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DISSERTATION

Three Essays on Terrorism, its Relationship with Natural Disasters and its Effect on Female Labor Force Participation

Jordan P. Ostwald

This document was submitted as a dissertation in September 2011 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Claude Berrebi (Chair), Paul Heaton, and Nicholas Burger.

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Three Essays on Terrorism, its Relationship with Natural Disasters, and its Effect on Female Labor Force Participation

1LT Jordan Ostwald

Committee
Dr. Claude Berrebi (Chair)
Dr. Paul Heaton
Dr. Nicholas Burger

Abstract

Nature's disasters and their aftermath have engendered fear and fascination in human minds for thousands of years. They have shaped the earth, the climate, and the makeup of human civilization for perhaps even longer. From the eruption of Mount Vesuvius in 79AD to the devastation wrought by Cyclone Nargis on Myanmar in 2008, these events and others have continually reminded us of nature's capricious temperament. As societies have expanded, they have adapted in an attempt to mitigate the effects of these devastating events, but all too often the propensity of disasters to overwhelm human adaptations has proved both humbling and daunting. The aftermath of a disaster is a particularly trying time for any government. A society vests much of its security within its government's ability to protect; thus, the effectiveness and efficiency of disaster preparedness and recovery measures are crucial to maintaining a government's legitimacy. As a result, natural disasters as possible catalysts of terrorism have serious implications for both national security and disaster policy both locally and regionally. The aim of this dissertation is to explore and illuminate the relationship between natural disasters and terrorism. The research will examine and test this link across many dimensions of both disasters and terrorism. Furthermore, these natural events introduce essentially random exogenous shocks which could affect terrorism. An added benefit of this randomness is that it can be used as an instrument to assess causal effects of terrorism on other factors. In particular, we utilize this fact to investigate and clarify causal links between terrorism, female labor force participation, and larger gender disparities in the labor market.

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Disclaimer: The views expressed in this dissertation are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the U.S. Government.

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

Claude Berrebi · Jordan Ostwald

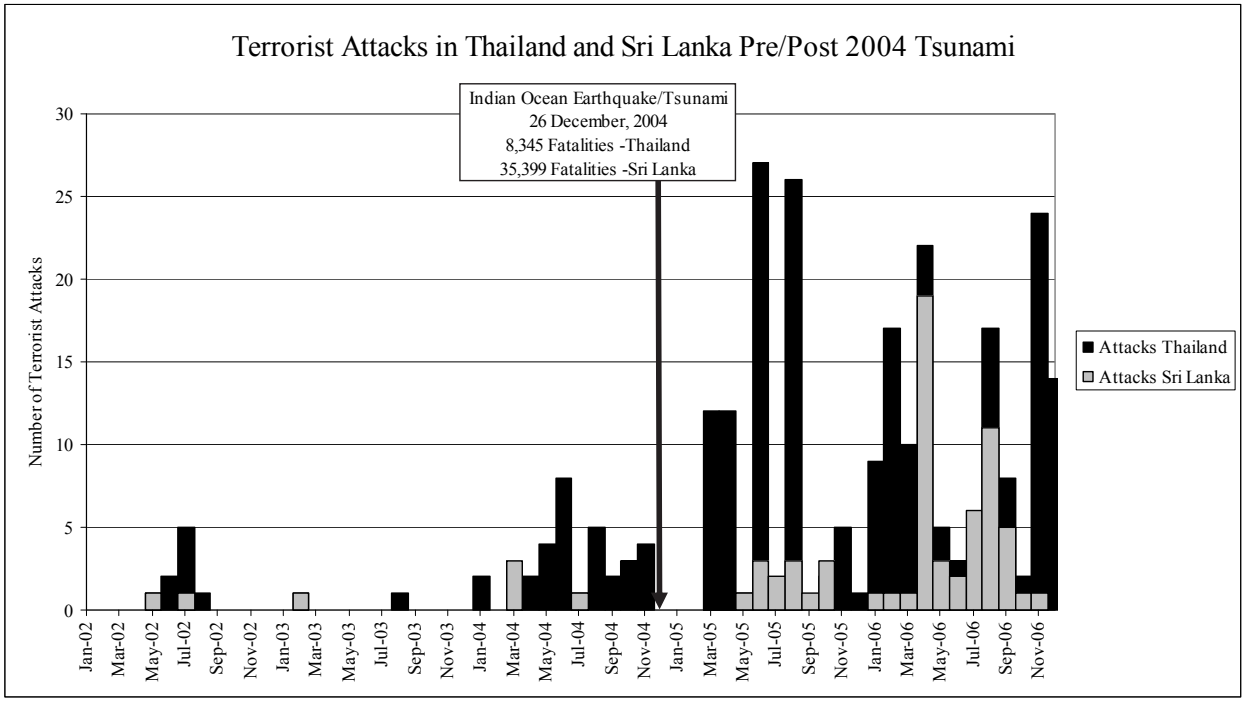
A novel and important issue in contemporary security policy is the impact of natural disasters on terrorism. Natural disasters can strain a society and its government, creating vulnerabilities which terrorist groups might exploit. Using a structured methodology and detailed data on terrorism, disasters, 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 over a diverse set of model specifications. The results have strong implications for both disaster and terrorism mitigation policy.

1.1 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). News reports indicated that the Liberation Tigers of Tamil Eelam (LTTE), while affected severely by

the tsunami, were increasing their attacks and attempting to recruit child tsunami victims for use as soldiers (Human Rights Watch 2005; Le Billon and Waizenegger 2007). With over 8,000 deaths, Thailand was also devastated by the tsunami. In the tragedy's wake, tourism suffered, unrest increased, and the violence of the South Thailand Insurgency escalated (McDowall and Wang 2009; Teeling 2006). As seen in Figure 1.1, the evidence was much the same with terrorist attacks rising dramatically following the events of December 26th.

Figure 1.1: Terrorist Attacks in Thailand and Sri Lanka Pre/Post 2004 Tsunami



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

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, urban-ization, 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 infra-structure 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.

1.2 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

[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.

(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 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.

1.2.1 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).

[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.

- 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.

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 1.1, 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 1.1: 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 5th percentiles for all variables in table were 0. Statistics are for countries with at least 1 terrorist attack between 1970 and 2007.

1.2.2 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 1.1 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.

1.2.3 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 (GDP) 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

[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.

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 found to be important in terrorism research (Krueger and Laitin 2008; Krueger and Malecková 2003).[5]

1.3 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*

[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 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.

$regional_{i,t-1}$: 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 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.[7] 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:

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

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

[7] For strictly positive variables in OLS, often a natural log transformation is used, which is inappropriate for our data since our data contains a significant fraction of observations where the dependent variable takes on the value zero. We therefore use a count model to directly estimate $E\left(y|\mathbf{x}\right)$ ensuring positivity for any values of x. Nevertheless, we include the log-linear OLS model in order to show the similarity and consistently of the results across model specifications.

where we assume the conditional mean[8] 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 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.[9] 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.

[8] 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).

[9] As a precaution we ran the model separately for the periods before 1998 and after 1998. Results remained qualitatively unchanged.

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

1.4 Empirical results

In Table 1.2 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. 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.

[10] 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.

Table 1.2: Poisson QML - Lagged deaths from natural disasters

Models:	(1)	(2)	(3)	(4)	(5)	(6)
# Terr Deaths	b/(se)	b/(se)	b/(se)	b/(se)	b/(se)	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.

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.[11] 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

[11] 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).

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).

In Table 1.3, 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 1.3: 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
# 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).

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 1.4 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 1.4: 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.

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 1.5, 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 1.5: 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	**0.081**	**0.114**	**0.111**
	(0.167)	**(0.079)**	**(0.110)**
# Deaths from Disaster (t-1) / 25K	**0.315*****	**0.203*****	**0.133***
	(0.110)	**(0.059)**	**(0.074)**
# Deaths from Disaster (t-2) / 25K	**-0.079**	**0.052**	**0.089**
	(0.192)	**(0.077)**	**(0.091)**
GDP Per Capita / 1K	0.172	-0.156**	0.072
	(0.110)	(0.071)	(0.065)
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	0.051	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	**-79103.8**	**-28007.5**	**-115869.0**
AIC	**158299.6**	**56107.0**	**231830.0**
BIC	**158587**	**56396.9**	**232116.9**

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.

As a further robustness check, in Table 1.6, 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 1.7, 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 disasters, and the number affected by natural disasters – are statistically significant at the 0.05 or 0.01 level in the subsequent year.

Table 1.6: 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	**0.098**	**-0.003**	**0.001****
	(0.165)	**(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	0.126	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	**-81843.7**	**-81585.7**	**-82304.8**
AIC	**163779.3**	**163263.5**	**164701.5**
BIC	**164068.6**	**163552.8**	**164990.8**

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.

Table 1.7: All measures of disaster

Terrorism Measures:	# of Deaths b/(se)	# of Attacks b/(se)
# Deaths from Disaster / 25K	**0.110**	**0.131***
	(0.152)	**(0.075)**
# Deaths from Disaster (t-1) / 25K	**0.294*****	**0.208*****
	(0.100)	**(0.057)**
# Deaths from Disaster (t-2) / 25K	**0.236**	**0.148**
	(0.187)	**(0.094)**
# Affected from Natural Disasters / 1M	**0.001***	**0.001****
	(0.001)	**(0.000)**
# Affected from Natural Disasters (t-1) / 1M	**0.002*****	**0.003*****
	(0.001)	**(0.000)**
# Affected from Natural Disasters (t-2) / 1M	**0.001**	**0.002*****
	(0.001)	**(0.001)**
# of Natural Disasters	**-0.003**	**-0.001**
	(0.016)	**(0.020)**
# of Natural Disasters (t-1)	**0.060*****	**0.019**
	(0.022)	**(0.015)**
# of Natural Disasters (t-2)	**-0.013**	**-0.002**
	(0.022)	**(0.013)**
Year-Effects	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**
Obs	**3980**	**4152**
Number of Countries	**146**	**153**
Log Likelihood	**-80788.3**	**-28480.7**
AIC	**161680.7**	**57065.5**
BIC	**162007.7**	**57394.7**

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 1.8 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.[12] 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 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

[12] The effect disappears with further lags.

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 1.8: 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 1.9: Varying by GDP per capita groupings

Terrorism Outcome:	Terrorism Deaths			Terrorism Incidence		
GDP Per Capita Grouping	Low	Middle	High	Low	Middle	High
	b/(se)	b/(se)	b/(se)	b/(se)	b/(se)	b/(se)
# Deaths from Disaster / 2σ	**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) / 2σ	**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) / 2σ	**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 2σ are scaled by 2 times the standard deviation of deaths from natural disasters of that grouping. Significance

We see in Table 1.9 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 1.9 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.

1.5 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 the effect to identify 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.

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).

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.

1.6 Appendix

1.6.1 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

1.6.2 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

Region	Country	G	Final	Region	Country	G	Final
9	Chad	L	Yes	20	Nigeria	L	No
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.

1.6.3 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 Wild fire	Drought
		Forest Fire
		Land fires (grass, scrub, bush, etc.)

Adapted from (CRED 2010a, 2010b)

2 Vulnerable States: Investigating Terrorism in the Wake of Natural Disasters

Jordan Ostwald

As an extension of previous work, this study significantly expands upon the research into the relationship between disasters and terrorism by exploring many factors and remaining questions surrounding this phenomenon. In particular, the possible transference of terrorism into and out of weakened states predicates the importance of investigating whether the effect of natural disasters on terrorism reflects change solely in a country's susceptibility or whether the effect may spill over into neighboring countries. Along these same lines, one might expect transnational terrorism to be driven by different motives than domestic terrorism, thus disasters may have dissimilar effects between these two groups. As the type of terrorism differs, the targets might also be influenced as previously "hard" targets are weakened in the wake of catastrophes. The essay explores disasters' effects on terrorism by separating terrorist incidents by category – transnational and domestic – in order to ascertain whether the influence of disasters on terrorism is concentrated within a particular terrorism type as well as to assess the effect of neighboring country terrorism, by type, on a country's level of terror. By differentiating the target types – private versus government – this analysis distinguishes some key disparities in post-disaster target choice for domestic versus transnational terrorism. Results show some evidence of the transference of terrorism between countries post-disaster. Specifically, the severity of natural disasters in neighboring countries, as measured by deaths from disasters per year, displays a negative association with the frequency of domestic terrorist attacks within a country and suggests possible transference as well as fungibility in terrorist activity. Findings also show that natural disasters impact both transnational and domestic terrorism with evidence of differential effects between the two, indicative of dissimilar motivations for post-disaster terrorism. These distinctions are highlighted when the primary targets are accounted for. Overall, the analysis presents a richer view of the subtle but significant ways through which catastrophes can influence terrorist activity and further reinforces the importance of accounting for such effects while planning, responding, and recovering from natural disasters.

2.1 Introduction

"As the police force is busy in rescue and relief work for flood affectees, militants tried to take advantage of the situation to attack Peshawar."

– Liaqat Ali Khan, Police Chief, Peshawar, Pakistan (As cited in Crilly and Nelson 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."

– Shah Mahmood Qureshi, Pakistan Foreign Minister (As cited in Varner 2010)

"What we are facing... calls for generous souls and brave men to take serious and prompt action to provide relief for their Muslim brothers in Pakistan."

– Osama Bin Laden, tape released circa (2010)

Beginning in late July, 2010, monsoon rains inundated Pakistan affecting an estimated 20 million people (Singapore Red Cross 2010). In the aftermath, the Pakistani government sought additional U.S. monies and supplies in order to bolster relief capacity over a concern that a growing number of militant groups were rushing into the flood-affected areas to provide aid and exert influence (DeYoung 2010). Media reports suggested that terrorist groups had been quick to seize upon the event in order to procure popular support by providing relief supplies (Porges 2010; Witte 2010). At the same time, reports also indicated these groups were engaging in a surge of attacks against police stations, other aid agencies, and civilians while the government was distracted by relief efforts (Hasan 2010; Shakir 2010; Waraich 2010). By providing relief aid to affected areas while simultaneously carrying out attacks, the terrorist groups were clearly attempting to exploit the disaster to their advantage.

As witnessed in Pakistan, natural disasters present opportunities which terrorist groups can exploit in order to bolster their legitimacy at the expense of the government. By pursuing relief efforts in cases where government measures are inadequate or disorganized, terrorists may seek to gain support from the disaster-afflicted population. It is important to note that this phenomenon is by no means limited to the case of Pakistan. In addition to the 2010 flooding in

Pakistan, evidence of this sort of posturing has been reported after a number of disasters, in particular, the 2004 Sumatra earthquake and tsunami. The 2004 tsunami was devastating for the small Republic of Maldives with total damages estimated at 62% of GDP (World Bank et al. 2005). In 2004, the Idara Khidmat-e-Khalq (IKK), a charitable front of Lashkhar-e-Tayyiba (LeT), sent members to the Maldives under a 'humanitarian' mission to aid tsunami victims. Reports indicated the group led the way for LeT's activities in the Maldives, focusing on recruitment (Roul 2010; US Department of State 2006). Less than three years after the tsunami, the Maldives suffered its first recorded transnational terrorist attack when a bomb exploded in a recreational park killing two Britons, eight Chinese, and two Japanese citizens (Global Terrorism Database 2007; Sherwell and Leapman 2007). In 2009, an article in the Asia Times Online declared that, following the tsunami, "scores of Maldivian boys were recruited through the IKK and the sent to seminaries in Pakistan (Ramachandran 2009)."

Research Question 1: Does the severity of natural disasters in neighboring states affect the incidence of terror within a state?

One may suspect disasters alter the relative balance of stability between countries in a region. If certain countries become marginally less stable, it could afford terrorist groups a reason to shift locations. This possibility brings to bear questions regarding the transference of terrorism to disaster-afflicted countries from neighboring states. On the other hand, the destabilization of a neighboring country from a natural disaster could damage a state's ability to control its border resulting in a flow to neighboring countries as instability spreads. The deluge of refugees from a disaster-stricken country to a more stable one could also contain elements of terrorist factions. This presents a concern that disasters affecting one country could result in an increased level of terrorism risk for neighboring countries. Measuring the effects of neighboring country disaster severity on a particular country's level of terrorism could provide a means to assess the fungibility of terrorism between countries. For policy makers, it is critical to establish a direction for this effect, if such an effect exists, so that recovery efforts and policies are directed effectively.

The transference of terrorism and possible shifts of domestic to transnational terrorism are noted in Enders et al. (2011). After recalibrating the Global Terrorism Database to allow for

the comparison between domestic and transnational terrorism, the study assessed contemporaneous and lagged cross-correlations of the different types of terrorism, and indicated large associations between the terrorism categories over a number of periods. Their research discussed six ways through which domestic and transnational attacks could be correlated in a country. In particular, three of the six channels discussed are notable in that disasters could act as major catalysts for such associations. First, in an effort to establish a greater presence in the media, domestic terrorist groups might begin to incorporate transnational attacks. Both media attention and public support are at stake after a disaster; thus, terrorist groups could use relief operations and increased attacks to garner additional support in a neighboring, disaster-afflicted country and to damage the legitimacy of that state's government.[13] Second, domestic terrorist groups may seek to utilize nearby countries as safe havens. As government capability and the relative stability and between countries can be affected by a catastrophe, terrorist groups may find a nearby, disaster-afflicted country more conducive to operations (Piazza 2007, 2008). Lastly, it is well known that terrorists seek out "soft" targets (Atkinson et al. 1987; Berman and Laitin 2008; Dugan et al. 2005; Landes 1978). A disaster can make a neighboring country relatively weaker and therefore more attractive for a nearby terrorist group to target.

Research Question 2: Do natural disasters affect transnational and/or domestic terrorism and, if so, do the effects differ?

As witnessed in Maldives, groups associated with transnational terrorist organizations moved in a concerted effort to establish a presence following the disaster. While the anecdotal evidence in the Maldives does not, by itself, constitute a causal relationship between natural disasters and transnational terrorism, it does establish grounds for exploring this association empirically. Initially, there are reasons to believe that disasters may only be affecting domestic terrorism. As governments carry the responsibility for ensuring the safety of their populations, it often falls on the state to provide or organize relief after a disaster. Dissatisfaction with the amount and relative share of relief could exacerbate pre-existing divisions and strife. Additionally, the

[13] While disasters may appeal to terrorist for the elevated the media attention, the media attention given to a disaster may take away from the focus of an attack. Berrebi and Ostwald (2011) note this possibility as one reason why disasters might decrease terrorist attacks; however, their results indicate that, while this could be a mitigating factor, natural disasters still lead to statistically higher levels of terrorism.

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). If the relative differences in disaster exposure manifest along these divisions, then domestic grievances could be triggered or intensified by a disaster.

While this logic leads to a clear basis for domestic terrorism following disasters, the characteristics of a disaster and subsequent recovery lead to possible motives for transnational terrorism. Influxes of foreign relief workers, especially those with religious affiliations, could be perceived by terrorist groups as an effort by foreigners to exploit the disaster so as to proselytize and convert disaster victims. Transnational attacks could occur as a result of domestic or transnational groups attacking foreign nationals in order to combat this sort of influence. Religious tones are not necessarily a requirement as any foreign involvement could be perceived as a threat and additional issues or difficulties resulting in the wake of a disaster might be blamed on outsiders within the country. Though not considered to be terrorism, in 2010, after the devastating earthquake in Haiti, there were multiple accounts of protesters hurling rocks and Molotov cocktails at treatment centers out of fear that foreign aid workers had been the source of the cholera outbreak (AP 2010). Furthermore, foreign influence needs not be unwanted for disasters to trigger transnational terrorism. As seen in the Maldives and Pakistan, transnational terrorist groups may *want* to influence the disaster-stricken nation and thus take on the role of the proselytizer. The attacks could be directly related to the efforts to damage the legitimacy of the government and establish a support base within a weakened population. As focus turns toward disaster response and recovery, the reduction in stability could reduce the risks for operating in previously stable nations through the deterioration of established borders and defenses.

Research Question 3: Do target types play a role in the effects of a disaster on terrorism?

Related to the possible variations between transnational and domestic terrorism following a natural disaster are the potential disparities between disasters' effects on the targets of terror. In particular, as domestic terrorist attacks could be driven by dissatisfaction over government response, attacks might be concentrated against government targets following a disaster. Grievances against a state's response to a disaster will take time to build as the adequacies and

inadequacies of the government's relief efforts are realized; thus, domestic attacks against a regime might foment over a period of time rather than occur immediately after the disaster. Alternatively, some domestic terrorist groups may attack immediately as they perceive a disaster as an opportunity to attack a distracted regime. Transnational attacks against the government are unlikely to result from internal grievances over a government's disaster response so such a fomenting period seems unnecessary. Instead, a transnational group may want to act quickly to exploit the chaos surrounding a disaster. Also, if terrorism results from attacks *against* foreigners, the concentration of transnational terrorist activity might be most evident in the immediate relief period when these foreign workers are present.

Other research on the links between disasters and terrorism is markedly recent. Berrebi and Ostwald (2011) demonstrated a clear link between the severity of natural disasters, as measured by disaster deaths, and subsequent increases in terrorism within a country. The study's findings were robust across many other measures of both terrorism and disasters for both incidence and severity. While the knowledge of this link is valuable in its own right, the findings elucidated many other related areas which beg further empirical investigation. This study seeks to advance this research into the relationships between disasters, terrorism, and the transference of terrorism along multiple fronts. First, using detailed data on transnational and domestic terrorism incidence, natural disaster deaths, country borders and distances, as well as other various country characteristics, it empirically estimates the effects of natural disaster fatalities in nearby countries on a country's level of terrorism in order to investigate the transference of terrorism. This serves the dual purpose of evaluating the effects of a country's natural disasters on its neighbors' level of terrorism. Second, by partitioning between domestic and transnational terrorism, the research assesses whether the impacts of disasters differ between these terrorism categories. Lastly, by differentiating by the primary targets of terrorism the research explores the underlying motives of this phenomenon.

While the three research questions were the primary motivation for the analysis, the methods allowed exploration of several additional aspects of terrorism. Specifically, controls for domestic and transnational terrorism in nearby countries were included to account for the effect of disasters on those countries level of terrorism. This allowed estimation of the effects of transnational and domestic terrorism in neighboring countries on the level of domestic and transnational terrorism within a country. Domestic and transnational terrorism incidents in

neighboring countries were associated with higher levels of domestic and transnational terrorism within a country; however, the effect appeared to be primarily a result of domestic terrorism in neighboring countries as this "homegrown" terrorist activity in neighboring countries drove both transnational and domestic terrorism in most specifications. This confirmed previous theory and literature regarding the possibilities of spillover terrorism between countries and the importance of accounting for domestic terrorism abroad.[14]

The results show statistically significant, positive effects of natural disasters on both domestic and transnational terrorism. Disaster deaths were associated with increased transnational terrorism primarily in the current year; whereas, disasters' effects on domestic terrorism were most evident in the first lag. These results could be an indication of different motivations between the attack types. Furthermore, natural disaster deaths in neighboring countries displayed negative associations with a country's level of domestic terrorism which could be a possible signal of terrorism transference to disaster-afflicted countries. Finally, analysis of the target type indicated that natural disaster fatalities were statistically associated with increases in attacks against private entities in both the current and lagged year for domestic and transnational terrorism; however, attacks against the government appeared to manifest differently between domestic and transnational terrorism. In particular, the effects of natural disasters on transnational terrorism against the government were observed in the immediate year of the disaster; whereas, a period of two years was needed before effects were observed on domestic terrorism targeting the government. This bolsters the evidence that the observed effects of natural disasters on terrorist activity are through a combination of increased dissatisfaction with a government and a perception of an exploitable weakness. It also highlights possible differences in the impetus for attacks between domestic and transnational terrorism.

2.2 Data

Data for this study was gathered and integrated from a wide variety of sources. For data on transnational and domestic terrorism, this analysis uses Enders', et al. (2011) recalibrated version of the Global Terrorism Database from the National Consortium for the Study of Terrorism and Responses to Terrorism (START 2010). Data on natural disasters were derived from the Center

[14] Additionally, the presence of terrorism spillovers suggests that previous research on the impacts of other factors (including disasters) on terrorist activity may not accurately measure causal effects as, without controlling for levels of terrorism in neighboring countries, the studies will suffer control group contamination.

for Research on the Epidemiology of Disasters (CRED), Emergency Events Database (CRED 2010a). Demographic and economic characteristics as well as civil liberties and political rights were acquired from the World Bank's (2010) World Development Indicators and Freedom House's (2010) Freedom in the World Reports. Finally, country distances and borders were obtained from the Bilateral Distance Dataset from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII 2010).

The unit of observation was the individual country-year. Base specifications contained data on a total of 176 countries between 1970 and 2007. Final specifications displayed smaller numbers of countries and years as a result of missing demographic measures and absence of terrorism. The most complete set using all covariates consisted of 145 countries and 4,000 individual country-year observations. The smallest set was observed for transnational attacks against a government and contained 117 countries and 3,326 individual county-year observations. It was vital to control for demographic factors as their influence affects both disaster outcomes and terrorist activity; however, while the absence of countries with missing demographic measures deserves consideration, the results remained statistically significant and similar in size regardless of their inclusion. Additionally, as the focus of the research is primarily on countries where terrorism occurs or is likely to occur, the exclusion of states without reported events of terrorism was not a concern.

2.2.1 Terrorism data

Within the empirical terrorism literature, the study of differences between domestic and transnational terrorism is nascent. Anecdotally, there is evidence that transnational terrorism arises out of related but special circumstances as compared to domestic terrorism (Addison and Murshed 2005). Much of the lacuna in empirical research has been due to a lack of consistently tracked data that distinguishes between these types over a broad range of countries. While there have been some empirical studies that have focused along these lines for particular areas of the world (Jongman 1992), until recently there have not been data available on a global scale to distinguish between these two types.

Berrebi and Ostwald (2011) utilized terrorism data from the Global Terrorism Database (2010) from the National Consortium for the Study of Terrorism and Responses to Terrorism (START) which includes data on both transnational and domestic terrorism; however, it does not distinguish between the two types. The Global Terrorism Database (GTD) contains information

on target type, weapons used, date of attack, number of casualties, and location. The data are obtained primarily from contemporary news articles and other news sources. The GTD refrains from establishing a single definition of terrorism and, instead, includes coded criteria covering 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 – includes damage to property.
- The perpetrators of the incidents had to be sub-national actors – does not include acts of state terrorism.

In order to further understand terrorism phenomena in circumstances where the two types might have differing impacts, Enders et al. (2011) established a method of decomposing the data within the GTD into transnational and domestic terrorist incidents as well as re-calibrating the GTD to account for discrepancies in the dataset.[15] Using their methodology, transnational attacks are defined as those attacks in which victims, targets, perpetrators, or venues differ in nationality. Additionally, an incident is categorized as transnational if the terrorist(s) transit international borders or target international organizations or peacekeepers. Domestic terrorist incidents are those in which all of these factors share the same nationality. They further restricted their data to require three additional criteria be present for an incident to be included, further narrowing the 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.

[15] The GTD was modified in 1998 from contemporaneous collection 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. In addition, the dataset contains a discontinuity in 1993; however, totals were available for that year. As this study used data aggregated at the year interval, this was not a concern. To alleviate these concerns, year fixed-effects are included in the entire analysis which can control for discrepancies where errors or methods have proportionate effects on all incidents over a year. As a precaution, the analysis was rerun using the recalibration methods developed by Enders et al. (2011) to address these issues. No significant differences in the results were apparent. This was not surprising as the recalibration techniques adjusted all incidence for certain periods proportionately.

- 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.

Additionally, cases labeled as "doubted" were removed. These include incidents involving insurgency or guerilla ware, internecine conflict, mass murder, and criminal acts. This cleaned and decomposed version of the GTD is the dataset used for this study's investigation of natural disasters' influence on terrorism.[16]

Distinctions between targets were maintained in order to assess whether natural disasters had any influence on target choice. The GTD uses a wide range of categories for target entities. In total, target types are broken down into 22 distinct categories. To ensure that an adequate number of events were included for statistical tests, the decision was made to aggregate some of the groups together to form two groups – government and private. Government incidents consist of attacks against government entities (diplomatic and general) and the military. The categories falling under the government group are: government (general), police, military, and government (diplomatic). Private targets consist of attacks against: businesses, abortion related entities, airports and airlines, education centers and schools, food or water, journalists and media, maritime – civilian, non-government organizations, private citizens and property, religious figures and institutions, tourists, transportation, and utilities.[17]

2.2.2 Disaster data

The Emergency Events Database (EM-DAT) contains records of over 17,000 disaster events from 1900 until the present. The data were acquired from a variety of resources including: United Nations agencies, non-governmental organizations, insurance companies, research institutes, and press agencies. Reports from UN agencies, governments, and the Red Cross and Red Crescent Societies (CRED 2010b) were given priority. Natural disasters are categorized into several groups: geophysical, meteorological, hydrological, climatologic, and biological. In

[16] Incidents where terrorism type was categorized as "unknown" were not included in the analysis of effects on transnational versus domestic terrorism; however, they are included in the analysis of total terrorist incidence and terrorist incidence partitioned by target type.

[17] Attacks with targets designated as "other" or "unknown" were not included in the analysis of target types due to the relatively few number of these events; however, they were included in all other analyses.

order to be included within the database an event must have met 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

Only natural disasters are used in this analysis as the frequency and effects of other disaster types – such as industrial or technological accidents – are likely to depend on government factors and conditions which might be endogenous to terrorism. The natural disaster types included 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 the proxy for a disaster's severity. The data were culled to match the year range available from our terrorism dataset.

2.2.3 Demographic data

Data were obtained from the World Bank's (2010) World Development Indicators on a range of demographic and economic characteristics. These included: population size, population growth, 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.

Population is included as it is an important factor in disaster and terrorism risk assessments (Berrebi and Lakdawalla 2007). Urban population as a percentage of population and population growth were added as controls to reflect theories of social disorganization and strain, but also because urbanization and growth can influence the susceptibility to and consequences of disasters (Albala-Bertrand 2000; Kandel 1992; Robison et al. 2006). GDP per capita is a good proxy for a state's ability to mitigate and recover from the effects of a disaster. It proxies for a variety of other development indicators and has been used in studies of conflict as

an all-inclusive approximation of a country's level of development (Hegre and Sambanis 2006; Nel and Righarts 2008). Foreign direct investment as a percentage of GDP is used as a measure of globalization. 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. 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). Finally, indicators for political rights and civil liberties are included (Freedom House 2010). 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).

2.2.4 Data on borders and country proximity

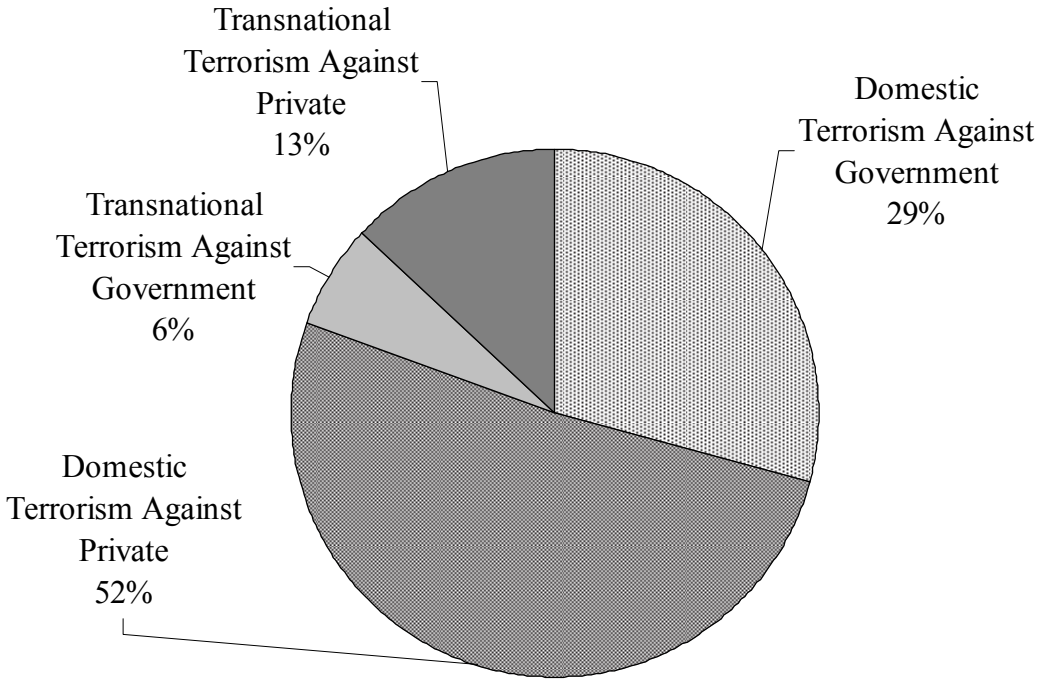
Data on country borders and distances was obtained from the bilateral distance file created by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII 2010). The dataset contains bilateral data on countries including country borders as well as the weighted distances based on city-level data of the geographic distribution of the population (2004) (Mayer and Zignago 2006). Using this information, measures were created of natural disaster deaths and domestic and transnational terrorism incidence in bordering countries. If a country did not share any borders, weighted distances were used to determine its five closest neighbors and then similar measures of natural disaster deaths and terrorism were created. The nearest five were chosen as the means and standard deviations at that cutoff were closest to the means and standard deviations for the contiguous groups.

In Table 2.1, we see that, each year, countries suffer an average of 341 deaths from disasters. Interestingly, each year, a country's neighbors suffer, on average, more than 2,000 natural disaster deaths. Within the terrorism measures there is significant variation between the average number of transnational incidents and domestic incidents. In particular, the average number of domestic incidents per country-year is more than four times larger than the average number of transnational incidents. Additionally, about a third of all domestic and transnational attacks are carried against the government. The variation between these types and targets might manipulate the channels through which natural disasters influence terrorism.

Table 2.1: Summary statistics

VARIABLE	N	MEAN	SD	MIN	MAX	MEDIAN	P5	P95
Terrorism Measures								
Attack Incidence	6336	9.6	41	0	727	0	0	43
Domestic Attack Incidence	6336	7	32.8	0	673	0	0	32
Transnational Attack Incidence	6336	1.7	6.2	0	135	0	0	8
Attacks Targeting Gov	6336	3.2	13.9	0	262	0	0	13
Attacks Targeting Private	6336	6.3	28	0	485	0	0	29
Domestic Attacks Targeting Gov	6336	2.5	12.1	0	233	0	0	11
Domestic Attacks Targeting Private	6336	4.5	22.1	0	453	0	0	20
Transnational Attacks Targeting Gov	6336	0.5	2.3	0	66	0	0	3
Transnational Attacks Targeting Private	6336	1.1	4.4	0	128	0	0	6
Neighboring Country Domestic Attacks	6336	30.8	81.2	0	1032	3	0	150
Neighboring Country Transnational Attacks	6336	7.4	15.8	0	172	1	0	37
Disaster Measures								
Disaster Deaths	6336	341.1	6332.5	0	300000	0	0	287
Neighboring Country Disaster Deaths	6336	2190	18157.8	0	450000	17	0	4275
Demographic Measures								
GDP per Capita	5212	6013.2	9008.4	62.2	72296	1778.6	175.7	24973.1
GFCE (% of GDP)	4967	16.1	6.9	1.4	76.2	15.3	7.2	28.2
Foreign Direct Investment (% of GDP)	4718	3.6	18.8	-82.9	564.9	1.1	-0.2	10.9
DAC Inflows (% of GDP)	4924	4	6.9	-0.8	115.8	1	0	16.5
Population Size	6190	3.00E+07	1.10E+08	18166	1.30E+09	6.50E+06	199098	1.00E+08
Population Growth	6186	1.8	1.5	-35.9	19	1.9	-0.3	3.7
Urban Population (% of total Population)	6210	49.8	24.4	2.7	100	50.1	12.4	90.5
Civil Liberties and Political Freedoms	5484	8.1	4.1	2	14	8	2	14

Figure 2.1: Breakdown of terrorist incidence by target and type



2.3 Methodology

The relationship between natural disasters and terrorism is assessed by estimating the model,

$$terrorism_{i,t} = f\left(disaster_{i,t-j}, demographic_{i,t}, near\_disaster_{i,t-j}, near\_terror_{i,t-1}, year_t, country_i\right), (1)$$

where:

$terrorism_{i,t}$: Terrorism incidence, transnational terrorism incidence, domestic terrorism incidence, attacks against a government and military, attacks against private citizens or private entities, domestic terrorist attacks against a government or military, domestic terrorist attacks against private citizens or private entities, transnational attacks against a government and military, or transnational attacks against private citizens or private entities in country *i,* year *t*

$disaster_{i,t-j}$: Deaths from natural disaster in country *i,* year *t-j* where j ranges from 0 to 2 (i.e., current as well as two lagged years).

$demographic_{i,t}$: Population size, population growth, urban population (% of total population), GDP per capita (constant 2000 USD), general government final consumption expenditure GFCE (% of GDP), DAC inflows (% of GDP), and political rights and civil liberties in country *i,* year *t*

$near\_disaster_{i,t-j}$: Number of deaths from natural disasters in neighboring countries of $country_i$ for year *t-j* where j ranges from 0 to 2 (i.e., current as well as two lagged years).

$near\_terror_{i,t-1}$: Incidence of transnational and domestic terrorism in neighboring countries of $country_i$ for year *t-1*

$year_t, country_i$: Year and country fixed-effects.

As terrorism incidence is a count, it is most appropriate to use panel estimators appropriate for count data. This analysis follows Berrebi and Ostwald (2011) and utilizes the Poisson quasi-maximum likelihood estimator (QMLE). Importantly, this estimator does not require that the conditional distribution of the dependent variable be Poisson-distributed. It

generates consistent estimates under a relatively weak assumption that only the conditional mean be correctly specified (Wooldridge 1999). Often a concern when implementing a Poisson model is the prospect of over/underdispersion in the data as its existence can miscalculate the standard errors. Tests of terrorism incidence indicated this possibility. Notably, the Poisson QMLE makes few assumptions regarding the distribution of the variance,[18] and the quasi-maximum likelihood framework preserves consistency even in cases of over/underdispersion. Because of this, the analysis is able to incorporate fully robust standard errors (Simcoe 2007; Wooldridge 1999, 2002).[19] The negative binomial model is another possible specification for addressing overdispersion; however, it involves more restrictive assumptions related to the conditional distribution of the dependent variable. The analysis continues with the Poisson QMLE as, in this context, the consistent estimates from this estimator are deemed more valuable than the possible efficiency gains of the negative binomial model. As a robustness check, the analysis tests the negative binomial specification along with other alternatives. Finally, country and year fixed-effects are incorporated to control for time invariant, country-specific factors and global trends.

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 the conditional mean[20] 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

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

The chosen specification uses both country and year fixed-effects. This assuages many of the concerns for potential omitted variable bias. By including country fixed-effects, the model

[18] This is aside from the standard regularity conditions.

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

[20] The exponential function was chosen for its clear interpretation and convenient computational and predictive properties. Wooldridge (2002) mentions it as the most common conditional mean in applications.

controls for all country-specific variables that are time-invariant. Nations that are in geographic areas more susceptible to catastrophes may experience a higher incidence of terrorism due to location irrespective of the timing of natural disasters. Terrorism studies have shown significant relationships between terrorism and elevation, tropical climate, and land area (Abadie 2006). Geographic location and the physical characteristics of countries have generally remained constant over the 37 year period of observation, and country fixed-effects control for these and any other time-invariant factors. Along with country fixed-effects, year fixed-effects are included to control for the average global effects of specific periods. They alleviate bias from overall trends and events that occurred in a specific year which might have influenced the average global level of transnational or domestic terrorism and/or natural disasters. For example, one might expect various worldwide trends in domestic or transnational terrorism during the era of communism or the period of the Global War on Terror.

As stated earlier, the recalibrated Global Terrorism Database, as derived in Enders et al. (2011), allows the analysis to differentiate along the lines of transnational and domestic terrorism. It is then possible to test for differential effects of disasters by employing each of these types individually as the dependent variable in the model. Furthermore, the data distinguishes between attacks by target allowing for an assessment of the choice of targets post-disaster. The model also incorporates natural disaster fatalities in neighboring countries to assess whether disasters can result in terrorism transference. This is an important consideration, especially in relation to the dynamics between domestic and transnational terrorism. Finally, as natural disasters in neighboring countries will affect the level of terrorism in those countries, it is crucial to include neighboring country domestic and transnational terrorism levels, especially as the levels of terrorism in neighboring countries could affect a particular country's level of terrorism; however, it is important to note the endogeneity concerns that arise from this. Neighboring country terrorism may cause changes in the level of terrorism with a country and vice versa. To lessen this concern, domestic and transnational terrorism incidence in neighboring countries are lagged one year. Finally, as Berrebi and Ostwald (2011) found that natural disasters most affect terrorism during the first lag. To account for this affect in adjacent nations, the final specifications include up to the second lag for natural disaster deaths in neighboring countries.

2.4 Empirical Results

Table 2.2 begins with the results of the analysis on terrorist attack incidence when we include both natural disaster deaths and terrorist attacks (transnational and domestic) in neighboring countries. Natural disaster deaths within a country are still statistically associated with increased terrorism incidence across all model specifications with very similar values as reported by Berrebi and Ostwald (2011).[21] Interestingly, lagged natural disaster deaths in neighboring countries appear to have a marginally significant effect on terrorist incidence in several of the specifications. The sign of this effect is negative indicating that natural disaster deaths in neighboring countries may result in a reduction in terrorism within a country. This could be an indication of terrorism transference between countries post-disaster; however, rather than acting as a destabilizing force to increase terrorism in the entire region, it would appear that disasters may be focusing terrorism from neighboring states into a disaster-afflicted country.

Berrebi and Ostwald (2011) reported a similar sign for their regional disaster deaths variable which measured disaster deaths in a region apart from those within a particular country. Their measure was not found to be statistically significant; however, it was an aggregated measure at the regional level rather than the higher fidelity measure used here. Additional evidence for terrorism transference is apparent when analyzing the effect of lagged domestic and transnational terrorism in neighboring countries. Both nearby transnational and domestic terrorist attacks in the previous year are statistically associated with a higher number of terrorist attacks within a country. Interestingly, while there is only approximately one transnational attack for every four domestic terrorist attacks in the dataset, the coefficient on neighboring transnational terrorist incidence is almost four times as large as that for domestic. Within the demographic covariates, GDP per capita and foreign direct investments are associated with lower levels of terrorist incidence while population size is statistically associated with higher levels. These results agree with Berrebi and Ostwald's (2011) findings for statistically significant covariates related to terrorism incidence.

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[21] 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).

Table 2.2: Natural disaster deaths and terrorism incidence in neighboring countries

Models:	(1)	(2)	(3)	(4)	(5)
Terrorist Attack Incidence	b/se	b/se	b/se	b/se	b/se
# Deaths from Disaster / 25K	**0.108****	**0.173***	**0.132***	**0.167****	**0.135***
	(0.049)	**(0.089)**	**(0.079)**	**(0.073)**	**(0.072)**
# Deaths from Disaster (t-1) / 25K	**0.117****	**0.224*****	**0.185*****	**0.215*****	**0.168*****
	(0.046)	**(0.076)**	**(0.071)**	**(0.056)**	**(0.049)**
# Deaths from Disaster (t-2) / 25K	**0.086**	**0.238****	**0.189**	**0.197***	**0.119**
	(0.083)	**(0.115)**	**(0.131)**	**(0.118)**	**(0.101)**
Near # Deaths from Disaster / 25K	**-0.028**	**-0.028**	**-0.022**	**-0.033**	**-0.020**
	(0.037)	**(0.039)**	**(0.042)**	**(0.042)**	**(0.042)**
Near # Deaths from Disaster (t-1) / 25K	**-0.054**	**-0.066****	**-0.061***	**-0.062**	**-0.063***
	(0.035)	**(0.032)**	**(0.032)**	**(0.039)**	**(0.034)**
Near # Deaths from Disaster (t-2) / 25K	**-0.028**	**-0.047**	**-0.043**	**-0.041**	**-0.044**
	(0.057)	**(0.057)**	**(0.061)**	**(0.065)**	**(0.067)**
GDP per Capita / 1K		-0.188***	-0.158**	-0.153**	-0.122**
		(0.072)	(0.072)	(0.069)	(0.059)
GFCE (% of GDP)		0.039*	0.038*	0.034	0.054***
		(0.023)	(0.023)	(0.021)	(0.019)
FDI (% of GDP)		-0.089**	-0.080**	-0.071*	-0.057*
		(0.044)	(0.040)	(0.041)	(0.032)
Net DAC Flows (% of GDP)		-0.009	-0.004	0.006	0.013
		(0.027)	(0.026)	(0.023)	(0.019)
Population Size / 1M			0.006***	0.006***	0.004***
			(0.002)	(0.002)	(0.001)
Population Growth			0.029	0.057	0.074
			(0.124)	(0.118)	(0.114)
Population Urban (% of total Population)			0.013	0.022	0.015
			(0.034)	(0.032)	(0.027)
Civil Liberties				-0.086	-0.076
				(0.060)	(0.061)
Near Transnational Terrorist Incidence (t-1)					**0.007****
					(0.003)
Near Domestic Terrorist Incidence (t-1)					**0.002****
					(0.001)
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**6049**	**4194**	**4193**	**4129**	**4129**
Number of Countries	**176**	**155**	**155**	**152**	**152**
Log Likelihood	**-42345.0**	**-29504.6**	**-28770.3**	**-28158.7**	**-26392.9**
AIC	**84772.0**	**59099.3**	**57636.6**	**56415.5**	**52887.8**
BIC	**85047.0**	**59384.7**	**57940.9**	**56725.5**	**53210.4**

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.

While the effects on total terrorist attack incidence are quite interesting, it might be more fruitful to breakup terrorist attacks by their type – transnational and domestic – in order to ascertain where the effects are most concentrated. Table 2.3 illustrates the same analysis as reported in Table 2.2; however, domestic terrorist attack incidence is used as the dependent variable. Effects are much the same as Table 2.2 in both size and significance which would indicate that much of the observed effect of disasters is through domestic terrorist incidence. The first lag of natural disasters is still the most statistically significant of the disaster lags. Effects are also seen in the current period; however, they are not as robust as the effect sizes observed in the year after. Like Table 2.2, the coefficient on disaster deaths in neighboring countries indicates a negative association between disasters in neighboring countries and a state's level of domestic terrorism. Interestingly, for the terrorism measures in neighboring countries, lagged domestic terrorist incidence is statistically significant at the 0.01 level of significance, whereas neighboring country transnational terrorism is only marginally significant ($p < 0.1$). This would suggest that countries should not ignore domestic terrorism abroad, especially in neighboring countries, as this homegrown terrorism could spillover.[22]

In Table 2.4, the analysis shifts to transnational incidents. While the results share many similarities in terms of size and significance to the results for domestic terrorism, there are a few key differences to point out. First, though effects are again seen in the first lag of disaster deaths, they are most concentrated and statistically significant in the year of the disaster. For domestic terrorism, the statistical significance of current year disaster effects was mixed. This could indicate that terrorist attacks are driven by different motivations between these categories of terrorism. After rises in disaster deaths, transnational attacks increase earlier as compared to domestic attacks. One reason for this could be the sudden influx in foreign relief workers to an area. If domestic groups oppose the intrusion or influence of some of these groups, they may be motivated to attack. These sorts of efforts in response to foreign relief could be driving the more immediate effects seen in the transnational terrorist attacks; however, other possibilities exist.

[22] Enders et al. (2011) suggest that domestic terrorist incidents could have a demonstration effect on transnational incidents and vice versa as terrorists imitate the innovations of other groups. In particular, it could be argued that this sort of mirroring has been witnessed in the various uprisings across the Middle East and North Africa as the spark of Tunisia and Egypt set fire to a variety of domestic issues in neighboring countries. For policy makers this illustrates that the domestic stability of one's neighbors is a crucial factor for one's own stability.

Table 2.3: Natural disaster deaths and domestic terrorism incidence

Models:	(1)	(2)	(3)	(4)	(5)
Domestic Terrorist Attack Incidence	b/se	b/se	b/se	b/se	b/se
# Deaths from Disaster / 25K	**0.133****	**0.182***	**0.136**	**0.180****	**0.147***
	(0.065)	**(0.103)**	**(0.094)**	**(0.084)**	**(0.085)**
# Deaths from Disaster (t-1) / 25K	**0.138*****	**0.231****	**0.190****	**0.232*****	**0.182*****
	(0.053)	**(0.091)**	**(0.083)**	**(0.065)**	**(0.059)**
# Deaths from Disaster (t-2) / 25K	**0.139**	**0.288****	**0.239***	**0.254****	**0.174***
	(0.092)	**(0.127)**	**(0.141)**	**(0.124)**	**(0.104)**
Near # Deaths from Disaster / 25K	**-0.018**	**-0.026**	**-0.025**	**-0.039**	**-0.024**
	(0.040)	**(0.044)**	**(0.046)**	**(0.047)**	**(0.047)**
Near # Deaths from Disaster (t-1) / 25K	**-0.054**	**-0.069****	**-0.067****	**-0.067**	**-0.068***
	(0.035)	**(0.034)**	**(0.033)**	**(0.044)**	**(0.036)**
Near # Deaths from Disaster (t-2) / 25K	**-0.015**	**-0.037**	**-0.036**	**-0.033**	**-0.036**
	(0.064)	**(0.063)**	**(0.069)**	**(0.072)**	**(0.076)**
GDP per Capita / 1K		-0.179**	-0.146**	-0.136**	-0.110*
		(0.074)	(0.072)	(0.068)	(0.058)
GFCE (% of GDP)		0.040	0.040	0.035	0.056***
		(0.025)	(0.024)	(0.023)	(0.020)
FDI (% of GDP)		-0.106**	-0.093*	-0.081	-0.062
		(0.053)	(0.048)	(0.050)	(0.038)
Net DAC Flows (% of GDP)		-0.013	-0.008	0.005	0.013
		(0.031)	(0.029)	(0.026)	(0.021)
Population Size / 1M			0.006***	0.006***	0.005***
			(0.002)	(0.002)	(0.001)
Population Growth			0.008	0.041	0.054
			(0.140)	(0.134)	(0.126)
Population Urban (% of total Population)			0.014	0.026	0.018
			(0.036)	(0.033)	(0.028)
Civil Liberties				-0.107*	-0.094
				(0.064)	(0.067)
Near Transnational Terrorist Incidence (t-1)					**0.007***
					(0.003)
Near Domestic Terrorist Incidence (t-1)					**0.002*****
					(0.001)
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**5782**	**4065**	**4064**	**4000**	**4000**
Number of Countries	**168**	**148**	**148**	**145**	**145**
Log Likelihood	**-32781.8**	**-23634.9**	**-23011.9**	**-22387.5**	**-21003.2**
AIC	**65645.7**	**47359.9**	**46119.9**	**44873.0**	**42108.4**
BIC	**65918.8**	**47643.8**	**46422.8**	**45181.4**	**42429.3**

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.

Table 2.4: Natural disaster deaths and transnational terrorism incidence

Models:	(1)	(2)	(3)	(4)	(5)
Transnational Terrorist Attack Incidence	b/se	b/se	b/se	b/se	b/se
# Deaths from Disaster / 25K	**0.061***	**0.213*****	**0.178*****	**0.190*****	**0.161*****
	(0.036)	**(0.051)**	**(0.055)**	**(0.056)**	**(0.046)**
# Deaths from Disaster (t-1) / 25K	**0.056**	**0.245*****	**0.198****	**0.207****	**0.194****
	(0.054)	**(0.082)**	**(0.089)**	**(0.087)**	**(0.080)**
# Deaths from Disaster (t-2) / 25K	**-0.021**	**0.125**	**0.068**	**0.073**	**0.045**
	(0.076)	**(0.121)**	**(0.134)**	**(0.136)**	**(0.133)**
Near # Deaths from Disaster / 25K	**-0.010**	**0.008**	**0.027**	**0.025**	**0.033**
	(0.041)	**(0.043)**	**(0.053)**	**(0.051)**	**(0.052)**
Near # Deaths from Disaster (t-1) / 25K	**0.004**	**-0.012**	**0.007**	**0.007**	**0.011**
	(0.032)	**(0.033)**	**(0.037)**	**(0.038)**	**(0.037)**
Near # Deaths from Disaster (t-2) / 25K	**-0.030**	**-0.051**	**-0.034**	**-0.034**	**-0.030**
	(0.031)	**(0.033)**	**(0.041)**	**(0.043)**	**(0.041)**
GDP per Capita / 1K		-0.170**	-0.141*	-0.140*	-0.119
		(0.082)	(0.084)	(0.083)	(0.076)
GFCE (% of GDP)		0.026	0.025	0.023	0.039**
		(0.018)	(0.019)	(0.018)	(0.018)
FDI (% of GDP)		-0.047**	-0.043**	-0.039*	-0.035
		(0.022)	(0.022)	(0.023)	(0.022)
Net DAC Flows (% of GDP)		0.013	0.017	0.021	0.023*
		(0.014)	(0.016)	(0.014)	(0.012)
Population Size / 1M			0.006***	0.006***	0.005***
			(0.002)	(0.001)	(0.001)
Population Growth			0.094	0.104	0.113
			(0.076)	(0.070)	(0.070)
Population Urban (% of total Population)			0.026	0.028	0.021
			(0.029)	(0.029)	(0.026)
Civil Liberties				-0.036	-0.033
				(0.041)	(0.036)
Near Transnational Terrorist Incidence (t-1)					**0.004**
					(0.003)
Near Domestic Terrorist Incidence (t-1)					**0.002*****
					(0.001)
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**5581**	**3892**	**3891**	**3828**	**3828**
Number of Countries	**163**	**142**	**142**	**139**	**139**
Log Likelihood	**-10585.6**	**-6847.7**	**-6764.5**	**-6661.0**	**-6473.1**
AIC	**21253.2**	**13785.4**	**13625.0**	**13420.0**	**13048.3**
BIC	**21524.9**	**14067.4**	**13925.8**	**13726.2**	**13367**

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 particular, transnational groups wishing to attack or exert influence in the disaster-afflicted area may be driven more by a perceived opportunity or weakness than any direct opposition to foreign relief workers. This opportunity may be fleeting; thus, transnational groups may need to act immediately to establish themselves before a government can shore up security. Anecdotally, there has been increasing evidence of this sort of terrorist group behavior (Crilly and Nelson 2010; Hasan 2010; Lancaster and Kahn 2005; Shakir 2010). While these results do not definitively substantiate the possible causes, disparities in the effects indicate their possibility. Furthermore, the results confirm that natural disaster effects aren't concentrated within one particular type of terrorism but span both transnational and domestic terrorist activity.

Within the other covariates, the results show that domestic terrorism incidence is statistically associated with increased levels of transnational terrorism. These results aligns with findings in Enders et al. (2011) and suggests that domestic terrorism can spill over into neighboring countries as transnational terrorism. The coefficient for neighboring country transnational terrorist incidence is positive but not found to be statistically different from zero. In addition, natural disaster deaths in neighboring countries are not statistically significant, indicating that nearby natural disasters primary reduce domestic terrorism incidence within a country, but do not affect transnational incidence. As discussed earlier, this could be the result of domestic groups seeking "safe havens" within the borders of their disaster-stricken neighbors. For the other demographic variables, the results are similar in direction, size, and significance to those found in previous tables.

As discussed earlier, this analysis utilizes the Poisson QMLE for its properties of consistency and fully robust standard errors. While the estimates produced by the Poisson QMLE are consistent even in cases of overdispersion, it important that the results be tested across other possible model specifications in order to establish robustness across model types. In Table 2.5, the panel log-linear (OLS) and panel negative binomial model are compared to the Poisson QMLE specification. The OLS models report standard errors robust to clustering and arbitrary heteroskedasticity. Additionally, the negative binomial estimators' standard errors are bootstrapped over 200 replications clustered by country. The findings for natural disasters are, once again, very similar to the previous tables. The effect of natural disaster deaths on domestic terrorist attacks appears most significant in the first lag. For transnational attacks, the effect is

statistically significant in the current year; once again, suggestive of different motivations between these attack types in the wake of disasters.

There is more variation in the results for the other demographic covariates. GDP per capita is generally associated with lower levels of both transnational and domestic terrorist incidence; however, the statistical significance of the result varies between specifications. GFCE is statistically significant only in the Poisson QMLE specifications though it enters with a positive sign in all specifications. Foreign direct investment is found to have a statistically significant positive association with terrorism incidence in the OLS model; however, the negative binomial model reports a negative effect while the Poisson QMLE shows no statistically significant association. Population size is positive and, generally, statistically significant. The results for the effects of neighboring country disasters and terrorism are more stable, with disasters in nearby countries having a negative association with terrorism incidence, although this result is only marginally significant for domestic terrorism incidence in the Poisson QMLE specification. Lagged domestic terrorism in nearby countries is statistically significant across all specifications, while the significance level of transnational terrorism in neighboring countries varies by specification and terrorism type.

Table 2.5: Model specification comparison

Outcome:	*Domestic Terrorism Incidence*			*Transnational Terrorism Incidence*		
Model:	Log linear (OLS)	Negative Binomial	Poisson QMLE	Log linear (OLS)	Negative Binomial	Poisson QMLE
	b/se	b/se	b/se	b/se	b/se	b/se
# Deaths from Disaster / 25K	**0.108****	**0.135***	**0.147***	**0.090*****	**0.213*****	**0.161*****
	(0.051)	**(0.081)**	**(0.085)**	**(0.031)**	**(0.072)**	**(0.046)**
# Deaths from Disaster (t-1) / 25K	**0.166*****	**0.193*****	**0.182*****	**0.102***	**0.184**	**0.194****
	(0.035)	**(0.072)**	**(0.059)**	**(0.059)**	**(0.118)**	**(0.080)**
# Deaths from Disaster (t-2) / 25K	**-0.008**	**0.097**	**0.174***	**0.021**	**0.081**	**0.045**
	(0.081)	**(0.107)**	**(0.104)**	**(0.044)**	**(0.125)**	**(0.133)**
Near # Deaths from Disaster / 25K	**-0.046****	**-0.055**	**-0.024**	**-0.013**	**-0.011**	**0.033**
	(0.019)	**(0.061)**	**(0.047)**	**(0.011)**	**(0.043)**	**(0.052)**
Near # Deaths from Disaster (t-1) / 25K	**-0.046***	**-0.045**	**-0.068***	**-0.021**	**-0.022**	**0.011**
	(0.024)	**(0.044)**	**(0.036)**	**(0.016)**	**(0.040)**	**(0.037)**
Near # Deaths from Disaster (t-2) / 25K	**-0.070****	**-0.080**	**-0.036**	**-0.032*****	**-0.040**	**-0.030**
	(0.032)	**(0.056)**	**(0.076)**	**(0.010)**	**(0.036)**	**(0.041)**
GDP per Capita / 1K	-0.038***	0.004	-0.110*	-0.038**	-0.021	-0.119
	(0.014)	(0.012)	(0.058)	(0.015)	(0.016)	(0.076)
GFCE (% of GDP)	0.009	0.009	0.056***	0.004	0.015	0.039**
	(0.009)	(0.012)	(0.020)	(0.005)	(0.012)	(0.018)
FDI (% of GDP)	0.002**	-0.042***	-0.062	0.003***	-0.038**	-0.035
	(0.001)	(0.011)	(0.038)	(0.001)	(0.015)	(0.022)
Net DAC Flows (% of GDP)	-0.001	0.004	0.013	0.005	0.019**	0.023*
	(0.006)	(0.010)	(0.021)	(0.004)	(0.010)	(0.012)
Population Size / 1M	0.006***	0.001	0.005***	0.002**	0.001	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)
Population Growth	-0.027	-0.102	0.054	0.014	-0.038	0.113
	(0.028)	(0.062)	(0.126)	(0.019)	(0.071)	(0.070)
Population Urban (% of total Population)	-0.005	0.011**	0.018	0.005	0.012*	0.021
	(0.010)	(0.005)	(0.028)	(0.007)	(0.007)	(0.026)
Civil Liberties	-0.036*	0.015	-0.094	-0.014	0.012	-0.033
	(0.021)	(0.028)	(0.067)	(0.011)	(0.026)	(0.036)
Near Transnational Terrorist Incidence (t-1)	**0.002**	**0.003**	**0.007***	**0.002***	**0.004****	**0.004**
	(0.002)	**(0.002)**	**(0.003)**	**(0.001)**	**(0.002)**	**(0.003)**
Near Domestic Terrorist Incidence (t-1)	**0.003*****	**0.002*****	**0.002*****	**0.001*****	**0.001****	**0.002*****
	(0.001)	**(0.001)**	**(0.001)**	**0.000**	**(0.001)**	**(0.001)**
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**4000**	**4000**	**4000**	**3828**	**3828**	**3828**
Number of Countries	**145**	**145**	**145**	**139**	**139**	**139**
Log Likelihood	**-4796.5**	**-6333.6**	**-21003.2**	**-3390.9**	**-4403.9**	**-6473.1**
AIC	**9694.9**	**12771.3**	**42108.4**	**6883.9**	**8911.8**	**13048.3**
BIC	**10015.9**	**13098.6**	**42429.3**	**7202.6**	**9236.8**	**13367.0**

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). OLS model standard errors are robust arbitrary heteroskedasticity and clustering. Outcome is log-transformed in log-linear models. The negative binomial model utilizes dummy indicators for country fixed-effects and bootstrapped standard errors over 200 replications clustered on country.

Table 2.6 illustrates the effects of natural disasters on terrorism incidence while separating terrorist attacks by target type – private and government. Most of the results show similarity between the two target groups. GDP per capita and population size both have statistically significant associations as seen in earlier results; however, GFCE and FDI are both statistically significant only for attacks against private entities. The lack of statistical significance for attacks against the government could be due to the fewer number of observed attacks against government entities. The most interesting result comes from the noticeable difference in the significance of the effects of disasters deaths across these two groups. Results for natural disaster's effects on attacks against entities falling under the "private" category are similar to many of the earlier results in both magnitude and significance where natural disasters' effects were most evident in the first lag; however, attacks against the "government" are no longer statistically significant. Interestingly, the results for attacks on the government indicate only marginally significant increases in attacks during the current year and second lag. The lack of statistical significance for the first lag warrants further investigation, especially since that period was largely the most significant lag found in previous specifications. In order to investigate this disparity, these groups were further separated by the type of terrorist attack – transnational and domestic.

Table 2.7 shows the results for domestic attacks against private and government entities. Once again, most of the covariates are in agreement in direction and significance. Several factors are no longer significant for attacks against the government (GFCE and FDI). When looking closely at the results for domestic attacks against the government, it is apparent that much of the finding's significance originates during the second lag of natural disasters. The coefficient for this period is statistically significant and of very similar magnitude to that found for attacks against the government in Table 2.6. Set side-by-side, these results indicate natural disasters first lead to increased levels of domestic terrorism against private entities and evolve into attacks against the government which could be an indication of an evolutional pattern of instability deriving from dissatisfaction with a government and political unrest following disasters. This is supported further when looking at the results for transnational terrorism.

Table 2.6: Natural disaster deaths and terrorist attack incidence by target type

Targets:	Private			Government		
Terrorist Attack Incidence	b/se	b/se	b/se	b/se	b/se	b/se
# Deaths from Disaster / 25K	**0.168****	**0.168****	**0.135***	**0.164***	**0.160***	**0.132**
	(0.070)	**(0.073)**	**(0.073)**	**(0.092)**	**(0.092)**	**(0.090)**
# Deaths from Disaster (t-1) / 25K	**0.246*****	**0.252*****	**0.209*****	**0.141**	**0.132**	**0.084**
	(0.053)	**(0.050)**	**(0.040)**	**(0.102)**	**(0.103)**	**(0.101)**
# Deaths from Disaster (t-2) / 25K	**0.142**	**0.140**	**0.065**	**0.287***	**0.281***	**0.210**
	(0.113)	**(0.113)**	**(0.101)**	**(0.154)**	**(0.150)**	**(0.131)**
GDP per Capita / 1K	-0.123*	-0.123**	-0.095*	-0.215**	-0.218**	-0.183**
	(0.063)	(0.062)	(0.053)	(0.095)	(0.094)	(0.081)
GFCE (% of GDP)	0.040*	0.040*	0.060***	0.019	0.020	0.040**
	(0.022)	(0.022)	(0.020)	(0.020)	(0.019)	(0.020)
FDI (% of GDP)	-0.083**	-0.083**	-0.069**	-0.046	-0.045	-0.028
	(0.041)	(0.041)	(0.031)	(0.048)	(0.048)	(0.038)
Net DAC Flows (% of GDP)	0.010	0.009	0.015	0.001	0.000	0.008
	(0.022)	(0.022)	(0.019)	(0.030)	(0.030)	(0.026)
Population Size / 1M	0.006***	0.006***	0.004***	0.005***	0.005***	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Population Growth	0.028	0.027	0.047	0.132	0.131	0.139
	(0.116)	(0.116)	(0.112)	(0.140)	(0.141)	(0.134)
Population Urban (% of total Population)	0.026	0.026	0.019	0.017	0.017	0.010
	(0.035)	(0.035)	(0.030)	(0.027)	(0.027)	(0.022)
Civil Liberties	-0.093	-0.093	-0.083	-0.068	-0.068	-0.057
	(0.060)	(0.061)	(0.062)	(0.060)	(0.061)	(0.062)
Near # Deaths from Disaster / 25K		**-0.047**	**-0.036**		**-0.006**	**0.007**
		(0.032)	**(0.032)**		**(0.059)**	**(0.059)**
Near # Deaths from Disaster (t-1) / 25K		**-0.058**	**-0.059***		**-0.069**	**-0.070***
		(0.038)	**(0.034)**		**(0.049)**	**(0.043)**
Near # Deaths from Disaster (t-2) / 25K		**-0.022**	**-0.025**		**-0.07**	**-0.073**
		(0.060)	**(0.063)**		**(0.074)**	**(0.077)**
Near Transnational Terrorist Incidence (t-1)			**0.007****			**0.007*****
			(0.003)			**(0.003)**
Near Domestic Terrorist Incidence (t-1)			**0.002****			**0.001****
			(0.001)			**(0.001)**
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**4012**	**4012**	**4012**	**3949**	**3949**	**3949**
Number of Countries	**148**	**148**	**148**	**142**	**142**	**142**
Log Likelihood	**-20697.7**	**-20671.5**	**-19401.8**	**-10893.5**	**-10869.5**	**-10412.6**
AIC	**41487.5**	**41441.0**	**38905.5**	**21879.0**	**21837.0**	**20927.2**
BIC	**41777.1**	**41749.6**	**39226.7**	**22167.9**	**22144.8**	**21247.5**

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.

Table 2.7: Natural disasters and domestic terrorist attack incidence by target type

Targets:	Private			Government		
Domestic Terrorist Attack Incidence	b/se	b/se	b/se	b/se	b/se	b/se
# Deaths from Disaster / 25K	**0.193****	**0.190****	**0.154***	**0.168**	**0.162**	**0.135**
	(0.078)	**(0.079)**	**(0.081)**	**(0.106)**	**(0.107)**	**(0.105)**
# Deaths from Disaster (t-1) / 25K	**0.268*****	**0.270*****	**0.223*****	**0.158**	**0.146**	**0.095**
	(0.061)	**(0.058)**	**(0.048)**	**(0.102)**	**(0.103)**	**(0.101)**
# Deaths from Disaster (t-2) / 25K	**0.195***	**0.191**	**0.112**	**0.336****	**0.328****	**0.253****
	(0.118)	**(0.117)**	**(0.102)**	**(0.151)**	**(0.146)**	**(0.124)**
GDP per Capita / 1K	-0.111*	-0.112*	-0.089*	-0.185*	-0.189*	-0.156*
	(0.059)	(0.059)	(0.051)	(0.101)	(0.100)	(0.087)
GFCE (% of GDP)	0.044*	0.045*	0.066***	0.011	0.012	0.033*
	(0.024)	(0.024)	(0.021)	(0.021)	(0.021)	(0.020)
FDI (% of GDP)	-0.097*	-0.096*	-0.078*	-0.053	-0.052	-0.033
	(0.052)	(0.052)	(0.042)	(0.052)	(0.052)	(0.042)
Net DAC Flows (% of GDP)	0.010	0.009	0.016	-0.004	-0.005	0.005
	(0.026)	(0.026)	(0.022)	(0.036)	(0.036)	(0.030)
Population Size / 1M	0.006***	0.006***	0.004***	0.005***	0.005***	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Population Growth	0.016	0.015	0.034	0.120	0.120	0.118
	(0.138)	(0.138)	(0.132)	(0.156)	(0.158)	(0.146)
Population Urban (% of total Population)	0.030	0.031	0.022	0.019	0.018	0.012
	(0.038)	(0.037)	(0.032)	(0.027)	(0.027)	(0.023)
Civil Liberties	-0.118*	-0.118*	-0.107	-0.080	-0.080	-0.066
	(0.065)	(0.066)	(0.070)	(0.064)	(0.065)	(0.067)
Near # Deaths from Disaster / 25K		**-0.056**	**-0.045**		**-0.008**	**0.009**
		(0.036)	**(0.034)**		**(0.065)**	**(0.065)**
Near # Deaths from Disaster (t-1) / 25K		**-0.061**	**-0.064***		**-0.079**	**-0.078***
		(0.046)	**(0.039)**		**(0.052)**	**(0.044)**
Near # Deaths from Disaster (t-2) / 25K		**-0.01**	**-0.015**		**-0.069**	**-0.07**
		(0.068)	**(0.072)**		**(0.083)**	**(0.086)**
Near Transnational Terrorist Incidence (t-1)			**0.006**			**0.008****
			(0.004)			**(0.003)**
Near Domestic Terrorist Incidence (t-1)			**0.002*****			**0.001****
			(0.001)			**(0.001)**
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**3821**	**3821**	**3821**	**3820**	**3820**	**3820**
Number of Countries	**139**	**139**	**139**	**135**	**135**	**135**
Log Likelihood	**-16013.6**	**-15992.9**	**-15000.1**	**-9364.9**	**-9341.3**	**-8966.2**
AIC	**32119.2**	**32083.8**	**30102.2**	**18821.8**	**18780.5**	**18034.5**
BIC	**32406.6**	**32390.0**	**30420.9**	**19109.2**	**19086.7**	**18353.1**

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.

Table 2.8 depicts the results of this analysis of target types for transnational attacks. It would appear that the motivations for attacks against private entities following disasters are comparable between the terrorism types. The coefficients and significance for transnational attacks against private targets are very similar to the results for domestic terrorism; however, the most interesting findings are for attacks against the government. Natural disasters have a highly statistically significant effect on transnational attacks against the government only in the first year which explains the discrepancies seen in Table 2.6. As the vast majority of events for this particular division are carried out by foreign terrorist groups attacking the disaster-affected government, it is quite interesting, though not entirely surprising, that the effects are primarily in the current year of the disaster. The earlier these groups can act, the better, as they are able to take advantage of the government in a weakened state. This result is highly indicative of transnational groups gaming disaster situations. Evidence for this has been reported anecdotally, but until now, has not been established empirically. The results differ significantly from those found for domestic terrorism where the delayed onset suggests motivations rooted in rising dissatisfaction with the government over time.

Table 2.8: Natural disasters and transnational terrorist attack incidence by target type

Targets:	Private			Government		
Transnational Terrorist Attack Incidence	b/se	b/se	b/se	b/se	b/se	b/se
# Deaths from Disaster / 25K	**0.176*** **	**0.172** **	**0.141** **	**0.230*** **	**0.217** **	**0.189** **
	(0.068)	**(0.072)**	**(0.070)**	**(0.075)**	**(0.091)**	**(0.084)**
# Deaths from Disaster (t-1) / 25K	**0.219*** **	**0.212*** **	**0.203*** **	**0.168**	**0.169**	**0.136**
	(0.066)	**(0.074)**	**(0.067)**	**(0.151)**	**(0.155)**	**(0.149)**
# Deaths from Disaster (t-2) / 25K	**0.092**	**0.102**	**0.082**	**-0.054**	**-0.058**	**-0.124**
	(0.111)	**(0.118)**	**(0.114)**	**(0.260)**	**(0.269)**	**(0.277)**
GDP per Capita / 1K	-0.118	-0.117	-0.099	-0.192**	-0.193**	-0.163**
	(0.093)	(0.093)	(0.084)	(0.080)	(0.080)	(0.072)
GFCE (% of GDP)	0.013	0.013	0.030*	0.041*	0.041*	0.056**
	(0.019)	(0.019)	(0.017)	(0.022)	(0.022)	(0.024)
FDI (% of GDP)	-0.050***	-0.050***	-0.048***	-0.002	-0.002	0.004
	(0.019)	(0.019)	(0.017)	(0.031)	(0.031)	(0.024)
Net DAC Flows (% of GDP)	0.017	0.017	0.019	0.030**	0.030**	0.030*
	(0.015)	(0.015)	(0.013)	(0.015)	(0.015)	(0.016)
Population Size / 1M	0.006***	0.006***	0.005***	0.006***	0.006***	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Population Growth	0.077	0.077	0.079	0.150*	0.151*	0.184**
	(0.071)	(0.071)	(0.069)	(0.080)	(0.080)	(0.080)
Population Urban (% of total Population)	0.035	0.035	0.028	0.026	0.026	0.016
	(0.031)	(0.031)	(0.029)	(0.031)	(0.031)	(0.026)
Civil Liberties	-0.033	-0.033	-0.031	-0.052	-0.052	-0.046
	(0.041)	(0.041)	(0.037)	(0.050)	(0.050)	(0.047)
Near # Deaths from Disaster / 25K		**0.008**	**0.017**		**0.050**	**0.054**
		(0.047)	**(0.047)**		**(0.064)**	**(0.066)**
Near # Deaths from Disaster (t-1) / 25K		**0.013**	**0.021**		**-0.005**	**-0.010**
		(0.034)	**(0.034)**		**(0.055)**	**(0.052)**
Near # Deaths from Disaster (t-2) / 25K		**-0.023**	**-0.015**		**-0.062**	**-0.069**
		(0.056)	**(0.055)**		**(0.053)**	**(0.055)**
Near Transnational Terrorist Incidence (t-1)			**0.002**			**0.007*** **
			(0.004)			**(0.002)**
Near Domestic Terrorist Incidence (t-1)			**0.002*** **			**0.001** **
			(0.001)			**0.000**
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**3651**	**3651**	**3651**	**3326**	**3326**	**3326**
Number of Countries	**131**	**131**	**131**	**117**	**117**	**117**
Log Likelihood	**-5255.8**	**-5255.2**	**-5129.3**	**-2912.1**	**-2909.9**	**-2844.5**
AIC	**10603.6**	**10608.4**	**10360.5**	**5916.3**	**5917.9**	**5791.1**
BIC	**10888.9**	**10912.3**	**10676.8**	**6197.3**	**6217.3**	**6102.7**

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.

2.5 Discussion

2.5.2 Research question 1: Does the severity of natural disasters in neighboring states affect the level of terror within a state?

The results of the analysis are only suggestive in this respect. Results showed a general negative association between neighboring country disaster severity and terrorist activity within a country; however, several specifications found marginally significant ($p<.1$) and statistically significant effects ($p<.05$) for lagged disaster deaths in neighboring countries. The sign of these effects indicated that disasters may be drawing terrorism from neighboring countries. Furthermore, it appeared that the reduction in attack incidence was entirely concentrated in domestic terrorism. As the literature suggests and the results of this analysis confirm, domestic terrorism is the most likely to spillover into other forms of terror in other, neighboring countries; thus, the reduction in domestic terrorism following a natural disaster is particularly worrisome as it could indicate that these domestic groups are shifting locations. As discussed earlier, domestic terrorist groups may seek to utilize nearby countries as safe havens. As the relative stability and government capability between countries can be affected by a catastrophe, terrorist groups may be using disaster-afflicted countries as they are more conducive to operations (Piazza 2007, 2008). Lastly, it is well known that terrorists seek out "soft" targets (Atkinson et al. 1987; Berman and Laitin 2008; Dugan et al. 2005; Landes 1978). The results could indicate that disasters are making neighboring countries relatively weaker and therefore more attractive for a terrorist group to target. Between transnational and domestic incidence, the high correspondence among the magnitudes and significance of the other covariates suggests a close association between these terrorism types; thus, the likelihood of a primarily domestic terrorist group uprooting to engage in transnational terror after disaster has weakened a neighboring country appears to be a possibility suggested by the results.

2.5.3 Research Question 2: Do natural disasters affect transnational and/or domestic terrorism and, if so, do the effects differ between these types?

Natural disaster deaths are statistically associated with higher levels of both domestic and transnational terror. As disasters often aggravate underlying tensions within a country and expose a government's inadequacies, initially, it was thought this might be a primarily domestic phenomenon; however, the results show that the effects of disasters span both types of terrorist activity. More specifically, the results suggest that transnational attacks occur earlier after

disasters; whereas, domestic terrorism take slightly longer to foment. As the impetus for these types may be expected to vary, the observed empirical disparities are a particularly valuable finding. These differences are illuminated further by the analysis of target choice.

2.5.4 Research Question 3: Do target types play a role in the effects of a disaster on terrorism?

Terrorists are well known for exhibiting a preference for "soft" targets (Atkinson et al. 1987; Berman and Laitin 2008; Dugan et al. 2005; Landes 1978), and the effects of natural disasters could diminish targeting costs for some previously "hard" targets (Berrebi and Ostwald 2011). There are perhaps no harder targets for a terrorist group than the government, police, and military. They are usually well-protected with extensive security and, in the case of police and military, they have the means to fight back. The results strengthen suspicions that disasters present opportunities to strike more effectively at a government, and this fact does not appear to be lost on transnational terrorist groups. Where natural disasters' effects on terrorist activity against private targets are generally similar between transnational and domestic terrorism, the results are in stark contrast when comparing attacks against the government. Natural disasters increase transnational terrorist attacks against the government only for the current year of the disaster. In further lags the effects are not statistically significant and diminish in magnitude. This is indicative of transnational groups "gaming" the chaos of a disaster to strike at objectives that they might not otherwise have targeted. As governments often recover more quickly than the general populace, attacking these targets earlier while the window of opportunity remains open could be viewed as crucial. For domestic terrorism against the government, the opposite is true. It would appear that domestic terrorist activity "builds" with time, which could be indicative of terrorist activity stirring as a result of pent up domestic frustration related to a government disaster response.

2.6 Conclusion

This analysis significantly expanded upon research on the links between natural disasters and terrorism. Findings showed indications that natural disaster deaths in neighboring countries were marginally associated with lower levels of domestic terrorism at home; an indication of the possibility of fungible terrorism transference in the wake of disasters. Using a version of the Global Terrorism Database which allowed for the distinction between transnational and domestic terrorism, the research further determined that the effects of disasters were not limited to

domestic terrorism, but spanned across both types with differing effects. The disparities in effects appeared to be directly explained by target choice and timing. For attacks against private targets, disasters exerted very similar effects on both domestic and transnational terrorism; however, it was found that the timing of attacks against the government differed significantly between "homegrown" and international terrorism. In particular, transnational terrorist activity against the government increased significantly in the year of the disaster, but diminished in subsequent years. For domestic incidence, the opposite was true, with terrorist activity taking longer to manifest. The disparity in results indicated the possibility of disasters triggering different underlying motives between the groups. If domestic grievances over a government's disaster response manifest as terrorist activity, a period of time between the catastrophe and any resulting violence would be expected in order to both observe and assess the government's response prior to any decision on whether to mount an offensive. For transnational attacks against the government, this sort of assessment seems unlikely and even detrimental, as the opportunity to exploit the government's weakness is fleeting.

This study significantly expands upon the research into disasters and terrorism; however, there exist remaining avenues yet to be explored. While the similarities in effect sizes between transnational and domestic terrorism helped to bolster further confidence in the effect of natural disasters, it also illuminated an issue related to the definition of transnational terrorism. In particular, some of the similarities could be due to the broad definition utilized for this category. As incidents in the database were considered transnational if the nationalities of the victims, perpetrators, targets, or venues differed, it was not possible to distinguish between events where the terrorist groups were attacking foreigners versus those where terrorists were traveling abroad to attack. The best that could be done was to look at transnational attacks against the government.[23] In the majority of cases, this ensured that the targets were local while the terrorists originated from abroad; however, because similar divisions were not available for attacks against private groups, the analysis could not investigate the timing of transnational attacks against foreign relief workers. Future research should strive to make this distinction as there are theoretical reasons to believe that the underlying motives differ along this partition. The terrorist group that attacks relief workers after a disaster might be doing so because of a

[23] This category still included attacks against diplomatic government targets which could be foreign diplomats, thus even this does to fully alleviate the possibility of capturing attacks against foreigners within a country.

perception of foreigners as an influential threat. The transnational terrorist group that moves in and attacks does not necessarily perceive the situation as a threat, but as an exploitable weakness. Both groups seek to establish influence, but the former engages in terrorism in defense against a perception of threat, whereas the latter acts out of an awareness of opportunity. While the results of the analysis were quite robust, additional research in this area should continue to investigate and verify these relationships. More explicit knowledge of the terrorist groups' origins and targets would go a long way toward confirming the empirical results as well as supporting the underlying causal suspicions.

The analysis confirms the concerns for policy makers expressed by Berrebi and Ostwald (2011) while elucidating many others. Both "homegrown" and international terrorist activity rose following disasters suggesting that these incidents are not rooted solely in domestic grievances, but a combination of frustrations with the government, societal grievances, and exploitable opportunities. The effects also indicated that terrorism within groups of nearby countries may be fungible, especially after disasters. Establishing mutual agreements between neighboring countries to assist in border security and stability efforts after a disaster could be a potentially fruitful venture which deserves consideration; however, as foreign involvement could possibly foment terrorism it should be considered carefully. Perhaps most important are the implications of the differential effects of disasters on transnational versus domestic attacks against the government. They suggest that states must be acutely aware of transnational groups attempting to exploit weaknesses immediately following a disaster while also being careful to deliver the best possible disaster response in order to head off the potential for future domestic discontent.

3 Terrorism and the Conservatism: Evidence of an Effect on Female Labor Force Participation and the Labor Gender Gap

Claude Berrebi · Jordan Ostwald

Past research and theory on the effects of terrorism on political ideologies has found that terrorism can instill a conservative shift following attacks or perceived threats (Berrebi and Klor 2006, 2008; Bonanno and Jost 2006; Echebarria and Fernández 2006). These studies have focused primarily on estimating the consequences of terrorism through electoral outcomes or survey assessments. In this paper, we take the step to explore these theories further by investigating whether terrorism might impact conservatism-related disparities in the labor force. In particular, research has shown that female labor force participation is significantly effected by cultural norms specifically related to conservatism (Contreras and Plaza 2010; Gerami 1996; Idil 2010; Offenhauer et al. 2005). Using a panel data set of 165 countries and terrorism data from 1980-2007, we find that terrorist attacks decrease female labor force participation and increase the gap between male and female labor force participation. In order to assess the direction of causality and address endogeneity concerns, we implement two novel instrumental variable approaches to obtain consistent causal estimates. Furthermore, the results are statistically significant and robust across a multitude of model specifications.

3.1 Introduction

There exists a large body of research in the field of political psychology documenting conservative shifts in populations following traumatic events. These ideological shifts are supported in the theoretical frameworks of System Justification Theory (SJT) which proposes that, when faced with crisis or instability, people will seek to defend the status quo and tend towards conservatism as a palliative means to minimize uncertainty and to achieve a sense of order in the face of fear (Jost et al. 2003; Jost et al. 2003; Jost et al. 2002). Within the system justification theory literature, the resulting shift can be characterized along two principal dimensions: resistance to change and endorsement of inequality (Jost et al. 2003). While issues of taxation and monetary policy often intermingle with issues of conservatism, reference to conservative shifts in this study will be defined and scoped by these two key dimensions rather than peripheral issues of fiscal or political conservatism. Movements along these principal axes

have important implications for a broad range of societal outcomes including views on religion, intergroup biases, and in particular, gender roles.

Terrorism research has begun to incorporate the theoretical framework of SJT into the analysis of societal reactions before and after terrorist attacks (Berrebi and Klor 2006, 2008; Bonanno and Jost 2006; Echebarria and Fernández 2006; Willer 2004). Echabe and Guede (2006) found that the Madrid railway bombings in 2004 precipitated increased prejudices toward Arabs and also against other minority groups. Furthermore, they revealed that regard towards traditional values increased while attachment to liberal values decreased. Bonanno and Jost (2006) established similar results in a sample of high-exposure survivors of the September 11th attacks. Ideological shifts in this group were associated with increased militarism, desire for revenge, and religiosity. This phenomenon has been investigated further in a number of studies exploring terrorism's effect on voting preferences and government support (Bali 2007; Gould and Klor 2010; Kibris 2010; Landau et al. 2004; Willer 2004). Results along the electoral front, once again, align closely with the expectations of SJT. Kibris (2010) found that terrorist attacks in Turkey have shifted the electorate towards a more right-wing stance. Berrebi and Klor, 2006 and 2008, established similar results in Palestinian conflict where support increased for the right-bloc following increases in local terror fatalities.

Previous research has investigated the impacts of terrorism on political behavior, but has largely ignored the implications of these ideological shifts beyond their effects on voting and survey results. Election results have focused largely on how terrorism has affected electoral outcomes in a particular country with a particular terrorist campaign, thus limiting the generalizability of findings. Research has also stopped short of analyzing other outcomes beyond electoral results which might be affected by shifts in conservatism. Studies utilizing survey methods have been more telling in terms of individual shifts of opinion, but the duration of the effect on personal views is hard to assess and the results do not lend insight into the macro-repercussions of the aggregate ideological shift.

The assumption has been that these shifts towards the status quo are not in the interest of the terrorist groups. Increased militarism and desire for revenge would seem to further distance the public and their government from granting concessions to the terrorist groups. Along these lines, some research has found that terrorist groups rarely achieve their stated policy objectives, especially when terrorists targeted civilians or when the public felt that the group sought the

destruction of the society or its values (Abrams 2006). While other empirical research has countered these claims and opened debate on the effectiveness of terrorism, the possibility of terrorism inducing ideological shifts warrants further research. Indeed, if theory suggests threats should shift societies towards conservatism, terror could theoretically induce a population to change their patterns of behavior in ways which further align with fundamentalist aims. This brings to bear several interesting questions to explore. First, besides electoral outcomes and public opinion, what repercussions might be expected from a general magnetism toward conservatism after a terrorist attack? Second, are the effects of terrorism observable in other outcomes linked with conservative shifts? And lastly, are effects related to terrorist's choice of targets or type of terrorism?

System Justification Theory provides us with a framework in which to envision a wider set of outcomes related to conservatism which might be affected by terrorism. With accumulating literature documenting the bolstering effect of uncertainty on conservatism and its related themes of authoritarianism, paternalism, and the endorsement of inequality (Jost et al. 2003; Jost and Kay 2005; McGregor et al. 2001; Sidanius and Pratto 2001), it follows that an empirical investigation of the effects of terrorism on outcomes related to these themes might be fruitful. When attempting to measure conservatism, we should naturally seek out an outcome which represents shifts towards perceived traditional values. The difficulty arises in contemplating particular outcomes which represent these shifts toward traditional values across a wide variety of cultures.

The participation of women in the workforce is often dictated by cultural norms within a society (Clark et al. 1991). Education, age, fertility, and numerous other factors play a role, but conservative cultural values have been shown to significantly impact female labor force participation across a variety of cultures (Contreras and Plaza 2010; El-Sanabiy 1989; Gerami 1996). Contreras and Plaza (2010) found that, for Chilean women, involvement in a "machista"/conservative cultural context decreased their likelihood of joining the labor market. In relation to fundamentalist movements in both Christian and Islamic contexts, women's roles are often linked with motherhood and the home (Gerami 1996; Offenhauer et al. 2005). More importantly, as discussed previously, SJT theorizes that terrorism can affect these conservative cultural values ultimately resulting in increased inequality with a push toward "traditional"

values. As such, the effects of terrorism may manifest through changes in female labor force participation and specifically the gap between male and female labor force participation.

Interestingly, empirical research in this area has focused primarily on just the opposite, that is, the impacts that female labor force participation have on resulting conflict and terrorism (Caprioli 2005; Robison et al. 2006). Caprioli (2005) found that gender inequality increased the likelihood of a state experiencing internal conflict, the idea being that states characterized by gender discrimination and structural hierarchy exhibit patterns of violence making internal conflict more likely. Robison (2006) proposed that female labor force participation might influence terrorism, especially religious terrorism, as the freedom/liberation of women can be seen as a threat to groups where gender relations are viewed as divinely ordained. Contrasting his initial hypothesis, he found that increased female labor force participation was negatively associated with Islamist attacks and had no effect on leftist terrorism.

Neither study addressed the possibility of an endogenous relationship between female terrorist attacks and female labor force participation, yet evidence and theory both indicate this possibility. By exploiting variation across countries and time, we are able to identify the effects of terrorism on female labor force participation and the labor gender gap. We find that, on average, terrorist attacks decrease female labor force participation, ultimately widening the labor gender gap. The results are statistically significant and robust across a multitude of model specifications. Furthermore, by using two novel instrumental variable approaches, we identify a causal link and address endogeneity concerns related to the possibility of transitional development and shifting gender relations inciting terrorism. While other possible explanations exist, overall, our results align closely with the propositions of Social Justification Theory and provide the first evidence of larger macro-economic implications of terrorism on disparities in the labor-market.

3.2 Data

Our analysis utilizes a panel dataset consisting of a total of 165 countries over the period of 1980-2007. The base specification consisted of 165 countries and 4450 individual country-year observations.

3.2.1 Data on labor, demographic, economic, and social indicators

Data on labor force participation outcomes and other demographic, labor, and economic related covariates were obtained from the World Bank Development Indicators database; indicators for civil liberties were obtained from the Freedom House: Freedom in the World survey[24] (Freedom House 2010; World Bank 2010). More specifically, the World Bank data on labor force participation by gender is based on the International Labour Organizations Key Indicators of the Labor Market dataset (International Labour Organization 2009). Data is available for labor force participation rate since 1980. This dataset was designed to allow for consistent cross-country comparison of aggregated labor statistics by collecting labor information from all sources within ILO member countries while employing sophisticated techniques to adjust for differences in measurement across countries and measures (Tarantino 2005).

For other covariates we included: population size, population urban (% of total population), gross domestic product (GDP) per capita in constant 2000 U.S. dollars, gross government final consumption expenditures (GFCE) (% of GDP), foreign direct investment (% of GDP), total fertility rate, and civil liberties. The covariates were chosen to best assess and control for a wide range of economic, demographic, labor market, and social characteristics which the literature suggests might influence both female labor market participation and terrorism. In addition, we utilize either country and year fixed-effects or first differences to control for time-invariant differences between countries and country-invariant changes over time.

3.2.2 Terrorism data

Data for our terrorism measures are derived from the from the National Consortium for the Study of Terrorism and Responses to Terrorism (START), Global Terrorism Database (2010). The Global Terrorism Database (GTD) contains information on target type, weapons used, date of attack, number of casualties, and location. The data are obtained primarily from contemporary news articles and other news sources. The GTD refrains from establishing a single definition of terrorism and instead includes coded criteria covering 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).

[24] We inverted the original scales for this indicator so that 7 indicated the highest levels for civil liberties or political rights. We then summed the civil liberties and political rights indicators from this survey into one indicator labeled civil liberties.

- 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 – includes damage to property.
- The perpetrators of the incidents had to be sub-national actors – does not include acts of state terrorism.

In order to further understand terrorism phenomena and the various types of terrorism, Enders et al. (2011) established a method of decomposing the data within the GTD into transnational and domestic terrorist incidents. Using their methodology, transnational attacks are defined as those attacks in which victims, targets, perpetrators, or venues differ in nationality. Additionally, an incident is categorized as transnational if the terrorist(s) transit international borders or target an international organization or peacekeepers. Domestic terrorist incidents are those in which all of these characteristics share the same nationality. They further restricted their data to require three additional criteria be present for an incident to be included. This narrowed our acceptable set of attacks to approximately 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.

Additionally, they cases labeled as "doubted" were removed. These include incidents involving insurgency or guerilla ware, internecine conflict, mass murder, and criminal acts. As the various datasets were combined, data distinguishing the primary target of the attack were maintained in order to assess whether effects might differ based upon the chosen targets of the terrorist group. The GTD uses a wide range of categories for target entities. In total, target types are broken down into 22 distinct groups. To ensure that an adequate number of events were included for statistical tests, the decision was made to aggregate some of the categories together to form two groups – government and private. The categories falling under the government group are: government (general), police, military, and government (diplomatic). Private targets

consist of attacks against: businesses, abortion related entities, airports and airlines, education centers and schools, food or water, journalists and media, maritime – civilian, non-government organizations, private citizens and property, religious figures and institutions, tourists, transportation, and utilities.[25] Government incidents consist of attacks against government entities (diplomatic and general) and the military.

3.2.3 Data on borders and country proximity

Data on country borders and distances was obtained from the bilateral distance file created by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII 2010). The dataset contains bilateral data on countries including whether two countries share a border as well as their weighted distances based on city-level data on the geographic distribution of the population (2004) within a nation (Mayer and Zignago 2006). Using this data, lagged measures of domestic terrorist incidence in bordering countries were created for use as an instrument of a country's level of terrorist incidence. When a country did not share any borders, weighted distances were used to determine its nearest five neighbors and then similar measures of nearby domestic terrorism were created. The nearest five were chosen as, at this cutoff, the means and standard deviations were closest to those observed in the contiguous group.

3.2.4 Natural disaster data

Data for natural disasters were obtained from the Center for the Research on the Epidemiology of Disasters' (CRED 2010a), Emergency Events Database (EM-DAT). EM-DAT has core data on 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 (CRED 2010b). We used only geophysical, meteorological, and hydrological disasters as these events do not span multiple years and there is a greater likelihood that the prevalence and outcomes of other disaster types such as industrial or technological accidents would be dependent on the types and capabilities of government and conditions within the country. The disaster types included in the natural disasters groups are: Earthquake, Flood, Mass Movement Dry, Mass Movement Wet, Storm,[26]

[25] Attacks with targets designated as "other" or "unknown" were not included in the analysis presented here due to the relatively few number of these events.
[26] Storms include tornados, hurricanes, typhoons, and more generally tropical cyclones.

Volcano, and Wildfire. Following Berrebi and Ostwald (2011), disaster deaths were used as our primary instrument variables for their predictive power on terrorist attacks.

Table 3.1: Summary statistics

MEASURES BY COUNTRY-YEAR	N	MEAN	SD	MIN	MAX	P50	P5	P95
Female Labor Force Participation Rate	4617	50.3	16.5	9.5	90.8	50.4	21.3	78.7
Labor Gender Gap	4617	27.1	15.7	-3	74.7	24.2	4.1	56.3
# of Terrorist Attacks	4617	11.7	46.3	0	727	0	0	56
# of Nearby Domestic Terrorist Attacks	4617	38.7	91.9	0	1032	6	0	194
# of Domestic Terrorist Attacks	4617	8.8	37.4	0	673	0	0	40
# of Transnational Terrorist Attacks	4617	1.8	6.6	0	135	0	0	9
# of Attacks Targeting Private Entities	4617	7.7	31.8	0	485	0	0	37
# of Attacks Targeting Government	4617	3.9	15.6	0	262	0	0	17
Population Size	4614	3.30E+07	1.20E+08	143000	1.30E+09	7.30E+06	288000	1.20E+08
Percent Urban Population	4617	51.1	24	4.3	100	52.1	13.7	89.7
Total Fertility Rate (births per woman)	4523	3.7	1.9	0.9	8.7	3.2	1.3	6.9
FDI (% of GDP)	3865	3.9	20.6	-82.9	564.9	1.3	-0.2	10.8
GDP per Capita	4125	5970.3	8716.2	62.2	56624.7	1715.7	179.4	25130.2
GFCE (% of GDP)	3957	16.2	6.9	1.4	76.2	15.3	7.2	28.4
Civil Liberties	4196	8.3	4	2	14	8	2	14
Deaths from Geophysical Disasters	4617	114	2882.5	0	165818	0	0	6
Deaths from Meteorological Disasters	4617	61.5	2082	0	138987	0	0	53
Deaths from Hydrological Disasters	4617	46.2	496.8	0	30005	0	0	137

Table 3.1 presents summary statistics for of the observations within the dataset. The average gap between male and female labor force participation rates over our time period is 27.1, but can be as high as 74.7. We included only countries with at least 1 terrorist attack, thus on average, countries within the dataset suffered 11.7 terrorist attacks per year. Interestingly, we see a large disparity in the average number of attacks between domestic and transnational terrorism. Within our dataset, on average, countries suffer 1.8 transnational attacks per year; whereas, each year the average number of domestic terrorist attacks stands at 8.8. Overall, transnational attacks constitute less than one fifth of all terrorist attacks.

3.3 Methodology

To assess the relationship between natural disasters and terrorism we estimate the models:

Fixed Effects Model:

$$labor\_outcome_{i,t} = \beta \cdot terrorism_{i,t-j} + \alpha \cdot demographic_{i,t} + \delta \cdot economic_{i,t} + \theta \cdot social_{i,t} + \rho \cdot year_t + \phi \cdot country_i + \mu_{i,t} \quad (1)$$

First Differenced Model:

$$\Delta labor\_outcome_{i,t} = \beta \cdot \Delta terrorism_{i,t-j} + \alpha \cdot \Delta demographic_{i,t} + \delta \cdot \Delta economic_{i,t} + \theta \cdot \Delta social_{i,t} + \rho \cdot \Delta year_t + \Delta\mu_{i,t} \quad (2)$$

Where:

$labor\_outcome_{i,t}$ Female labor force participation or the gap between male and female labor force participation in country *i,* year *t*.

$terrorism_{i,t-j}$: Terrorism incidence in country *i,* year *t-j* where *j* ranges from 0 to 2 (i.e., terrorist attacks in current year as well as two years lagged)

$demographic_{i,t}$: Population size, percent of population urban, and total fertility rate in country *i,* year *t*.

$economic_{i,t}$: GDP per capita (constant 2000 USD), general government final consumption expenditure GFCE (% of GDP), and foreign direct investment as a percentage of GDP in country *i,* year *t*.

$social_{i,t}$: Civil liberties and political freedoms in country *i,* year *t*.

$year_t, country_i$: Year and country fixed effects

$\Delta outcome_{i,t}$: $\left(outcome_{i,t} - outcome_{i,t-1}\right)$ or $\left(outcome_{i,t-j} - outcome_{i,t-j-1}\right)$.

We estimate the effect of terrorism on female labor force participation using a panel dataset of 165 countries over a period of 27 years. Our specifications utilize a panel, ordinary least squares (OLS), framework with both country and year fixed effects or differencing, which assuage many concerns for omitted variable bias. Country fixed-effects control for any country-specific variables which are time-invariant. Year fixed-effects control for any country-invariant factors such as global trends in labor force participation. Differencing serves the same purpose

as country fixed-effects, eliminating country-specific, time-invariant factors, but has the additional benefit of alleviating concerns of serial correlation as well as focusing explicitly on the effects of a change in terrorism on changes in the female labor force participation rate.

As mentioned earlier, there is some concern regarding an endogenous relationship between terrorism and female labor force participation. One way to avoid endogeneity problems between terrorism and our outcomes is to utilize an instrumental variable approach in order to isolate terrorism's effect. What's necessary for such an approach is to find a variable strongly associated with levels of terrorism, but not associated with the female labor force participation rates or the gender labor gap. Seemingly simple, this turns out to be a difficult quest. In order to be valid, the instrumental variable must both be highly predictive of the endogenous regressor while maintaining it's independence from the error term of the dependent variable. This study implements two such instrumental variable approaches. First, we exploit an association between disasters and terrorist attacks in order to assess the causal direction of terrorism on our outcome. Berrebi and Ostwald (2011) painted a compelling picture of how natural disasters could create weaknesses in a government and society which might incite terrorist groups to act thus increasing the incidence and severity of terrorism subsequent to a disaster. Their empirical results were robust and significant across a wide range of specifications of terrorism and disaster measures. We contend that after controlling for a few important population characteristics, natural disasters will be both highly correlated with terrorism and exogenous to the gap between male and female labor force participation. We estimate the model using a two-stage least squares estimator.

The second approach utilizes lagged domestic terrorism incidence in neighboring countries as an instrument for a country's level of terrorism. Empirical studies have shown that shocks to domestic terrorism can influence levels of transnational and domestic terrorism (Enders et al. 2011; Ostwald 2011). We use only domestic terrorism in neighboring countries as, unlike transnational terrorism, grievances and aims of domestic terrorism are often local to the country in which they occur, and, as both the targets and perpetrators are not in our particular country of observation, it seems highly unlikely that lagged domestic attacks in a neighboring country would manipulate or be endogenously related to a country's level of female labor force participation and vice versa.

The methodology assumes there is exogeneity in the our instruments, and that, after controlling for the above mentioned covariates, female labor force participation and the labor gender gap are affected by natural disaster deaths or neighboring country domestic terrorism only through their effect on a local country's terrorist attacks. In the case of the number of deaths from natural disasters, one may think of ways in which the instrument is affected by population characteristics which are also likely regressors in any normal econometric model of our outcome. Therefore, even though natural disasters have an inherent randomness, we must control for several population characteristics in order to obtain consistent estimates at both stages. The possibility of differential gender effects of disasters on labor force participation rate could be a concern; however, since we utilize multiple instruments for one endogenous regressor we are able to test this assumption. Perhaps more convincingly, we utilize two different instruments allowing us to compare the results of both approaches to establish more confidence in this assumption.

For our instrumental variable specifications we utilized the second and third lag of neighboring domestic terrorism incidents or the first three lags of the deaths caused by natural disasters broken down by disaster type.[27] We controlled for time and individual country-effects to account for inherent year shocks and fixed differences over time between countries. In addition we included a variety of demographic factors to better predict the true effect of disaster deaths on terrorist attack incidence and deaths. These controls then must be included at both stages of the 2SLS and estimators. What follows are the specifications of our formal 2SLS instrumental variable model for the effect of terrorist attacks on the labor gender gap.

Second Stage:

$$Labor\_Gap_{it} = \ln(Terrorism\_Measure_{it-1})\alpha + Pop\_Char'_{it}\rho + year_t\beta_t + country_i\lambda_i + u_{it} \quad (3)$$

First Stage Disasters:

[27] We take the natural log of the number of our terrorism measure as modeling the first stage as a non-linear count model presents a host of challenges for coefficient interpretation and error estimation. Natural logs were also used for the instruments as they provided a better fit and explained more of the variance in the first stage regressions.

$$Terrorism\_Measure_{it-1} = \sum_{k=1}^{3}\sum_{j=1}^{3}\left(\ln\left(Disaster\_Deaths_{i,j,t-k}\right)\right)\omega_{j,t-k} + Pop\_Char'_{it}\rho + year_t\beta_t + country_i\lambda_i + \varepsilon_{it} \quad (4)$$

<u>*First Stage Neighboring Domestic Terrorism:*</u>

$$Terrorism\_Measure_{it-1} = \sum_{k=2}^{3}\left(\ln\left(Near\_Dom_{i,t-k}\right)\right)\omega_{t-k} + Pop\_Char'_{it}\rho + year_t\beta_t + country_i\lambda_i + \varepsilon_{it} \quad (5)$$

$Disaster\_Deaths_{i,j,t}$ and $Near\_Dom_{i,t-k}$ are our excluded instruments, *i* designates country, *j* designates disaster type (geophysical, meteorological, and hydrological), and *t* designates year.[28] Year and country fixed effects are designated as $year_t$ and $country_i$ respectively, and Pop_Char' is a vector of our labor, demographic, economic, and social freedom characteristics. In addition, we report standard errors that are robust for both arbitrary heteroskedasticity and arbitrary intragroup correlation.

[28] For the IV approach using lagged neighboring country domestic terrorism, we use the second and third lag to ensure exogeneity in the IV as there is some concern that the contemporaneous period could be endogenous.

3.4 Empirical Results

Table 3.2: Panel OLS – Female labor force participation rate

Models:	(1)	(2)	(3)	(4)	(5)
Female Labor Force Participation Rate	b/se	b/se	b/se	b/se	b/se
Terrorist Attacks	**-0.004***	**-0.003***	**-0.003****	**-0.003**	**-0.003**
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**
Terrorist Attacks (t-1)	**-0.004*****	**-0.002*****	**-0.002*****	**-0.002****	**-0.002*****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Terrorist Attacks (t-2)	**-0.004****	**-0.002***	**-0.002**	**-0.001**	**-0.001**
	(0.002)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Population Size / 1M			-0.016***	-0.018***	-0.017***
			(0.006)	(0.006)	(0.006)
Population Urban (% of total Population)			0.030	0.057	0.071
			(0.064)	(0.071)	(0.073)
Total Fertility Rate (births per woman)			-0.714	-1.396***	-1.227**
			(0.516)	(0.509)	(0.526)
FDI (% of GDP)				-0.008	-0.007
				(0.005)	(0.005)
GDP per Capita / 1K				0.487***	0.444***
				(0.119)	(0.126)
GFCE (% of GDP)				0.065*	0.055
				(0.036)	(0.036)
Civil Liberties					-0.061
					(0.111)
Year Effects	**No**	**Yes**	**Yes**	**Yes**	**Yes**
Country Effects	**No**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**4450**	**4450**	**4362**	**3550**	**3481**
Number of Countries	**165**	**165**	**165**	**155**	**151**
Log Likelihood	**.**	**-11116**	**-10852.5**	**-8274.2**	**-8101.7**
AIC	**.**	**22291.9**	**21771.0**	**16620.4**	**16277.3**
BIC	**.**	**22484.0**	**21981.6**	**16842.7**	**16505.0**

Note: Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering and arbitrary heterorskedasticity. Coefficients that have been scaled are indicated as such with their scaling factor.

Table 3.2 reports the results of the effect of lagged terrorism incidence on the female labor force participation rate as covariates are introduced into the fixed-effects specifications. We lag terrorism incidence in order to better address endogeneity concerns. The first lag of terrorism incidence is statistically associated with lower levels of female labor force participation at the 0.01 level of significance. We find that a one standard deviation increase in terrorism incidence[29] correlates to a .07 reduction the in female labor force participation rate. Though seemingly small, as compared to the effects of some other regressors, this result is significant.

[29] One standard deviation for within group terrorism is approximately 33 terrorist incidents.

For instance, this is a larger impact than an increase in the population size by 1 million. Additionally, when considering the size of work force, for some countries this could amount to a considerable number of women leaving the labor market. In the other covariates we find that GDP per capita is associated with higher levels of female labor force participation. Population size and total fertility rates are statistically associated with lower levels of female labor force participation.

Table 3.3: Panel OLS – First difference female labor force participation

Models: ***First Difference*** ***Female Labor Force Participation***	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se
Δ Terrorist Attacks	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Δ Terrorist Attacks (t-1)	**-0.001****	**-0.001****	**-0.001****	**-0.001****	**-0.001****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Δ Terrorist Attacks (t-2)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Δ Population Size / 1M			-0.011**	-0.010**	-0.010*
			(0.005)	(0.005)	(0.005)
Δ Population Urban (% of total Population)			0.121*	0.121*	0.129**
			(0.062)	(0.064)	(0.065)
Δ Total Fertility Rate (births per woman)			-0.332	-0.714**	-0.665*
			(0.290)	(0.350)	(0.356)
Δ FDI (% of GDP)				0.000	0.000
				(0.001)	(0.001)
Δ GDP per Capita / 1K				0.292***	0.268***
				(0.072)	(0.081)
Δ GFCE (% of GDP)				0.004	0.003
				(0.004)	(0.004)
Δ Civil Liberties					-0.007
					(0.014)
Year Effects	**No**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**4299**	**4299**	**4149**	**3334**	**3272**
Number of Countries	**165**	**165**	**165**	**154**	**151**
Log Likelihood	**-4870.9**	**-4843.9**	**-4690.4**	**-3797.7**	**-3671.9**
AIC	**9749.9**	**9747.9**	**9446.8**	**7667.5**	**7417.9**
BIC	**9775.3**	**9938.9**	**9655.7**	**7887.5**	**7643.3**

Note: Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering and arbitrary heterorskedasticity. Coefficients that have been scaled are indicated as such with their scaling factor. The symbol, Δ, before a covariate indicates that it was first differenced in the specification.

Given the close association between female labor force participation year to year, there is a possibility of serial correlation in the fixed effects models. To address this and in order to test

the robustness of our findings, in Table 3.3, we implemented a first differenced model. This helped to isolate the temporal duration of the effect and to address concerns of serial correlation. We reassessed for the presence of serial correlation using the Arellano and Bond (1991), test for AR(1) errors in our first-differenced model; results indicated that the first differencing had addressed the serial correlation concerns. In the other covariates, we see many of the same statistically significant results as the fixed effects specifications. One notable difference is in the coefficient for urban population (% of total population). The results indicate that increases in the urban population are statistically associated with increases in female labor force participation. We also took the difference between male and female labor force participation to assess the impacts of terrorism on the overall labor gender gap.

Table 3.4 contains our estimates of the effects of terrorism incidence on the labor gender gap. We define the labor gender gap as the difference between male and female labor force participation rates. It is important to test the effects on this measure, as terrorism could be decreasing both male and female labor force participation which would indicate other pressures of terrorism on the labor market outside of factors directly related to females or conservatism. As the concern for serial correlation remains, we again implement a first differenced model. We find that, indeed, increased terrorism attacks are statistically associated with rises in the disparity between male and female labor force participation. A non-statistically significant finding would have indicated that terrorism was reducing both male and female labor force participation. The fact that we witness the gap widening is indicative of an effect primarily on females and supportive of the possibility of a relationship to conservatism.

Within the other covariates, we find that higher GDP per capita is statistically associated with a smaller disparity in the labor gender gap and total fertility rate increases the labor gender gap. In the previous tables, total fertility rate was statistically associated with lower levels of female labor force participation. As expected, it indicates that countries with higher fertility rates have lower female labor force participation. The fact that GDP per capita could be endogenous with the labor gender gap deserves some discussion. In particular, higher female participation in the labor force could amount to a higher GDP per capita just as a more developed economy could persuade females to substitute away from activities such as child rearing to participate in the labor force. As a test, we excluded it from our models and found that the

exclusion or inclusion of GDP per capita changed neither the coefficient direction nor the statistical significance of our lagged terrorism measure.

Table 3.4: First difference labor gender gap

Models:	(1)	(2)	(3)	(4)	(5)
First Difference Labor Gender Gap	b/se	b/se	b/se	b/se	b/se
Δ Terrorist Attacks	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Δ Terrorist Attacks (t-1)	**0.002****	**0.002****	**0.002****	**0.002****	**0.002****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Δ Terrorist Attacks (t-2)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Δ Population Size / 1M			0.005	0.006	0.005
			(0.004)	(0.004)	(0.004)
Δ Population Urban (% of total Population)			0.027	0.003	-0.001
			(0.056)	(0.058)	(0.058)
Δ Total Fertility Rate (births per woman)			0.361	0.711*	0.697*
			(0.304)	(0.397)	(0.403)
Δ FDI (% of GDP)				0.000	0.000
				(0.001)	(0.001)
Δ GDP per Capita / 1K				-0.256***	-0.244***
				(0.047)	(0.056)
Δ GFCE (% of GDP)				-0.004	-0.004
				(0.004)	(0.004)
Δ Civil Liberties					0.013
					(0.014)
Year Effects	**No**	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**4299**	**4299**	**4149**	**3334**	**3272**
Number of Countries	**165**	**165**	**165**	**154**	**151**
Log Likelihood	**-4800.1**	**-4778.3**	**-4637.7**	**-3827.1**	**-3742.1**
AIC	**9608.2**	**9616.6**	**9341.3**	**7726.2**	**7558.2**
BIC	**9633.7**	**9807.6**	**9550.2**	**7946.2**	**7783.6**

Note: Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering and arbitrary heterorskedasticity. Coefficients that have been scaled are indicated as such with their scaling factor.

As a further test on robustness we employ a falsification approach to the fixed effects and first differenced models. To implement this, we introduce future terrorist attacks into the specifications to assess whether something which should clearly be unrelated to current year fluctuations in labor force participation rates, in fact, does not have an impact. As theoretically expected, in Table 3.5, future terrorist attacks are not statistically associated with current year changes in labor force participation. Within the fixed effects model for female labor force participation there is some evidence of a marginally significant result for future terrorist attacks.

While this could be a result of the serial correlation concerns, it could also be an indication of endogeneity between the two. The differenced models do not suffer this result and are statistically indistinguishable from zero. This bolsters confidence in the timing, direction, and the identification of a causal effect of terrorist attacks on female labor force participation rate and the labor gender gap.

Table 3.5: Falsification Test

Models: ***First Difference and Fixed Effects***	Fixed Effects		First Difference	
Outcome: ***Labor Gender Gap and Female LFPR***	Female LFPR b/se	LFPR Gap b/se	Female LFPR b/se	LFPR Gap b/se
Terrorist Attacks (t+1)	**-0.003***	**0.000**	**0.000**	**-0.001**
	(0.002)	**(0.002)**	**(0.000)**	**(0.000)**
Terrorist Attacks	**-0.001**	**0.000**	**0.000**	**0.000**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**
Terrorist Attacks (t-1)	**-0.002****	**0.003****	**-0.001***	**0.002****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**
Terrorist Attacks (t-2)	**-0.001**	**0.003****	**0.000**	**0.000**
	(0.001)	**(0.001)**	**(0.000)**	**(0.000)**
Population Size / 1M	-0.017***	0.013**	-0.009*	0.007
	(0.006)	(0.005)	(0.005)	(0.004)
Population Urban (% of total Population)	0.069	0.034	0.128*	0.009
	(0.073)	(0.072)	(0.065)	(0.058)
Total Fertility Rate (births per woman)	-1.199**	0.842	-0.695*	0.616
	(0.529)	(0.628)	(0.365)	(0.415)
FDI (% of GDP)	-0.007	0.006	0.000	0.000
	(0.005)	(0.005)	(0.001)	(0.001)
GDP per Capita / 1K	0.446***	-0.483***	0.277***	-0.251***
	(0.126)	(0.125)	(0.084)	(0.058)
GFCE (% of GDP)	0.057	-0.083*	0.003	-0.004
	(0.035)	(0.043)	(0.004)	(0.004)
Civil Liberties	-0.056	0.152	-0.007	0.013
	(0.110)	(0.119)	(0.014)	(0.014)
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**No**	**Yes**	**No**
Obs	**3345**	**3345**	**3136**	**3136**
Number of Countries	**151**	**151**	**151**	**151**
Log Likelihood	**-7715.3**	**-7814.8**	**-3555.3**	**-3617.4**
AIC	**15504.6**	**15703.6**	**7184.7**	**7308.8**
BIC	**15730.9**	**15929.9**	**7408.6**	**7532.6**

Note: Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering and arbitrary heterorskedasticity. Coefficients that have been scaled are indicated as such with their scaling factor.

Within the first differenced models, we find that GDP per capita is associated with increases in female labor force participation rates and reductions in the labor gender gap. As

discussed previously, our falsification approach supports a causal interpretation of terrorism on gender disparities in the labor market. While this is a good start, we further reinforce our causal argument by implementing two novel instrumental variable approaches using natural disasters' effect on terrorism as first reported in Berrebi and Ostwald (2011) as well as lagged domestic terrorism in neighboring countries. As a further precaution to ensure exogeneity, and because the results indicated an effect in the first lag, we use only the first lag of terrorism incidence. Table 3.6 reports the results of this analysis.

Table 3.6: Instrumental variable approach

Outcome:	Female LFPR		Gender Labor Gap	
Instrument:	Natural Disasters	Near Domestic Terrorism	Natural Disasters	Near Domestic Terrorism
	b/se	b/se	b/se	b/se
Log Terrorist Attacks (t-1)	**-1.587***	**-1.859*****	**1.377***	**1.365****
	(0.823)	**(0.687)**	**(0.725)**	**(0.666)**
Population Size / 1M	-0.009	-0.007	0.006	0.006
	(0.007)	(0.007)	(0.006)	(0.006)
Population Urban (% of total Population)	0.061	0.059	0.033	0.033
	(0.073)	(0.072)	(0.070)	(0.069)
Total Fertility Rate (births per woman)	-1.350**	-1.371**	1.017*	1.016*
	(0.606)	(0.629)	(0.580)	(0.587)
FDI (% of GDP)	-0.004	-0.004	0.004	0.004
	(0.005)	(0.005)	(0.005)	(0.005)
GDP per Capita / 1K	0.400***	0.392***	-0.439***	-0.439***
	(0.122)	(0.120)	(0.115)	(0.112)
GFCE (% of GDP)	0.060	0.061	-0.087**	-0.087**
	(0.037)	(0.038)	(0.043)	(0.043)
Civil Liberties	-0.140	-0.156	0.224*	0.224*
	(0.119)	(0.117)	(0.126)	(0.128)
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**
Fixed Effects (Country)	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**3481**	**3481**	**3481**	**3481**
Number of Countries	**151**	**151**	**151**	**151**
Log Likelihood	**-8418.5**	**-8545**	**-8360.3**	**-8356.2**
AIC	**16906.9**	**17160.0**	**16790.5**	**16782.4**
BIC	**17122.3**	**17375.4**	**17006.0**	**16997.8**

Note: Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering and arbitrary heterorskedasticity. Coefficients that have been scaled are indicated as such with their scaling factor.

Perhaps most surprising is the similarity between the resulting magnitude and standard errors of terrorist attacks across both instrumental variable approaches.[30] Once again we find statistically significant effects of terrorism on female labor force participation rates. Specifically, we find that terrorist attack incidence decreases female labor force participation and increases the labor gender gap. Most of the other covariates display similar results to the findings of earlier specifications. In particular, GDP per capita is associated with increases in female labor force participation and a smaller labor gender gap while a higher total fertility is associated with lower female labor force participation and a larger labor gender gap.

We report both the effects on female labor force participation as well as the gap between male and female labor force participation, as their could be reason to question the validity of certain instruments when labor force participation is considered separately. Specifically, natural disasters can have large impact on an economy. Recovery efforts might create more jobs and increase labor force participation, or a loss of infrastructure could force some people out of work. Using the gender labor gap the assumption is no longer that natural disasters have no effects on female labor force participation, only that there is no differential effect between male and female labor force participation. We control for many other factors which might influence the two or act as mediators; however, there could still be reason for believe that disasters induce dissimilar effects on labor force participation between men and women. The use of a second instrument, lagged domestic terrorism in nearby countries, helps to assuage these concerns. Domestic terrorism in neighboring countries could influence levels of terrorism in other countries and the association of one country's level of terrorism to its neighbors' is quite significant (Enders et al. 2011; Ostwald 2011); however, the aims of these domestic terrorists are often concerned specifically with local country issues. As such, it seems unlikely that that domestic terrorism in a neighboring country would influence female labor force participation directly other than through its influence on that country's level of terrorism. While some may think of other elaborate possibilities, the similarity between the results for the two, very different, IV approaches further supports the causal relationship.

[30] While both instrumental variables passed tests of underidentification at the 0.01 level of significance, the natural disasters IV did not pass the rule of thumb for weak instruments (F-stat > 10) even though first stage regressions indicated it's statistically significant relationship with terrorist incidence. This was part of the reason for using two IV approaches as it created a concern the results might be biased toward OLS. The second IV approach using lagged nearby domestic terrorism easily passed all tests of strength (F-stat of approximately 18), and the similar coefficient magnitudes of the two approaches further assuaged concerns of weak-instrument bias for the first IV approach.

Thus far, our results align closely with System Justification Theory. In general, it would appear that terrorist threats to a society increase gender inequalities in the labor market which could be explained through ideological shifts towards conservatism. What remains to be explored is whether the type or targets of terrorist activity play any part in determining the reaction in the labor force. Transnational attacks or attacks on civilians may impact the resulting shifts in labor force participation differently than domestic attacks or attacks against the government. We explore this by conducting our analysis of the first differenced specifications after dividing the attacks based on the primary target of the attack and the type of terrorism: private versus government, transnational versus domestic.

Table 3.7 illustrates the effects of terrorist attacks on female labor force participation and the labor gender gap as partitioned by terrorist type. The slightly larger coefficient on transnational attacks is particularly notable due to the significantly smaller incidence of transnational attacks compared to domestic incidents. The similar significance and larger magnitude could indicate a larger impact of transnational attacks on female labor force participation than domestic attacks, and a larger impact of transnational events might be an indication of increased shifts toward conservatism when the attack involves a perception of an outside threat. The statistical significance of both transnational and domestic attacks in the first differenced models is equally interesting as it suggests that the phenomenon is not the result of a single "type" of terrorist attack. It also supports the robustness of the overall finding.

As a further check, we split the attacks based on target type – government or private. Table 3.8 displays the results of our analysis of the effects of terrorist attacks on female labor force participation and the labor gender gap when attacks are differentiated by their primary target. Interestingly, we find the largest coefficient magnitudes when the attacks are against a government rather than private entity. An increase in terrorist attacks in the previous year is still statistically associated with a decrease in female labor force participation and a similarly sized increase in the labor gender gap; however, an attack against the government is associated with larger changes in the outcomes. This could indicate other possible causes of this phenomenon related to the government rather than conservatism; however, the statistically significant effects are still observed when the attacks are against private groups.

Table 3.7: First difference – Female FLFP and gender labor gap by terrorism type

Outcome:	Female LFPR		Gender Labor Gap	
Terrorism Type:	Domestic b/se	Transnational b/se	Domestic b/se	Transnational b/se
Δ Terrorist Attacks	**0.000**	**0.000**	**0.000**	**0.000**
	(0.001)	**(0.002)**	**(0.001)**	**(0.002)**
Δ Terrorist Attacks (t-1)	**-0.002***	**-0.003****	**0.002****	**0.005****
	(0.001)	**(0.002)**	**(0.001)**	**(0.002)**
Δ Terrorist Attacks (t-2)	**0.000**	**-0.002**	**0.000**	**0.002**
	(0.001)	**(0.003)**	**(0.001)**	**(0.003)**
Δ Population Size / 1M	-0.010*	-0.010*	0.005	0.005
	(0.005)	(0.005)	(0.004)	(0.004)
Δ Population Urban (% of total Population)	0.129**	0.130**	-0.001	-0.002
	(0.065)	(0.065)	(0.058)	(0.058)
Δ Total Fertility Rate (births per woman)	-0.666*	-0.656*	0.699*	0.687*
	(0.355)	(0.356)	(0.403)	(0.404)
Δ FDI (% of GDP)	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Δ GDP per Capita / 1K	0.268***	0.267***	-0.244***	-0.242***
	(0.081)	(0.081)	(0.056)	(0.057)
Δ GFCE (% of GDP)	0.003	0.003	-0.004	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Δ Civil Liberties	-0.007	-0.007	0.012	0.012
	(0.014)	(0.014)	(0.014)	(0.015)
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**3272**	**3272**	**3272**	**3272**
Number of Countries	**151**	**151**	**151**	**151**
Log Likelihood	**-3671.7**	**-3677.7**	**-3741.9**	**-3750.2**
AIC	**7417.5**	**7429.4**	**7557.8**	**7574.3**
BIC	**7642.9**	**7654.9**	**7783.3**	**7799.8**

Note: Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering and arbitrary heterorskedasticity. Coefficients that have been scaled are indicated as such with their scaling factor.

Table 3.8: First difference – Female FLFP and gender labor gap by attack target type

Outcome:	Female LFPR		Gender Labor Gap	
Target Type:	Private b/se	Government b/se	Private b/se	Government b/se
Δ Terrorist Attacks	**0.000**	**0.001**	**0.000**	**0.000**
	(0.001)	**(0.002)**	**(0.001)**	**(0.002)**
Δ Terrorist Attacks (t-1)	**-0.002****	**-0.005****	**0.002****	**0.005****
	(0.001)	**(0.003)**	**(0.001)**	**(0.002)**
Δ Terrorist Attacks (t-2)	**0.000**	**0.000**	**0.000**	**0.001**
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**
Δ Population Size / 1M	-0.010*	-0.010*	0.005	0.005
	(0.005)	(0.005)	(0.004)	(0.004)
Δ Population Urban (% of total Population)	0.129**	0.129**	-0.001	-0.001
	(0.065)	(0.065)	(0.058)	(0.058)
Δ Total Fertility Rate (births per woman)	-0.664*	-0.663*	0.696*	0.698*
	(0.356)	(0.355)	(0.404)	(0.403)
Δ FDI (% of GDP)	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Δ GDP per Capita / 1K	0.268***	0.269***	-0.244***	-0.244***
	(0.081)	(0.081)	(0.056)	(0.056)
Δ GFCE (% of GDP)	0.003	0.003	-0.004	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Δ Civil Liberties	-0.007	-0.007	0.012	0.013
	(0.014)	(0.013)	(0.014)	(0.014)
Year Effects	**Yes**	**Yes**	**Yes**	**Yes**
Obs	**3272**	**3272**	**3272**	**3272**
Number of Countries	**151**	**151**	**151**	**151**
Log Likelihood	**-3674.1**	**-3668.4**	**-3742.7**	**-3744.3**
AIC	**7422.3**	**7410.8**	**7559.4**	**7562.7**
BIC	**7647.7**	**7636.3**	**7784.8**	**7788.1**

Note: Significance level at which the null hypothesis is rejected: *** 1%; ** 5%; and * 10%. Reported standard errors are robust to clustering and arbitrary heterorskedasticity. Coefficients that have been scaled are indicated as such with their scaling factor.

3.5 Conclusion

This study set out to expand upon a growing body of literature documenting conservative shifts following terrorist attacks by investigating whether such effects might be measurable in the labor market. In addition, we explored the possibility of the type and target of terrorism influencing such shifts. We found that increases in terrorist attacks decrease female labor force participation and increase the labor gender gap. Results were statistically significant and robust across a multitude of specifications. In order to establish causality and avoid endogeneity concerns we utilized multiple instrumental variable approaches. Our findings provide a fresh view aligned with prevailing theories of conservatism in political sociology. The causal analysis serves to

resolve the disparities between the empirical results and previous theories of the link between female labor force participation and terrorism.

By partitioning the terrorist attacks by terrorist targets, we found that the effects are prominent when attacks are perpetrated against both civilian and government entities. When attacks are differentiated by type – transnational versus domestic – we observed similar magnitudes and significance levels for both transnational and domestic terrorism, even though transnational attacks constituted less than one fifth of all terrorist attacks. The differing results by terrorism type serve to strengthen the ideological underpinnings of our effect; however, while we feel that SJT is a strong theory for explaining the observed differences in effects as well as our overall results, other possibilities remain. In particular, though the first differenced specifications indicated an effect isolated in a particular timeframe following an attack, a larger conservative shift in a population due to other factors could be occurring and might influence both female labor force participation and terrorism. The results of the instrumental variable and first difference approaches assuage some of these concerns as well as others, but it important to think critically and discuss the possibilities of other confounding factors.

Our focus was on gender disparities and the macro-economic impacts of terrorism on labor force participation, thus we are unable to isolate the particular micro-economic levers related to conservatism which influence women's decision to leave the labor force following increases in terrorism. For instance, we are unable to say whether the reductions in the likelihood of participation for women are related to shifts in relative wages for men versus women, changes in policy, subtle shifts in gender preferences by employers, or simply the increased preference for traditional values and gender roles. While SJT aligns well with our results, it is important to include the appropriate caveats. We did not measure conservatism directly; thus, there could be other factors at play influencing this relationship aside from increases in conservatism. Our results might also be explained if jobs predominately occupied by males (military, police, etc.) expand after terrorism enough for the income effect to incentivize females to seek more leisure in a marriage/couple relationship. This would still be a result of a conservative shift (militarism); however, the increases in husband's income rather than traditional values may be the driving factor for the reduction in female labor force participation. While this deserves consideration, the concentration of effect in female labor force participation as observed in the labor gender gap suggests against this possibility.

Another possibility is the effect that terrorism has on perceptions of risk. In an environment of heightened threat, families might be concerned to leave their homes, children, or belongings unprotected. Mothers may be taking on the added responsibilities for this and opting to stay at home to watch over the home and family. Along similar lines, the closing of schools due to terrorism could force mothers home if other sources of child care aren't available. In March of this year, rocket attacks in southern Israel caused schools in several cities to close resulting in 150,000 students staying home (Pfeffer et al. 2011). While single school closings would not be likely to influence employment, frequent attacks causing consistent closures might lead to an increased need for child care services and possibly a reduction in female labor force participation. It is important to note that this explanation does not disqualify a shift toward conservatism; the choice of the mother over the father as caregiver could simply be a more specific example of the shift toward the status quo. However much SJT aligns with the results of this study and helps to explain the theoretical reason for the relationship between terrorism and female labor force participation, future research should be conducted to isolate the particular drivers for this effect. How societies act in response to perceived threats from terrorist groups has implications for policy makers, and while our results suggest that responses appear to be toward conservatism and increased gender disparities in the labor market, it is important to understand these relationships completely before policy decisions are made. That said, these considerations do not diminish the importance of the overall findings. Contrary to the existing empirical work, we find causal evidence that terrorism exerts an effect on female labor force participation and the gender labor gap which would explain the previous disparity between other theories and results. Furthermore, these findings suggest that policy makers must be acutely aware of possible implications of terrorism on the labor market, especially when gender parity is a concern.

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