WORKING PAPER

# Earthquakes, Hurricanes, and Terrorism

## Do Natural Disasters Incite Terror?

CLAUDE BERREBI AND JORDAN OSTWALD

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# Earthquakes, Hurricanes, and Terrorism: Do Natural Disasters Incite Terror?

Claude Berrebi, Hebrew University and RAND
Jordan Ostwald, RAND

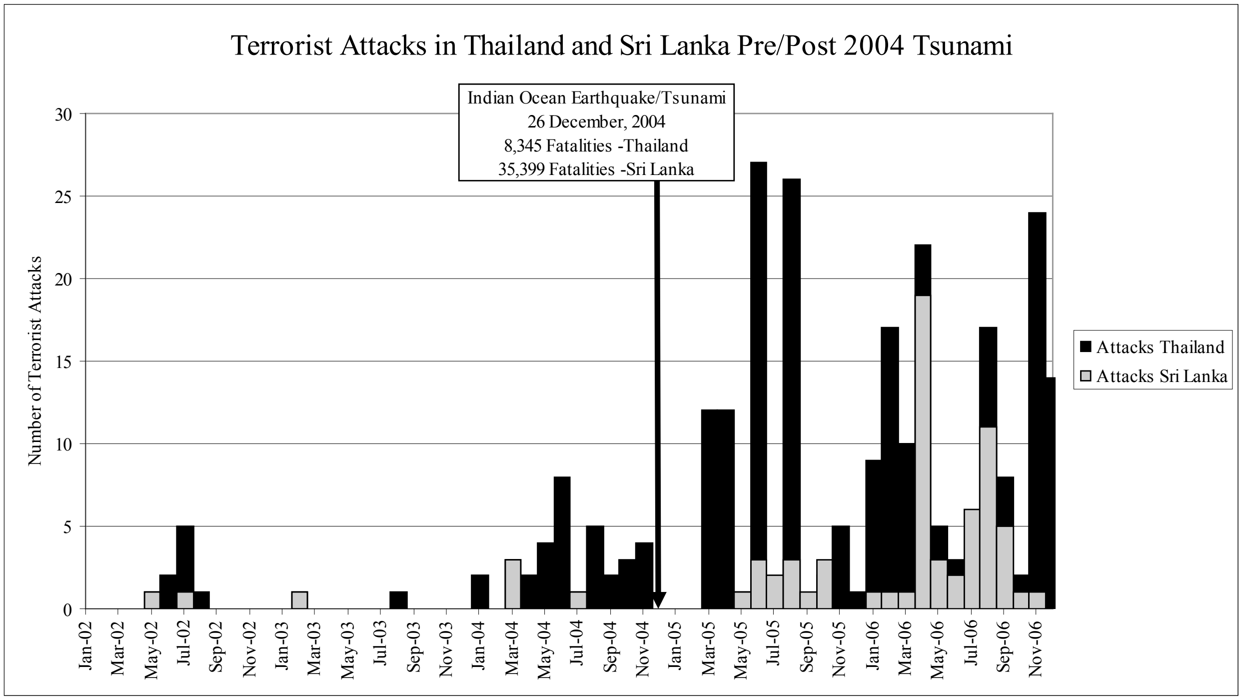
**Abstract**

A novel and important issue in contemporary security policy is the impact of natural disasters on terrorism. Natural disasters can strain a society and its government, creating vulnerabilities which terrorist groups might exploit. Using a structured methodology and detailed data on terrorism, disasters, and other relevant controls for 167 countries between 1970 and 2007, we find a strong positive impact of disaster-related deaths on subsequent terrorism deaths and incidence. We find that, on average, an increase in deaths from natural disasters of 25,000 leads to an increase in the following year of approximately 33 percent in the number of deaths from terrorism, an increase of approximately 22 percent in the number of terrorist attacks, and an increase of approximately 16 percent in the number wounded in terrorist attacks, holding all other factors constant. Furthermore, the effects differ by disaster types and country characteristics. Results were consistently significant and robust across a multitude of disaster and terrorism measures for a diverse set of model specifications. The results have strong implications for both disaster and terrorism mitigation policy.

## 1 Introduction

On December 26, 2004, a large subduction earthquake, measuring 9.3 in magnitude, triggered off the west coast of Sumatra, Indonesia. Lasting between 8.3 and 10 minutes, it was powerful enough to vibrate the entire planet as much as 1 centimeter and trigger other earthquakes as distant as Alaska (Walton 2005; West et al. 2005). The earthquake released tsunamis which devastated the coastlines of countries bordering the Indian Ocean and resulted in casualty estimates exceeding 200,000 (Le Billon and Waizenegger 2007). In the aftermath, those who survived began the process of rebuilding, and their governments, weakened and strained, faced a host of new challenges. One of those challenges, not previously explored, is the effect that disasters have on terrorism within a country. It is plausible that the turmoil after a catastrophe creates or exacerbates vulnerabilities within a state which terrorist groups might exploit. In Sri Lanka, case evidence and data both suggest that terrorism escalated significantly in the years following the tsunami (Le Billon and Waizenegger 2007; Renner and Chafe 2007). With over 8,000 deaths, Thailand was also devastated by the tsunami. In the tragedy's wake, tourism suffered and unrest increased (McDowall and Wang 2009). As seen in Figure 1, the evidence was much the same with terrorist attacks rising dramatically following the events of December 26th.

**Figure 1: Terrorist Attacks in Thailand and Sri Lanka Pre/Post 2004 Tsunami**

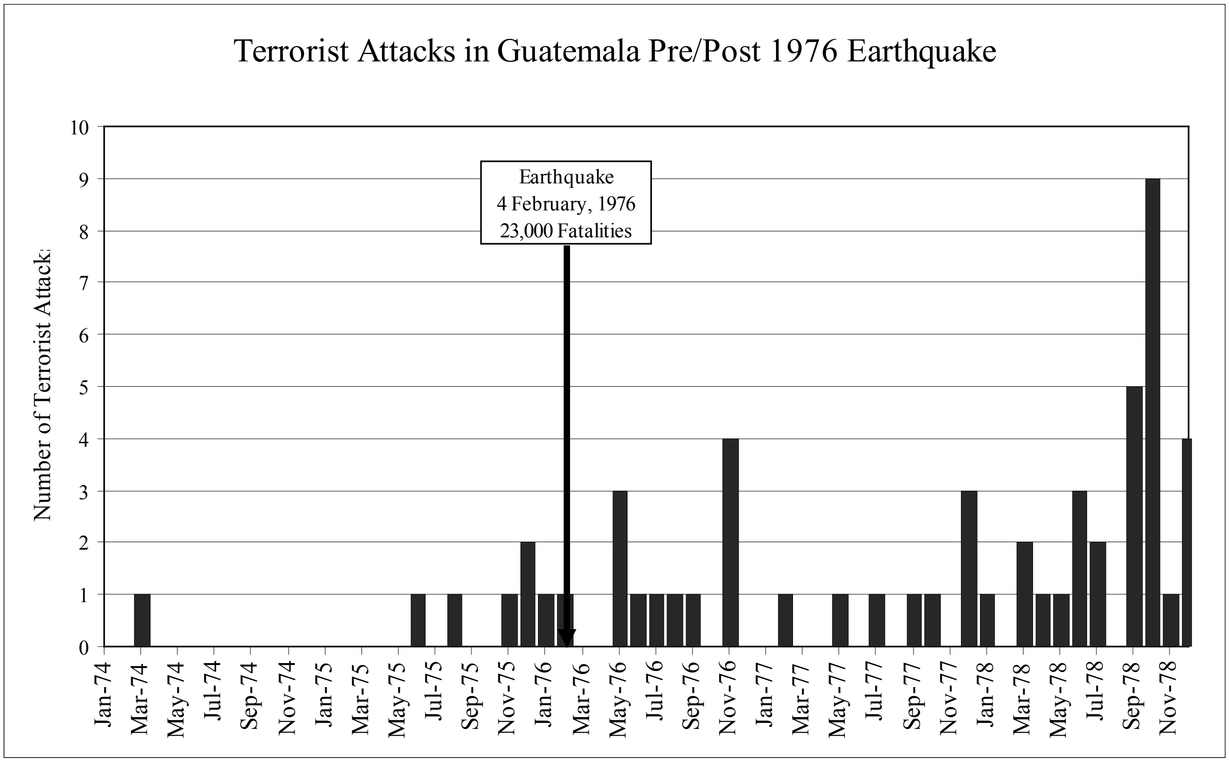



*Notes:* Terrorism data from the National Consortium for the Study of Terrorism and Responses to Terrorism (START 2010), Global Terrorism Database. Data for natural disasters obtained from the Center for Research on the Epidemioloy of Disasters (CRED 2010a), Emergency Events Database.

Furthermore, this phenomenon does not seem to be limited to Asia or the last decade. On February 4, 1976 at 09:01:43 UTC a 7.5 magnitude earthquake struck 100 miles northeast of Guatemala City resulting in a death toll near 23,000 (CRED, 2010). Divisive reconstruction policies in Guatemala combined with intensifying progressive and reactionary politics to deepen fissures between classes (Levenson, 2002). Like Thailand and Sri Lanka, the cracks pre-existed the disaster but acted as the fuel for the disaster to spark. Once again, on the other side of the planet and almost 30 years earlier, terrorism appeared to follow the same pattern.

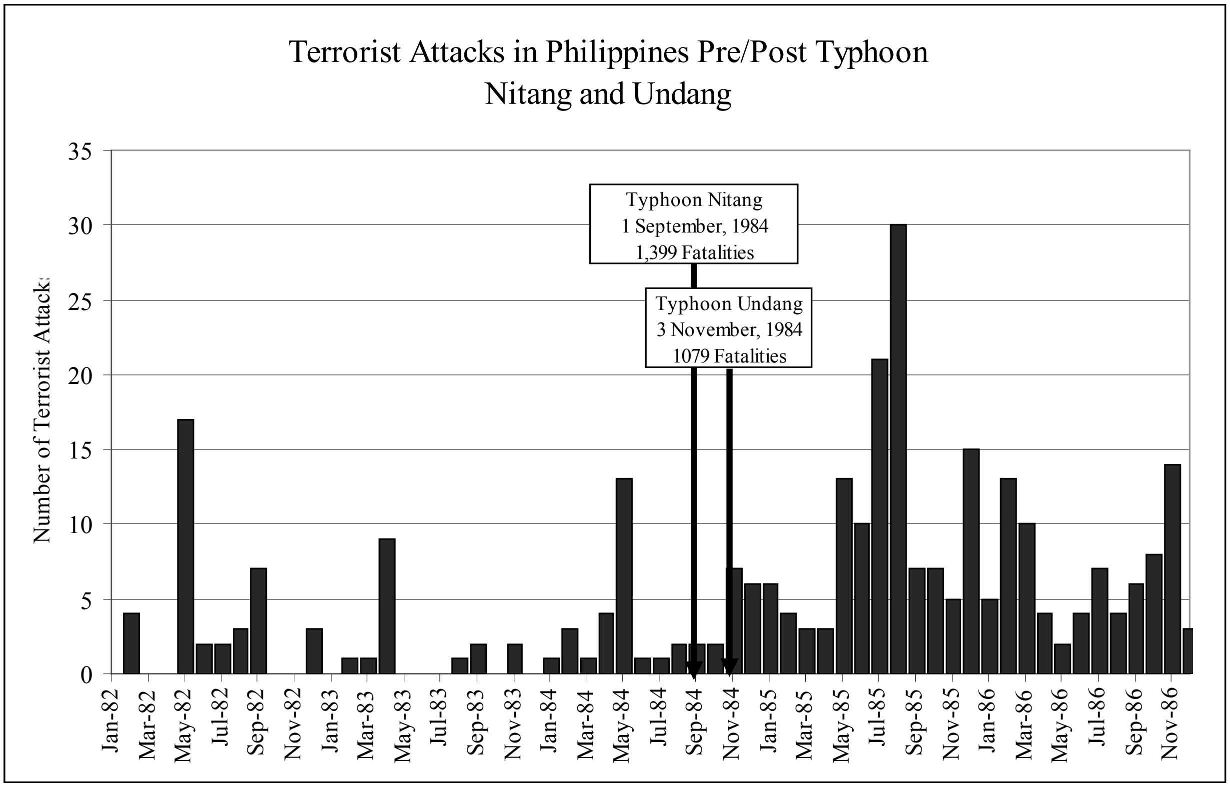
Similarly, the trend does not appear to be limited by type of disaster. In 1984, the Philippines was the unfortunate victim of two severe typhoons in the same season, Nitang and Undang. With over 1,000 fatalities confirmed in each storm it was one of the deadliest typhoon seasons in Philippine history (EM-DAT, 2010). In the next two years, the New People's Army, the armed wing of the Communist Party of the Philippines, significantly increased the frequency of their attacks (START, 2011).

**Figure 2: Terrorist Attacks in Guatemala Pre/Post 1976 Earthquake**




Note: Terrorism data from START. 2011. *Global Terrorism Database.* Data on natural disasters from CRED. (2010, January). EM-DAT: The OFDA/CRED International Disaster Database - www.emdat.net – Université catholique de Louvain –. Brussels, Belgium.

**Figure 3: Terrorist Attacks in Philippines Pre/Post Typhoon Nitang and Undang**




Note: Terrorism data from START. 2011. *Global Terrorism Database.* Data on natural disasters from CRED. (2010, January). EM-DAT: The OFDA/CRED International Disaster Database - www.emdat.net – Université catholique de Louvain –. Brussels, Belgium.

It is said that terrorism does not arise in a vacuum (Shughart 2006). Similarly, natural disasters are not, in and of themselves, defined by the physical shocks which induce them. A large earthquake, far from human civilization, may be felt only by a few individuals inhabiting that area and is not likely to constitute a disaster. Pre-existing vulnerabilities, both political and societal, largely determine the extent to which an environmental shock induces destruction (Albala-Bertrand 1993; Cannon 1994; Kahn 2005; Wisner et al. 2003). Infrastructure, urbanization, and socio-economic opportunities and divisions all factor into a society's exposure to these extreme events (Albala-Bertrand 2000); thus, theory suggests there are several key mechanisms through which disasters could ultimately influence terrorism.

As a government's resources are directed toward disaster recovery, those resources must be re-directed from some other purpose. In particular, a government's ability to provide security and maintain control in disaster-afflicted areas can suffer significantly in an event's aftermath. Research has noted terrorist's ability to exploit existing vulnerabilities as a result of their tactical agility (Berrebi and Lakdawalla 2007; Hirshleifer 1991; Shughart 2006). From a rational-choice perspective, a government's diminished security capacity amounts to a reduction in the potential costs of participating in terrorism. The loss of government security and control in a disaster-afflicted area may also incentivize terrorist action by reducing the costs associated with attacking specific targets. Terrorists' preferences for "soft" targets are well documented (Atkinson et al. 1987; Berman and Laitin 2008; Dugan et al. 2005; Landes 1978). Diminished targeting costs for some previously "hard" targets could, in turn, increase terrorist action. Following Pakistan's devastating floods in 2010, Pakistani Foreign Minister, Shah Mahmood Qureshi, expressed grave concern that the Taliban and other terrorist groups would use the disaster to take advantage of the government in a weakened state, and, indeed, reports indicated that militant groups utilized the disruption to carry out attacks (Hasan 2010; Shakir 2010; Waraich 2010).

> "We are not going to allow them to take advantage or exploit this natural disaster," the outcome "depends on how effective and quick the response is. That is why it is so important that the international assistance comes immediately" … "If we fail, it could undermine the hard-won gains made by the government in our difficult and painful war against terrorism." (Qureshi, as cited in Varner 2010, para. 2)

Disasters also expose governments to greater scrutiny. Despite evidence that victims can pull together to provide mutual support in a disaster's wake, the perceived failure of a government to provide a fair and sufficient level of assistance can lead to political discontent (Olson and Drury 1997). Political tension and spontaneous collective action by non-government groups can result as the inability to provide an adequate or equitable distribution of public services after a disaster erodes the legitimacy of that government in the eyes of the general public and any opposition groups (Pelling and Dill 2006). This has important implications for terrorism along two fronts. First, political transformation and instability has a long history as a determinant of terrorism (Lai 2007; Piazza 2007, 2008; Weinberg and Eubank 1998). Instability and political tensions post-disaster could thus manifest as terrorism. Second, evidence has accumulated to support the hypothesis that, after a disaster, regimes interpret such actions by non-government groups as possible threats and often respond with repression (Pelling and Dill

2006). Repression and government intrusiveness have been found in terrorism research to be determinants of terrorism, though the direction of their effects is still contested (Basuchoudhary and Shughart 2010; Burgoon 2006; Krieger and Meierrieks 2011; Lai 2007; Robison et al. 2006).

Lastly, pre-existing societal divisions can be exacerbated by disasters. Poor infrastructure or unsafe construction can significantly increase vulnerability to disasters, and governments often spend less on disaster prevention in areas that are politically weak or hostile (Cohen and Werker 2008). The existing literature has noted that disasters tend to disproportionately affect marginalized or disempowered groups (Albala-Bertrand 1993; Bolin 2007; Cohen and Werker 2008; Mustafa 1998). Along similar lines, the distribution of aid has also been a focus of much research within terrorism literature (Azam and Delacroix 2006; Azam and Thelen 2008; Bandyopadhyay et al. 2011; Basuchoudhary and Shughart 2010). Unequal relief efforts or aid allocation present additional avenues through which natural disasters could affect terrorism.

Though disasters are not necessarily the source of underlying strains and vulnerabilities within a country, the randomness of these natural events introduces exogenous shocks which research has indicated can exacerbate certain pre-existing factors. The terrorism literature suggests that these same factors are key determinants of both the sources and targets of terror. This line of reasoning identifies clear channels through which natural disasters could influence terrorist activity; however, there are several other aspects left to consider. Though a disaster may be an opportunity for a group to strike more effectively at a regime, it is not clear whether striking a population preoccupied with the effects of a catastrophe would be effective. An immediate attack might instill resentment among those who would otherwise have been sympathetic to the terrorist's cause and supportive of their actions. In addition to affecting a society and government, a disaster can also impact the dynamics of a terrorist group. Loss of resources, damaged group infrastructure, and the need to reestablish the group's own capabilities may necessitate a period of recovery or even a reduction in attacks; therefore, there are clear reasons to believe that natural disasters could create favorable or unfavorable conditions for terrorist groups. Whether these conditions translate to a rise or fall in terrorist activity remains an empirical question.

The 2010 Quadrennial Defense Review (QDR) and other reports have expressed concern over the lack of quantitative research into the consequences of natural disasters for violence, including non-state conflicts (Buhaug et al. 2010; Gates and US Department of Defense 2010). Nonetheless, to the best of our knowledge, there are no empirical studies which analyze the relationship between natural disasters and terrorism.[1] This is a novel and important issue in contemporary security policy supported by mounting public rhetoric and case evidence relating the two topics; however, given the inherent difficulty in properly estimating the effect of disasters on terror, it is not too surprising that there exists a dearth of empirical research on the connection between the two.

In this study, we analyze the relationship between natural disasters and terrorism using a dataset of 5,709 individual country-year observations on 167 countries over the period 1970-2007. Using a carefully designed empirical framework, we estimate the effect of natural disasters on terrorism within a country. We find statistically significant positive impacts of natural disasters on terrorism over several years following a disaster. Additionally, the results suggest that the period for terrorist action following a disaster is dependent upon several factors. In particular, geophysical and hydrological disasters prompt a more sustained and escalating effect on terrorism than climatologic or meteorological disasters. We further analyzed the effects across varying levels of GDP per capita and found the effect to be concentrated in countries with low to middle GDP per capita. The results are consistently significant and robust across a multitude of disaster and terrorism measures as well as a variety of model specifications. Our findings align with the concern expressed in the recent QDR and have strong implications for both disaster and security policy in an area that has not been previously explored.

## 2 Data

To assess the relationship between natural disasters and terrorism, we utilized data on terrorist attacks from the National Consortium for the Study of Terrorism and Responses to Terrorism (START), Global Terrorism Database (START 2010); data on global natural disasters from the Center for Research on the Epidemiology of Disasters (CRED), Emergency Events Database (CRED 2010a); data on country demographic and economic characteristics from the World Bank's (2010) World Development Indicators; and data on civil liberties and political rights from Freedom House's (2010) Freedom in the World Reports. Our preferred model specification uses deaths from terrorist attacks as the measure of terrorism; however, we test for

[1] Among the few empirical studies that quantitatively evaluate related topics of political unrest and civil conflict are Olson and Drury (1997) and Nel and Righarts (2008); however, neither study examined terrorism specifically.

robustness across several other measures. The unit of observation in our analysis is an individual country-year. Only countries which had at least one death from a terrorist attack between 1970 and 2007 could be included in the count models, thus the base specification consisted of a set of 5,709 individual country-year observations on 167 countries over the period 1970-2007. Due to missing demographic data, an additional 21 countries were excluded from the final specification leaving 3,980 individual country-year observations from 146 countries.[2] The number of observations in our final specification was driven principally by the availability of the demographic characteristics and measures of terrorism. We were not particularly concerned by the exclusion of these countries as our interest is in the set of countries in which terrorism has occurred or is likely to occur, and because it is crucial to control for time-varying demographic characteristics. A list of all countries contained in our dataset and whether they were part of our final specification can be found in the appendix.

### *2.1 Terrorism data*

The Global Terrorism Database (GTD) contains more than 80,000 cases of terrorism between the years 1970 and 2007. It includes data on transnational and domestic terrorist incidents, though it does not distinguish between these two incident types. Target type, weapons used, date of attack, number of casualties, and location are all available. The data are drawn primarily from contemporary news articles and other news sources. Though the GTD refrains from establishing a single definition of terrorism, it includes various coded criteria which cover a broad set of definitions for terrorism. For an event to be included in the database, it must first meet the three following base criteria (START 2010b).

- The incident had to be intentional – the result of a conscious calculation on the part of the perpetrator.
- It had to entail some level of violence or threat of violence – this includes damage to property.
- The perpetrators of the incidents had to be sub-national actors. The database does not include acts of state terrorism.

[2] To ascertain that the excluded countries did not introduce a bias in our sample, we repeated the analysis using only those covariates available to all. The results remain qualitatively similar and statistically significant.

We required that three additional criteria be present for an incident to be included in our analysis, further narrowing our acceptable set to about 66,000 terrorist incidents:

- The act had to be aimed at attaining a political, economic, religious, or social goal. Exclusive pursuit of profit does not satisfy this criterion.
- There had to be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims.
- The action had to be outside the context of legitimate warfare activities.

While there are various possible measures of the severity of a terrorist attack, the number of deaths is considered the least likely to be manipulated or to suffer from cross-country differences in recording, definitions, or classifications. The terrorism literature often has adopted this measure as best reflecting levels of terrorist activity (Benmelech and Berrebi 2007; Berrebi and Klor 2006, 2008; Enders and Sandler 2000, 2002). It was decided that we would follow the literature's best practices and use the number of deaths from terrorism in a country-year; however, we test for robustness using several other measures including the number of attacks and the number wounded.

It is important to note that the data collection method used by the GTD was modified in 1998 from collection as events occurred to collection retrospectively at the end of each year. Therefore, it is possible that the observed drop in attacks after 1998 could be attributed partially to the differences in data collection. To alleviate this concern we used year fixed-effects in our entire analysis. In addition, the dataset contains a discontinuity in 1993; however, totals were available for that year. As we used data aggregated at the year interval, this was not a concern. A more in depth discussion of these issues and the discontinuity is discussed in Enders et al. (2011).

According to Table 1, on average, a country suffers approximately 10 attacks per year; however, even more interesting is the large variation across countries and years with some suffering over 600 attacks in a given year and others none at all. Per year, the average number of attacks corresponds to approximately half the number of deaths from terrorism and a third of the number wounded in terrorist attacks.

**Table 1: Terrorism and Disaster Statistics**

| VARIABLE | N | MEAN | SD | MAX | P95 |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| ***Terrorism Measures by Country-Year*** | | | | | |
| # Deaths From Terrorist Attacks | **6507** | **19** | **121.8** | **4102** | **73** |
| # of Terrorist Attacks | **6507** | **9.9** | **41.6** | **605** | **45** |
| # Wounded in Terrorist Attacks | **6507** | **26.1** | **210.3** | **10226** | **104** |
| ***Natural Disaster Measures by Country-Year*** | | | | | |
| # of Natural Disasters | **6507** | **1.2** | **2.7** | **37** | **5** |
| # of Deaths from Natural Disaster | **6507** | **398** | **7326.9** | **300317** | **300** |
| # of Affected in Natural Disaster | **6507** | **864995.5** | **1.10E+07** | **3.40E+08** | **950000** |
| # Climatologic Disasters | **6507** | **0.1** | **0.4** | **9** | **1** |
| # Climatologic Disaster Deaths | **6507** | **104.4** | **4517.9** | **300000** | **0** |
| # Climatologic Disaster Affected | **6507** | **277248.9** | **6.30E+06** | **3.00E+08** | **1436** |
| # Geophysical Disasters | **6507** | **0.2** | **0.6** | **11** | **1** |
| # Geophysical Disaster Deaths | **6507** | **153** | **3996** | **242000** | **5** |
| # Geophysical Disaster Affected | **6507** | **16976** | **306324.5** | **2.00E+07** | **3000** |
| # Meteorological Disasters | **6507** | **0.4** | **1.3** | **27** | **2** |
| # Meteorological Disaster Deaths | **6507** | **98.7** | **4122.2** | **300317** | **41** |
| # Meteorological Disaster Affected | **6507** | **115074.7** | **1.80E+06** | **1.10E+08** | **25100** |
| # Hydrological Disasters | **6507** | **0.5** | **1.3** | **21** | **3** |
| # Hydrological Disaster Deaths | **6507** | **41.9** | **554.6** | **30005** | **104** |
| # Hydrological Disaster Affected | **6507** | **455696** | **6.50E+06** | **2.40E+08** | **201965** |
| # of Regional Deaths from Natural Disasters | **6507** | **3571.1** | **22749.1** | **301960** | **7638** |

*Notes:* Medians, minimums, and $5^{th}$ percentiles for all variables in table were 0. Statistics are for countries with at least 1 terrorist attack between 1970 and 2007.

### *2.2 Disaster data*

The Emergency Events Database (EM-DAT) contains data on disasters from 1900 until the present that meet at least one of the following criteria (CRED 2010a):

- 10 or more people killed
- 100 or more people affected
- Declaration of a state of emergency
- Call for international assistance

EM-DAT records both the occurrence and outcomes of over 17,000 disasters. The data have been compiled from a variety of sources including: United Nations agencies, non-governmental organizations, insurance companies, research institutes, and press agencies. Priority was given to data from the UN agencies, governments, and the Red Cross and Red Crescent Societies (CRED 2010b). Natural disasters are categorized into several groups: geophysical, meteorological, hydrological, climatologic, and biological. Each group is further divided by disaster type. The appendix details the breakdown of the types included in our analysis.

We chose to use only natural disasters as the prevalence and outcomes of other disaster types, such as industrial or technological accidents, seemed more likely to depend on government factors and conditions endogenous to terrorism. The natural disaster types included in our analysis are: drought, earthquake, flood, mass movement dry, mass movement wet, storm (hurricanes, typhoons, etc.), volcano, and wildfire. Deaths caused by natural disasters are used as a proxy for the disaster's severity. We also tested the relationship using disaster incidence and the number of people affected which consists of the total number injured, homeless, and requiring immediate assistance following a disaster. Rather than incidence, we chose to use disaster deaths as our primary measure as it acts as gauge of disaster severity. The data were culled to match the year range available from our terrorism dataset. In addition, we aggregated the number of disaster deaths in a region apart from the number of deaths for a particular country in order to control for possible influences of regional disasters. Regions were based on geographic location using the GTD codebook definitions (START 2010c).

We see in Table 1 that, each year, countries suffer on average 1.2 disasters and approximately 400 deaths from disasters. The large variation is remarkable as many disasters do not result in deaths whereas a few have resulted in more than 300,000 deaths. The average number of people affected by disasters is much higher, at around 865,000. Perhaps more interesting is the variation between disaster types, in particular, the comparison between geophysical disasters (e.g., earthquakes) and meteorological disasters (e.g., hurricanes). Geophysical disasters were deadlier, contributing 1.5 times more to the total number of deaths; however, there were twice as many meteorological incidents as compared to geophysical. It is worth noting that geophysical disasters are also typically less predictable and do not follow seasonal patterns seen with meteorological disasters. On average a country suffered 153 deaths from geophysical disasters per year, and 98.7 deaths from meteorological catastrophes. The variation between these types might manipulate the channels through which terrorism could be influenced.

### *2.3 Demographic, economic, and social indicators*

From the World Bank's (2010) World Development Indicators database we obtained data on a range of demographic and economic characteristics. These included: population size, percentage of population in an urban environment, gross domestic product per capita in constant 2000 US dollars, gross government final consumption expenditures as a percentage of GDP

(GFCE), foreign direct investment as a percentage of GDP, and Development Assistance Committee (DAC) country inflows as a percentage of GDP. The choice of indicators was based primarily on previous literature exploring the social, political, and economic contexts that influence terrorism activity and disaster effects and secondly on the availability and consistency of collection.

We controlled for population as it is an important factor in disaster and terrorism risk assessments (Berrebi and Lakdawalla 2007). Urban population as a percentage of total population was added as a control to reflect theories of social disorganization and strain, but also because urbanization can influence the susceptibility to and consequences of disasters (Albala-Bertrand 2000; Robison et al. 2006). GDP per capita was included as it is considered a good proxy for a country's ability to mitigate the effects of a disaster. It also acts as a proxy for a number of other development indicators and has been used in conflict and civil war studies as a comprehensive approximation of a country's level of development (Hegre and Sambanis 2006; Nel and Righarts 2008). Globalization is represented by foreign direct investment as a percentage of GDP. In addition, the level of foreign investment and DAC country inflows might be expected to correlate with both natural disasters and terrorism, thus they are particularly important covariates to control for.[3] Government final consumption expenditures are used as a measure of the size of the government and can act as a proxy for the degree of "government intrusiveness" into societal affairs (Robison et al. 2006). Along similar lines, indicators for political rights and civil liberties are included (Freedom House 2010).[4] Political rights reflect freedom of political participation and elections that are competitive. The civil liberties indicator measures the level of freedoms of speech, press, and association which have been shown important in terrorism research (Krueger and Laitin 2008; Krueger and Malecková 2003).[5]

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[3] In cases where aid inflows appeared to be missing, for DAC donor countries, we replaced the observations with 0 in order to keep those countries in our data. It should be noted that donor countries are unlikely to receive disaster aid monies.

[4] We reversed the scoring for the freedom indicators so that, on the scale of 1 to 7, 1 was least free and 7 indicated most free. Due to collinearity, we then summed these two indicators together to create a single measure of the two which was labeled, civil liberties.

[5] Other factors have been suggested as determinants of natural disasters and terrorism. In particular, public sector corruption has been found to have a positive association with earthquake fatalities and the political manipulation of disaster relief (Escaleras et al. 2007; Sobel and Leeson 2006). After obtaining yearly data from Political Risk Services' (2011) International Country Risk Guide on corruption and ethnic tensions, we conducted our analysis while including these factors. Results for our natural disaster measures remained statistically significant and quantitatively similar across all terrorism outcomes. We ultimately chose not to include these covariates since the

## 3 Methodology

To assess the relationship between natural disasters and terrorism we estimate the model

$$terrorism_{i,t} = f\left(disaster_{i,t-j}, demographic_{i,t}, economic_{i,t}, social_{i,t}, regional_{i,t-1}, year_t, country_i\right), \quad (1)$$

where:

| | |
|---|---|
| $terrorism_{i,t}$: | Deaths from terrorism, terrorism incidence, or number wounded from terrorism in country *i,* year *t* |
| $disaster_{i,t-j}$: | Deaths from natural disaster, disaster incidence, and number affected by disaster in country *i,* year *t-j* where j ranges from 0 to 2 (i.e. current as well as two lagged years). These are also broken down further by disaster type: climatologic/meteorological and geophysical/ hydrological |
| $demographic_{i,t}$: | Population size and urban population (% of total population) in country *i,* year *t* |
| $economic_{i,t}$: | GDP per capita (constant 2000 USD), general government final consumption expenditure GFCE (% of GDP), DAC inflows (% of GDP), and foreign direct investment (% of GDP) in country *i,* year *t* |
| $social_{i,t}$: | Political rights and civil liberties in country *i,* year *t* |
| $regional_{i,t-1}$: | Number of deaths from natural disasters in a region apart from those in $country_i$ for year *t-1* |
| $year_t, country_i$: | Year and country fixed-effects. |

Given the count nature of our data, we chose to use the Poisson quasi-maximum likelihood estimator (QMLE) as it produces consistent estimates under the relatively weak assumption that only the conditional mean be correctly specified (Wooldridge 1999). This implies that the conditional distribution of the dependent variable need not be Poisson-distributed. A concern that arises when implementing a Poisson model is the possibility of over/underdispersion in the data as its presence can underestimate the standard errors. Initial

data were restricted to a limited set of countries and years as compared to our other data sources; however, results for these analyses are available from the authors upon request.

tests of our data indicated the presence of overdispersion. Consequently, the quasi-maximum likelihood framework retains consistency even in cases of over/underdispersion and makes few distributional assumptions regarding the variance, aside from regularity conditions, allowing us to incorporate fully robust standard errors (Simcoe 2007; Wooldridge 1999, 2002).[6] Another possible specification for dealing with overdispersion is the negative binomial model; however, this requires a more restrictive assumption that the conditional distribution of the dependent variable follows a negative binomial distribution. We would argue that the consistent estimates provided by the Poisson QMLE are more valuable in this context than the possible efficiency gains from the negative binomial model. As a robustness check, we use the negative binomial model along with other alternative models for comparison. Lastly, we included country and year fixed-effects to control for overall trends and time invariant, country-specific factors.

**Fixed-Effects Poisson QMLE:**

The conditional probability density function for the panel Poisson model is given as:

$$f\left(terrorism_{i,t} \middle| \mathbf{x}_{i,t}, country_i\right) = \frac{\exp\left(-\mu_{i,t}\right)\mu_{i,t}^{\;terrorism_{i,t}}}{terrorism_{i,t}!}, \tag{2}$$

where we assume the conditional mean[7] of terrorism with country specific fixed-effects is:

$$\mu_{i,t} = E\left[terrorism_{i,t} \middle| \mathbf{x}_{i,t}, country_i\right] = country_i \cdot \exp\left(\mathbf{x}_{i,t}\boldsymbol{\beta}\right) \tag{3}$$

and

$$\begin{aligned} \mathbf{x}_{i,t}\boldsymbol{\beta} = {} & disaster_{i,t-j} \cdot \alpha + demographic_{i,t} \cdot \varphi + economic_{i,t}\delta \\ & + social_{i,t}\theta + regional_{i,t-1} \cdot \gamma + year_t \cdot \lambda. \end{aligned} \tag{4}$$

The coefficients can be interpreted as the semi-elasticities of the conditional expectation of terrorism with respect to natural disaster covariates (Wooldridge 2002). This allows a relatively simple interpretation as a small change in the natural disaster variable can be

[6] Standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999).

[7] We chose the exponential function as the conditional mean for its convenient computational and prediction properties as well as for its simple interpretation. It is considered to be the most common conditional mean in applications (Wooldridge 2002).

approximately interpreted as a fixed percent change in the expected value of the terrorism measure.

Our specifications allow us to utilize both country and year fixed-effects, which alleviate many concerns related to potential omitted variable bias. Country fixed-effects control for any country-specific variables which are time-invariant. This is important as countries that are in areas more prone to natural disasters may also have a higher number of terrorist attacks simply due to their geographic characteristics irrespective of the timing of natural disasters. Other studies have shown significant relationships between geographic factors - such as elevation, tropical location, and country area – and terrorism (Abadie 2006). Since a country's geographic location and physical characteristics do not generally change over our time span, the country fixed-effects model controls for these and any other time-invariant factors. Along with country fixed-effects, year fixed-effects help account for the potential recollection bias in the GTD between 1998 and 2007.[8] Year fixed-effects also allow us to control for the average effects of specific periods over all countries. Moreover, they help reduce bias from overall trends and events that occurred at a specific time which might have influenced the average global level of terrorism and/or natural disasters. For example, we might want to account for the global effects of the era of communism and the period of the Global War on Terror, or we might be concerned with changes in the global level of natural disasters due to climate change.

In order to test for differential effects of disasters by disaster type and country characteristics, we combined meteorological and climatologic disaster deaths together to form an aggregated number of deaths for climate and weather-related natural disasters. We then combined hydrological and geophysical disasters into an aggregate of the two and implemented the analysis while differentiating by disaster type.[9] Finally, we split countries that were a part of our final specification into three approximately equal groupings based on each country's average GDP per capita over the time period. We then rescaled our disaster measures by twice the standard deviation for disasters in each group to improve the comparability of the coefficients. Finally, we re-estimated our final model specification for each group to check for variations in disaster effects by level of GDP per capita. We used this method as the results were easily

[8] As a precaution we ran the model separately for the periods before 1998 and after 1998. Results remained qualitatively unchanged.
[9] Hydrological disasters consist of floods and mudslide effects. We considered these effects more closely related to geophysical disasters than to climate-related disasters; however, arguments could be made for its inclusion into the climatologic category.

comparable, nonlinear patterns could be detected, and interpretation of coefficients with the nonlinear model was clearer than with interaction terms.

## 4 Empirical results

In Table 2 we estimate the effect of natural disasters on terrorism from the year of the disaster through the next two years. Here we observe a statistically significant and positive correlation between one year's disaster deaths and terrorism fatalities in the following year. The results are decidedly significant and remain stable across all specifications.

**Table 1: Poisson QML - Lagged deaths from natural disasters**

| Models:<br>***# Terr Deaths*** | (1)<br>b/(se) | (2)<br>b/(se) | (3)<br>b/(se) | (4)<br>b/(se) | (5)<br>b/(se) | (6)<br>b/(se) |
|---|---|---|---|---|---|---|
| # Deaths from Disaster / 25K | **-0.033** | **-0.019** | **0.096** | **0.040** | **0.039** | **0.098** |
| | **(0.099)** | **(0.113)** | **(0.131)** | **(0.177)** | **(0.177)** | **(0.165)** |
| # Deaths from Disaster (t-1) / 25K | **0.183*** | **0.178*** | **0.312*** | **0.298*** | **0.296*** | **0.328*** |
| | **(0.055)** | **(0.047)** | **(0.087)** | **(0.098)** | **(0.099)** | **(0.102)** |
| # Deaths from Disaster (t-2) / 25K | **0.041** | **0.065** | **0.218** | **0.202** | **0.201** | **0.232** |
| | **(0.131)** | **(0.134)** | **(0.200)** | **(0.208)** | **(0.209)** | **(0.192)** |
| GDP Per Capita / 1K | | | 0.132 | 0.145 | 0.145 | 0.146 |
| | | | (0.114) | (0.106) | (0.106) | (0.097) |
| GFCE (% of GDP) | | | 0.066*** | 0.068*** | 0.068*** | 0.064** |
| | | | (0.022) | (0.022) | (0.021) | (0.026) |
| FDI (% of GDP) | | | -0.102 | -0.097 | -0.097 | -0.088 |
| | | | (0.063) | (0.062) | (0.062) | (0.069) |
| Net DAC Flows (% of GDP) | | | 0.016 | 0.017 | 0.016 | 0.026* |
| | | | (0.026) | (0.026) | (0.026) | (0.016) |
| Population /1M | | | | 0.004*** | 0.004*** | 0.004*** |
| | | | | (0.001) | (0.001) | (0.001) |
| Percent of Population Urban | | | | 0.022 | 0.022 | 0.051 |
| | | | | (0.042) | (0.042) | (0.041) |
| # of Regional Disaster Deaths (t-1) /25K | | | | | -0.010 | -0.020 |
| | | | | | (0.054) | (0.049) |
| Civil Liberties | | | | | | -0.213** |
| | | | | | | (0.083) |
| Year-Effects | **No** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |
| Fixed Effects (Country) | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |
| Obs | **5709** | **5709** | **4044** | **4044** | **4044** | **3980** |
| Number of Countries | **167** | **167** | **149** | **149** | **149** | **146** |
| Log Likelihood | **-157918.2** | **-125348.5** | **-87347.5** | **-86342.8** | **-86339** | **-81843.7** |
| AIC | **315842.4** | **250772.9** | **174779.0** | **172773.7** | **172768.0** | **163779.3** |
| BIC | **315862.3** | **251025.6** | **175043.8** | **173051.1** | **173051.7** | **164068.6** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). Coefficients that have been scaled are indicated as such with the scaling factor. For example, " / 1K" would indicate the variable was scaled to thousands.

Though mechanisms for reverse causality between terrorism fatalities and natural disaster deaths seem unlikely, lagging the natural disaster measure strengthens the evidence for exogeneity. Using the variance in our panel data to exploit both spatial and temporal variation, as well as including both year and country fixed-effects, further reinforces evidence of a causal connection between disaster severity and terrorism. In our final specification, the magnitude of the resulting coefficients indicates that increasing deaths from natural disasters by 25,000 leads to an average increase of approximately 33 % in the expected number of terrorism fatalities in the following year.[10] Interestingly, it appears that the relationship between natural disasters and terrorism for the current year either does not exist, or alternatively, the timeframe analyzed is insufficient. This may be due to yearly aggregation as, during the current year, there is the possibility of capturing attacks that took place prior to a disaster. Additionally, if a disaster occurred late in the year, even if terrorism increased shortly thereafter, the effect might only be observed in the following year. Alternatively, the present year period might be too soon for a terrorist group to exploit disaster-related vulnerabilities for reasons discussed earlier including: reduced resources, damaged group infrastructure, and the need to reestablish the group's own capabilities.

In the other covariates, we see that population size and GFCE are both statistically significant. The direction of the coefficients would suggest that larger populations and more involvement by the government in societal matters are associated with higher levels of terrorism. The coefficient on civil liberties is statistically significant, with a negative coefficient indicating that higher levels of civil liberties are associated with lower levels of terrorism deaths. These results are qualitatively similar to those found in previous literature (Krueger and Laitin 2008; Li and Schaub 2004; Robison et al. 2006).

**Table 2: Model specification comparison**

| Models: | Pooled Log-linear (OLS) | First Differenced Log-linear (OLS) | First Differenced Log-Linear Year-Effects (OLS) | Log-linear Year & Country Effects (OLS) | Panel Negative Binomial | Panel Poisson QML |
|---|---|---|---|---|---|---|

[10] The Poisson model and choice of conditional mean allows a simple interpretation of the coefficients as $100 \cdot \beta_j$ is the semi-elasticity of $E[y|\mathbf{x}]$ with respect to $x_j$. Small changes in our covariates can be interpreted approximately as fixed percentage changes in the expected value of the terrorism measure (Wooldridge 2002).

| **# Terr Deaths** *(Log(#Terr Death+1) for OLS)* | b/(se) | b/(se) | b/(se) | b/(se) | b/(se) | b/(se) |
|---|---|---|---|---|---|---|
| # Deaths from Disaster / 25K | **0.133** | **0.094** | **0.098** | **0.145** | **0.194** | **0.098** |
| | **(0.111)** | **(0.095)** | **(0.093)** | **(0.102)** | **(0.228)** | **(0.165)** |
| # Deaths from Disaster (t-1) / 25K | **0.335*** ** | **0.263** ** | **0.260** ** | **0.342*** ** | **0.354** ** | **0.328*** ** |
| | **(0.122)** | **(0.127)** | **(0.131)** | **(0.103)** | **(0.162)** | **(0.102)** |
| # Deaths from Disaster (t-2) / 25K | **0.007** | **-0.027** | **-0.028** | **0.024** | **-0.106** | **0.232** |
| | **(0.126)** | **(0.094)** | **(0.082)** | **(0.110)** | **(0.122)** | **(0.192)** |
| GDP Per Capita / 1K | -0.056*** | -0.016 | -0.042 | -0.073*** | -0.159** | 0.146 |
| | (0.015) | (0.035) | (0.031) | (0.020) | (0.081) | (0.097) |
| GFCE (% of GDP) | 0.020* | 0.010 | 0.011 | 0.016 | 0.049* | 0.064** |
| | (0.011) | (0.008) | (0.008) | (0.011) | (0.028) | (0.026) |
| FDI (% of GDP) | -0.007* | 0.003 | 0.005 | -0.003 | -0.008 | -0.088 |
| | (0.004) | (0.005) | (0.005) | (0.003) | (0.022) | (0.069) |
| Net DAC Flows (% of GDP) | 0.025* | -0.013 | -0.013 | 0.005 | 0.048 | 0.026* |
| | (0.013) | (0.009) | (0.009) | (0.012) | (0.032) | (0.016) |
| Population /1M | 0.009*** | 0.009*** | 0.009*** | 0.009*** | 0.016* | 0.004*** |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.009) | (0.001) |
| Percent of Population Urban | 0.015 | 0.043*** | 0.005 | -0.004 | 0.013 | 0.051 |
| | (0.010) | (0.014) | (0.015) | (0.015) | (0.037) | (0.041) |
| # of Regional Disaster Deaths (t-1) /25K | -0.014 | 0.012 | 0.007 | -0.005 | -0.048 | -0.020 |
| | (0.029) | (0.018) | (0.018) | (0.029) | (0.078) | (0.049) |
| Civil Liberties | -0.079*** | -0.070*** | -0.065** | -0.074** | -0.167*** | -0.213** |
| | (0.029) | (0.027) | (0.026) | (0.029) | (0.061) | (0.083) |
| Year-Effects | **No** | **No** | **Yes** | **Yes** | **Yes** | **Yes** |
| Fixed-Effects (Country) | **No** | **No** | **No** | **Yes** | **Yes** | **Yes** |
| Obs | **3980** | **3810** | **3810** | **3980** | **3980** | **3980** |
| Number of Countries | **146** | **146** | **146** | **146** | **146** | **146** |
| Log Likelihood | **-6215.2** | **-5803.0** | **-5735.6** | **-6038.1** | **-7565.7** | **-81843.7** |
| AIC | **12452.4** | **11630.0** | **11563.1** | **12168.2** | **15225.3** | **163779.3** |
| BIC | **12521.5** | **11705.0** | **11850.4** | **12457.5** | **15520.9** | **164068.6** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors in Poisson QML are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). The panel negative binomial is the unconditional negative binomial estimator with year and country dummies (Allison and Waterman 2002).

In Table 3, we test the results from the fixed-effects Poisson QMLE model specification against other models. We see that the effect of natural disaster severity on terrorism remains stable and statistically significant across all specifications. Furthermore, there is similarity in the magnitudes of the effects for disaster deaths over all model specifications. The robustness is particularly notable as the effects in the differenced models are similar in size to those that utilize fixed-effects. Generally, the results for the other covariates are also in agreement with the results reported previously. Population size and civil liberties are statistically significant and have similar signs across all specifications. GFCE enters positively in all specifications and is statistically significant in both count model specifications. Both the panel negative binomial and OLS specifications show a statistically significant negative association between GDP per capita and terrorism; however, GDP per capita is not statistically significant in the Poisson or first-differenced specifications.

**Table 3: Varying measures of terrorism**

| Terrorism Measures: | # of Deaths b/(se) | # of Attacks b/(se) | # Wounded b/(se) |
|---|---|---|---|
| # Deaths from Disaster / 25K | **0.098** | **0.129*** | **0.128** |
| | **(0.165)** | **(0.075)** | **(0.104)** |
| # Deaths from Disaster (t-1) / 25K | **0.328***** | **0.217***** | **0.159*** |
| | **(0.102)** | **(0.060)** | **(0.082)** |
| # Deaths from Disaster (t-2) / 25K | **0.232** | **0.157** | **0.230*** |
| | **(0.192)** | **(0.095)** | **(0.121)** |
| GDP Per Capita / 1K | 0.146 | -0.160** | 0.053 |
| | (0.097) | (0.070) | (0.062) |
| GFCE (% of GDP) | 0.064** | 0.032 | 0.056** |
| | (0.026) | (0.023) | (0.023) |
| FDI (% of GDP) | -0.088 | -0.067 | -0.135 |
| | (0.069) | (0.041) | (0.087) |
| Net DAC Flows (% of GDP) | 0.026* | 0.001 | -0.008 |
| | (0.016) | (0.023) | (0.037) |
| Population /1M | 0.004*** | 0.006*** | 0.004*** |
| | (0.001) | (0.002) | (0.001) |
| Percent of Population Urban | 0.051 | 0.023 | 0.008 |
| | (0.041) | (0.033) | (0.031) |
| # of Regional Disaster Deaths (t-1) /25K | -0.020 | -0.038 | 0.017 |
| | (0.049) | (0.044) | (0.048) |
| Civil Liberties | -0.213** | -0.085 | -0.014 |
| | (0.083) | (0.060) | (0.087) |
| Year-Effects | **Yes** | **Yes** | **Yes** |
| Fixed Effects (Country) | **Yes** | **Yes** | **Yes** |
| Obs | **3980** | **4152** | **3893** |
| Number of Countries | **146** | **153** | **140** |
| Log Likelihood | **-81843.7** | **-28696.6** | **-119811.6** |
| AIC | **163779.3** | **57485.1** | **239715.2** |
| BIC | **164068.6** | **57776.4** | **240003.5** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). Coefficients that have been scaled are indicated as such with the scaling factor. For example, " / 1K" would indicate the variable was scaled to thousands.

It is important to test whether our findings are robust to alternative measures of terrorism. Using the fixed-effects Poisson QMLE specification, we assessed the effect of disasters on both the incidence and severity of terrorism. The results in Table 4 indicate statistically significant effects of natural disaster deaths across all measures of terrorism. Holding all other factors constant, the magnitude of the coefficients implies that, on average, raising natural disaster deaths by 25,000 leads to an increase in the following year of approximately 33% in the number of deaths from terrorism, an increase of approximately 22% in the number of terrorist attacks, and an increase of approximately 16% in the number wounded from terrorist attacks.

**Table 4: Falsification test**

| Terrorism Measures: | # of Deaths b/(se) | # of Attacks b/(se) | # Wounded b/(se) |
|---|---|---|---|
| # Deaths from Disaster (t+1) / 25K | **0.045** | **-0.007** | **0.116** |
| | **(0.142)** | **(0.103)** | **(0.122)** |
| # Deaths from Disaster / 25K | **0.082** | **0.115** | **0.112** |
| | **(0.166)** | **(0.079)** | **(0.110)** |
| # Deaths from Disaster (t-1) / 25K | **0.315***** | **0.202***** | **0.132*** |
| | **(0.110)** | **(0.059)** | **(0.074)** |
| # Deaths from Disaster (t-2) / 25K | **-0.078** | **0.053** | **0.089** |
| | **(0.191)** | **(0.076)** | **(0.090)** |
| GDP Per Capita / 1K | 0.172 | -0.156** | 0.071 |
| | (0.110) | (0.071) | (0.064) |
| GFCE (% of GDP) | 0.069** | 0.033 | 0.064*** |
| | (0.028) | (0.023) | (0.024) |
| FDI (% of GDP) | -0.098 | -0.068* | -0.146 |
| | (0.068) | (0.041) | (0.089) |
| Net DAC Flows (% of GDP) | 0.024 | 0.000 | -0.014 |
| | (0.018) | (0.023) | (0.037) |
| Population /1M | 0.004*** | 0.006*** | 0.004*** |
| | (0.002) | (0.002) | (0.001) |
| Percent of Population Urban | 0.052 | 0.026 | 0.004 |
| | (0.046) | (0.034) | (0.034) |
| # of Regional Disaster Deaths (t-1) /25K | -0.018 | -0.039 | 0.020 |
| | (0.049) | (0.041) | (0.047) |
| Civil Liberties | -0.200** | -0.078 | 0.010 |
| | (0.084) | (0.060) | (0.088) |
| Year-Effects | **Yes** | **Yes** | **Yes** |
| Fixed Effects (Country) | **Yes** | **Yes** | **Yes** |
| Obs | **3821** | **4028** | **3774** |
| Number of Countries | **144** | **153** | **139** |
| Log Likelihood | **-79101.0** | **-28008.7** | **-115887.0** |
| AIC | **158293.9** | **56109.4** | **231865.2** |
| BIC | **158581.4** | **56399.2** | **232152** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). Coefficients that have been scaled are indicated as such with the scaling factor. For example, " / 1K" would indicate the variable was scaled to thousands.

Given the unpredictable aspects of natural disasters, future disaster deaths should be completely unrelated to present period terrorism and we would expect the coefficients not to be statistically different from zero. As a robustness check, in Table 5, we implemented a falsification approach to alleviate possible endogeneity concerns by introducing future disaster deaths into the specifications and found no statistically significant effect of future disaster deaths on current period terrorism.

**Table 5: Varying measures of disaster**

| ***# Terr Deaths*** | # Deaths from Disaster / 25K b/(se) | # of Natural Disasters b/(se) | # Affected from Natural Disasters / 1M b/(se) |
|---|---|---|---|
| Disaster Measure | **0.099** | **-0.003** | **0.001**** |
| | **(0.164)** | **(0.016)** | **(0.001)** |
| Disaster Measure (t-1) | **0.328***** | **0.061***** | **0.002***** |
| | **(0.102)** | **(0.022)** | **(0.001)** |
| Disaster Measure (t-2) | **0.232** | **-0.011** | **0.000** |
| | **(0.192)** | **(0.022)** | **(0.001)** |
| GDP Per Capita / 1K | 0.146 | 0.127 | 0.141 |
| | (0.097) | (0.101) | (0.099) |
| GFCE (% of GDP) | 0.064** | 0.068** | 0.065** |
| | (0.026) | (0.027) | (0.027) |
| FDI (% of GDP) | -0.088 | -0.087 | -0.089 |
| | (0.069) | (0.068) | (0.068) |
| Net DAC Flows (% of GDP) | 0.026* | 0.022 | 0.023 |
| | (0.016) | (0.018) | (0.018) |
| Population /1M | 0.004*** | 0.003** | 0.004*** |
| | (0.001) | (0.001) | (0.002) |
| Percent of Population Urban | 0.051 | 0.041 | 0.045 |
| | (0.041) | (0.041) | (0.040) |
| # of Regional Disaster Deaths (t-1) /25K | -0.020 | -0.035 | -0.022 |
| | (0.049) | (0.045) | (0.053) |
| Civil Liberties | -0.213** | -0.211** | -0.210** |
| | (0.083) | (0.082) | (0.084) |
| Year-Effects | **Yes** | **Yes** | **Yes** |
| Fixed Effects (Country) | **Yes** | **Yes** | **Yes** |
| Obs | **3980** | **3980** | **3980** |
| Number of Countries | **146** | **146** | **146** |
| Log Likelihood | **-81840.5** | **-81583.2** | **-82300.2** |
| AIC | **163772.9** | **163258.4** | **164692.5** |
| BIC | **164062.2** | **163547.7** | **164981.8** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). Coefficients that have been scaled are indicated as such with the scaling factor. For example, " / 1K" would indicate the variable was scaled to thousands.

As a further robustness check, in Table 6, we tested the model using other measures of disaster severity and incidence. The effect of disasters on terrorism was both robust and statistically significant across all other disaster measures. Overall, the number of deaths, people affected, and disaster incidence had statistically significant, positive associations with terrorism in the subsequent year at a 0.01 level of significance. Furthermore, in Table 7, we include a specification where all of the measures of disasters are included. While this may result in some issues of multicollinearity between the measures of disaster severity, it allows us to determine if a particular aspect of disasters is driving the results. We find that that all measures – deaths from disaster, number of natural disaster, and the number affected by natural disasters – are statistically significant at the 0.05 or 0.01 level in the subsequent year.

**Table 6: All measures of disaster**

| Terrorism Measures: | # of Deaths b/(se) | # of Attacks b/(se) |
|---|---|---|
| # Deaths from Disaster / 25K | **0.11** | **0.131*** |
| | **-0.152** | **-0.075** |
| # Deaths from Disaster (t-1) / 25K | **0.294***** | **0.207***** |
| | **-0.1** | **-0.057** |
| # Deaths from Disaster (t-2) / 25K | **0.236** | **0.149** |
| | **-0.187** | **-0.094** |
| # Affected from Natural Disasters / 1M | **0.001*** | **0.001**** |
| | **-0.001** | **0** |
| # Affected from Natural Disasters (t-1) / 1M | **0.002***** | **0.003***** |
| | **-0.001** | **0** |
| # Affected from Natural Disasters (t-2) / 1M | **0.001** | **0.002***** |
| | **-0.001** | **-0.001** |
| # of Natural Disasters | **-0.003** | **-0.001** |
| | **-0.016** | **-0.02** |
| # of Natural Disasters (t-1) | **0.060***** | **0.019** |
| | **-0.022** | **-0.015** |
| # of Natural Disasters (t-2) | **-0.013** | **-0.003** |
| | **-0.022** | **-0.013** |
| Year-Effects | **Yes** | **Yes** |
| Fixed Effects (Country) | **Yes** | **Yes** |
| Obs | **3980** | **4152** |
| Number of Countries | **146** | **153** |
| Log Likelihood | **-80783.8** | **-28481.1** |
| AIC | **161671.5** | **57066.2** |
| BIC | **161998.6** | **57395.4** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). Coefficients that have been scaled are indicated as such with the scaling factor. For example, " / 1K" would indicate the variable was scaled to thousands. All other covariates were included in the specifications; however, results are omitted for brevity.

Table 8 displays the results of our analysis after separating natural disasters by disaster type. Climatologic and meteorological disasters are likely to be more predictable in comparison to geophysical/hydrological disasters due to the inherent seasonality of events such as tropical cyclones (Landsea 2000). We find that the coefficient on disaster deaths for climatologic and meteorological disasters loses significance in the second lag, whereas the effects of geophysical and hydrological disasters are sustained and escalating through a second lag.[11] The most significant of the events which comprise the geophysical and hydrological disasters are volcanoes, earthquakes, and tsunamis which tend to be more deadly and less predictable than

[11] The effect disappears with further lags.

tropical cyclones (Buhaug et al. 2010; Sorensen 2000). Additionally, warning times differ between disaster types with cyclones being monitored for days while earthquakes often occur with little or no warning. Finally, geophysical events affect infrastructure quite differently than storms. The combination of an unpredictable nature, deadliness, and differing effects on infrastructure may explain the observed deviations.

**Table 7: Varying disaster measures by disaster type and terrorism outcome**

| Disaster Measure: | Geophysical & Hydrological | | Climatologic & Meteorological | |
|---|---|---|---|---|
| Terrorism Outcome: | # of Deaths | # of Attacks | # of Deaths | # of Attacks |
| | b/(se) | b/(se) | b/(se) | b/(se) |
| # Deaths from Disaster / 25K | **0.193** | **0.274***** | **0.000** | **-0.008** |
| | **(0.315)** | **(0.095)** | **(0.181)** | **(0.062)** |
| # Deaths from Disaster (t-1) / 25K | **0.413**** | **0.348***** | **0.288**** | **0.127**** |
| | **(0.165)** | **(0.108)** | **(0.136)** | **(0.051)** |
| # Deaths from Disaster (t-2) / 25K | **0.624***** | **0.280**** | **-0.379** | **0.025** |
| | **(0.181)** | **(0.137)** | **(0.382)** | **(0.055)** |
| GDP Per Capita / 1K | 0.156 | -0.161** | 0.141 | -0.161** |
| | (0.100) | (0.070) | (0.099) | (0.071) |
| GFCE (% of GDP) | 0.068*** | 0.033 | 0.066** | 0.032 |
| | (0.026) | (0.023) | (0.027) | (0.023) |
| FDI (% of GDP) | -0.091 | -0.068* | -0.088 | -0.066 |
| | (0.068) | (0.041) | (0.069) | (0.041) |
| Net DAC Flows (% of GDP) | 0.023 | -0.002 | 0.023 | -0.001 |
| | (0.017) | (0.023) | (0.018) | (0.023) |
| Population /1M | 0.004*** | 0.006*** | 0.004*** | 0.006*** |
| | (0.001) | (0.002) | (0.002) | (0.002) |
| Percent of Population Urban | 0.047 | 0.022 | 0.046 | 0.023 |
| | (0.040) | (0.032) | (0.041) | (0.034) |
| # of Regional Disaster Deaths (t-1) /25K | -0.030 | -0.038 | -0.025 | -0.041 |
| | (0.050) | (0.043) | (0.049) | (0.044) |
| Civil Liberties | -0.207** | -0.082 | -0.210** | -0.083 |
| | (0.083) | (0.060) | (0.083) | (0.060) |
| Year-Effects | **Yes** | **Yes** | **Yes** | **Yes** |
| Fixed Effects (Country) | **Yes** | **Yes** | **Yes** | **Yes** |
| Obs | **3980** | **4152** | **3980** | **4152** |
| Number of Countries | **146** | **153** | **146** | **153** |
| Log Likelihood | **-81421.9** | **-28650.5** | **-82101.7** | **-28791.1** |
| AIC | **162935.9** | **57393.0** | **164295.5** | **57674.2** |
| BIC | **163225.2** | **57684.2** | **164584.8** | **57965.4** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). Coefficients that have been scaled are indicated as such with the scaling factor. For example, " / 1K" would indicate the variable was scaled to thousands.

In order to better understand the type of country in which this phenomenon occurs, we separated countries in our final specification into approximately equal groupings based on their average GDP per capita over the time period. Since the typical number of disaster deaths also varies over these groups, we rescaled disaster deaths by twice the standard deviation of disaster deaths for that group. This was done in order to scale the coefficients across groups for comparability. We then ran our analysis across the three groups using the final model specification with terrorism incidence and deaths.

**Table 8: Varying by GDP per capita groupings**

| Terrorism Outcome: | Terrorism Deaths | | | Terrorism Incidence | | |
|---|---|---|---|---|---|---|
| GDP Per Capita Grouping | Low<br>b/(se) | Middle<br>b/(se) | High<br>b/(se) | Low<br>b/(se) | Middle<br>b/(se) | High<br>b/(se) |
| # Deaths from Disaster / 2 $\sigma$ | **0.119** | **0.188*** ** | **-0.126** | **0.027** | **0.067*** | **0.060** |
| | **(0.171)** | **(0.055)** | **(0.339)** | **(0.058)** | **(0.039)** | **(0.048)** |
| # Deaths from Disaster (t-1) / 2 $\sigma$ | **0.440*** ** | **0.190*** ** | **-2.160** | **0.145** ** | **0.112** | **-0.002** |
| | **(0.131)** | **(0.056)** | **(3.033)** | **(0.066)** | **(0.077)** | **(0.095)** |
| # Deaths from Disaster (t-2) / 2 $\sigma$ | **0.328*** ** | **0.046** | **-1.826*** | **0.080** | **0.052** | **-0.013** |
| | **(0.093)** | **(0.072)** | **(1.103)** | **(0.083)** | **(0.051)** | **(0.061)** |
| GDP Per Capita in / 1K | -2.343** | -0.560 | 0.059 | -0.679 | 0.123 | -0.012 |
| | (1.037) | (0.713) | (0.068) | (0.866) | (0.287) | (0.064) |
| GFCE (% of GDP) | 0.078** | 0.086* | -0.086** | 0.010 | 0.061 | -0.093*** |
| | (0.032) | (0.047) | (0.034) | (0.034) | (0.040) | (0.022) |
| FDI (% of GDP) | -0.059* | -0.101 | 0.033 | -0.079 | -0.056* | 0.010 |
| | (0.033) | (0.150) | (0.058) | (0.067) | (0.034) | (0.024) |
| Net DAC Flows (% of GDP) | 0.012 | -0.141 | -0.312 | 0.015 | -0.024 | 0.012 |
| | (0.022) | (0.087) | (0.201) | (0.017) | (0.040) | (0.079) |
| Population /1M | 0.000 | -0.014 | 0.063*** | -0.001 | 0.058 | -0.015* |
| | (0.001) | (0.059) | (0.012) | (0.002) | (0.038) | (0.008) |
| Percent of Population Urban | 0.050 | 0.165 | 0.145** | 0.076* | -0.005 | 0.111 |
| | (0.052) | (0.117) | (0.071) | (0.043) | (0.060) | (0.070) |
| # of Regional Disaster Deaths (t-1) /25K | 0.032 | -0.208* | 0.190 | -0.012 | 0.051 | -0.209*** |
| | (0.065) | (0.115) | (0.173) | (0.045) | (0.140) | (0.072) |
| Civil Liberties | -0.235*** | -0.207* | -0.013 | 0.004 | -0.101 | 0.007 |
| | (0.086) | (0.109) | (0.094) | (0.062) | (0.064) | (0.051) |
| Year-Effects | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |
| Fixed Effects (Country) | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |
| Obs | **1336** | **1357** | **1287** | **1336** | **1357** | **1287** |
| Number of Countries | **50** | **51** | **45** | **50** | **51** | **45** |
| Log Likelihood | **-21683.6** | **-30148.7** | **-8769.4** | **-5099.1** | **-12566.6** | **-5111.9** |
| AIC | **43459.3** | **60389.4** | **17626.7** | **10290.3** | **25225.3** | **10311.9** |
| BIC | **43698.4** | **60629.2** | **17853.8** | **10529.4** | **25465.1** | **10538.9** |

*Notes:* Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering, over/underdispersion, arbitrary heteroskedasticity, and arbitrary serial correlation (Wooldridge 1999). Coefficients that have been scaled are indicated as such with the scaling factor. For example, " / 1K" would indicate the variable was scaled to thousands. Coefficients scaled by $2\sigma$ are scaled by 2 times the standard deviation of deaths from natural disasters of that grouping. Significance

We see in Table 9 that disasters' effect on terrorism is most salient in countries with low to middle levels of GDP per capita. Interestingly, for high GDP countries, the coefficient loses significance and changes sign. This result is important as it suggests that the recent devastation in

Japan wrought by the Tōhoku earthquake and tsunami is unlikely to result in a surge of terrorism owing to Japan's relatively high GDP per capita. For the countries in the middle group, we find statistically significant effects in the year of the disaster and the year following. In the low GDP per capita group, the effect is not statistically significant in the current year but is statistically significant and escalating in the following two years. The differences between the effects in these two groups could be a result of differences in the ability of each group to recover from a disaster. Presumably, richer countries have more resources at their disposal to aid in the recovery process and to combat terrorism.

Again, we see interesting patterns in the other covariates. The coefficient for civil liberties suggests that the negative correlation between civil liberties and terrorism decreases as GDP per capita increases. Notably, sign reversal is apparent for GFCE as GDP per capita rises. In previous specifications, higher levels of GFCE were associated with a larger number of terrorism deaths; indicating that growing size and intrusiveness of government is associated with increased levels of terror. The pattern we see in Table 9 hints that the relationship is perhaps more subtle. The result suggests that government intrusiveness into the private sphere may trigger more terrorism in poorer countries. In richer countries this same intrusiveness is associated with lower levels of terrorism. It is important to note that this variable could be exhibiting endogeneity with terrorism. Governments may increase government expenditures for individual consumption goods to placate terrorists or opposition groups just as terrorist groups may change their attack strategies to try to influence the distribution of these expenditures. Similarly, distribution of foreign aid may be plagued by its possible endogeneity with terrorism (Azam and Delacroix 2006). While this issue begs further investigation, it is comforting to note that the inclusion or exclusion of these variables does not significantly alter the observed effects of disasters on terrorism.

### *4.1 Conclusion*

This study is the first to assess empirically whether natural disasters have an effect on terrorism. Using detailed information on terrorism, natural disasters, and other relevant economic and demographic variables of 167 countries between 1970 and 2007, we were able to identify and estimate the effect of natural disasters on terrorism. We found that disasters have a strong positive association with subsequent terrorism incidence and fatalities. When focusing on the type of disaster, we found differences between the effects that could be attributable to the variation in predictability and deadliness of the disaster types. Differing impacts on infrastructure, early warning systems, and seasonal expectations for meteorological events may play a part in the preparedness of a country and could influence the speed and complexity of the recovery process. By breaking down our data into groups based on GDP per capita, we were able to further isolate our effect to identify the country types in which the phenomenon has been most prevalent. We found that natural disasters primarily affected terrorism in low to middle GDP per capita countries with effects most concentrated in poorer, low GDP per capita, countries. Additionally, the findings indicated countries with high GDP per capita did not experience terrorism following a natural disaster.

The possible transference of terrorism into and out of a state predicates the importance of studying whether the effect of the severity of a disaster on a country's terrorism reflects changes only in that country's susceptibility or if the effect spills over to neighboring countries as well. The answer to that question will have direct policy implications with respect to the most effective and appropriate strategies for mitigating terrorist actions during disaster recovery. Though natural disasters can put a strain on entire regions, the chief responsibility for protecting a people falls onto a country's government, and there is reason to believe that the country-wide impact of a disaster should reflect primarily the weaknesses of that régime. It is therefore important to assess whether a natural disaster's effects on subsequent terrorism are more localized and country-specific or whether regional recovery efforts may be necessary instead for effective mitigation. Overall, we found evidence that the effect of natural disasters on terrorism is local to a country. Our analysis of possible regional spillover effects suggests that there is no significant effect of either regional disasters on local terrorism or local disasters on regional terrorism. This implies that country-specific disaster mitigation strategies have potential for reducing subsequent violence. Our findings also indicate that any interplay at the regional level might be due to displacement of terrorism caused by local disasters though we are not able to determine this conclusively.

In addition to elucidating some of the connections between disaster and terrorism research, our analysis revealed possibilities for future research on the links between disasters and terrorism and their interplay with state legitimacy and terrorism displacement. Our results showed that terrorist attacks rise following a natural disaster; however, the duration of these effects appeared to be related to economic and disaster characteristics. Further differentiation by target type may shed light on these relationships and allow researchers to determine whether target choice is affected by a disaster. One might also suspect that, as opposed to domestic terrorism, transnational terrorism might be driven by other motives; thus, disasters could have dissimilar effects between these two groups. As of yet, our data and analysis does not differentiate along this partition. Along similar lines, the possibility of natural disasters inducing spillover terrorism to neighboring countries associated with transnational rather than domestic terrorist activity warrants further research (Enders and Sandler 2006).

Because we used country fixed-effects we were unable to identify the effect of many factors that do not change over time for a given country. Location, elevation, and environment are all likely to influence the both the specifics of the disaster, recovery efforts, and subsequent violence, but they generally do not change with time. In theory, if we could identify all the variables at play we would have no need for fixed-effects. In reality, we can't control for these factors as they increase ad infinitum. We use fixed-effect to control for the average effect of all these factors on terrorism while still being able to consistently identify the effect of our variable of interest.

As is said, "hindsight is 20/20." If the earthquake and tsunami alert system established by the Association of Southeast Asian Nations had been developed sufficiently perhaps there would have been adequate warning of the impending tsunami in Thailand and Sri Lanka. Even with the limitations discussed, our results present compelling evidence that a reduction in the impacts of disasters could prevent substantial escalations in terrorism. Investments in prevention, resiliency, and international cooperation towards disaster mitigation could produce potentially significant security benefits. Additionally, efforts should be made to address some of pre-existing societal factors that make countries more susceptible than others to both disasters and terrorism. Over the last decade, policy makers have placed an emphasis on establishing security ties between countries to combat terrorism; however, cooperation against non-military threats like natural disasters has remained inchoate (Huxley 2005). Previous strategies have by and large considered these threats disjointly. Our findings suggest this can no longer be. Future policies for thwarting terrorism must also include efforts in order to understand and bolster resiliency to natural disasters. In that way we might attenuate the devastating consequences of both.

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## Appendix

### *5.1 List of regions (START 2010, 2010b)*

1. North America
2. Central America & Caribbean
3. South America
4. East Asia
5. Southeast Asia
6. South Asia
7. Central Asia
8. Western Europe
9. Eastern Europe
10. Middle East & North Africa
11. Sub-Saharan Africa
12. Russia & Newly Independent States
13. Australasia & Oceania

### *5.2 List of all countries by model inclusion and grouping*

| Region | Country | G | Final | Region | Country | G | Final |
|---|---|---|---|---|---|---|---|
| 18 | Afghanistan | H | No | 6 | Korea Dem P Rep | H | No |
| 19 | Albania | M | Yes | 6 | Korea Rep | H | Yes |
| 10 | Algeria | M | Yes | 21 | Kuwait | H | Yes |
| 9 | Angola | L | Yes | 4 | Kyrgyzstan | L | Yes |
| 2 | Antigua and Barbuda | H | Yes | 16 | Lao P Dem Rep | L | No |
| 15 | Argentina | H | Yes | 12 | Latvia | M | Yes |
| 21 | Armenia | L | Yes | 21 | Lebanon | H | Yes |
| 1 | Australia | H | Yes | 17 | Lesotho | L | Yes |
| 22 | Austria | H | Yes | 20 | Liberia | L | No |
| 21 | Azerbaijan | M | Yes | 10 | Libyan Arab Jamah | H | No |
| 2 | Bahamas | H | Yes | 12 | Lithuania | H | Yes |
| 21 | Bahrain | H | Yes | 6 | Macau | H | No |
| 18 | Bangladesh | L | Yes | 19 | Macedonia FRY | M | Yes |
| 2 | Barbados | H | Yes | 5 | Madagascar | L | Yes |
| 7 | Belarus | M | Yes | 5 | Malawi | L | Yes |
| 22 | Belgium | H | Yes | 16 | Malaysia | M | Yes |
| 3 | Belize | M | Yes | 20 | Mali | L | Yes |
| 11 | Bermuda | H | No | 20 | Mauritania | L | Yes |
| 18 | Bhutan | L | Yes | 3 | Mexico | H | Yes |
| 15 | Bolivia | M | Yes | 7 | Moldova Rep | L | Yes |
| 19 | Bosnia-Hercegovenia | M | Yes | 10 | Morocco | M | Yes |
| 17 | Botswana | M | Yes | 5 | Mozambique | L | Yes |
| 15 | Brazil | M | Yes | 16 | Myanmar | H | No |
| 7 | Bulgaria | M | Yes | 17 | Namibia | M | Yes |
| 20 | Burkina Faso | L | Yes | 18 | Nepal | L | Yes |
| 5 | Burundi | L | Yes | 22 | Netherlands | H | Yes |
| 16 | Cambodia | L | Yes | 8 | New Caledonia | H | No |
| 9 | Cameroon | L | Yes | 1 | New Zealand | H | Yes |
| 11 | Canada | H | Yes | 3 | Nicaragua | M | Yes |
| 9 | Central African Rep | L | Yes | 20 | Niger | L | Yes |
| 9 | Chad | L | Yes | 20 | Nigeria | L | No |

| Region | Country | G | Final | Region | Country | G | Final |
|---|---|---|---|---|---|---|---|
| 15 | Chile | M | Yes | 12 | Norway | H | Yes |
| 6 | China P Rep | L | Yes | 18 | Pakistan | L | Yes |
| 15 | Colombia | M | Yes | 3 | Panama | M | Yes |
| 5 | Comoros | L | Yes | 8 | Papua New Guinea | L | Yes |
| 9 | Congo | M | Yes | 15 | Paraguay | M | Yes |
| 3 | Costa Rica | M | Yes | 15 | Peru | M | Yes |
| 20 | Cote d'Ivoire | L | Yes | 16 | Philippines | M | Yes |
| 19 | Croatia | H | Yes | 7 | Poland | H | Yes |
| 2 | Cuba | M | No | 19 | Portugal | H | Yes |
| 21 | Cyprus | H | No | 2 | Puerto Rico | H | No |
| 7 | Czech Rep | H | Yes | 7 | Romania | M | Yes |
| 12 | Denmark | H | Yes | 7 | Russia | M | Yes |
| 5 | Djibouti | M | Yes | 5 | Rwanda | L | Yes |
| 2 | Dominica | M | Yes | 21 | Saudi Arabia | H | Yes |
| 2 | Dominican Rep | M | Yes | 20 | Senegal | L | Yes |
| 15 | Ecuador | M | Yes | 19 | Serbia | M | Yes |
| 10 | Egypt | M | Yes | 20 | Sierra Leone | L | Yes |
| 3 | El Salvador | M | Yes | 16 | Singapore | H | Yes |
| 9 | Equatorial Guinea | M | Yes | 7 | Slovakia | H | Yes |
| 5 | Eritrea | L | Yes | 19 | Slovenia | H | Yes |
| 12 | Estonia | H | Yes | 5 | Somalia | H | No |
| 5 | Ethiopia | L | Yes | 17 | South Africa | M | Yes |
| 8 | Fiji | M | Yes | 14 | Soviet Union | H | No |
| 12 | Finland | H | Yes | 19 | Spain | H | Yes |
| 22 | France | H | Yes | 18 | Sri Lanka | L | Yes |
| 9 | Gabon | H | Yes | 10 | Sudan | L | Yes |
| 20 | Gambia The | L | Yes | 15 | Suriname | M | Yes |
| 21 | Georgia | M | Yes | 17 | Swaziland | M | Yes |
| 22 | Germany | H | Yes | 12 | Sweden | H | Yes |
| 20 | Ghana | L | Yes | 22 | Switzerland | H | Yes |
| 19 | Greece | H | Yes | 21 | Syrian Arab Rep | M | Yes |
| 2 | Grenada | M | No | 6 | Taiwan (China) | H | No |
| 2 | Guadeloupe | H | No | 4 | Tajikistan | L | Yes |
| 3 | Guatemala | M | Yes | 5 | Tanzania Uni Rep | L | Yes |
| 20 | Guinea | L | Yes | 16 | Thailand | M | Yes |
| 20 | Guinea Bissau | L | Yes | 20 | Togo | L | Yes |
| 15 | Guyana | M | Yes | 2 | Trinidad and Tobago | H | Yes |
| 2 | Haiti | L | Yes | 10 | Tunisia | M | Yes |
| 3 | Honduras | M | Yes | 21 | Turkey | M | Yes |
| 6 | Hong Kong (China) | H | No | 5 | Uganda | L | Yes |
| 7 | Hungary | H | Yes | 7 | Ukraine | M | Yes |
| 18 | India | L | Yes | 12 | United Kingdom | H | Yes |
| 16 | Indonesia | L | Yes | 11 | United States | H | Yes |
| 18 | Iran Islam Rep | M | Yes | 15 | Uruguay | H | Yes |
| 21 | Iraq | M | No | 4 | Uzbekistan | L | Yes |
| 12 | Ireland | H | Yes | 15 | Venezuela | H | Yes |
| 21 | Israel | H | Yes | 16 | Viet Nam | L | Yes |
| 19 | Italy | H | Yes | 2 | Virgin Is (US) | H | No |
| 2 | Jamaica | M | Yes | 21 | Yemen | L | Yes |
| 6 | Japan | H | Yes | 9 | Zaire/Congo Dem Rep | L | Yes |
| 21 | Jordan | M | Yes | 5 | Zambia | L | Yes |
| 4 | Kazakhstan | M | Yes | 5 | Zimbabwe | L | Yes |
| 5 | Kenya | L | Yes | | | | |

Notes: Table contains list of all countries in analysis. Region indicates the region ID which can be found in the list of regions, 7.1. Final indicates whether the country was included in our final specification of the Poisson QML model with lagged natural disaster deaths. The heading G stands for GDP per Capita groupings.. An “H” in that column designates they were part of the high group, “M” designates middle group, and “L” designates low group. A “-” in any of those three columns indicates they were not part of any group as they were not in the final specification.

The dataset introduced a few instances where countries combined, separated, ceased to exist, or came into being over the period of observation--largely as a result of the breakup of the Union of Soviet Socialist Republics. For these countries we used only the years for which each country was extant as a separate entity. The only deviations from this methodology were in the cases of Germany and Yugoslavia. The German observations consist of the combination of observations from East and West Germany prior to unification. Until 2003, “Serbia” refers to Yugoslavia; it then refers to the State Union of Serbia and Montenegro; finally, in 2006-2007, it refers to the independent State of Serbia alone.

### *5.3 Disaster groups and sub-types*

| Disaster Sub-Group | Disaster Main Type | Disaster Sub-Type |
|---|---|---|
| Geophysical | Earthquake | Ground Shaking |
| | | Tsunami |
| | Volcano | Volcanic eruption |
| | Mass Movement (dry) | Rockfall |
| | | Avalanche |
| | | Landslide |
| | | Subsidence |
| Hydrological | Flood | General |
| | | River flood |
| | | Flash flood |
| | | Storm surge/coastal flood |
| | Mass Movement (wet) | Rockfall |
| | | Avalanche |
| | | Landslide |
| | | Subsidence |
| Meteorological | Storm | Tropical Storm |
| | | Extra-Tropical cyclone (winter storm) |
| Climatologic | Drought<br>Wild fire | Drought |
| | | Forest Fire |
| | | Land fires (grass, scrub, bush, etc.) |

Adapted from (CRED 2010a, 2010b)