characteristics and transitions, 1800-2002.

Melnick, R. and Eldor, R. (2010). Small investment and large returns: Terrorism, media and the economy. *European Economic Review*, 54(8):963–973.

Merrill, J. (1999). The global elite: World's best newspapers reflect political changes. *IPI Report*, pages 13–15.

Mindframe (2014). Reporting suicide and mental illness: A mindframe resource for media professionals. `www.mindframe-media.info/`.

Mueller, J. E. (2006). *Overblown: How politicians and the terrorism industry inflate national security threats, and why we believe them*. Simon and Schuster.

Nelson, P. S. and Scott, J. L. (1992). Terrorism and the media: An empirical analysis. *Defence and Peace Economics*, 3(4):329–339.

Nohlen, D. (2005). *Elections in the Americas: A Data Handbook: Volume 2 South America*, volume 2. OUP Oxford.

Nohlen, D. (2010). *Elections in Europe: A data handbook*. Nomos Verlag-Ges.

Nohlen, D., Grotz, F., and Hartmann, C. (2001). *Elections in Asia and the Pacific: A Data Handbook: Volume I: Middle East, Central Asia, and South Asia: Volume I: Middle East, Central Asia, and South Asia*, volume 1. Oxford University Press.

Nohlen, D., Thibaut, B., and Krennerich, M. (1999). *Elections in Africa: A Data Handbook: A Data Handbook*. OUP Oxford.

Pries-Shimsh, Y. (2005). Creating a citizenry prepared for terrorism: Education, media, and public awareness. *International Institute for Counter-Terrorism*.

PRRI (2015). Survey: Nearly half of Americans worried that they or their family will be a victim of terrorism. *Public Religion Research Institute, December 10, 2015*.

Puglisi, R. (2011). Being the New York Times: The political behaviour of a newspaper. *The BE Journal of Economic Analysis & Policy*, 11(1).

Puglisi, R. and Snyder, J. M. (2015). Empirical studies of media bias. *Handbook of Media Economics*, 1B:647–667.

Rohner, D. and Frey, B. S. (2007). Blood and ink! The common-interest-game between terrorists and the media. *Public Choice*, 133(1-2):129–145.

Sandler, T. (2015). Terrorism and counterterrorism: An overview. *Oxford Economic Papers*, pages 1–20.

Santifort-Jordan, C. and Sandler, T. (2014). An empirical study of suicide terrorism: A global analysis. *Southern Economic Journal*, 80(4):981–1001.

Scott, J. L. (2001). Media congestion limits media terrorism. *Defence and Peace Economics*, 12(3):215–227.

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics*, 118:26–40.

Stock, J. H. and Watson, M. W. (2012). *Introduction to Econometrics: Global Edition*. Pearson Education.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4):518–29.

Voeten, E. and Merdzanovic, A. (2013). United Nations general assembly voting data. *Accessed online November 2013*.

Walsh, J. I. (2010). Media attention to terrorist attacks: Causes and consequences. *Institute for Homeland Security Solutions, Research Brief*.

Wilkinson, P. (1997). The media and terrorism: A reassessment. *Terrorism and Political Violence*, 9(2):51–64.

Wooldridge, J. M. (1995). Score diagnostics for linear models estimated by two stage least squares. *Advances in econometrics and quantitative economics*, pages 66–87.

WVS (2015). World values survey 1981-2014 longitudinal aggregate v.20150418.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Figures

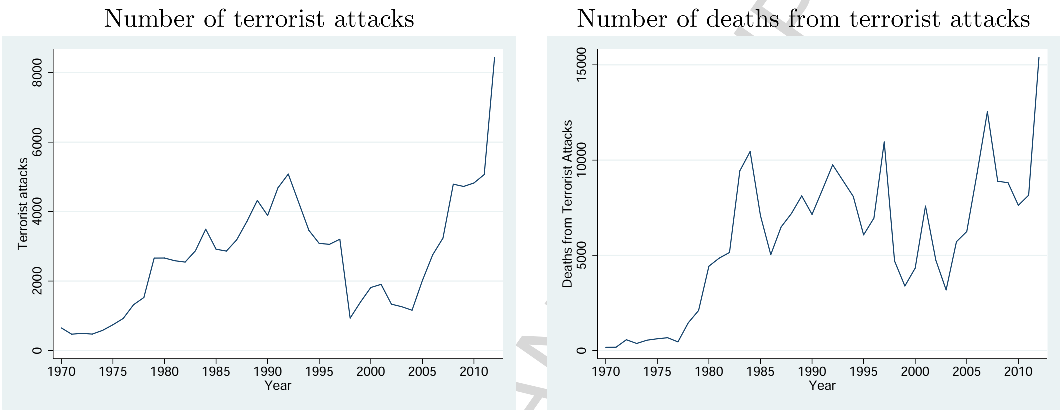


Figure 1: Terrorism over time, using data from the Global Terrorism Database (GTD).

ACCEPTED MANUSCRIPT

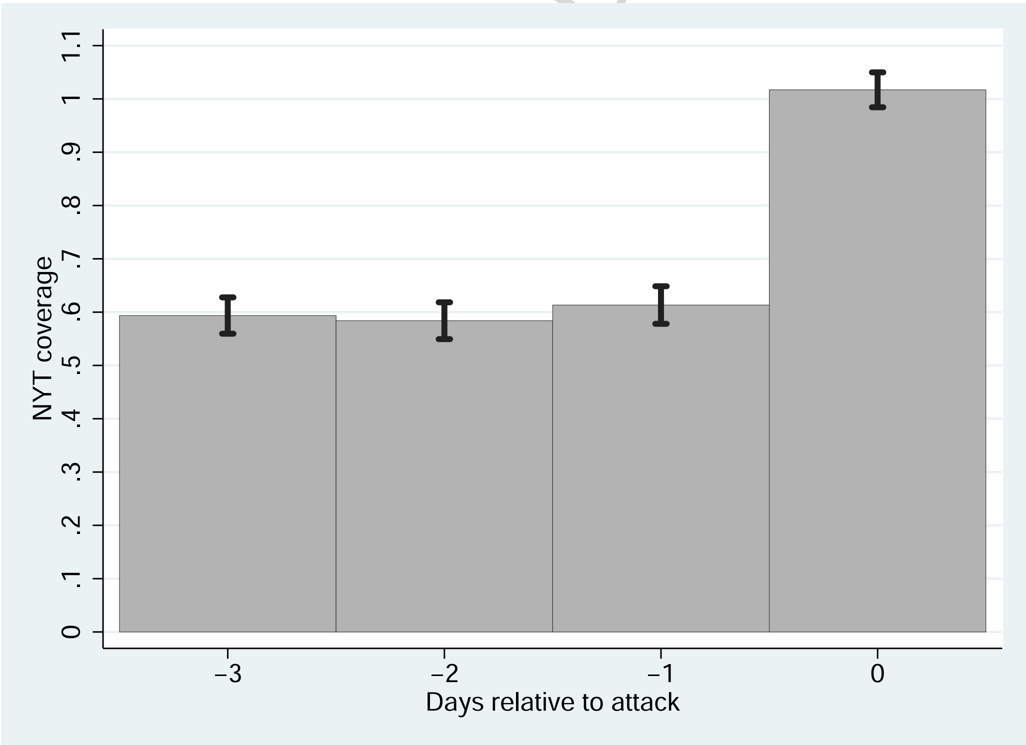
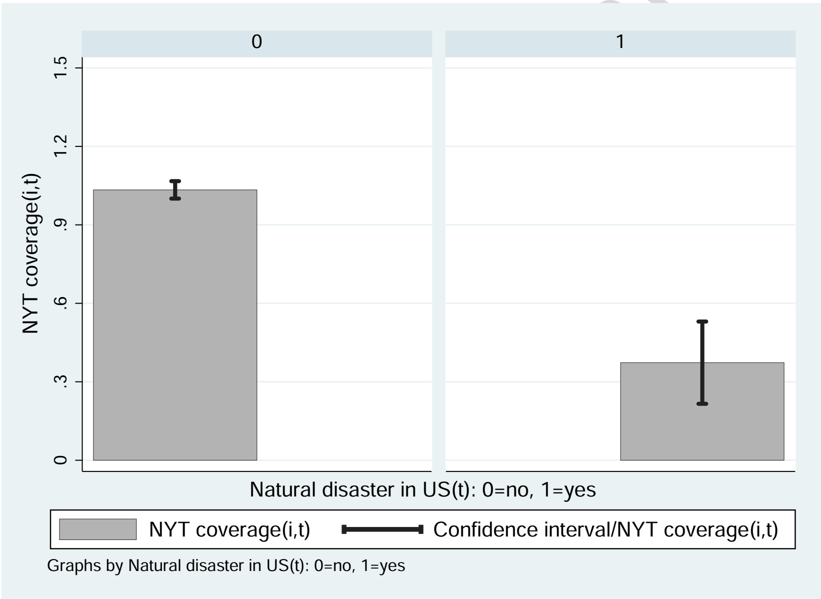


Figure 2: *NYT* coverage on days relative to attack day. Days prior to the attack exclude observations with an attack in the same country.

ACCEPTED MANUSCRIPT

Panel A: NYT coverage



Panel B: Subsequent attacks from $t + 1$ until $t + 7$

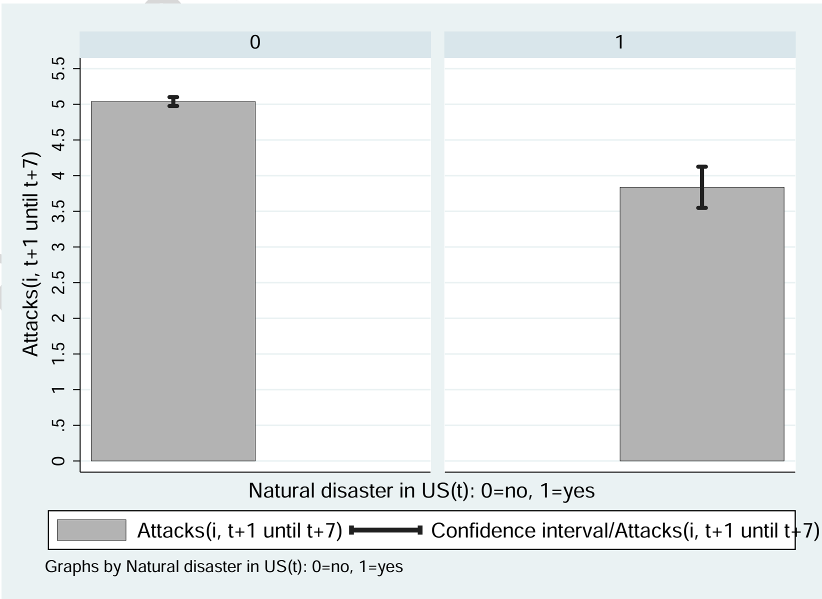
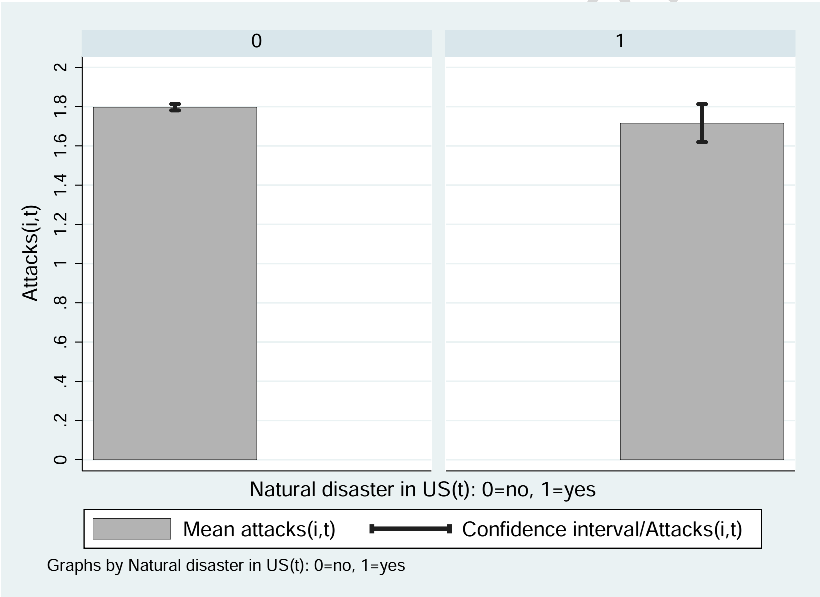


Figure 3: Key variables for regular attack days and attack days coinciding with a natural disaster in the US.

ACCEPTED MANUSCRIPT

Panel A: Natural disaster in US (t)



Panel B: Natural disaster in US ($t+1$)

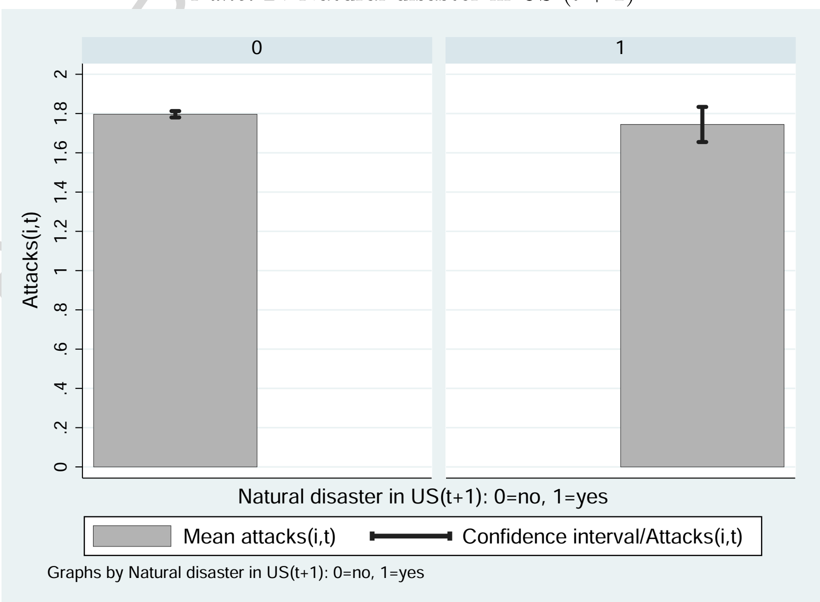


Figure 4: Number of attacks on regular days and days with a natural disaster in the US.

ACCEPTED MANUSCRIPT

Attacks on regular days and during soccer World Cup

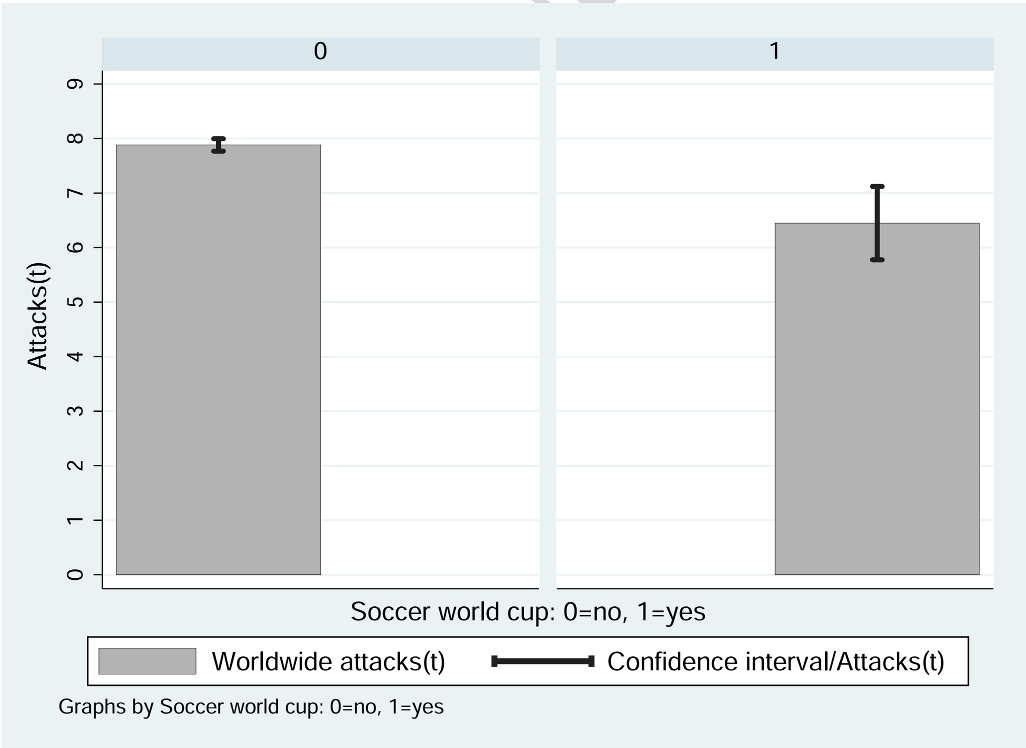


Figure 5: Worldwide terrorist attacks per day, using all 15,706 days from January 1, 1970, to December31, 2012.

ACCEPTED MANUSCRIPT

Subsequent attacks on days $t+1$ until $t+3$, $t+4$, ..., $t+20$

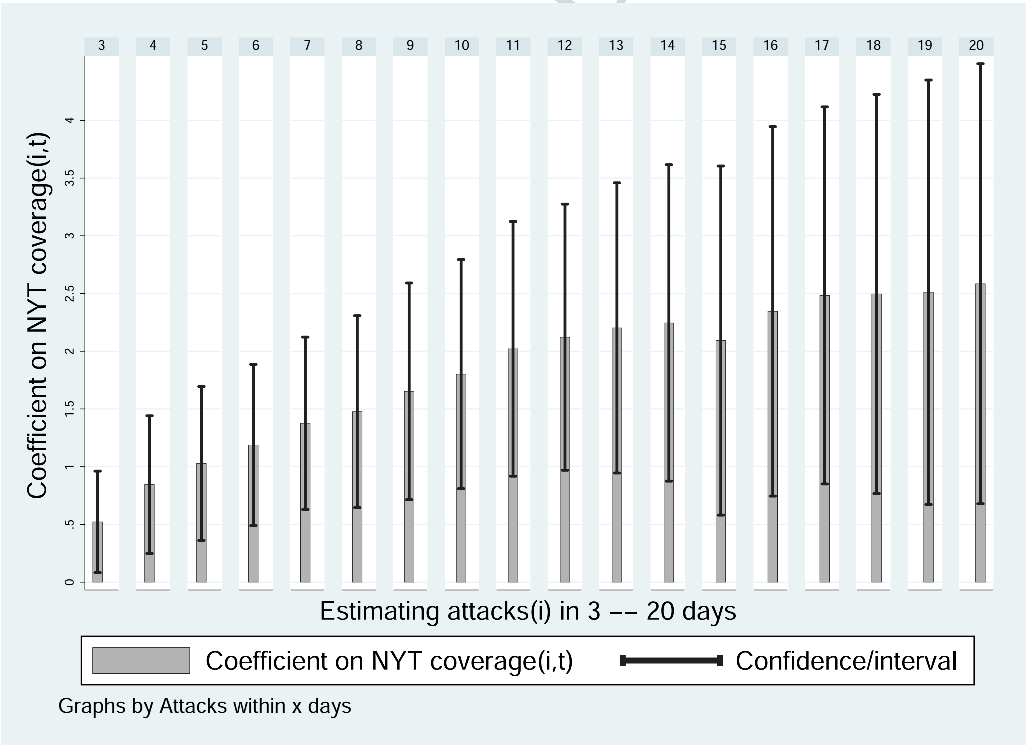


Figure 6: Displaying results from IV regressions for *NYT* coverage, estimating different time frames for subsequent attacks. All regressions include the control variables applied in column (6), Table 6.

ACCEPTED MANUSCRIPT

Estimated coefficient for *natural disaster in US (t)*, predicting subsequent attacks on days $t+1$ until $t+3$, $t+4$, ..., $t+20$ (reduced form estimation)

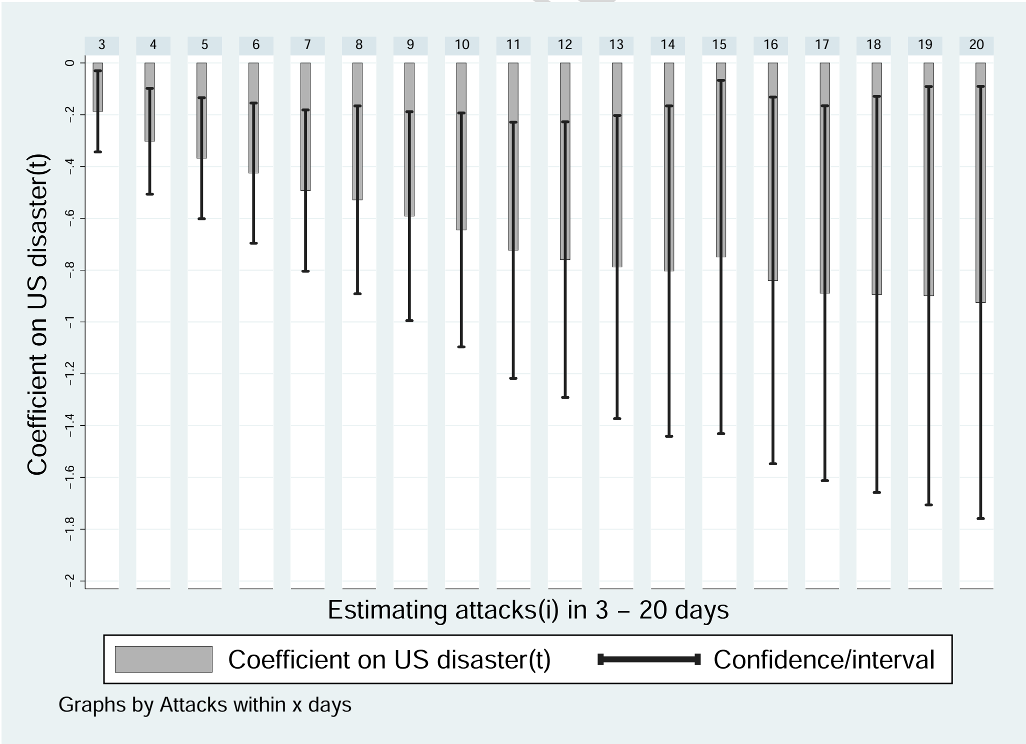


Figure 7: Displaying results from reduced form regressions for *natural disaster in the US*, estimating different time frames for subsequent attacks. All regressions include the control variables applied in column (6), Table 6.

ACCEPTED MANUSCRIPT

Estimated coefficient for *natural disaster in US (t)*, predicting subsequent attacks on days $t + 14$ until $t + 16$, $t + 17$, ..., $t + 60$ (reduced form estimation)

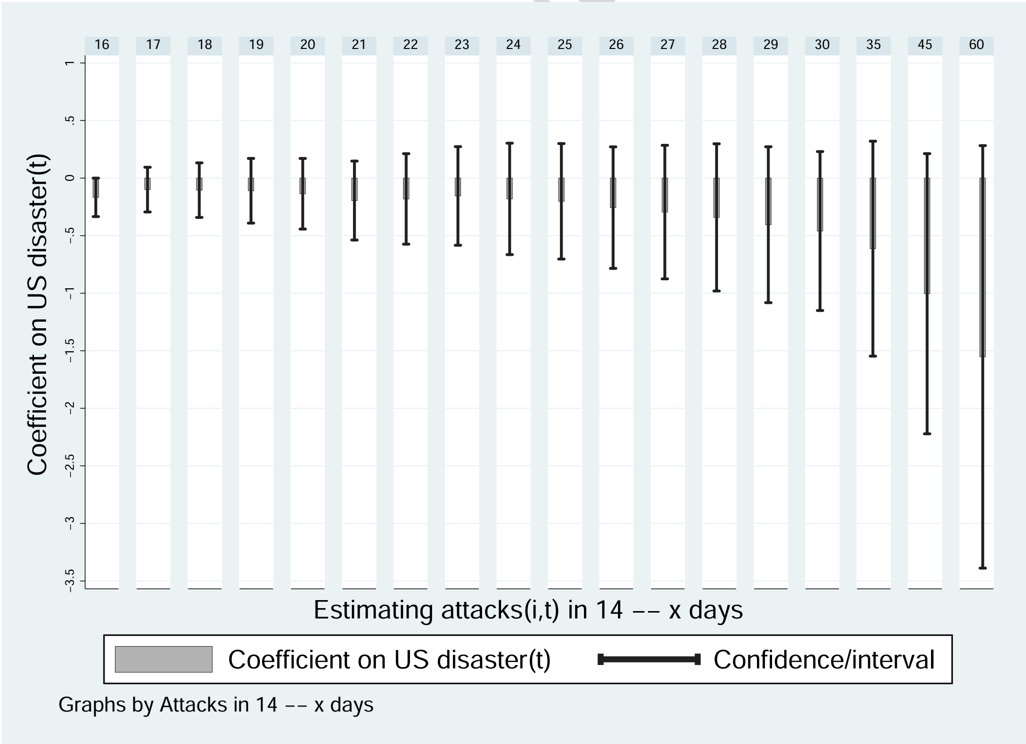


Figure 8: Displaying results from reduced form regressions for *natural disaster in the US*, estimating different time frames for subsequent attacks. All regressions include the control variables applied in column (6), Table 6.

ACCEPTED MANUSCRIPT

Tables

Table 1: 10 Countries with most terrorist attacks from 1970 to 2012 (using GTD data).

Absolute number of Attacks		Number of Attacks Per 1,000 citizens	
Country	**Attacks**	**Country**	**Attacks**
Iraq	9,224	El Salvador	9.0
Colombia	7,491	Lebanon	4.6
India	7,484	Nicaragua	3.8
Pakistan	7,119	Iraq	2.8
Peru	6,015	Israel	2.1
El Salvador	5,277	Peru	2.0
United Kingdom	4,607	New Caledonia	1.7
Afghanistan	4,497	Colombia	1.6
Philippines	3,555	Afghanistan	1.5
Spain	3,197	Suriname	1.5

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Table 2: Summary statistics of main variables (61,132 observations).

Variable	Mean	(Std. Dev.)	Min.	Max.	Source[a]
Subsequent attacks on days $t+1$ until $t+7$	5.01	(7.74)	0	108	GTD
NYT coverage$^{b}_{i,t}$	1.02	(4.13)	-10.25	107	*NYT*
Casualties$_{i,t}$	3.90	(13.57)	0	1,181	GTD
Attacks$_{i,t}$	1.80	(2.02)	1	61	GTD
Preceding attacks on days $t-7$ until $t-1$	5.08	(7.70)	0	108	GTD
Natural disaster in US$_t$	0.03	(0.16)	0	1	EM-DAT
Assassination	0.24	(0.59)	0	1	GTD
Armed assault	0.46	(0.92)	0	1	GTD
Bombing/explosion	0.83	(1.67)	0	1	GTD
Kidnapping	0.09	(0.36)	0	1	GTD
Facility/infrastructure attack	0.11	(0.58)	0	1	GTD
Unknown attack type	0.04	(0.31)	0	1	GTD

Notes: [a]Sources: GTD = Global Terrorism Database (based on LaFree and Dugan, 2007), *NYT* = New York Times archives, EM-DAT = International Disaster Database (Guha-Sapir et al., 2014). [b]Number of articles on attack day minus average daily number of *NYT* articles from 1/1/1970 to 12/31/2012.

ACCEPTED MANUSCRIPT

Table 3: OLS regression results, predicting *NYT coverage*$_{i,t}$ and subsequent attacks in country i on days $t+1$ until $t+7$.

Dependent variable:	*NYT coverage*$_{i,t}$ (*mean = 1.02*)			Subsequent attacks on $t+1$ until $t+7$ (*mean = 5.01*)		
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster in US$_t$	-0.661***	-0.563***	-0.357***	-1.202*	-0.979**	-0.493***
	(0.218)	(0.142)	(0.088)	(0.651)	(0.475)	(0.159)
Time trend, FE for days of the week and months		yes	yes		yes	yes
Country FE & preceding attacks on days $t-7$ until $t-1$			yes			yes
# of countries	201	201	201	201	201	201
N	61,132	61,132	61,132	61,132	61,132	61,132
Adjusted R^2	0.001	0.093	0.292	0.001	0.051	0.517

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a]Includes the number of attacks, the number of casualties, the number of attacks in the preceding 7 days, and fixed effects for attack types, targets, and weapons. Fixed effects are estimated using the *xtreg* command in Stata.

Table 4: OLS regression results, estimating the number of attacks per attack day.

Dependent variable: attacks in country i on t (mean = 1.80)						
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster in US$_t$	-0.081	-0.074	-0.025			
	(0.087)	(0.074)	(0.041)			
Natural disaster in US$_{t+1}$				-0.052	-0.043	0.003
				(0.084)	(0.071)	(0.048)
Time trend, FE for days of the week and months		yes	yes		yes	yes
Country FE & preceding attacks on days $t-7$ until $t-1$			yes			yes
# of countries	201	201	201	201	201	201
N	61,132	61,132	61,132	61,132	61,132	61,132
Adjusted R^2	0.000	0.002	0.122	0.000	0.002	0.122

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Fixed effects are estimated using the *xtreg* command in Stata.

ACCEPTED MANUSCRIPT

Table 5: Exogeneity tests, estimating whether a natural disaster on day t predicts several outcomes on day $t-1$. Regressions displayed in columns (9) – (12) are estimated using fixed-effects negative binomial models (command *xtnbreg* in Stata) due to the large number of zeros in the dependent variable.

Dependent variable:	NYT coverage (1)	Attacks (2)	International attacks (3)	Attacks on business (4)	Attacks on government (5)	Attacks on police (6)	Attacks on private targets (7)	Sources[b] (8)	Deaths (9)	Wounded (10)	Deaths US (11)	Wounded US (12)
Panel A: Dependent variable taken in $t-1$												
Natural disaster in US_t	-0.069	0.016	0.019*	-0.010	-0.002	-0.003	-0.004	-0.033	0.042	0.059		
	(0.102)	(0.035)	(0.010)	(0.012)	(0.008)	(0.013)	(0.011)	(0.047)	(0.034)	(0.041)		
N	61,132	61,132	61,132	61,132	61,132	61,132	61,132	24,659	61,060	61,068		
Panel B: Dependent variable taken as average from $t-1$ and $t-2$												
Natural disaster in US_t	-0.075	-0.010	0.009	-0.012	0.001	0.000	-0.005	0.013	0.041	0.052	0.012	0.059
	(0.081)	(0.020)	(0.006)	(0.008)	(0.005)	(0.010)	(0.012)	(0.041)	(0.028)	(0.033)	(0.240)	(0.037)
N	61,131	61,131	61,131	61,131	61,131	61,131	61,131	24,659	61,054	61,062	50,518	60,676
Panel C: Dependent variable taken as average from $t-1$, $t-2$, and $t-3$												
Natural disaster in US_t	-0.105	-0.015	0.006	-0.013*	0.003	0.003	-0.010	0.004	0.055**	0.063**	-0.056	0.040
	(0.071)	(0.013)	(0.006)	(0.007)	(0.004)	(0.008)	(0.010)	(0.037)	(0.025)	(0.029)	(0.207)	(0.035)
N	61,131	61,131	61,131	61,131	61,131	61,131	61,131	24,659	61,045	61,059	50,518	60,673
Panel D: Control variables												
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Control variables$_t^a$	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects are estimated using the *xtreg* command in Stata. [a]Includes all control variables discussed in equation 1: Fixed effects for attack, target, and weapon types; variables counting the number of attacks, the number of casualties, the number of attacks in the preceding 7 days; a linear time trend, and fixed effects for each day of the week and months. All control variables are taken at time t. [b]Sources (variables *scite*1, *scite*2, and *scite*3 in the GTD Codebook) are only available after 1997. The variable measures the average number of sources reported for the attacks documented on days $t-1$ (Panel A), $t-1$ and $t-2$ (Panel B), and $t-1$, $t-2$, and $t-3$ (Panel C).

ACCEPTED MANUSCRIPT

Table 6: Results from IV regressions predicting subsequent attacks in country i on days $t+1$ until $t+7$.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS results predicting subsequent attacks on days $t+1$ until $t+7$						
NYT coverage$_{i,t}$	0.452***	0.094	0.087	0.088	0.052	0.048
	(0.092)	(0.092)	(0.082)	(0.081)	(0.038)	(0.036)
N	61,132	61,132	61,132	61,132	61,132	61,132
Adjusted R^2	0.058	0.336	0.386	0.386	0.515	0.517
Panel B: IV second stage results predicting subsequent attacks on days $t+1$ until $t+7$						
NYT coverage$_{i,t}$	1.819***	1.980**	1.915***	1.832***	1.488***	1.382***
	(0.540)	(0.790)	(0.699)	(0.642)	(0.423)	(0.383)
Panel C: IV first stage results predicting *NYT coverage*$_{i,t}$						
Natural disaster in US$_t$	-0.661***	-0.349***	-0.334***	-0.345***	-0.337***	-0.357***
	(0.217)	(0.111)	(0.105)	(0.106)	(0.098)	(0.088)
Panel D: Control variables included in all regressions (OLS, first- and second-stage of IV)						
Country FE		yes	yes	yes	yes	yes
Attack, target & weapon type FE			yes	yes	yes	yes
Control variables[a]				yes	yes	yes
Preceding attacks on days $t-7$ until $t-1$					yes	yes
Time trend, FE for days of the week & months						yes
Panel E: Test-statistics IV regressions						
F-test insignificance of IV	9.21***	9.92***	10.07***	10.51***	11.65***	16.33***
Weak IV test (Wald)[b]	11.35***	6.28**	7.50***	8.13***	12.11***	12.61***
Kleibergen-Paap weak IV test[c]	62.53***	22.06***	20.26***	21.61***	20.75***	25.13***
F-test endogeneity[d] 3.04*	3.43*	3.95**	4.01**	8.30***	8.39***	
# of countries	201	201	201	201	201	201
N	61,132	61,132	61,132	61,132	61,132	61,132

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Includes the number of attacks and the number of casualties. [b]Following Magnusson (2010), the *weakiv* command is applied in Stata to test for weak instruments. [c]Following Kleibergen and Paap (2006) and Kleibergen and Schaffer (2007), the command *ranktest* produces the Kleibergen-Paap statistic. [d]Following Wooldridge (1995), I test for whether endogenous regressors are in fact exogenous (Stata command *estat endogenous* after the *ivregress 2sls* command). Statistical significance indicates variables must be treated as endogenous.

ACCEPTED MANUSCRIPT

Table 7: Robustness checks I, displaying results from IV regressions predicting subsequent attacks in country i on days $t+1$ until $t+7$. Please see footnotes for details.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second stage predicting subsequent attacks on days $t+1$ until $t+7$						
NYT coverage$_{i,t}$	1.372***	1.476***	2.358*	1.347***	1.274***	1.458***
	(0.371)	(0.566)	(1.214)	(0.369)	(0.346)	(0.454)
Attacks worldwide$_t$	0.070**					
	(0.034)					
Country-specific time trends		yes				
Country-year FE for 10 biggest terrorism victims[a]			yes			
Control variables[b]	yes	yes	yes	yes	yes	yes
Panel B: First stage predicting *NYT coverage*$_{i,t}$						
Natural disaster in US$_t$	-0.358***	-0.203***	-0.118**	-0.366***	-0.433***	-0.360***
	(0.088)	(0.067)	(0.055)	(0.088)	(0.126)	(0.135)
Attacks worldwide$_t$	0.070**					
	(0.034)					
Country-specific time trends		yes				
Country-year FE for 10 biggest terrorism victims[a]			yes			
Control variables[b]	yes	yes	yes	yes	yes	yes
# of countries	201	201	201	201	140	95
N	61,132	61,132	61,132	61,132	40,198	33,026

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Includes country-year fixed effects for the 10 countries that suffered most from terrorist attacks: Afghanistan, Algeria, Colombia, India, Iraq, Northern Ireland, Pakistan, Peru, Philippines and Spain. [b]Includes all control variables from column (6), Table 6. Column (4): Uses *NYT* coverage of the day after the attack for the Americas. Column (5): Excluding the Americas. Column (6): Excluding the Americas and Europe.

ACCEPTED MANUSCRIPT

Table 8: Robustness checks II, displaying results from IV regressions predicting subsequent attacks in country i on days $t+1$ until $t+7$. Please see footnotes for details.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Second stage predicting subsequent attacks on days $t+1$ until $t+7$							
NYT coverage$_{i,t}$	0.2**	2.425***	1.391***	1.134***	1.378***	0.747	0.443
	(0.124)	(0.749)	(0.385)	(0.310)	(0.383)	(0.880)	(0.303)
NYT coverage$_{i,t-1}$		-1.228***					
		(0.451)					
Domestic election$_{i,t}$			-2.730**				
			(1.106)				
Republican president in US$_t$				-0.946			
				(0.753)			
Presidential campaign in US$_t$				0.713			
				(0.482)			
Republican president$_t$ × presidential campaign$_t$				-0.659			
				(0.543)			
International event$_t^a$					-0.169		
					(0.272)		
Control variables^b	yes	yes	yes	yes	yes	yes	yes
Panel B: First stage predicting *NYT coverage*$_{i,t}$							
Natural disaster in US$_t$	-0.191***	-0.197***	-0.356***	-0.391***	-0.359***	-0.363***	-0.363***
	(0.058)	(0.059)	(0.088)	(0.072)	(0.088)	(0.092)	(0.093)
NYT coverage$_{i,t-1}$		0.526***					
		(0.065)					
Domestic election$_{i,t}$			0.757*				
			(0.403)				
Republican president in US$_t$				0.396***			
				(0.034)			
Presidential campaign in US$_t$				0.062			
				(0.090)			
Republican president$_t$ × presidential campaign$_t$				-0.164			
				(0.113)			
International event$_t^c$					0.270**		
					(0.120)		
Control variables^b	yes	yes	yes	yes	yes	yes	yes
# of countries	201	201	201	201	201	201	201
N	61,132	61,132	61,132	61,132	61,132	61,132	61,132

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Dummy = 1 if any of the following happened on the same day: Academy Awards, G8 meeting, Olympic games, soccer World Cup, or the Super Bowl. [b]Includes all control variables from column (6), Table 6. Column (1): Applying Ln(0.01+*NYT articles* to the dependent variable, *NYT* coverage, and to all other count variables. Count variables that can take on the value of zero are calculated as $Ln(1 + variable)$ to preserve observations. Columns (6) and (7): Placebo regressions, estimating the number of attacks in previous 7 days and previous 3 days.

ACCEPTED MANUSCRIPT

Table 9: OLS regression results, testing whether the GTD systematically reports differently after natural disasters in the US or when news pressure is high.

Dependent variable: Attacks in country i on days	$t+2$ until $t+7$		$t+1$ until $t+7$		t	
	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster in US_{t+1}	-0.151	-0.052				
	(0.208)	(0.183)				
Natural disaster in US_{t-1}			-0.233	-0.190		
			(0.208)	(0.193)		
News pressure_t					0.006	-0.004
					(0.009)	(0.006)
Time trend, FE for days of the week and months		yes		yes		yes
Country FE		yes		yes		yes
# of countries	201	201	201	201	201	201
N	40,695	40,695	40,695	40,695	59,830	59,830

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects are estimated using the *xtreg* command in Stata.

Table 10: OLS regression results, testing whether the GTD systematically reports fewer attacks on days with a natural disaster in the US.

Dependent variable: Worldwide number of attacks on day t	(1)	(2)	(3)	(4)	(5)	(6)
Natural disaster in US_t	0.637*	0.100				
	(0.360)	(0.375)				
Natural disaster in US_{t-1}			0.686*	0.170		
			(0.373)	(0.384)		
News pressure_t					0.270***	0.037
					(0.023)	(0.023)
Time trend, FE for days of the week and months		yes		yes		yes
N	15,705	15,705	15,704	15,704	13,558	13,558

Notes: Robust standard errors are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ACCEPTED MANUSCRIPT

Appendix Tables for Online Publication

Table AI provides country averages for the number of *NYT* articles on attack days and regular days for all sample countries. Table AII displays summary statistics of additional variables employed in further robustness checks, most notably Tables 7, 8, and AVI. Tables AIII and AIV check for the importance of outliers in the main variables of interest and alternative definitions of terrorism, as provided by the GTD. Table AV acknowledges the different categories of terrorism, as worked out by Kis-Katos et al. (2014).

Finally, Table AVI adds a number of economic, social and political factors to the analysis, all of which are available on the country-year level. Specifically, GDP per capita, population size, education, trade, natural resources, bilateral imports from the US, the political regime form, voting affinity to the US in the United Nations, political rights and civil liberties are considered. In all of these estimations, *NYT* coverage retains its importance in predicting upcoming terrorist attacks.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Table AI: List of sample countries by average *NYT* articles between 1/1/1970 – 12/31/2012 and average *NYT* articles on attack day.

Country	Average *NYT* articles/		Country	Average *NYT* articles/		Country	Average *NYT* articles/	
	day	**attack day**		**day**	**attack day**		**day**	**attack day**
Afghanistan	3.14	8.03	Gambia	0.06	0.00	Nigeria	0.85	1.21
Albania	0.26	0.56	Georgia	4.08	4.49	Northern Ireland	0.93	1.11
Algeria	0.64	0.50	Germany	8.83	8.14	Norway	1.13	1.71
Andorra	0.03	0.00	Ghana	0.37	0.33	Pakistan	2.24	3.67
Angola	0.61	0.53	Gibraltar	0.12	1.00	Panama	1.03	1.14
Antigua & Barbuda	0.02	0.00	Greece	1.73	1.71	Papua New Guinea	0.08	0.09
Argentina	1.80	1.69	Grenada	0.23	0.00	Paraguay	0.21	0.14
Armenia	0.19	0.11	Guadeloupe	0.06	0.13	Peru	0.90	0.93
Australia	3.46	3.22	Guatemala	0.53	0.71	Philippines	1.25	1.31
Austria	1.39	1.33	Guinea	0.58	0.53	Poland	2.23	1.91
Azerbaijan	0.19	0.45	Guinea-Bissau	0.04	0.00	Portugal	1.02	0.93
Bahamas	0.47	0.75	Guyana	0.18	0.10	Puerto Rico	1.27	1.41
Bahrain	0.27	0.60	Haiti	0.81	1.82	Qatar	0.36	0.17
Bangladesh	0.48	0.45	Honduras	0.47	0.79	Romania	0.40	1.00
Barbados	0.22	0.33	Hong Kong	2.12	1.81	Russia	7.50	7.92
Belarus	0.19	0.38	Hungary	0.95	0.89	Rwanda	0.35	0.91
Belgium	1.27	1.16	Iceland	0.38	2.00	Saudi Arabia	1.91	2.70
Belize	0.09	0.14	India	4.42	5.91	Senegal	0.28	0.17
Benin	0.09	0.25	Indonesia	1.15	1.56	Serbia	0.70	0.55
Bermuda	0.65	1.00	Iran	4.13	5.36	Seychelles	0.04	0.00
Bhutan	0.06	0.00	Iraq	6.00	14.36	Sierra Leone	0.18	0.35
Bolivia	0.36	0.36	Ireland	2.54	2.77	Singapore	1.01	0.17
Bosnia & Herz.	0.41	1.17	Israel	8.17	8.39	Slovakia	0.20	0.18
Botswana	0.15	0.00	Italy	5.84	5.69	Slovenia	0.18	0.17
Brazil	2.65	2.20	Jamaica	1.77	2.21	Solomon Islands	0.05	0.00
Brunei	0.06	0.00	Japan	8.12	8.56	Somalia	0.55	1.01
Bulgaria	0.49	0.40	Jordan	3.50	3.64	South Africa	3.71	3.81
Burkina Faso	0.06	0.00	Kazakhstan	0.25	0.50	South Sudan	0.22	1.00
Burundi	0.12	0.23	Kenya	0.88	1.28	South Vietnam	1.91	10.00
Cambodia	1.20	0.65	North Korea	1.36	2.00	South Yemen	0.11	0.00
Cameroon	0.17	0.04	South Korea	2.24	1.86	Spain	3.71	3.02
Canada	6.46	7.81	Kosovo	0.51	2.65	Sri Lanka	0.35	0.49
Cayman Islands	0.09	0.00	Kuwait	1.19	2.89	St. Kitts & Nevis	0.02	0.00
Central Afr. Rep.	0.18	0.05	Kyrgyzstan	0.07	0.15	St. Lucia	0.15	1.00
Chad	0.86	1.73	Laos	0.51	0.11	Sudan	0.66	1.01
Chile	1.21	0.99	Latvia	0.22	0.13	Suriname	0.04	0.00
China	8.52	8.96	Lebanon	2.33	2.78	Swaziland	0.05	0.00
Colombia	1.09	1.11	Lesotho	0.05	0.10	Sweden	1.90	1.68
Comoros	0.02	0.00	Liberia	0.25	0.20	Switzerland	2.36	2.48
Congo/Kinshasa	0.06	0.14	Libya	1.21	2.73	Syria	1.70	3.88
Congo	0.02	0.50	Lithuania	0.30	0.25	Tajikistan	0.07	0.21
Corsica	0.05	0.08	Luxembourg	0.44	0.46	Tanzania	0.42	0.65
Costa Rica	0.49	0.66	Macau	0.02	0.08	Thailand	1.17	1.49
Cote d'Ivoire	0.32	0.78	Macedonia	0.18	1.10	Timor-Leste	0.11	0.00
Croatia	0.48	0.79	Madagascar	0.14	0.13	Togo	0.11	0.14
Cuba	2.14	1.25	Malawi	0.09	0.00	Trinidad/Tobago	0.12	0.40
Cyprus	0.54	0.37	Malaysia	0.58	0.56	Tunisia	0.36	0.68
Czech Republic	0.92	0.85	Maldives	0.04	0.33	Turkey	2.42	2.37
Denmark	0.93	0.83	Mali	0.20	0.26	Turkmenistan	0.04	0.00
Djibouti	0.06	0.00	Malta	0.21	0.08	Uganda	0.44	0.29
Dominica	0.05	0.00	Martinique	0.09	0.10	Ukraine	0.72	1.45
Dominican Republic	0.61	0.61	Mauritania	0.09	0.19	United Arab Emirates	0.37	0.63
East Germany	0.00	8.70	Mauritius	0.07	0.50	Great Britain/England	3.46	8.39
Ecuador	0.48	0.39	Mexico	6.26	6.01	Uruguay	0.36	0.40
Egypt	2.79	2.38	Moldova	0.05	0.31	Uzbekistan	0.18	0.55
El Salvador	0.79	1.88	Montenegro	0.17	0.00	Vanuatu	0.02	0.00
Equatorial Guinea	0.04	0.00	Morocco	0.70	0.64	Vatican City	0.32	0.00
Eritrea	0.11	0.00	Mozambique	0.31	0.22	Venezuela	1.04	0.68
Estonia	0.19	0.18	Myanmar	0.23	0.38	Vietnam	5.38	2.80
Ethiopia	0.61	0.58	Namibia	0.25	0.55	Virgin Islands	0.05	0.00
Falkland Islands	0.14	0.00	Nepal	0.27	0.40	Wallis and Futuna	0.00	0.00
Fiji	0.12	0.20	Netherlands	2.12	1.89	West Bank/Gaza	0.52	1.45
Finland	0.76	1.17	New Caledonia	0.04	0.39	Western Sahara	0.09	0.00
France	10.25	9.45	New Hebrides	0.04	2.00	Yemen	0.44	1.21
French Guiana	0.03	0.00	New Zealand	1.16	1.07	Yugoslavia	1.48	1.82
French Polynesia	0.02	0.00	Nicaragua	1.04	2.96	Zambia	0.32	0.30
Gabon	0.11	0.25	Niger	0.18	0.22	Zimbabwe	0.49	1.45

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Table AII: Summary statistics of variables used in robustness checks.

Variable	Mean	(Std. Dev.)	N	Source[a]
Country-day level controls				
Attacks worldwide$_t$	9.33	(7.50)	61,132	GTD
Attacks$_{i,t-1}$	0.78	(1.81)	61,132	GTD
NYT coverage$_{i,t-1}$	1.06	(4.18)	61,132	*NYT*
Domestic election$_{i,t}$	0.00	(0.04)	61,132	Various
Republican president in US	0.58	(0.49)	61,132	own
Presidential campaign in US	0.08	(0.27)	61,132	Puglisi and Snyder (2015)
News pressure	8.13	(2.50)	59,830	Eisensee and Strömberg (2007)
International event$_t^b$	0.06	(0.24)	61,132	own
International terror attacks$_{i,t-1}$	0.29	(0.71)	61,132	GTD
Country-year level controls				
GDP/capita$_{i,t-1}$ (applying Ln)	5,121	(7,770)	53,708	WB
Population size in million$_{i,t-1}$	114.31	(263.84)	56,415	WB
Primary school enrollment$_{i,t-1}$ (% gross)	100.76	(14.80)	46,861	WB
Trade/GDP$_{i,t-1}$	54.54	(30.05)	53,035	WB
Natural resource rents$_{i,t-1}$ (% of GDP)	9.25	(13.87)	56,429	WB
Bilateral imports from US$_{i,t-1}$ (applying Ln)	2,452	(11,241)	61,132	US Census
Polity IV index$_{i,t-1}$ (variable *polity*2)	4.25	(5.42)	51,227	Polity IV
Voting affinity with US in UN$_{i,t-1}$	0.34	(0.16)	51,576	UN Voting
Political rights$_{i,t-1}$ (1 – 7)	3.8	(1.85)	55,102	FH
Civil liberties$_{i,t-1}$ (1 – 7)	4.11	(1.48)	55,102	FH

Notes: [a]Sources: GTD = Global Terrorism Database (based on LaFree and Dugan, 2007); *NYT* = New York Times archives; Various = (following Nohlen et al., 1999, Nohlen et al., 2001, Nohlen, 2005 and Nohlen, 2010); WB = World Bank (Group, 2012); Polity IV = Polity IV (Marshall and Jaggers, 2002); UN Voting = UN General Assembly voting data (Voeten and Merdzanovic, 2013); FH = Freedom House (Freedom House, 2011). [b]Dummy = 1 if any of the following happened on the same day: Academy Awards, G8 meeting, Olympic games, soccer World Cup, or the Super Bowl.

ACCEPTED MANUSCRIPT

Table AIII: Alternative estimations from IV regressions predicting subsequent attacks in country i on days $t+1$ until $t+7$, removing outliers. Please see footnotes for detailed descriptions of each estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second stage predicting subsequent attacks on days $t+1$ until $t+7$						
NYT coverage$_{i,t}$	1.603***	2.500***	2.720***	0.969***	0.779***	0.702***
	(0.506)	(0.868)	(0.942)	(0.280)	(0.234)	(0.243)
Control variables[a]	yes	yes	yes	yes	yes	yes
Panel B: First stage predicting *NYT coverage*$_{i,t}$						
Natural disaster in US$_t$	-0.310***	-0.191***	-0.173***	-0.367***	-0.377***	-0.336***
	(0.070)	(0.042)	(0.037)	(0.092)	(0.102)	(0.095)
Control variables[a]	yes	yes	yes	yes	yes	yes
# of countries	201	201	200	201	201	201
N	60,471	58,102	54,860	60,458	58,059	54,807

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a]Includes all variables from column (6), Table 6. Column (1): Excluding the top 1% of *NYT* coverage (above 18). Column (2): Excluding the top 1% of *NYT* coverage (above 8.42). Column (3): Excluding the top 1% of *NYT* coverage (above 4.86). Column (4): Excluding the top 1% of subsequent attacks (above 35). Column (5): Excluding the top 5% of subsequent attacks (above 20). Column (6): Excluding the top 10% of subsequent attacks (above 13).

ACCEPTED MANUSCRIPT

Table AIV: Additional estimations from IV regressions predicting subsequent attacks in country i on days $t+1$ until $t+7$, using alternative definitions of terrorism from the GTD. Please see footnotes for detailed descriptions of each estimation.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second stage predicting subsequent attacks on days $t+1$ until $t+7$						
NYT coverage$_{i,t}$	1.390***	1.970*	1.381***	1.335***	1.456***	1.243***
	(0.384)	(1.108)	(0.446)	(0.386)	(0.415)	(0.397)
International terrorist attacks$_{i,t}$	-0.172					
	(0.168)					
Control variables^{a}	yes	yes	yes	yes	yes	yes
Panel B: First stage predicting *NYT coverage*$_{i,t}$						
Natural disaster in US$_t$	-0.356***	-0.246**	-0.328***	-0.361***	-0.345***	-0.373***
	(0.088)	(0.107)	(0.081)	(0.089)	(0.086)	(0.098)
International terrorist attack$_{i,t}$	0.066					
	(0.060)					
Control variables^{a}	yes	yes	yes	yes	yes	yes
# of countries	201	149	201	201	199	200
N	61,132	29,388	55,570	59,986	56,451	55,279

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Includes all variables from column (6), Table 6. Column (2): Only using domestic terrorist attacks. Column (3): Only using observations where terrorism was undoubted. Column (4): Only using attacks following criterion 1 in the GTD (political, economic, religious, or social goal). Column (5): Only using attacks following criterion 2 in the GTD (intention to coerce, intimidate or publicize to larger audience(s)). Column (6): Only using attacks following criterion 3 in the GTD (outside international humanitarian law).

ACCEPTED MANUSCRIPT

Table AV: Results from IV regressions predicting subsequent attacks in country i on days $t+1$ until $t+7$, including identifiers of terrorist groups from Kis-Katos et al. (2014). Please see footnotes for details.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second stage predicting subsequent attacks on days $t+1$ until $t+7$						
NYT coverage	1.394***	1.392***	1.387***	1.378***	1.435***	1.462***
	(0.382)	(0.388)	(0.387)	(0.381)	(0.401)	(0.403)
Political identity categories$^{a}_{i,t}$	yes					yes
Ethnic-separatist identity categories$^{b}_{i,t}$		yes				yes
Religious identity categories$^{c}_{i,t}$			yes			yes
Primary ideology categories$^{d}_{i,t}$				yes		yes
Organizational identity categories$^{e}_{i,t}$					yes	yes
Control variables^{f}	yes	yes	yes	yes	yes	yes
Panel B: First stage predicting *NYT coverage*$_{i,t}$						
Natural disaster in US$_t$	-0.351***	-0.353***	-0.354***	-0.357***	-0.342***	-0.333***
	(0.083)	(0.087)	(0.089)	(0.088)	(0.080)	(0.079)
Political identity categories$^{a}_{i,t}$	yes					yes
Ethnic-separatist identity categories$^{b}_{i,t}$		yes				yes
Religious identity categories$^{c}_{i,t}$			yes			yes
Primary ideology categories$^{d}_{i,t}$				yes		yes
Organizational identity categories$^{e}_{i,t}$					yes	yes
Control variables^{f}	yes	yes	yes	yes	yes	yes
# of countries	201	201	201	201	201	201
N	61,132	61,132	61,132	61,132	61,132	61,132

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Includes categorical variables for left, right, anti-left, other leftist, and unknown. [b]Includes categorical variables for none, ethnic-separatist, anti-separatist, and unknown. [c]Includes categorical variables for none, Islamist, Christian, Hindu, Jewish, other religions, and unknown. [d]Includes categorical variables for none, political, ethnic/separatist, religious, green/human/animal rights, anti-war, and unknown. [e]Includes categorical variables for no, yes, bandits, imputed identity, and unknown. [f]Includes all variables from column (6), Table 6.

ACCEPTED MANUSCRIPT

Table AVI: Results from IV regressions predicting subsequent attacks in country i on days $t+1$ until $t+7$, including country-year level control variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Second stage predicting subsequent attacks on days $t+1$ until $t+7$										
NYT coverage$_{i,t}$	1.698*** (0.555)	1.433*** (0.376)	1.386*** (0.396)	1.583*** (0.461)	1.743*** (0.620)	1.612*** (0.469)	2.149*** (0.749)	1.486*** (0.373)	1.848*** (0.517)	1.708*** (0.483)
Ln(GDP per capita)$_{i,t}$	-2.644 (3.607)									
Ln(population size)$_{i,t}$		1.245 (2.556)								
Primary school enrollment$_{i,t}$ (% gross)			-0.009 (0.023)							
Trade/GDP$_{i,t}$ (% of GDP)				-0.066 (0.042)						
Natural resources$_{i,t}$ (% of GDP)					-0.173 (0.126)					
Ln(bilateral imports from US)$_{i,t}$						0.148 (0.135)				
Polity IV$_{i,t}$							0.162** (0.067)			
Voting affinity with US in UN$_{i,t}$								4.098 (6.292)		
Political rights$_{i,t}$									-0.466 (0.380)	
Civil liberties$_{i,t}$										0.716 (0.442)
Control variables[a]	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Panel B: First stage predicting *NYT coverage*$_{i,t}$										
Natural disaster in US	-0.276*** (0.092)	-0.365*** (0.089)	-0.350*** (0.089)	-0.317*** (0.083)	-0.304*** (0.084)	-0.276*** (0.093)	-0.244*** (0.077)	-0.357*** (0.096)	-0.295*** (0.089)	-0.311*** (0.088)
Control variables[a]	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Additional variable[b]	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
# of countries	174	184	170	178	184	211	162	172	175	175
N	53,708	56,415	46,861	53,035	56,429	61,132	51,227	51,576	55,102	55,102

Notes: Standard errors clustered at the country level are displayed in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. [a] Includes all variables from column (6), Table 6. [b] Includes the respective control variable from Panel A.

ACCEPTED MANUSCRIPT

Highlights

- Analyzing NYT coverage of 61,132 terrorist attack days in 201 countries and 43 years
- Testing for a causal effect of media coverage of terrorism on subsequent attacks
- Natural disasters in the US provide an IV that exogenously diminishes media coverage
- IV results show strong positive effect
- 1 NYT article translates to 1.4 attacks in following week or 3 casualties

ACCEPTED MANUSCRIPT