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THE EFFECTS OF DESTRUCTION: A MACROECONOMIC STORY

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THE EFFECTS OF DESTRUCTION: A MACROECONOMIC STORY

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Business and Economics at the University of Kentucky

By
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ABSTRACT OF DISSERTATION

THE EFFECTS OF DESTRUCTION: A MACROECONOMIC STORY

Destructive events such as natural disasters and terrorist attacks occur not only in developing economies but also developed economies. Consequently, the response of these economies has been observed in case of both type of events. This dissertation is a collection of essays regarding natural disasters, terrorist attacks and the macroeconomy. Specifically, I examine the response of local labor markets that reflect a wide spectrum of economies, but also have a safety-net in the form of being part of a developed country in the aftermath of a violent tornado. Further, I explore the heterogeneity in the economies response to natural disasters and terrorist attacks. Additionally, I investigate the effects of terrorism on growth and its disaggregated value added components.

The first chapter focuses on the effects of tornadoes on local labor markets. I examine the change in local labor markets caused by extreme tornadoes that occur in counties of the contiguous United States. I also investigate the effect these tornadoes have on neighboring counties and evaluate the labor market response in urban and rural counties separately as well. Using a generalized difference-in-difference approach on quarterly data spanning from 1975 to 2016, I find that counties experience persistently higher wages per worker two years following a violent tornado. The effects on urban county can be observed on employment, while the effect in the rural county is observed on wages per worker. Further, evaluating the response of labor markets by sectors reveals the industrial sectors that experience increased labor market activity.

The second chapter evaluates the long-run effects of natural disasters and terrorist attacks on growth and the channels through which they affect growth. Using the conceptual framework of a Solow-Swan model I examine an unbalanced annual panel of 125 countries spanning from 1970 to 2015 and find that domestic terrorist attacks, floods, and storms have a similar negative effect on growth, while transnational terrorist attacks and earthquakes have no significant effect on growth. Examining the channels through which they affect growth brings to the forefront the differences between these different types of events. I find that domestic terrorist attacks lead to increased military expenditures in their wake, while floods lead to increased non-military expenditures in their aftermath. Reviewing the data by developed and emerging economies reveals that developed economies are better able to absorb the shock of terrorist attacks as well as natural disasters. I find that although emerging economies are able to absorb the shock of transnational and domestic terrorist attacks, they experience some adverse effects from floods and storms.

The third chapter examines the path of GDP growth and its disaggregated industrial, service, and agricultural sector value added components in the aftermath of two types of terrorism - transnational and domestic terrorism. Using a panel VAR model on cross country annual data from 1970 to 2015 I find that fatalities caused by neither domestic nor transnational terrorist attacks lead to a significant change in GDP growth. Examining the disaggregated industrial, service, and agricultural sector components of GDP growth reveals that even disaggregated the value added components of GDP growth experience no adverse effects from the deaths caused by transnational and domestic terrorist attacks. I also distinguish the emerging economies from the entire sample to find that GDP growth in emerging economies experience no significant effects due to the casualties of transnational and domestic terrorist attacks.

KEYWORDS: Natural Disasters; Terrorist Attacks; Growth; Employment; Wage per worker

Author's signature: Kara Riesing

Date: July 26, 2019

THE EFFECTS OF DESTRUCTION: A MACROECONOMIC STORY

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I dedicate this dissertation to my parents, Mukesh S. Shah and Chitra M. Shah,
who supported and encouraged me every step of the way.

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Chapter 1 Introduction

The tsunami of 2004 that affected several coastal countries of the Indian Ocean was the largest of its kind in the last several decades. The US Geological Survey said that it believed the Tsunami in 2004 released energy equivalent to 23,000 Hiroshima-type atomic bombs. Considering this magnitude, it would not be a surprise if its impact were still visible in these countries. Although natural disasters that cause devastation of such a large magnitude are few, their occurrence nevertheless makes disaster management an important aspect of effective governance. Compared to natural disasters, terrorist attacks are smaller and more targeted, but they too have the potential of lasting ramifications. For example, the terrorist attack in the United States in 2001 and in India in 2008 both led to widespread changes in security measures. A similar change in security measures can be observed in the aftermath of many domestic and transnational terrorist attacks.

Understanding the economic costs associated with these different types of destructive events could aid policymakers to better gauge the benefits of implementing disaster management tools in case of either of these negative shocks. In response to this a vast body of literature has emerged regarding natural disasters as well as terrorist attacks. Despite this, there is more to explore about the effects that these events can have on the macroeconomy. In this dissertation, I first examine the effects of a specific natural disaster – tornadoes – on local labor markets across the United States. Incomes and labor market conditions vary across these locations, but are located in a developed country. In the next two chapters, I use cross-country data to investigate the effects of a broad range of natural disasters and terrorist attacks on growth and its components.

In the first chapter, I focus on the change in local labor markets caused by extreme tornadoes that occur in counties of the contiguous United States. Each year, on average, the U.S. experiences 1,200 tornadoes. These tornadoes kill 60 people, injure 1,500 people, and cause damages of over $400 million. Disaster management and its effectiveness is therefore an important aspect of governance for local governments. While a robust empirical literature regarding the effects of less commonly occurring natural disasters like hurricanes in the U.S. exists, few studies focus on the effects of tornadoes.

I use data from Bureau of Labor Statistics' Quarterly Census on Employment and Wages from 1975:Q1 – 2016:Q4. Using a generalized difference-in-difference approach on these quarterly data, I find that violent tornadoes lead to persistently higher wages per worker two years following a tornado. I also evaluate the labor market response separately for urban and rural counties and find that the effects on an urban county can be observed as an increase in employment, while the effect in a rural county is observed as an increase in wages per worker. Additionally, I also examine the response of labor markets by sectors to identify the industrial sectors that experience increased labor market activity. I find that the construction sector experiences higher labor demand a quarter after a violent tornado. Finance, insurance, and real estate (FIRE) experiences higher demand for its services in the aftermath of tornadoes.

Terrorist attacks and natural disasters are instances of exogenous negative shocks that can affect both human and physical capital. Although the magnitude of the shock varies considerably, a vast body of literature on terrorist attacks and natural disasters have found similar negative effects on GDP growth. In the second chapter, I examine the long-run effects of natural disasters and terrorist attacks on growth and the transmission channels through which they affect growth using a common conceptual framework.

I use World Bank's World Development Indicator data combined with Emergency Disaster Database (EM-DAT) and Global Terrorism Database (GTD) to compile an unbalanced annual panel of 125 countries spanning from 1970 to 2015. I find that domestic terrorist attacks, floods, and storms have a similar negative effect on growth, while transnational terrorist attacks and earthquakes have no significant effect on growth. Further, evaluating the channels through which they affect growth, I find that domestic terrorist attacks lead to increased military expenditures in their wake, while floods lead to increased non-military expenditures in their aftermath. Additionally, examining the data by developed and emerging economies reveals that developed economies are better able to absorb the shock of terrorist attacks as well as natural disasters. However, I find that although emerging economies are able to absorb the shock of transnational and domestic terrorist attacks, they experience some adverse effects from floods and storms.

The third chapter examines the path of GDP growth and its disaggregated industrial, service, and agricultural sector value added components in the aftermath of two types of terrorism - transnational and domestic terrorism. Transnational and domestic terrorist attacks, aim to cause the most damage on the economies of the countries that they target. Several studies have found that terrorist attacks increase uncertainty leading to decreased foreign direct investment (FDI). For emerging economies, FDI is a crucial source of financing. Hence, examining the response of growth and its disaggregated industrial, service, and agricultural sector value added component can help quantify the effect that terrorism has on an economy through the obstruction of normal business operations.

Using a panel VAR model on an unbalanced annual panel of 109 countries spanning from 1970 to 2015, I find that casualties caused by domestic terrorism and transnational terrorism lead to no significant change in GDP growth. Further examining the disaggregated industrial, service, and agricultural sector components of GDP growth reveals that the disaggregated sectors too remain unaffected by the fatalities caused by these terrorist attacks. Additionally, evaluating the response of GDP growth and its value added components for only emerging economies, I find that GDP growth in emerging economies experience no significant adverse effects from the deaths caused by transnational and domestic terrorist attacks.

Chapter 2 The Effect of Tornadoes on Local Labor Markets

2.1 Introduction

On May 22, 2011, the seventh deadliest tornado in U.S. history struck Joplin, Missouri, resulting in losses of over $2 billion in 2011 US Dollars[1]. The U.S. experiences about 1,200 tornadoes that on average, kill 60 people, injure 1,500 people and cause more than $400 million in damages each year [2]. These damages do not take into consideration the economic impact in the aftermath of the tornado. In this chapter, I examine the economic impact of tornadoes on local economies.

Tornadoes are one of the most common natural disasters that occur in the United States[3]. Unlike hurricanes that mostly occur in the Gulf and the Southeastern states, and earthquakes that mostly occur in the west, tornadoes can occur almost anywhere in the US[4]. Hence, they are also geographically dispersed across the country as can be seen in figure 2.1. Despite the frequent occurrence and the vast geographic dispersion, very few studies focus on the effects of tornadoes on the local economy.

For local governments, disaster management and its effectiveness is an important aspect of governance. Research about the economic aftermath of tornadoes can aid local governments make disaster management related decisions. In this chapter, I focus on the effects of tornadoes across the contiguous US on employment and wages. I find that while violent (EF4 and EF5) tornadoes result in no significant change in employment in a directly affected county for a two-year duration after the event, wages per worker are persistently higher in the affected county at the end of the same

[1] http://www.noaanews.noaa.gov/stories2011/20110920_joplin.html
https://www.joplinmo.org/DocumentCenter/View/1985/Joplin_Tornado_factsheet
https://www.thebalance.com/tornado-damage-to-the-economy-3305667

[2] http://www.crh.noaa.gov/Image/dvn/downloads/quickfacts_Tornadoes.pdf

[3] https://www.toptenreviews.com/the-10-most-common-natural-disasters-in-the-us

[4] https://www.spc.noaa.gov/faq/tornado/

duration. The results show that the effects of a violent tornado are not as short lived as one would expect. The results also imply that at the end of two years demand due to reconstruction effort leads to a rise in wage growth.

This chapter is related to several articles by Ewing et al. (2003, 2004, 2009) that focus on the effect of specific tornado incidents on employment growth. Ewing et al. (2003) focuses on the 2000 Fort Worth tornado, while Ewing et al. (2004) examines the 1998 Nashville tornado, and Ewing et al. (2009) focuses on the 1999 Oklahoma City tornado. These papers focus on specific tornadoes that occurred within a few years of each other. However, examining several tornadoes simultaneously over an extended period allows me to present a more comprehensive analysis of the effect of tornadoes on labor markets.

Ewing et al. (2004, 2009) also examine the response of labor markets on different industrial sectors. They find that construction experienced a positive shift in employment growth while the finance, insurance and real estate sector experienced a positive shift in employment growth in Oklahoma City and a negative shift in Nashville in the wake of a F5 tornado. The magnitude and direction of the effect on different industries is an empirical question to be investigated. This chapter examines the response of labor markets by sectors to deduce the response that can be expected in the aftermath of a tornado. The sectors examined in this chapter are construction; manufacturing; finance, insurance, and real estate (FIRE); trade, transportation, and utility (hereafter TTU); services; mining; and agriculture. Investigating the response of the labor market of each of these sectors exhibits the heterogeneity in their responses to tornadoes. I find that the construction sector experiences higher labor demand a quarter after the tornado as suggested by the higher employment and wages per worker. I also find that the FIRE sector experiences eventual but persistently higher employment in the directly affected county indicating greater activity in that sector in the aftermath of a tornado.

Other papers that are closely related to this chapter are papers by Belasen and Polachek (2008, 2009) who examine the effect of hurricanes on local labor markets and Pietro and Mora (2015) who evaluate the effect of an earthquake on labor markets. Belasen and Polachek (2009) focus on hurricanes that occur in Florida counties between 1988 and 2005. Using a generalized difference-in-difference method, they find that hurricanes decrease employment while increasing wages in the county that suffers the hurricane, indicating that hurricanes result in a negative shift in the supply curve of the labor market of the affected county. Belasen and Polachek (2008) also examine the effects that hurricanes have on the labor markets for broadly defined industrial sectors. Using the same data and methodology as Belasen and Polachek (2009), they find that hurricanes generally represent unexpected increase in labor demand in the directly hit counties since employment and earnings move in the same direction for each of the industrial sectors. Pietro and Mora (2015) focus on the earthquake in L'Aquila, Italy, that occurred on April 6, 2009. They examine quarterly data from 2009 to 2010 using difference-in-difference approach and find that the earthquake led to a decline in the probability of participating in the labor force for a period of nine months after the earthquake.

Studies evaluating the economic effect of natural disasters have been both cross-country and cross-US county. Cross-country studies largely examine the effect of several types of natural disasters on economic growth and the channels through which they affect growth. Some of these studies find that natural disasters have a positive effect on growth (Albala-Bertrand, 1993; Skidmore and Toya, 2002). However, the vast majority of studies find that natural disasters influence growth negatively (Raddatz, 2009; Jaramillo, 2009; Cavallo et al., 2013; Hochrainer, 2009; Cuaresma et al., 2008; Hallegatte and Dumas, 2009; Noy and Nualsri, 2007). Other studies focus on the differential effects of natural disasters on developing and developed countries and find that the adverse effect on growth of developing countries is much larger than on developed countries (Noy, 2009; Fomby et al. 2013). Focusing on counties in the United States provides a unique opportunity to examine a smaller economy within a developed country. Additionally, cross-US county studies have the advantage of focusing on some microeconomic activities that affect the economy of these counties. Several studies have taken advantage of this unique situation. Boustan et al. (2017) examine the effect of natural disasters on migration and housing prices at the US county level. Strobl (2011) explores the effect of hurricanes on income growth of coastal counties, and Belasen and Polachek (2008, 2009) evaluate the effect of hurricanes on local labor markets in Florida. This chapter adds to this body of natural disaster literature by focusing on the effect of a specific natural disaster, tornadoes, on the local labor market.

Fomby et al. (2013) find that the response to natural disasters varies between agricultural and non-agricultural GDP growth. This would suggest that there may exist heterogeneous effects between urban and rural regions. Focusing on counties for this study allows me to study the heterogeneous effects of tornadoes on urban and rural counties following the cross-country literature that examines the differential effects between developed and developing countries. Estimating the model separately for rural and urban counties, I find that a strong positive effect is observed on the employment levels of an urban county that is struck by a tornado. Labor markets in rural affected counties on the other hand are affected through higher wages per worker. This suggests that rural counties need to provide more of an incentive to attract labor.

2.2 Economic Framework of a Tornado Shock

In a standard labor demand and labor supply model an exogenous negative shock has the potential to influence both labor supply and labor demand. A tornado can be that exogenous negative shock to the labor market, since a tornado could result in disruption of production and regular economic activity due to the destruction of capital stock and even the loss of human life, though, casualties in the United States due to tornadoes tend to be small. Boustan et al. (2012) find that, on net, young men move away from areas struck by tornado to areas experiencing floods. As people flee the destruction caused by extremely large tornadoes creating a negative influence on labor supply, businesses attempt to fill this void created by fatalities, injuries and even migration of people, which creates positive pressure on labor demand. Thus the initial effect is unknown due to these two counter-acting forces. After the initial shock of the tornado, once reconstruction efforts kick in, labor demand would further experience a positive movement, and labor supply may flow in to offset the demand. The later shifts in labor supply and labor demand could shift the labor market equilibrium. Whether this is a positive or negative shift in equilibrium is ambiguous and may differ by sector.

The response to a negative shock can depend on the perception that agents in an economy have of the shock. A persistent negative shock may lead to more long lasting responses. Studies by Boustan et al. (2012) and (2017) suggest that there are individuals that perceive a tornado shock to be persistent. Boustan et al. (2012) find that on net young men out-migrate from areas that experience a tornado. Boustan et al. (2017) find that counties affected by severe disasters experience greater out-migration. Out-migration may therefore lead to a decline in labor supply in a county that experiences a tornado. However, at the same time there are individuals that stay in the county despite the massive destruction. Lucas and Rapping (1969) find that individuals tend not to alter their long-term expectations if they perceive a shock to be temporary. It can be because these individuals perceive the tornado shock to be temporary that they don't alter their long-term expectations and stay in the same area. Hence, the magnitude of the shift in labor supply is ambiguous and depends on the perceptions and decisions of individuals in the area.

Over the years, technology has made it possible to issue advance warnings of tornadoes. The average lead time of tornado warnings is 13 minutes[5]. Simmons et al. (2013) normalize tornado damages in the United States and find a sharp decline in tornado damages. Simmons and Sutter (2005) find that expected fatalities and injuries fell significantly after the installation of WSR-88D radars across the country. However, the more accurate warning system is not the fail-safe that it could be. People also rely on other sources of information like a visual of the tornado to heed a tornado warning during the daytime (Bakkensen, 2016). Even though technology has made it possible to reduce casualties, the warnings are unable to stop or reduce the destruction of physical capital.

A decline in physical capital increases the marginal product of capital, giving rise to increased investment. This in turn, should speed up recovery (Barro and Sala-i-Martin, 2003). Financial aid, disaster assistance, clean-up and recovery tend to be a counter-acting positive shock (Horowich, 2000). After the initial shock of the tornado, once reconstruction efforts to restore the damaged physical capital kicks in, demand for labor would increase. This increase in labor demand could be offset by in-migration of individuals that foresee labor market opportunity leading to a shift in the labor market outcomes from its pre-tornado levels. With time, labor demand and supply may adjust as reconstruction requirements evolve. As a result, the labor market may experience some fluctuation around its steady state. These shifts and adjustments inform us about a relatively longer period effect of a tornado on the labor market outcomes.

The proximity of counties means that individuals living in tornado struck counties may be employed in a neighboring county. This would suggest some spill-over effects in the neighboring counties due to out-migration. A neighboring county may also receive some spill-over from disaster assistance. For instance, first responders may

[5] `http://www.noaa.gov/stories/tornadoes-101`

choose a neighboring county as a base of operation and increase economic activity in that county. Belasen and Polachek (2008, 2009) find some spillover effects of hurricanes. They find that extremely large hurricanes lead to no significant change in employment but a decrease in wages of neighboring counties.

2.3 Methodology

Local labor markets may be influenced by state business cycles (Ewing et al., 2009; Belasen and Polachek, 2008, 2009). Therefore, along with the exogenous tornado shock the state's labor market variables should be accounted for. Along with counties that are directly struck by a tornado, there exists a possibility that neighboring counties may experience some spill-over effects. Labor markets have a seasonal component that should also be included in the equation. Therefore, the final labor market equation can be described by the following function

$$Y_{i,t} = f(Y_{s,t}, T^D_{i,t}, T^N_{i,j,t}) \tag{2.1}$$

where, $Y_{i,t}$ is a labor market outcome - employment or wages per worker. $Y_{s,t}$ is the corresponding state's labor market outcome that controls for the state's business cycle. The coefficients of $T^D_{i,t}$ capture the direct effect of tornadoes, while the coefficients of $T^N_{i,j,t}$ capture the spill-over effect of tornadoes.

I use a generalized difference-in-difference technique to identify the average effect of tornadoes on local labor markets. Like a standard difference-in-difference model, a generalized difference-in-difference method not only allows one to compare affected regions (treatment) to unaffected regions (control), but also allows for multiple exogenous events occurring at different times. Hence, the equation I estimate is as follows

$$Y_{i,t} = \alpha_0 + \sum_{p=1}^{P} \alpha_p Y_{i,t-p} + \sum_{q=0}^{Q} \beta_q Y_{s,t-q} + \sum_{k=-K}^{-2} (\delta_k^D T_{i,t-k}^D + \delta_k^N . \mathbb{1}(\sum_{j \neq i} T_{i,j,t-k}^N > 0)) + \sum_{k=0}^{k} (\phi_k^D T_{i,t-k}^D + \phi_k^N . \mathbb{1}(\sum_{j \neq i} T_{i,j,t-k}^N > 0)) + \lambda_i + \gamma_t + \varepsilon_{it} \tag{2.2}$$

In the above equation $T_{i,t-k}^D$ takes the value one if county i experiences a tornado at time t. $T_{i,j,t-k}^N$ takes the value one when a border sharing neighbor j of county i experiences a tornado in time t. The lags of the tornado inform us of the effects of tornadoes over time. Belasen and Polachek (2009) explain that historically destruction from hurricanes is repaired within two years. Compared to hurricanes, tornadoes are more focused in nature. I therefore assume that the repair duration post-tornado is no larger than hurricanes and include eight lags in my analysis. I find that the results are robust to the inclusion of more lags. I report the estimates with 20 lags (5 years) in the appendix. Including the same number of leads of the tornado as the lags allows me to test for pre-treatment trends. I exclude the period just before the tornado as the base period.

The series for employment and wages can be non-stationary for some panels. If this is the case for counties as well as for states, it gives rise to the problem of spurious regression. To resolve this, I include lags of the counties labor market outcome as well as lags of the corresponding states labor market outcomes. I select 8 lags of the labor market outcomes on the right hand side of the estimation equation using akaike information criterion and bayesian information criterion. To account for any endogeneity between the county and state labor market outcomes, I remove county i's labor market outcome from the state's labor market outcome. λ_i and γ_t account for county and year-quarter fixed effects respectively. I cluster the standard errors at the county level to account for correlation between panels as well as serial correlation within the panel[6].

Belasen and Polachek (2008, 2009) use a similar generalized difference-in-difference approach to examine the effect of hurricanes on local labor markets of counties in Florida. Even though other techniques such as propensity score matching may also be suitable approaches, using a generalized difference-in-difference approach considers the effects of observed and unobserved characteristics.

2.4 Data

The data on tornadoes are obtained from National Oceanic and Atmospheric Administration's (NOAA) Storm Events Database. These data include the start date, and the F-scale or the EF-scale of the tornadoes. They also include number of deaths, injuries, and damages (property and crop) caused by a tornado. The Fujita (F) Scale is a scale classifying the damage that a tornado has caused. The F-Scale ranges from F0 to F5, with an F5 tornado causing incredibly extensive damage. This scale was replaced by the Enhanced Fujita (EF) Scale in 2007. The Enhanced Fujita scale is a more precise and robust way of assessing damages caused by tornadoes. This scale ranges from EF0 to EF5 with EF5 being the strongest tornado causing extensive damages. The Storm Events database allows for a clear and exogenous identification of counties that experienced a violent tornado based on their F/EF scale classification. As both the F and EF scale are based on damages, there have been tornadoes that have been ranked as F2/EF2 or lower in open areas that could have been classified as F2/EF2 or greater if they hit a sufficiently well-constructed area[7]. Since the classification of tornadoes is a measure of the destruction that it caused, the results

[6] Wooldridge (2010) mentions that a robust variance estimator is valid in the presence of heteroskedasticity or serial correlation if T is small relative to N

[7] `https://www.spc.noaa.gov/faq/tornado/`

of this study could be extended to other disasters, natural or man-made, that cause destruction of a similar nature and magnitude.

Cavallo et al. (2013) find that only extremely large disasters have a significant impact on output in the short and the long run. Boustan et al. (2017) find that out-migration and housing prices are affected by severe disasters. Following this strain of literature, I focus on violent tornadoes and define a violent tornado as a tornado that has been ranked as either an F-4/EF-4 or F-5/EF-5. I define two tornado variables in my dataset. One accounts for the direct component. This variable takes the value one if the county experiences at least one F4/EF4 or F5/EF5 tornado in a quarter. If a tornado crosses county lines, so long as the tornado ranking does not drop below the threshold between counties the variable for directly affected county is one for each of these counties. My second tornado variable accounts for a violent tornado in a neighboring county. This variable takes the value one if a neighboring county experiences at least one F4/EF4 or F5/EF5 tornado in a quarter.

The data for employment are from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW). These data include employment levels by industry for counties at a monthly frequency and total wages by industry at a quarterly frequency. The QCEW occasionally suppresses data to protect the identity or identifiable information of cooperating employers. These observations have a non-disclosure flag associated with them and the value recorded for them is 0. At the more aggregate level of industry and geography, the non-disclosed employment levels and wages are included in the reported values. However, for some counties, data for a few monthly observations are not disclosed even at the all industry level. For these observations, I linearly interpolate the employment levels and the total wages. I aggregate the employment levels to their respective quarters to examine a more complete story along with wages per worker. I begin this chapter by focusing on all industries in the private sector. I also examine the labor market based on specific industrial sectors, specifically, construction; manufacturing; finance, insurance, and real estate (FIRE); trade, transportation, and utility (TTU); services; mining; and agriculture. I also evaluate the effect of a tornado on employment at a monthly level to inspect the nuances of the changes in employment within a smaller time frame from the time of the tornado. I use census region CPI data made available by BLS to compute real wages.

My final data for all industries and counties consist of an unbalanced panel of 3,106 counties in the contiguous United States spanning from 1975q1 to 2016q4. Data for each of the industrial sectors in all the 3,106 counties are not available. The number of counties for each sector varies from 2,196 to 3,105 counties. Table 2.1 describes the summary statistics by industrial sectors. This summary shows the pooled average employment and wages per worker between 1975 and 2016. It shows that the largest employment levels are observed in the services sector and the lowest are observed in mining followed closely by agriculture. On the other hand, mining has the highest wages per worker and services sector the lowest. Figure 2.2, shows the maps for violent tornadoes that occurred between 1975 and 2016. This figure shows that, most violent tornadoes affect the mid-western and eastern region of the United States. It also shows that a large number of counties have experienced only one violent tornado, although there are counties that have experienced several violent tornadoes as can be seen in table 2.2. Table 2.2 also describes the total number of violent tornadoes that have occurred between 1975 and 2016 in the contiguous United States. This shows that there have been 574 violent tornadoes throughout the contiguous United States, a number far greater than the number of violent hurricanes experienced. Between the same period the United States experienced approximately 110 major hurricanes that were classified as category 3, 4, or 5 on the Saffir-Simpson scale[8]. However, far less research has been done on the aftereffects of these tornadoes.

[8] http://www.aoml.noaa.gov/hrd/tcfaq/E11.html

Using United States Department of Agriculture's Rural-Urban Continuum Codes, I identify counties as urban or rural. These codes are updated every 10 years starting with 1974. I define a county to be rural or urban based on its status during a period of plus/minus 5 years from the census year. For instance, a county is defined to be rural or urban between 1998 and 2008 based on its status in the 2003 rural urban continuum codes. I use this to evaluate the heterogeneous effect of a tornado on the labor markets in rural and urban counties. Table 2.3 reports the summary statistics for rural and urban counties respectively. As would be expected, employment and wages per worker in urban counties is higher than in rural counties. Table 2.2 describes the total number of violent tornadoes that have occurred between 1975 and 2016 in the contiguous United States by rural and urban counties. This table shows that the number of violent tornadoes that occurred in rural counties far exceeds the number that have occurred in urban counties. However, as a percent the occurrence is well-balanced with 15% of rural counties and 15% of urban counties experiencing at least one violent tornadoes.

A potential data concern is whether the labor market data collected around the time of a tremendously extensive tornado is reliable. Garber et al. (2006) review the quick adaptation measures adopted by BLS's QCEW to account for data gathering problems because of Hurricane Katrina. They conclude that despite the adjustments in the estimation and imputation procedures to accommodate the situation, due to the high level of non-response some uncertainty remains regarding the employment and wages measured during that period. It is possible that there may be some uncertainty in the measured employment and wages around the period of a violent tornado, however the adjustments made by the QCEW ensures a relatively lower uncertainty than what it could have otherwise been.

2.5 The Effects of Violent Tornadoes on Local Labor Markets

Figure 2.3 plots the effect of violent tornadoes on employment and wages per worker. The top panel plots the effects of a violent tornado in directly affected counties, while the lower panel plots the effects in neighboring counties. These results show that violent tornadoes have no significant effect on employment throughout the two-year period on the directly affected county. On the other hand, wages per worker, on average, experience a contemporaneous increase of 0.31% as compared to the previous period. This increase in wages per worker is statistically significant at the 95% confidence level. The response of wages per worker seven quarters after the tornado increases by 0.46%. This increase too is statistically significant at the 95% confidence level. The increase in wages per worker is persistent eight quarters after the tornado with an increase of 1.37% as evidenced from the multiplier effect[9]. This higher multiplier effect is statistically significant at the 95% confidence level.

The results support the previous discussion of a fall in employment due to potential out-migration, while businesses trying to fill the void created by an increase in out-migration apply positive pressure on demand leading to mostly insignificant change in employment and increased wages per worker. Looking through the lens of a standard labor supply – labor demand model provides intuition behind the movements of the labor market. Initially labor supply may not change much as individuals prepare for migration and demand experiences positive pressure due to recovery and reconstruction efforts. This leads to an insignificant change in employment and a positive change in wages per worker contemporaneously. In later quarters, labor supply experiences less scarcity due to out-migration because of individuals leaving the area as in-migration due to people seeking job opportunities created as a result of reconstruction efforts is experienced in the directly affected county. This is evidenced by

[9]The multiplier effect is the sum of the lagged coefficients of the tornado variable. The confidence intervals are computed by inverting the Wald test of the null hypothesis that the sum of the coefficients is different from zero.

the insignificant change in employment along with the interim period of insignificant change in wages per worker as it adjusts to this movement in the labor supply and the labor demand. Two years after the tornado, wage growth is persistently higher than its pre-tornado rates. The higher wages per worker persist even 5 years later. The multiplier effects show that wages per worker settle at an approximate 3.09% higher level starting sixteen quarters after the tornado. The increase in wages per worker observed here is in line with findings of Skidmore and Toya (2002) who find that climatic disasters like tornadoes, cyclones, hurricanes, etc. lead to higher economic growth.

Belasen and Polachek (2009) find that hurricanes have an opposing effect on employment growth and wage growth. They find that the direct effect of a hurricane on growth of earning is higher and lasts through the seventh quarter after the hurricane. I find that the effects of a tornado on wages per worker are felt eight quarters after the tornado. They also find a significant persistent decrease in employment growth rate in the directly affected counties two years after the hurricane indicating a stronger influence of labor supply and potentially migration. On the other hand, I find that employment remains mostly unchanged throughout the two-year period after the tornado, though wages per worker increase and remain persistently higher two years after the tornado. The difference in findings could be attributed to the difference in disasters or a difference in geography. Examining the data for the same period as Belasen and Polachek (2009), I find that the post-tornado path of employment and wages per worker are similar to my entire sample, although the effects are subdued and insignificant. The estimate of employment in the contemporaneous period is negative, though insignificant. The estimate using the entire sample is also negative and insignificant. This would suggest that the differences in the response of employment that is observed may be due to the difference in the two disaster types. Compared to hurricanes, tornadoes are more focused in nature and for the most part they are not accompanied by the additional damage caused by floods. There also exists a possibility that the differences may be a result of geography. However, since there are no violent tornadoes in Florida in my sample, testing that is not feasible.

Employment in neighboring counties experiences a rise of 0.34% and 0.31% four and seven quarters after the tornado respectively. These increases are statistically significant at the 90% confidence levels. However, the results also show a statistically significant fall in employment of 0.8% three quarters before the tornado suggesting there exists some uncertainty in the estimated response, though the joint significance test of the coefficients reveals that the effect is jointly statistically insignificant. Wages per worker, on the other hand, experience no significant change for most of the quarters after the tornado. Although, seven quarters after the tornado wages per worker fall by 0.3%, this fall is marginally significant at the 90% confidence level. Since the data being evaluated accounts for the employment in the county and not the populace of the county that is employed, there may be some spill-over labor supply available to the neighboring counties due to potential in-migration of people seeking job opportunities created as a result of reconstruction efforts in the neighboring tornado struck county.

Violent tornadoes apply opposing forces to labor supply and labor demand as attested by the persistently higher wages per worker and the insignificant change in employment post-tornado in the directly affected counties. These results suggest a better than the pre-tornado labor market outcome for these counties in the wake of the tornado. Neighboring counties experience some spillover effects several quarters after the tornado when they exhibit a rise in employment and a fall in wages per worker suggesting labor supply spillover.

2.5.1 Urban Vs. Rural

Demographics and income levels vary between urban and rural counties [10]. As described by the summary statistics in table 2.3, employment and wages per worker between these types of counties also differ. For this reason, it should be expected that the response of the labor market would vary between urban and rural counties. Figure 2.4 shows the multiplier effect of a violent tornado on employment and wages per worker in directly affected counties by urban and rural counties.[11] These graphs show that the average effects on directly affected counties that we observe across the country are driven by the effects of violent tornadoes in rural counties. On average, 15% of both urban and rural counties have experienced at least one violent tornado between 1975 and 2016. This implies that the results are not driven by the greater number of tornadoes striking rural counties.

The effect of a violent tornado on employment in directly affected urban counties is insignificant for the two-year period after the tornado that we observe here. However, employment experiences a marginally significant multiplier effect starting three quarters after the tornado which persists eight quarters later. The multiplier effect shows a marginally significant rise of 0.98% in employment three quarters after the tornado. This increase continues to increase gradually to 1.43% eight quarters after the tornado. This increase in the multiplier effect of employment almost a year after the tornado suggests that reconstruction takes place more gradually than expected. Wages per worker in the directly affected urban county experience no significant change until eight quarters after the tornado. Wages per worker eight quarters after the tornado are 0.5% higher than the quarter prior to the tornado. This increase in wages per worker is only marginally significant. Although the pre-trend period shows

[10] https://www.census.gov/newsroom/press-releases/2016/cb16-210.html

[11] The multiplier effect is the sum of the lagged coefficients of the tornado variable. The confidence intervals are computed by inverting the Wald test of the null hypothesis that the sum of the coefficients is different from zero.

an increase in wages per worker seven quarters prior to the tornado suggesting some uncertainty in the estimation, testing for joint significance shows that the period-by-period effects are jointly insignificant. Examining the multiplier effect on wages per worker for a longer duration (20 quarters) reveals that wages per worker in directly affected urban counties are 4.24% higher ten quarters after the tornado and it continues to steadily increase to 5.04% twenty quarters after the tornado. This suggests that over-time the in-migration of individuals experienced due to possible job opportunities may be moving on to greener pastures before complete recovery is achieved. The higher wages in later quarters could also be an indication that reconstruction led to technological upgrades that led to eventual higher wages.

Rural counties that are directly struck by a violent tornado experience no significant change in employment as shown by figure 2.4. Wages per worker, on the other hand, contemporaneously, as well as a quarter after the tornado, experience a statistically significant increase of 0.3% and 0.4%, respectively, at the 90% confidence level. In the following quarters the change in wages per worker is not significantly different from the quarter prior to the tornado until seven quarters after the tornado when wages per worker are 0.4% higher. Although three quarters prior to the tornado wages per worker experience a rise of 0.4% with a significance of 10%, testing for joint significance shows that the coefficients are not jointly significant. Even though the interim quarters show insignificant change in wages per worker post-tornado, the multiplier effect shown in the figure divulge that wages per worker are steadily increasing throughout the two-year period after the tornado. After eight quarters the multiplier effect shows wages per worker are higher by 1.79% at 95% confidence level. This suggests that even though each quarter doesn't see any strong effects to the labor markets, there is a silver lining to the tornado in the directly affected rural county in the form of cumulatively rising wages per worker. Reviewing estimates for a longer duration reveals that wages per worker continues to increase steadily to about 2.5% twelve quarters after the tornado. Beyond the twelve quarters wages per worker settle at the 2.5% higher level.

Many rural towns and villages have experienced a loss in easy access to necessities like food and clothing and other goods as local businesses close resulting in residents traveling a greater distance to obtain these goods and services (Glasgow 2000). This implies that the sudden increase in demand of these goods and services would be observed in the labor market as well. The difference in responses between urban and rural counties could potentially be because rural counties may need to provide incentive to fill the void created by out-migration as well as the demand created by reconstruction and recovery. This would explain the persistently higher wages per worker that are observed. On the other hand, since urban counties face no such lack in access to resources including access to labor, an increase in demands for goods and services to meet recovery efforts do not translate into a change in wages per worker but they do translate to higher employment levels.

Figure 2.5 plots the multiplier neighboring effect of violent tornadoes on employment and wages per worker by urban and rural counties. Urban neighboring counties experience a marginally significant fall in employment of 0.4% five quarters after the tornado. This decline in employment is observed only in that one quarter and is suggestive of some out-migration of labor that may have resided in the directly affected county but worked in the neighboring urban county. Wages per worker, on the other hand, experience a significant increase of 0.59% four quarters after the event. This rise is statistically significant at 95% confidence. Wages per workers consequently experience a marginally significant fall of 0.7% seven quarters after the tornado. However, wages per worker also experience an increase eight quarters prior to the tornado, though the pre-tornado coefficients are jointly insignificant. These responses suggest that the spill-over effects of a tornado are felt through employment in the urban neighboring county, although this effect is only felt in that one quarter.

The response of employment in rural neighboring counties to the tornado show an increase in employment of 0.5% and 0.4% four and seven quarters after the tornado. These increases are significant at the 95% confidence. The estimates also reveal a fall in employment of 1.01% three quarters prior to the tornado, suggesting the effect that we observe may lack precision although, the pre-tornado coefficients are jointly insignificant. Wages per worker in the neighboring rural county also show that there are no significant effects of the tornado. The results suggest that there may be no significant spill-over effects of tornadoes on the labor market of rural neighboring counties.

The response of directly affected urban and rural counties to a violent tornado shows that the response of wages per worker that we observe for the entire sample are also observed in rural counties. However, urban counties on the other hand, experience persistently higher employment. This difference in response between urban and rural counties may be a result of rural counties having to provide stronger incentive to attract the labor that they need to meet the demands of reconstruction. The neighboring effects on urban and rural counties vary as well. Neighboring urban counties experience a fall in employment while neighboring rural counties experience no significant effects. This difference in response in urban and rural neighboring counties is potentially due to the possibility that people moving away from the affected county worked in the neighboring urban county leading to a decline in employment in these counties. An eventual increase in wages per worker suggesting that the demand for labor due to reconstruction may also spillover into the neighboring urban county.

2.5.2 Time Disaggregation

Figure 2.6 shows the monthly effect of violent tornadoes on employment. This gives a more detailed view of the response of employment to a violent tornado. I include 24 lags of the dependent variable as well as the corresponding state's labor market outcome in the estimation model to account for the same time duration as in the quarterly analysis. The figure shows that employment in the directly affected county experiences a marginally significant increase of 0.35% two months after the tornado. A significant increase in employment is observed in various months following the tornado. Although, like the quarterly frequency, the multiplier effect of monthly employment displays no lasting effects. The figure shows a 0.24% and 0.30% increase in employment four and seven months after the tornado. These increases are significant at the 95% confidence level. Month nine, eighteen, and twenty also show an increase in employment of 0.19%, 0.2%, and 0.23% respectively. These short-lived increases in employment suggest adjustment in labor supply and labor demand. However, whether the movement is in labor supply or labor demand is ambiguous since the corresponding data for monthly wages per worker are unavailable. Although, based on the higher wages per worker contemporaneously along with the persistently higher wages per worker two years after the tornado it may be the case that the short lived increase in employment is a result of changing labor supply due to in- and out-migration. However, these nuances are not observed in the quarterly data.

On the other hand, when examining the neighboring effects of a violent tornado the monthly response of employment shows a marginally significant fall of 0.24% contemporaneously. This initial decline in employment is followed by declines of 0.2% and 0.27% six and seven months after the tornado respectively. Although we also observe significant change in employment prior to the tornado which suggests that the estimates lack precision, the pre and post-tornado coefficients are jointly insignificant.

Examining monthly employment data reveals that there are months that experience a positive significant change in employment. This indicates that there are employment effects in the very short run that disappear so quickly that they cannot be observed in the quarterly data. Hence it is beneficial to examine the monthly changes in employment in the aftermath of the tornado.

2.5.3 Does the Intensity of Tornado Matter?

Figure 2.7 plots the effects of a broader range of tornadoes on employment and wages per worker. The variable Large Tornado takes the value one if county i is struck by at least one tornado in time t that is ranked F2/EF2 or higher. There have been 7,908 tornadoes ranked F2/EF2 or higher between 1975 and 2016. Of these 2,625 tornadoes have occurred in urban counties while 5,283 have been in rural counties. The figure shows that large tornadoes have no significant effect on employment of the directly affected county. On the other hand, wages per worker in the directly tornado struck county fall by 0.1% contemporaneously as well as two quarters after the tornado. This fall in wages per worker is statistically significant at 95% confidence. This effect is observed in the contemporaneous quarter alone. The contemporaneous response of wages per worker to a large tornado varies from that of its response to a violent tornado. The wages per worker in the directly affected county are higher in the quarter of a violent tornado. This fall in wages per worker due to large tornadoes can largely be attributed to tornadoes ranked as F2/EF2 or F3/EF3. Since the destruction caused by a F2/EF2 or F3/EF3 classified tornado is far less than a F4/EF4 or F5/EF5 classified tornado, aid and reconstruction and recovery efforts initiated are less for these tornadoes. Hence, on net, the destruction could lead to lower wages per worker. Even though direct effects display some difference when the intensity of tornadoes is lowered, the neighboring effects show insignificant response of employment, while wages per worker experience a 0.1% increase two quarters after the tornado. The figure shows that the effect of a large tornado on the labor market of a neighboring county is insignificant.

The direct and the neighboring effects to a large tornado suggests that the intensity of the tornado does indeed matters. In corroboration with studies by Cavallo et al.

(2013) and Boustan et al. (2017) who find that only extremely large disasters have a significant impact on economic activity, these results indicate that it is the extreme tornadoes that cause a strong response in the local labor markets.

2.5.4 Sector Disaggregation

Examining labor market response by specific sectors can reveal the industries that experience change after a devastating tornado. This uncovers the demands and needs of the county in the aftermath of the tornado. This could potentially aid in establishing policies that strengthen disaster management in particular sectors of the economy. Figures 2.8 and 2.9 plot the effect of a violent tornado on employment and wages per worker respectively in directly affected counties by industrial sectors - construction; manufacturing; finance, insurance, and real estate (FIRE); trade, transportation, and utility (hereafter TTU); services; mining; and agriculture. The results show that only the construction sector experiences a change in employment as well as wages per worker after the tornado in the tornado struck county. The FIRE sector experiences some changes in its employment post-tornado in the directly affected county. The remaining sectors experience some significant change prior to the tornado indicating a lack of precision in the estimation of these sectors.

The construction sector experiences significant increase of 2.02% a quarter after the tornado. This increase is significant at the 99% confidence level. Examining the multiplier effect reveals that higher employment levels persist from a quarter after the tornado to seven quarters after the tornado when the multiplier employment level is 4.5% higher. The effect on wages per worker in the construction sector are also observed a quarter after the tornado. Wages per worker in the construction sector are 0.99% higher a quarter after the tornado. This increase is significant at 90% confidence. However, wages per worker also experience a marginally significant decline two quarters prior to the tornado. Although, examining the multiplier effect shows higher wages per worker of 1.5% a quarter after the tornado and 2.16% higher three quarters later suggesting that there may be some increase in wages per worker in the construction sector. The increase in employment and wages per worker is likely due to the start of recovery and reconstruction. This suggests a more dominant increase in labor demand in the construction sector.

The FIRE sector experiences significant increase of 0.5% in employment three quarters after the tornado. This increase is statistically significant at the 90% confidence level. Examining the multiplier effect reveals that employment is steadily increasing from 1.03% three quarters after the tornado until at least eight quarters after the tornado when the multiplier effect reveals that the effect is 1.67% higher. The multiplier effects are statistically significant at the 90% confidence level. Wages per worker of the FIRE sector are lower by 0.5% at the 90% confidence level four quarters after the tornado. Although the multiplier effect is statistically insignificant throughout the eight-quarter period. The persistently higher employment in the FIRE sector suggests that the sector experiences greater activity in the aftermath of the tornado. Belasen and Polachek (2008) find that hurricanes result in a fall in growth in earnings of the FIRE sector which is in-line with my findings. However, they also find that the decline in growth in earnings is accompanied by an insignificant change in employment growth. Their results for the construction sector show that growth in earnings increases while growth in employment remains unchanged. Their results suggest a stronger demand shock is at play in these sectors in the aftermath of the tornado. I find the same to be true in case of the construction sector, although for the FIRE sector that may not be the case. These differences in findings could be a result of the difference between hurricanes and tornadoes or even the fact that my analysis focuses on the changes observed over time while they focus on the contemporaneous period.

Figures 2.10 and 2.11 plot the effects of a violent tornado on employment and wages per worker respectively in a neighboring county by industrial sectors. The results show that employment in each of the sectors experience no significant change in a neighboring county. Wages per worker in the FIRE sector experience some spillover effects. The FIRE sector experiences higher wages per worker of 0.68% contemporaneously. In the following quarters wages per worker in the FIRE sector experience no significant change. This suggests that the neighboring counties experience some spillover demand in the FIRE sector that translates to higher wages in the contemporaneous quarter. This additional demand in the FIRE sector may be a result of disaster insurance claims.

The results illustrate that construction and FIRE sector experience increased activity in the directly affected county in the aftermath of the tornado. Construction sector experiences an increase in employment and wages a quarter after the tornado, while FIRE sector experiences higher employment three quarters after the tornado and the multiplier effect show that the effect is persistent. This indicates increased activity in both these sectors, while the other sectors experience very short lived or no significant effect from the tornado. The spillover effect felt in a neighboring county is concentrated in the FIRE sector in the contemporaneous period in the form of higher wages per worker.

2.6 Robustness Check

A concern with examining tornadoes is that they predominantly occur in the mid-west and the southern regions of the U.S. The vast majority of violent tornadoes in my sample occur in the mid-west and the Southern region of the country. To ensure the robustness of the main results presented above, I estimate the above with data from these regions alone. Figure A.4 illustrates these results. They show that the average effects observed on the labor market indicators for the smaller sample of mid-west and southern regions are the same as that observed for the complete sample that covers the entire country. The period-to-period change in employment and wages per worker in the directly affected counties and the neighboring counties shows that it follows a similar path as the main results.

Next I include an indicator term in the estimating equation that takes the value one if in one of the previous twenty quarters the county has had a violent tornado. This variable controls for any effect from a previous tornado. I also include a similar indicator term to control for a neighboring county having experienced a violent tornado in the past 20 quarters. The estimates are plotted in figure A.5. These results also support the main results reported in the previous section.

Lastly, I re-estimate the effects of tornadoes on labor market outcomes using local projection method. Although local projection method does not account for the effects of previous tornadoes on labor market outcomes, the method provides an alternate method to plot impulse response function without the restriction of VARs. They are also more robust to misspecifications. Figure A.6 plots the estimates derived using local projection. These results show that the effect of tornadoes on employment of a directly affected county, like the main results is insignificant for most of the horizon being examined, except for two quarters after the tornado when employment is significantly higher. The results show that wages per worker in the aftermath of the tornado for eight quarters follows a similar path as shown by the main results. In neighboring counties the path followed by wages per worker is similar to that observed in the main results, however there are some differences in the response of employment. The graph shows that the adjustments experienced by employment due to ebb and flow of labor supply and labor demand, unlike the main results, are significant in several quarters. These results suggest a far stronger adjustment of labor supply and demand due to in- and out-migration than the main results.

Predominantly the robustness checks suggest that the effect of violent tornadoes on labor market outcomes are robust and not sensitive to the originally defined specification.

2.7 Key Findings

Violent tornadoes in directly affected counties result in opposing effects on labor supply and labor demand. This is evident from the persistently higher wages per worker and insignificant change in employment two years after the event. These results suggest that the state of the labor market two years after the tornado is better than its pre-tornado state due to persistently higher wages per worker. These results are in line with the positive effect on growth deduced by Skidmore and Toya (2001). Disaggregation of the sample between urban and rural counties shows that this change in wages per worker is stronger in rural counties while they experience insignificant change in employment. On the other hand, directly affected urban counties experience persistently higher employment three quarter onwards and no significant change in wages per worker. This difference in response between urban and rural counties can be attributed to the possibility that rural counties may have to offer more incentive to attract the needed labor supply to meet the demands of reconstruction resulting in higher wages while urban counties require no such incentive.

Neighboring counties after a violent tornado experiences a quarter of lower wages per worker five quarters after the tornado indicating that the labor market experiences a brief period of labor supply excess. Examining the data separately for urban and rural counties reveals that neighboring urban counties experience a decline in employment five quarters after the tornado. This fall in employment in the urban neighboring counties suggest a decline in the labor supply due to net out-migration or a decline in labor demand due to lower consumption in the directly affected county. This also implies a worse labor market outcome for a brief period following the tornado in the neighboring urban county due to lower employment.

Lowering the threshold of the tornadoes to F2/EF2 and higher reveals that the counties directly affected experience lower wages per worker contemporaneously while employment remains unchanged. This effect on wages per worker is not felt beyond the contemporaneous quarter. Counties struck by violent tornadoes on the other hand, experience persistently higher wages per worker two years after the event. This difference raises the question whether lower intensity tornadoes lead to lower aid and reconstruction efforts which fall short of meeting the needs of the local economy. Although the brevity of the response suggests that the shortfall is not felt beyond that one quarter.

Examining the labor markets by industrial sectors reveals that the construction sector experiences higher labor demand a quarter after the tornado as suggested by the higher employment and wages per worker. These higher levels are persistent for employment until seven quarters after the tornado, however that is not the case for wages per worker. The increased employment and one quarter of increased wages per worker are indicative of demand generated due to reconstruction and recovery efforts. FIRE sector reveals that employment experiences a persistent increase starting three quarter after the tornado. Employment in the FIRE sector continues to steadily increase and is persistently higher eight quarters after the tornado. This suggests higher demand for FIRE sector services potentially due to insurance claims and increases in other financial activities in the aftermath of the tornado.

2.8 Tables

Table 2.1: Quarterly Summary Statistics

	All	Construction	Manufacturing	FIRE	TTU	Services	Mining	Agriculture
Employment	29,695	1,703	5,462	2,134	7,109	11,473	381	391
	(115,249)	(5,988)	(20,343)	(11,588)	(27,304)	(51,061)	(1,905)	(2,103)
State Employment	2,488,258	148,440	444,894	173,541	594,438	970,199	38,417	29,057
	(2,300,202)	(146,117)	(383,459)	(177,665)	(539,313)	(1,044,107)	(66,003)	(66,463)
Wages per worker ($)	3,615	4,111	4,491	4,253	3,055	2,743	6,911	3,281
	(933)	(4,203)	(3,297)	(8,465)	(817)	(983)	(33,118)	(7,642)
States Wages per worker ($)	4,517	5,214	5,651	5,781	4,048	3,905	8,360	3,796
	(1,179)	(14,464)	(21,749)	(6,436)	(653)	(781)	(164,846)	(138,975)
Observations	520,034	515,261	503,316	509,781	519,173	518,781	311,714	456,650
Counties	3,106	3,099	3,052	3,081	3,105	3,105	2,196	3,048

Note: The table reports the pooled average of the variables for an unbalanced panel of counties spanning from 1975 to 2016.The standard deviations are reported in parenthesis.

Table 2.2: Number of Tornadoes

	All Counties	Urban Counties	Rural Counties
Violent Tornado (EF4 and EF5)	574	193	381
Counties with 1 Violent Tornado	340	111	235
Counties with 2 Violent Tornadoes	73	20	50
Counties with 3 Violent Tornadoes	21	10	11
Counties with 4 Violent Tornadoes	5	3	2
Counties with 5 Violent Tornadoes	1	0	1
No. of Counties	3106	1237	2522

Note: The table reports the total number of counties that have experienced an EF4 and EF5 tornado between 1975 to 2016. It also lists the number of counties that have experienced 1, 2, 3, 4, and 5 such tornadoes between this period.

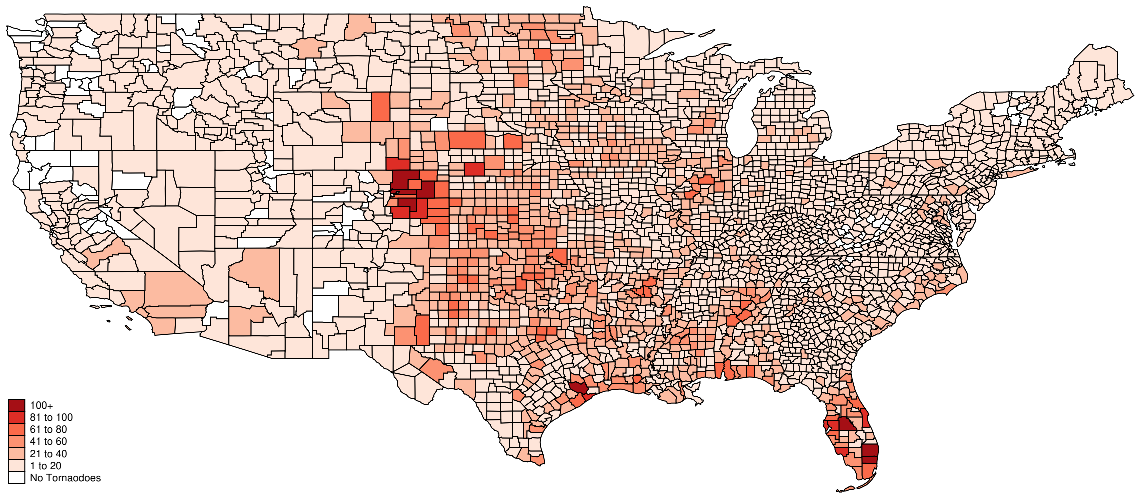
Table 2.3: Quarterly Summary Statistics for Urban and Rural Counties

	Urban Counties	Rural Counties
Employment	85,094	6,129
	(200,036)	(7,100)
Wages per worker	4,136	3,394
	(980)	(817)

Note: The table reports the pooled average of employment and wages per worker by urban and rural counties spanning from 1975 to 2016.The standard deviations are reported in parenthesis.

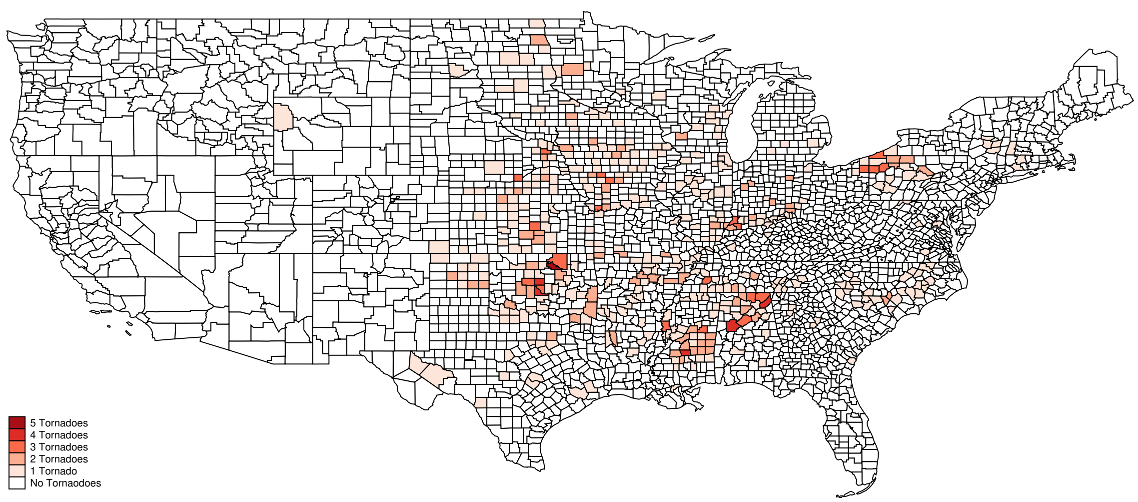
2.9 Figures

Figure 2.1: All Tornadoes Between 1975 and 2016



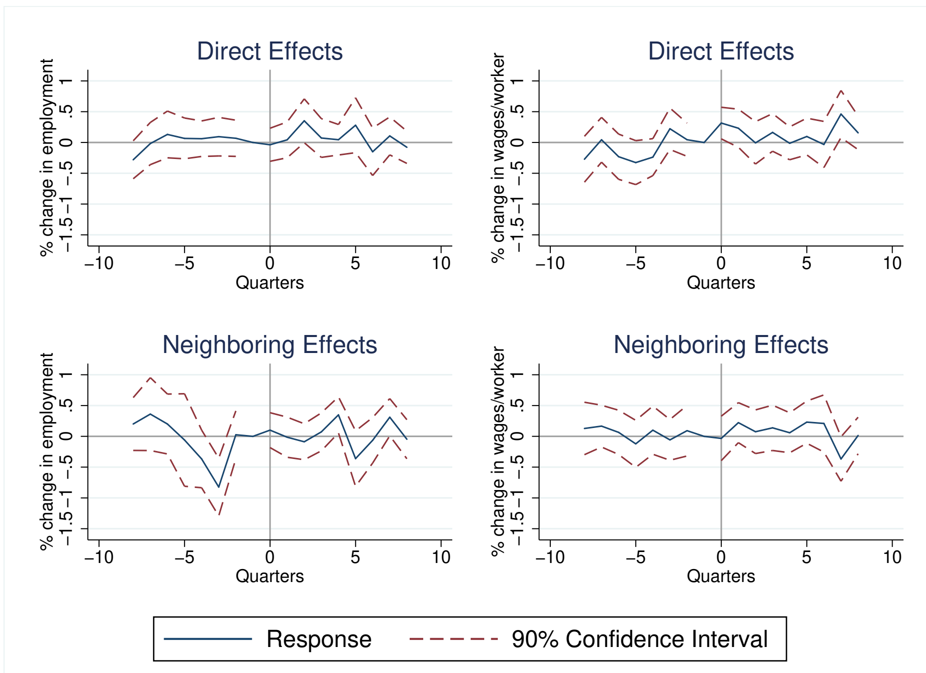
Note: The figure plots all the number of tornadoes that have occurred in each of the counties of the United States between 1975 and 2016.

Figure 2.2: EF4 and EF5 (Violent) Tornadoes Between 1975 and 2016



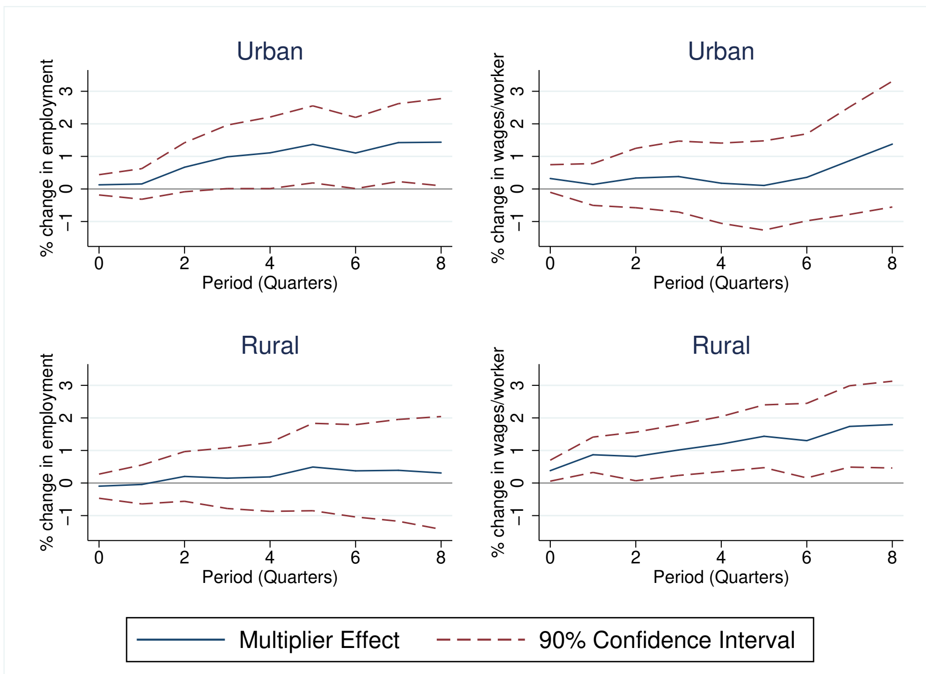
Note: The figure plots the number of EF4 and EF5 tornadoes that have occurred in counties of the United States between 1975 and 2016.

Figure 2.3: Effect of Violent Tornadoes on Labor Market Outcomes (All Industries)



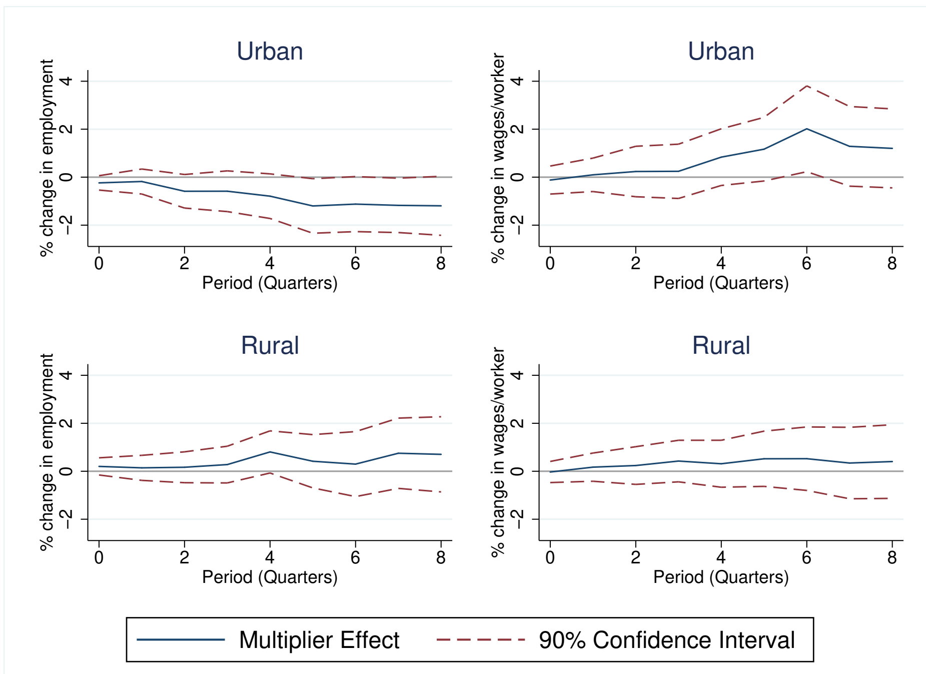
Note: The solid line plots the response of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the direct effects and the lower panel plots the neighboring effects

Figure 2.4: Multiplier Effect of Violent Tornadoes on Labor Market Outcomes (All Industries) of Directly Affected Urban and Rural Counties



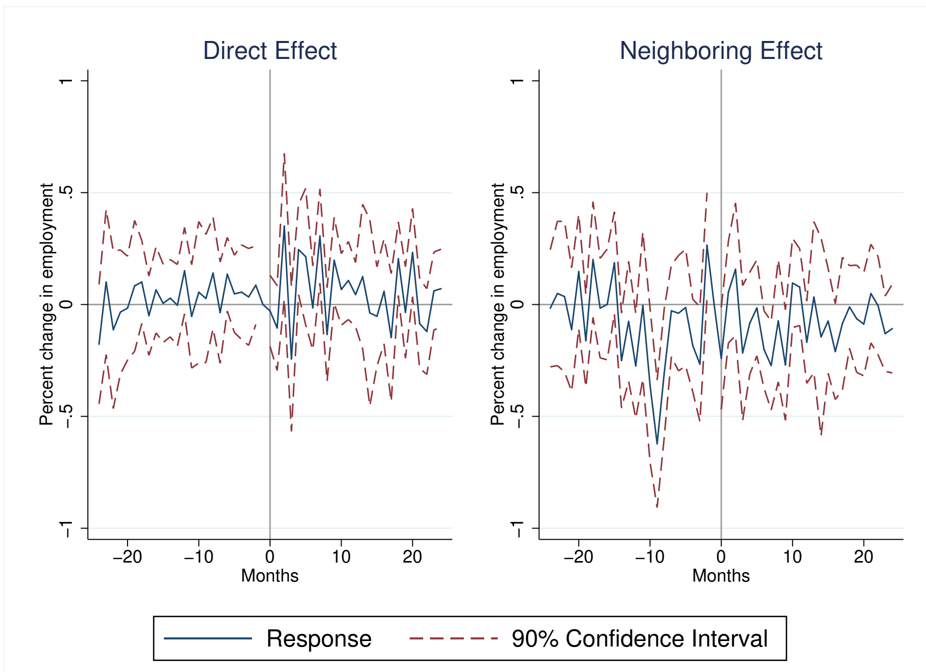
Note: The solid line plots the multiplier effect of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the effect on Urban counties and the lower panel plots effects for Rural counties

Figure 2.5: Multiplier Effect of Violent Tornadoes on Labor Market Outcomes (All Industries) of Neighboring Urban and Rural counties



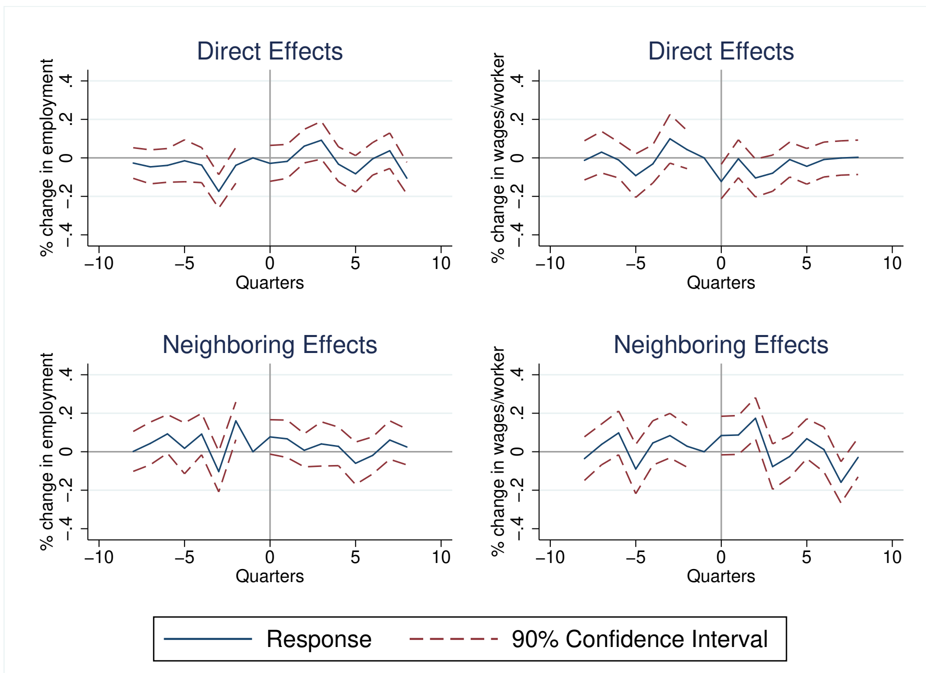
Note: The solid line plots the multiplier effect of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the effect on Urban counties and the lower panel plots effects for Rural counties

Figure 2.6: Effect of Violent Tornadoes on Employment (Monthly)



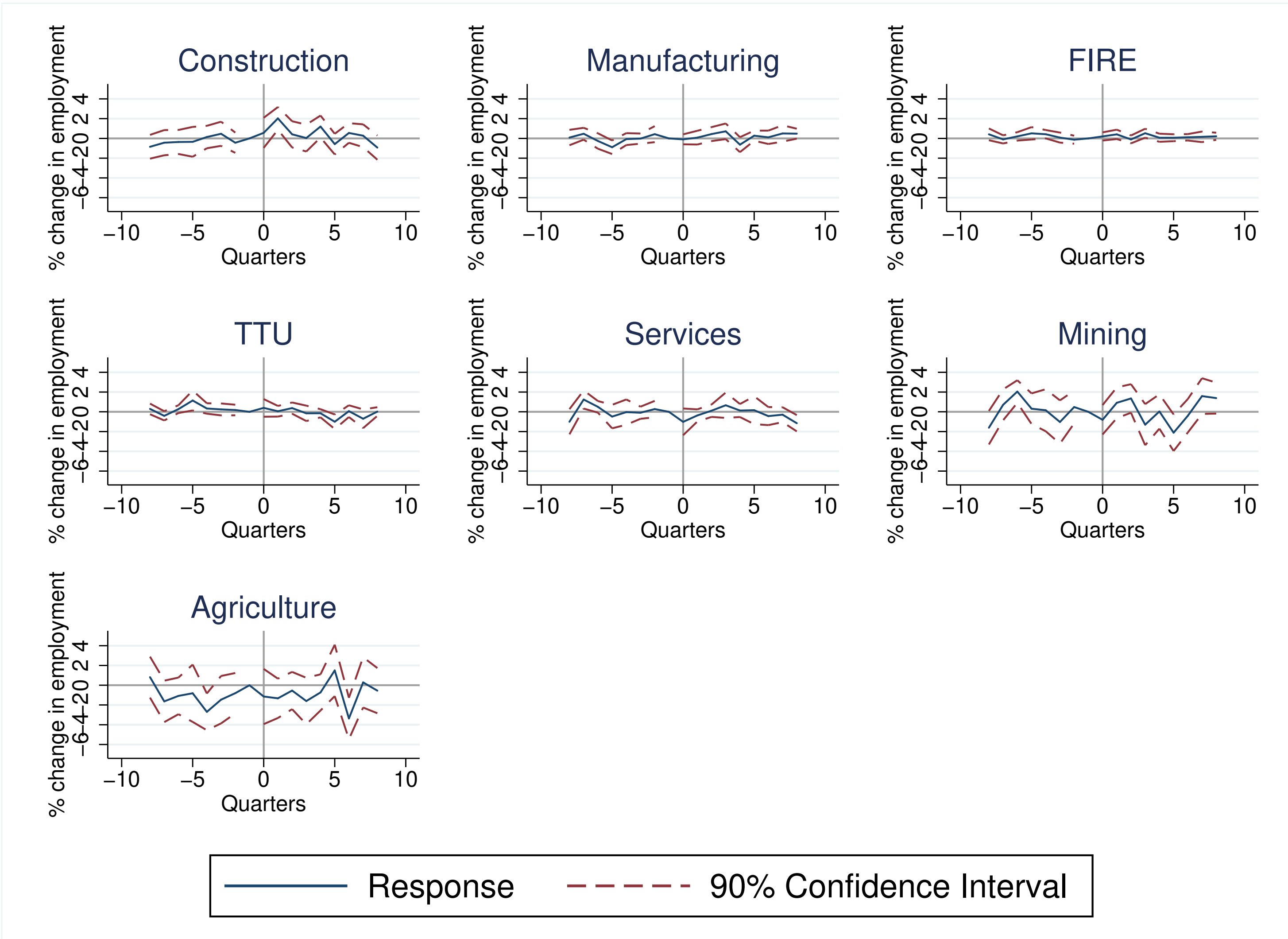
Note: The solid line plots the monthly response of employment. The dotted line plots the 90% confidence interval.

Figure 2.7: Effect of Large Tornadoes on Labor Market Outcomes (All Industries)



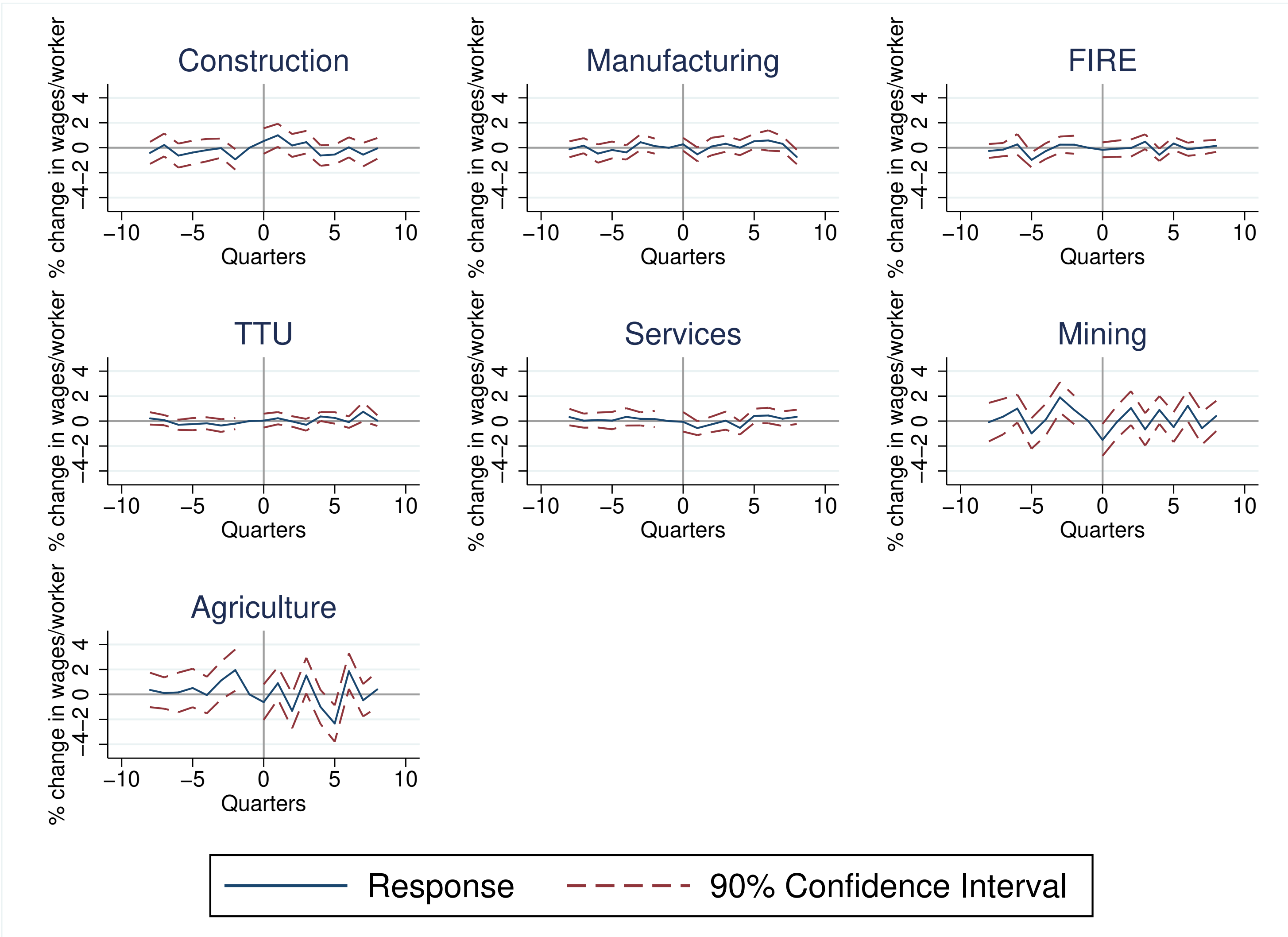
Note: The solid line plots the response of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the direct effect and the lower panel plots neighboring effects. Large tornadoes are defined as the tornadoes that are classified as EF2 or higher.

Figure 2.8: Effect of Violent Tornado on Employment in Directly Affected Counties



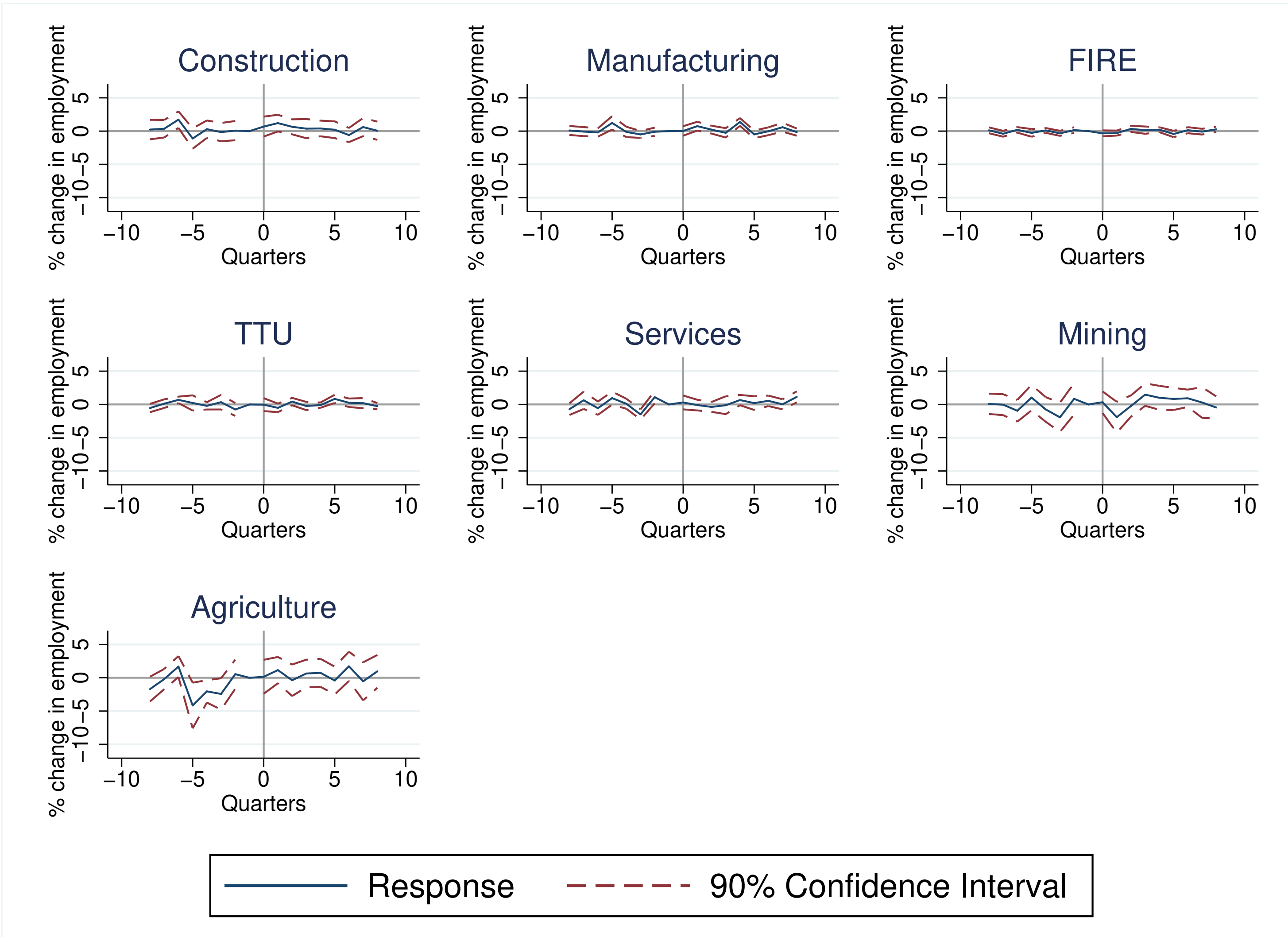
Note: The solid line plots the response of employment. The dotted line plots the 90% confidence interval.

Figure 2.9: Effect of Violent Tornado on Wages per Worker in Directly Affected Counties



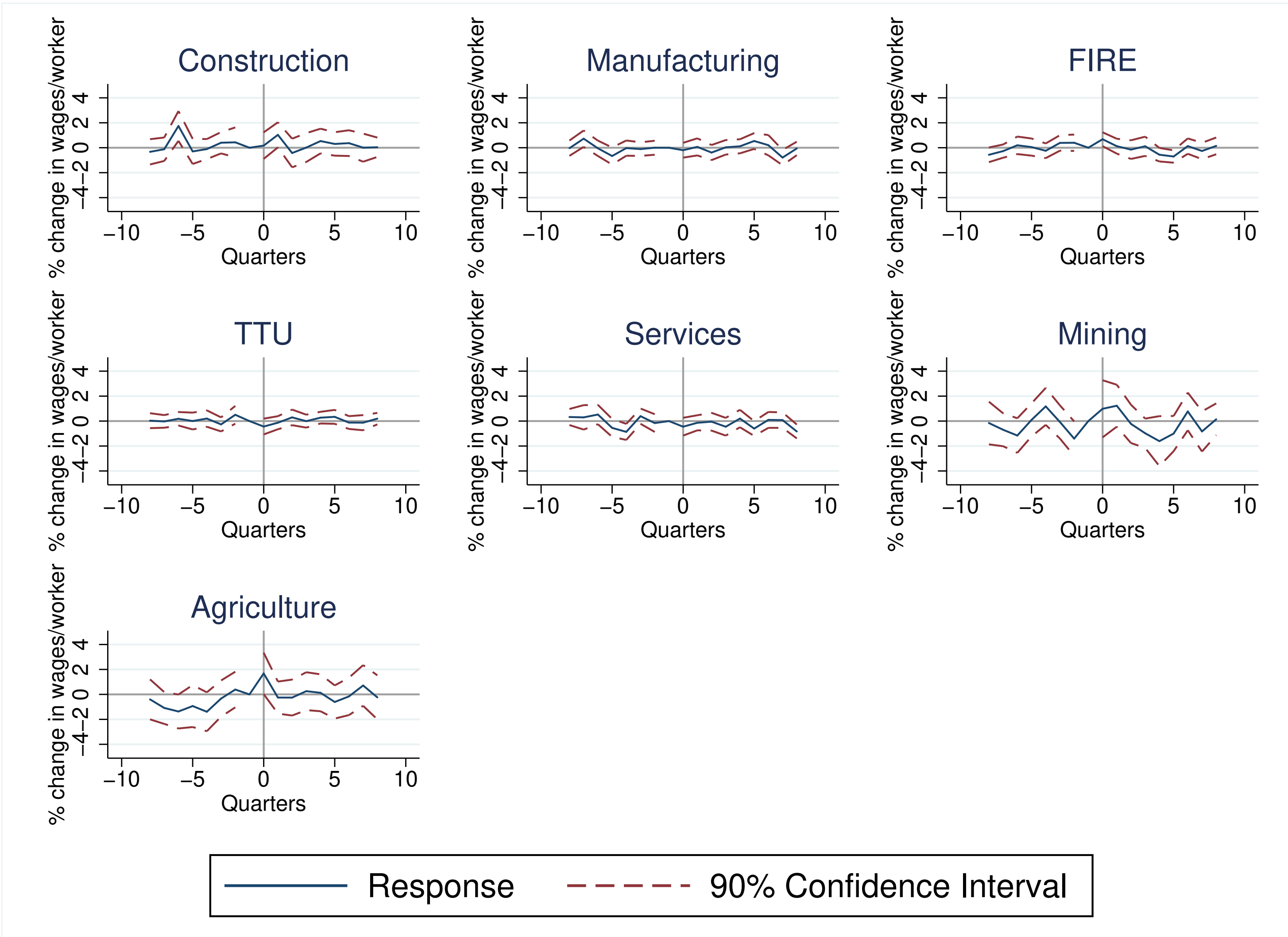
Note: The solid line plots the response of wages per worker. The dotted line plots the 90% confidence interval.

Figure 2.10: Effect of Violent Tornado on Employment in Neighboring Counties



Note: The solid line plots the response of employment. The dotted line plots the 90% confidence interval.

Figure 2.11: Effect of Violent Tornado on Wages per Worker in Neighboring Counties



Note: The solid line plots the response of wages per worker. The dotted line plots the 90% confidence interval.

Chapter 3 The Long-Run Effects of Natural Disasters and Terrorist Attacks

3.1 Introduction

Over the last several decades, infrequent disasters like terrorist attacks and natural disasters have become an increasing concern for countries across the globe. Some of these events have resulted in destruction of catastrophic proportions in terms of human life as well as monetary value. For instance, the 2011 earthquake in Japan resulted in 19,846 deaths, 368,820 people affected, and property damage of $210 million[1]. In contrast, terrorist attacks usually target a small region of a nation, but they can have large consequences. For example, the September 11, 2001 attacks on the U.S. led to 2,996 deaths and property loss of catastrophic proportion (likely greater than $1 billion)[2]. Countries have since stepped up their efforts to reduce both external and internal threats.

These events - terrorist attacks and natural disasters - are instances of arguably exogenous negative shocks that can affect both human and physical capital. However, the magnitude of the shock varies considerably. Despite this, several studies have found similar negative effects on GDP growth. In this chapter, I use a common conceptual framework of the Solow-Swan growth model, to examine the dynamics of GDP growth in the aftermath of these different types of shocks. I also distinguish between the different channels through which natural disasters and terrorist attacks affect growth. I find that although natural disasters collectively lead to lower GDP growth, this is not true for all types of natural disasters considered separately. I find that the same is true for terrorist attacks. While terrorist attacks result in

[1]These values are from EM-DAT, the database for natural disasters)
[2]These values are from the Global terrorism database.

insignificant changes in GDP growth, domestic terrorist attacks have a declining effect on GDP growth. Examining the different channels through which each shock affects GDP growth reveals some of the reasons behind the negative effects observed despite the difference in magnitude of the shock. Most revealing of the channels is the decomposed government expenditure. Terrorist attacks generally lead to increased military spending, such as war efforts or defense spending to strengthen a nation's borders, and reconstruction spending. After a natural disaster, on the other hand, the government's response is usually focused on reconstruction efforts.

Previous studies have addressed the impact of transnational and domestic terrorism on economic growth. Transnational terrorism results in a decline in GDP per capita (Abadie and Gardeazabal, 2003; Blomberg et al., 2004; Gaibulloev and Sandler, 2008, 2009, 2011). While domestic terrorism has a negative effect on growth in Western Europe (Gaibulloev and Sandler, 2008), it has no significant effect on growth in Africa (Gaibulloev and Sandler, 2011). Thus studies have found heterogeneous effects of the transnational and domestic terrorist attacks. Additionally, Gaibulloev and Sandler (2011) suggest that transnational and domestic terrorist attacks affect growth differently for various reasons. They argue that as the frequency of occurrence of domestic terrorism exceeds that of transnational terrorist attacks it leads to a perception of persistence. People and businesses accept domestic terrorism as part of their daily routine. They contend that it is cheaper to counter domestic terrorism than transnational terrorism since they do not require additional border security measures nor do they require offensive operations in foreign countries. Studies focused on transnational terrorism have found a negative effect of transnational terrorist attacks on foreign direct investment (Abadie and Gardeazabal, 2008; Enders and Sandler, 1996) which is an important source of savings for developing countries. Furthermore, the threat of transnational terrorism may curb the inflow of foreign aid. Hence following the example of previous studies, I distinguish between transnational and domestic terrorist attacks and find that there are some differences in the way that growth and its components respond to these different types of terrorism.

On the other hand, literature is inconclusive on the response of GDP to natural disasters. Albala-Bertrand (1993) and Skidmore and Toya (2002) find that disasters have a positive impact on economic growth. In contrast, Noy and Nualsri (2007) find a decline in output per capita due to a decline in human capital as a result of disasters. Raddatz (2009) and Jaramillo (2009) also find support for Noy and Nualsri (2007) using a different set of countries and different sample periods. Fomby et. al (2013) find that droughts, earthquakes and storms result in a drop in GDP. However, they find that floods have a positive effect on GDP, which may indicate the benefit that floods may have on agricultural productivity. Several other studies also find that natural disasters have a negative effect on growth (Cavallo et al., 2013; Hochrainer, 2009; Cuaresma et al., 2008; Hallegatte and Dumas, 2009).

Much of the research on terrorism focuses on the channels through which terrorism affects short run economic growth. Studies show that terrorism gives rise to uncertainty which in turn reduces investment and foreign direct investment (Abadie and Gardeazabal, 2003, 2008; Enders and Sandler, 1996; Bandyopadhyay et. al, 2013). Another channel through which terrorism affects growth is government spending. Terrorist attacks cause governments to redirect spending towards security and away from more growth-enhancing investments (Gaibulloev and Sandler, 2008). Terrorist attacks also increase the cost of doing business because of larger insurance premiums and greater security expenditures. Destroyed infrastructure leads to business disruption. For example, the IRA attacks on London's financial district at the Baltic Exchange on April 10, 1992 is estimated to have resulted in $800 million in lost business (Gaibulloev and Sandler, 2009).

On the other hand, the literature on disasters focuses on financing reconstruction and policy-making in their aftermath. Although there are means to predict the occurrence of a disaster, uncertainty regarding the magnitude of the loss, moral hazard, and adverse selection lead to under-insurance. For instance, Hurricane Katrina resulted in insurance claims of $46.3 billion while the estimated damage was $158.2 billion (Kunreuther and Pauly, 2010). The problem of insuring against disasters is larger for developing economies. They face market limitations and political resistance as well as inadequate and inefficient institutions (Healy and Malhotra, 2009; Pettersen et. al.,2005) along with resource constraints.

Studies have also focused on the differential effects of natural disasters on developing and developed countries and find that the adverse effect on growth of developing countries is much larger than on developed countries (Noy, 2009; Fomby et al. 2013). Similar studies have also been done for transnational terrorism. Gaibulloev and Sandler (2009) find that developed Asian countries absorb the effects of a transnational terrorist attack, while developing Asian countries experience a declining effect in income per capita growth. Following this vein of literature, I examine the growth effects of terrorism and natural disasters on developing and emerging economies separately. I find that developed and emerging economies are able to absorb the shock of transnational and domestic terrorism, however, only developed economies are able to absorb the shock of natural disasters. I also examine the channels through which growth is affected for developed and emerging economies and find that the channels through which different disasters affect GDP growth also varies.

3.2 Conceptual Framework

The basic Solow-Swan growth model helps in understanding how negative shocks like natural disasters and terrorist attacks may affect GDP growth. Consider the following Cobb-Douglas production function with decreasing marginal returns and constant returns to scale.

$$Y = AK^{\alpha}L^{1-\alpha} \tag{3.1}$$

Where Y is output, A is the level of technology or a general productivity parameter, K is capital, L is labor, and α and $(1-\alpha)$ represent the factor shares of capital and labor respectively.

The Solow model assumes that only capital is accumulated over time and a constant fraction of the output is saved and invested as capital formation. The model also assumes that labor experiences a fixed growth rate that is the same as the population growth rate and the level of technology grows at an exogenous growth rate g. Hence,

$$\Delta K = sY - \delta K \tag{3.2}$$

$$\Delta L = nL \tag{3.3}$$

where s is the constant fraction of the output that is saved and invested as capital formation, δ is the depreciation rate of the capital, and n is the population growth rate. The next step is to identify the growth rate of capital and output in the transition to the steady state. After converting the variables to per-worker and some algebra, the growth rates of capital per worker and output per worker can be given by

$$\dot{k} = \frac{\Delta k}{k} = s\frac{y}{k} - (\delta + n + g) \tag{3.4}$$

$$\dot{y} = \frac{\Delta y}{y} = \alpha \dot{k} \tag{3.5}$$

The growth rate of output and capital go hand-in-hand. Therefore the growth rate of capital per worker and thus output per worker is given by the difference of sy and $(\delta + n + g)k$.

Examining this model suggests that natural disasters and terrorist attacks may affect growth through the following channels (1) the level of capital per worker and (2) the destruction of labor. Natural disasters and terrorist attacks may destroy capital by destroying railway lines, roads, dams, communication lines, etc. They also destroy labor due to the deaths that they cause. Table 3.1 shows that on average the number of deaths caused by natural disasters is far greater than the deaths caused by terrorist attacks. On average natural disasters result in 0.012 deaths per thousand inhabitants of a country whereas terrorist attacks result in 0.001 deaths per thousand inhabitants. The nature of natural disasters would suggest that they can also cause huge destruction of capital. If a natural disaster destroys more capital than labor, reducing k, the model suggests that the economy will experience a short period of higher growth as the economy transitions back to its steady state. Although a country may experience higher growth in the short run, it is not "better off". On the other hand, if the number of deaths caused by a natural disaster exceeds the level of capital destroyed, capital per worker in the economy will be greater than before and the economy will experience a decline in growth. This suggests that the immediate after effect on growth is ambiguous in the aftermath of natural disasters. Despite terrorist attacks, on average, causing lower number of deaths and capital destruction than natural disasters, their effect on growth too is ambiguous for the same reasons as that of natural disasters. Additionally, if skilled or more productive labor leave due to natural disasters or terrorist attacks, productivity would decline. This would result in the marginal product of capital to decline for every level of capital per worker resulting in a decline in growth.

3.3 Data

3.3.1 Data Description

The data on natural disasters were obtained from the Emergency Disaster Database (EM-DAT) collected by the Center for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain (UCL). This dataset has worldwide coverage. It contains data on the occurrence of natural disasters, the number of fatalities, the number affected, and the monetary damage that was inflicted by said natural disaster. Disasters are recorded in the EM-DAT database when at least one of the following criteria is fulfilled: (1) 10 or more people are reported killed; (2) 100 people are reported affected; (3) a state of emergency is declared: and/or (4) international assistance is called for. These disasters can be hydro-meteorological disasters that include floods, wave surges, storms, droughts, landslides, and avalanches; geophysical disasters that include earthquakes, tsunamis, and volcanic eruptions; or biological disasters that include epidemics and insect infestations. This paper excludes disasters that could have been prevented or cured by human intervention, and focuses on three of the most commonly occurring hydro-meteorological and geophysical disasters - floods, earthquakes, and storms. These events include the earthquake in Japan in 2011 as well as the earthquake in Indian Ocean in 2004. Although EM-DAT includes the earthquake in Haiti in 2010, the final dataset does not include this due to lack of macroeconomic data for Haiti. The dataset classifies hurricanes primarily as storms. Therefore, the final data includes hurricanes like Hurricane Katrina as a storm.

The U.S. Department of State (2003: xii) defines terrorism as 'terrorism means premeditated, politically motivated violence against non-combatant targets by subnational groups or clandestine agents, usually intended to influence an audience'. My definition of terrorism closely follows this definition. I broadly define terrorism as the use of violence and intimidation to gain political or social leverage. A key aspect of terrorism is that it usually circumvents democratic processes by threatening the citizens of the target country. This would suggest that the objective behind the violence goes beyond the victims of the incident. Another aspect of terrorism is that either individuals or groups initiate the violence. The definition of terrorism includes state-sponsored terrorism, but does not include incidents of a state employing violence against its own citizens. That is, the state may provide assistance like safe-haven, financing, or information, but does not itself employ violence.

The data on terrorism is from the Global Terrorist Database (GTD). This dataset includes violent incidents that are initiated by individuals or groups to propagate a political or religious goal. The dataset requires that two out of the following three conditions be met for an incident to be classified as a terrorist attack: (1) the incident must be aimed at achieving a political, economic, religious, or social goal; (2) it must be intended to influence or be a message to individuals other than the direct victims; and (3) it violated International Humanitarian Law.

Terrorism can be classified into two types: domestic terrorism and transnational terrorism. Domestic terrorism is home grown and affects only the institutions, citizens, property, and policies of the host country. The venue, target, and victims along with the initiators of the incident are from the same country. For example, the series of bombings across Mumbai, India on March 12, 1993 that killed 317 people and injured 1,250 is an example of a domestic terror attack. This incident was instigated by home grown extremists in the wake of religious riots. Another example is the Oklahoma City bombing on April 19, 1995 where the perpetrator, target and the victims of this incident were all from the same country. This incident killed 168 people and injured 650. Transnational terrorism concerns more than one country. International skyjacking or the mailing of a letter bomb to another country involves more than one country. An example of transnational terror attack is the shooting down of a Russian airline in Egypt on October 31, 2015. GTD includes data on both domestic and transnational terrorist attacks. However, it does not distinguish between the two. For this reason, I follow the steps outlined by Enders et. al (2011) to distinguish between domestic and transnational terrorist attack. These steps are outlined in the appendix.

The measure for natural disasters and terrorist attacks accounts for the accumulated deaths per thousand inhabitants of a country in a given year. That is, if a country has experienced multiple natural disasters in a given year, the measure accounts for the sum of these deaths per thousand inhabitants of said country. It is also possible that a country can experience the different types of natural disasters and terrorist attacks in the same year, e.g., a domestic terrorism and transnational terrorism in the same year or floods and an earthquake in the same year. The measure for these separate types of natural disasters and terrorist attacks only takes into account the deaths caused by these specific types of events. In my analysis I include events that result in deaths that are greater than the 75th percentile of deaths caused by that type of event throughout the world[3]. This definition is similar to the one used by Cavallo et al. (2013), who use the 99th, 90th, and the 75th as their thresholds[4]. The 75th percentile cutoff can be quantified as a natural disaster that kills more than 0.002 people per thousand inhabitants of a country, and terrorist attacks that have caused more than 0.0006 deaths per thousand inhabitants of a country. The cut off for specific natural disasters and terrorist attacks are listed in Table 3.2. This table clearly shows that there is a huge disparity in the magnitude of the destruction (shock) caused by the different natural disasters and terrorist attacks. The incidents accounted for in the final dataset include the Oklahoma City bombing of 1995 as a

[3]I examine the assumption of non-linear response to deaths by estimating the results with all deaths and their squared variable and find a convex relationship between number of deaths and GDP growth. These results can be seen in table A.3 in the appendix. This suggests that it is events that result in high number of deaths that have the strongest effect on GDP growth.

[4]I examine my data with the 99th and 90th percentile as the threshold and baring a few differences the results are similar to that of the 75th percentile intensity. These estimations are described as part of robustness checks

domestic terrorist attack, as well as the Mumbai transnational terrorist attacks of 2008. They also include Hurricane Katrina in 2005, although Hurricane Sandy in 2012 is not included as the number of deaths caused by this storm falls short of the threshold.

Table 3.3 lists the frequency of occurrence of instances of the different types of natural disasters that result in accumulated deaths greater than the 75^{th} percentile of the world pooled deaths due to a specific type of event that a country experiences in a given year. The table shows that the instances of natural disasters that have occurred in the dataset are equivalent to the instances of terrorist attacks, although there is a disparity in the number of occurrence of each specific type of event. Examining the table reveals that the most frequent natural disasters in the dataset are floods, whereas the frequency of transnational and domestic terrorist attacks are comparable. It is clear from the table that not all countries have experienced a large event. Among the countries that have experienced instances of large transnational terrorist attacks, countries like Israel and Ireland have experienced 26 and 18 instances respectively between 1970 and 2015, while countries like the United States, France, and Sweden have experienced only one instance of a transnational terrorist attack of a similar magnitude between 1970 and 2015. There have also been transnational terrorist incidents in countries like Australia, Brazil and Germany, but the incidents on collectively did not yield a death toll greater than the threshold in any given year. The dataset also consists of countries like Mauritius that have not experienced a transnational terrorist attack between 1970 and 2015. For domestic terrorism too there are some countries like the Philippines and Sri Lanka that experience 19 instances of large domestic terrorist attacks, while countries like Austria and Switzerland experience only one year where accumulated deaths by domestic terrorism exceeded the threshold. Although countries like Portugal, Sweden, and Japan have experienced domestic terrorist attacks between 1970 and 2015, none of the attacks resulted in casualties greater than the defined threshold. Additionally, United Kingdom and Mongolia are rare instances of countries that have not experienced a domestic terrorist attack between 1970 and 2015 (The IRA attacks have been identified by the GTD database as either having international ideologies or logistics and are therefore classified as transnational terrorist attacks). Variation in the frequency of natural disasters also occurs across countries. India, Bangladesh, and Sri Lanka have experienced 13 or more instances where the accumulated deaths due to floods exceeded the threshold, while countries like Italy and Malaysia have only experienced one such instance. Countries like Netherlands and France have experienced floods between 1970 and 2015, however these floods have not caused fatalities to exceed the defined threshold. Countries like New Zealand and Japan have experienced one instance where the accumulated deaths due to earthquake exceeds the cutoff, whereas Indonesia and Iran have experienced more than 11 such earthquakes. Despite regions of United States being prone to earthquakes, in none of the years did the death toll due to earthquakes exceed the threshold. Storms are concentrated between relatively few countries, with the Philippines experiencing the maximum instances of storms that lead to higher than the cutoff deaths due to storms in a given year, followed by Bangladesh. Countries like United Kingdom and Kenya experienced one instance of higher than threshold accumulated deaths due to storms. Whereas countries like Kuwait and Bahrain have experienced no storms between 1970 and 2015.

The economic indicators - real GDP per capita, government expenditure as a share of GDP, military expenditure as a share of GDP, gross fixed capital formation as a share of GDP, trade as a share of GDP, and population - are from the World Bank's World Development Indicators (WDI). I identify non-military government expenditure as a share of GDP as the part of government expenditure that is left after subtracting military expenditures from it. Military expenditure is not available for all of the countries and hence the analysis for the military and non-military expenditures comprises of fewer countries than the entire sample. Educational attainment is from Barro and Lee (2013), and Polity 2 score is from the Polity IV dataset. The World Bank Analytical Classification classifies countries based on income. Using this data, I identify high income countries in 2015 as developed economies and the remaining as emerging economies.

The resulting dataset consists of an unbalanced annual panel of 125 countries spanning from 1970 to 2015. This sample includes 41 developed economies and 84 emerging economies. Table 3.1 reports the summary statistics of the economic indicators along with the frequency of occurrence of different disasters. The table shows that average annual GDP growth for all countries is 1.89 percent. The table also shows that the emerging economies in the sample have been growing at a slower rate than developed economies. Capital formation and government expenditures as a share of GDP does not vary much between developed and emerging economies. The table shows that developed economies enjoy more trade openness than emerging economies. The summary statistics show that, on average, fewer people per thousand inhabitants of a country are killed due to transnational and domestic terrorist attacks as compared to floods, earthquake, and storms. It also illustrates that on average, the number of deaths per thousand inhabitants of a country is greater in emerging economies regardless of the type of incident.

3.4 Methodology

To determine the effect that these disasters have on the economic growth, I use a standard growth regression equation.

$$\Delta ln(y_{it}) = \beta_0 + \beta_1 ND_{it} + \beta_2 Terror_{it} + X'_{it}\delta + \alpha_i + \lambda_t + v_{it} \tag{3.6}$$

where, y_{it} is the real GDP per capita for country i in year t. ND_{it}, and $Terror_{it}$ are the natural log of the number of deaths per thousand inhabitants that occurred due to the events in country i in time t. X_{it} is the vector of controls and α_i and λ_t are the country and year fixed effects.

I include some determinants of GDP growth in the estimation equation as controls, drawing from the vast growth literature (Barro, 1991; Barro and Sala-i-Martin, 2003; Mankiw, Romer and Weil, 1992; among others). These are (1) the initial level of real GDP per capita, (2) trade openness (real exports plus real imports over real GDP), (3) investment, (4) government consumption, (6) population growth from WDI; (6) educational attainment from Barro and Lee (2013); and (7) Polity 2 score (a measure of democracy) from Polity IV dataset.

To examine the channels through which these destructive events affect GDP growth I estimate the following equation:

$$Channel_{it} = \theta_0 + \theta_1 ND_{it} + \theta_2 Terror_{it} + \gamma X_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.7}$$

where $Channel_{it}$ is the mechanism for country i in time t through which a destructive event can affect GDP growth. I investigate investment share of GDP, military expenditures as a share of GDP and non-military government expenditures as a share of GDP as possible channels through which these events may affect GDP growth. X_{it} is a vector of controls. Based on previous literature that has examined channels through which growth may be affected such as Gaibulloev and Sandler (2008, 2009), I use the same controls as in growth equation 3.6.

3.5 The Growth Effects of Natural Disasters and Terrorist attacks

Table 3.4 reports the estimation results of the effect of large natural disasters and terrorist attacks on GDP growth using the full sample. The first three specifications examine the different types of natural disasters and terrorist incidents when combined into two variables. The results from these specifications show that on average large terrorist attacks lead to an insignificant change in GDP growth, while a one percent increase in number of deaths per thousand inhabitants of a country due to a large natural disaster leads to a marginally significant decrease of 0.02 percentage points in GDP growth contemporaneously. This decline in GDP growth due to natural disasters is also supported by the vast majority of disaster literature. This reduction in GDP growth rate is also consistent with the short-run Solow model effects described in the previous section.

The results in the fourth specification of Table 3.4 examines transnational terrorist attacks, domestic terrorist attacks, floods, earthquakes, and storms separately. Although large terrorist attacks have no significant effect on GDP growth, when disaggregated into transnational and domestic terrorist attacks, we observe a significant decline in GDP growth in the aftermath of large domestic terrorist attacks. While the decline in GDP growth in the wake of a transnational terrorist attack is not statistically significant, the decline is not different from the statistically significant decline in GDP growth due to domestic terrorist attacks. The results show that a one percent increase in the number of deaths per thousand inhabitants of a country due to domestic terrorism leads to a marginally significant decline of 0.30 percentage points in GDP growth in the year of the attack. Although these results are consistent with findings of Gaibulloev and Sandler (2008) who find that domestic terrorism adversely affect GDP growth in Western Europe, they are at odds with findings of Gaibulloev and Sandler (2011) who show that domestic terrorism has an insignificant effect on GDP growth in Africa. The difference in results can be attributed to a difference in the sample and sample period or in the controls included in the analysis. Although I find no significant effect of transnational terrorism on GDP growth, Gaibulloev and Sandler (2009, 2011) find that transnational terrorist attacks have a negative effect on GDP growth in Asia as well as in Africa. The difference in results could be a due to sample period, geography, or even the control variables included in the model. Gaibulloev and Sandler (2009) focus only on Asia from 1970 to 2004, while Gaibulloev and Sandler (2011) examine countries in Africa from 1970 to 2007.

The response of GDP growth to floods, earthquakes, and storms shows that large floods and storms negatively affect GDP growth, while large earthquakes lead to no significant change in growth. A one percent increase in the number of deaths per thousand inhabitants of a country due to large floods lead to a 0.14 percentage points decline in GDP growth in the contemporaneous year. This decline in growth is statistically significant at the 99% confidence level. A one percent increase in the deaths per thousand inhabitants due to a large storm leads to a smaller decline of 0.03 percentage points in GDP growth in the year of the large storm, although the decline is as statistically significant as the decline from floods. These results vary from findings of Loayza et al. (2009) and Fomby et al. (2013), who find that floods positively affect growth, while the effect of storms is insignificant. They too find that earthquakes have no significant effect on GDP growth. In the framework of the Solow model, these results suggest that floods and storms cause considerable destruction of capital, since the nature of floods and storms suggest far more capital to be destroyed than deaths.

Investigating the channels through which these events may affect GDP growth by estimating equation 3.7 provides a framework to examine how the economy is affected by these different incidents. Tables 3.5 to 3.7 report these estimates. Table 3.5 presents the results of the estimated effects of large natural disasters and terrorist attacks on investment. These results show that investment as a share of GDP does not experience a significant change due to either natural disasters or terrorist attacks examined here. This would suggest that the effect of natural disasters and terrorist attacks on GDP growth through private and public capital is weak at best.

Table 3.6 presents the response of military expenditure to large natural disasters and terrorist attacks. The results show that on average a one percent increase in the number of people killed per thousand inhabitants of a country due to a large terrorist attack increases military expenditures as a share of GDP contemporaneously by 4.54 percent. This increase is significant at the 95% confidence level. Evaluating disaggregated terrorism shows that the increase in military expenditures is mainly due to domestic terrorist attacks. A one percent increase in deaths per thousand inhabitants due to domestic terrorism leads to a 5.97 percent increase in military expenditures as a share of GDP in the year of the attack. The increase in military expenditures suggests that countries attempt to increase safety measures for its citizens in the wake of domestic terrorist attacks. Additionally, increased security measures may act as a signal to businesses that they may not incur as high a cost of doing business in the affected country as they previously believed. Transnational terrorism also increases military expenditures, however this increase is not statistically significant. although the increase in military spending due to transnational terrorism is not significantly different from the increase due to domestic terrorism. This suggests that countries do focus on security even in the wake of transnational terrorism. The table also shows that on average natural disasters do not significantly change military expenditure as a share of GDP.

Table 3.7 reports the response of non-military expenditures to large natural disasters and terrorist attacks. The estimations in this table show that large natural disasters and terrorist attacks do not significantly affect non-military expenditures. However, examining the disaggregated response to natural disasters shows that in the aftermath of floods non-military expenditures increase. A one percent increase in the number of deaths per thousand inhabitants of a country results in a 0.19 percent increase in non-military expenditures as a share of GDP in the contemporaneous year. In the previously conceptualized framework, this result suggests that floods cause destruction of capital in the form of destroyed roads, railways, power lines, etc. Increased non-military government expenditures suggest that resources are being utilized to fix the disrupted flow of these services.

On average, large natural disasters lead to a decline in GDP growth, while large terrorist attacks lead to no significant change. Examining natural disasters and terrorist attacks by type reveals the disparity among these events. I find that although terrorist attacks overall do not decrease GDP growth, domestic terrorism leads to a decline in GDP growth. A channel through which this decline in GDP growth is experienced is increased military expenditures. Among natural disasters, I find that it is floods and storms that reduce GDP growth. It is evident that floods increase non-military government expenditures as infrastructure services are repaired in the aftermath of floods. Domestic terrorist attacks increase military expenditures at the expense of non-military expenses to increase security.

3.5.1 Developed Vs. Emerging Economies

Developed economies are more diversified, have better infrastructure and may also have resources dedicated towards disasters, while emerging economies are more resource constrained. For this reason, developed and emerging economies may respond to negative shocks differently. Examining the effects of the different types of terrorism and natural disasters on GDP growth and the channels through which they affect growth separately for developed and emerging economies could provide a clearer picture of the response to be expected. I define countries that are classified as high income in 2015 as developed and the remaining countries as emerging.

Table 3.8 reports the effect of each type of terrorist attack and natural disasters on GDP growth for developed and emerging economies. The results show that despite the marginal negative effect of domestic terrorism on GDP growth for the full sample, both transnational terrorism and domestic terrorism have no significant effect on GDP growth in either developed or emerging economies. This would suggest that both developed and emerging economies have learned to cope with terrorist attacks. The results also reveal that aggregated natural disasters have no significant effect on GDP growth of developed and emerging economies. However, examining specific disasters shows that while developed economies are indeed better able to absorb the shock of floods, earthquakes, and storms, emerging economies are not as successful. Emerging economies experience a decline in GDP growth due to floods as well as storms. The results indicate that a one percent increase in the number of deaths per thousand inhabitants of a country due to floods leads to a 0.13 percentage points decline in GDP growth, while an increase in the number of deaths per thousand inhabitants of a country due to storms leads to a 0.03 percentage points decline in GDP growth of emerging economies contemporaneously.

Similar to the difference in the response of GDP growth in developed and emerging economies to these disasters, the channels through which they affect growth may also be heterogeneous. Table 3.9 displays the estimates for the effect of large terrorist attacks and natural disasters on investment. These results show that investment as a share of GDP remains statistically unchanged irrespective of the type of event examined here and regardless of whether it occurred in a developed or an emerging economy.

Table 3.10 presents the estimations of the effect of large natural disasters and terrorist attacks on military expenditure as a share of GDP. The results illustrate increased military expenditures due to terrorist attacks in emerging economies. This increase in military expenditures in emerging economies is driven by domestic terrorist attacks. A one percent increase in deaths per thousand inhabitants of a country due to domestic terrorism increases military expenditures as a share of GDP contemporaneously by 6.03 percent in emerging economies. Although military expenditures increase in the wake of domestic terrorist attacks in emerging economies, this increase does not translate to a change in GDP growth. Additionally, although transnational terrorism leads to an insignificant increase in military expenditures, the increase is not statistically different from the increase due to domestic terrorism. This suggests that there is some increase in military expenditures of emerging economies due to transnational terrorism as well.

Table 3.11 reports the results of the response of non-military expenditures to large terrorist attacks and natural disasters as well as their different types. The estimates show that on average terrorist attacks and natural disasters do not significantly affect non-military expenditures in developed and emerging economies. However, examining the different types of natural disasters shows an increase in emerging economies due to floods, while these expenditures decrease in developed countries as a result of storms. The increase in non-military expenditures in the aftermath of floods in emerging economies indicates that resources are being used to repair and resume destroyed infrastructure.

On average, developed countries are better able to absorb negative shocks in the form of natural disasters as well as terrorist attacks. Although emerging economies experience no adverse effects on GDP growth due to transnational and domestic terrorist attacks, military expenditures as a share of GDP experiences an increase in the wake of domestic terrorist attacks. Emerging economies also experience adverse effects on their GDP growth due to floods and storms. Floods in emerging economies result in increased non-military government expenditures due to clean up and restoration. The effect of storms on GDP growth, however, seems to mostly be due to the loss of human life.

3.6 Robustness Checks

I consider an alternate specification to ensure the robustness of the main results presented above. I use an indicator variable in place of the natural log of deaths per thousand inhabitants. In this specification the event variable takes the value one if the number of deaths caused by an event exceeds the threshold of the 75 percentile deaths caused by the same event in a given year. These estimates are reported in tables A.4 to A.7 in the appendix. Table A.4 reports the GDP growth model. These results show that like the main results the occurrence of large terrorist attacks has no significant effect on GDP growth, however the occurrence of large natural disasters has a negative effect on growth. Although the main results show a decline in GDP growth due to domestic terrorism, floods and storms, this effect is not visible in this specification.

Table A.5 shows the response of investment as a share of GDP to this alternate specification. These results support the response observed in the main results. Table A.6 reports the estimates for the military expenditure channel. These results show that, similar to the main results, terrorist attacks and domestic terrorist attacks lead to increased military spending. However, this specification also shows a marginal increase in military expenditures due to transnational terrorist attacks. Table A.7 displays the estimates of the non-military expenditure channel. Unlike the main specification, these results reveal a decline in non-military expenditures in the aftermath of terrorism, although this effect is not observed for the disaggregated transnational and domestic terrorism. Also, unlike the main specification, this specification does not reveal any effects of floods on non-military expenditure.

For the next robustness check I relax the large event criteria and include all the years when a country has experienced at least one event. Tables A.8 to A.11 report these estimates. I find that these results closely follow the main results presented in the previous section. This indicates that the effects that we observe for this specification are driven by larger events.

Further, following the example of Cavallo et al. (2013) I redefine large events as events that have led to fatalities greater than the 90$^{\text{th}}$ percentile and 99$^{\text{th}}$ percentile of the world pooled distribution. Tables A.12 to A.15 presents the estimates when the 90$^{\text{th}}$

percentile is used as the threshold to define large events. For the growth model these results are very similar to the main results. For the channels, this specification shows similar results for all models except for non-military government expenditures. Table A.15 reports the results for non-military government expenditures. These results show that like the main results domestic terrorist attacks reduced these expenditures and floods increase them. Additionally, these results also show that these high intensity storms lead to a marginally significant decline in non-military government expenditures.

Table A.16 displays the results for GDP growth when the intensity measure for natural disasters and terrorist attacks are further escalated to the 99^{th} percentile. These results show that even though collectively these highly intensive natural disasters do not affect GDP growth, separately floods and storms continue to affect GDP growth negatively. For domestic terrorism the marginal decline that is observed in the main results is not significant for these specifications, although the sign on the coefficient continues to be negative. Examining the channels for this specification in tables A.17 to A.19 shows that the results are similar to the main results except for in the case of non-military government expenditures. Table A.19 shows that like the main results floods increase non-military government expenditures, although the marginal decline in these expenditures due to domestic terrorism is not observed. Furthermore, these results also show that these high intensity storms lead to a marginally significant decline in non-military government expenditures.

Overall, some of the differences in results suggest that the estimates are sensitive to the measure of the events. This indicates that there are some details lost when using an indicator variable as opposed to an intensity measure variable that varies within the event type. The results also show that the response of growth and their channels varies based on the intensity of the events.

3.7 Key Findings

Natural disasters and terrorist attacks are similar in that they destroy physical and human capital. In the aftermath of each, reconstruction efforts aim to bring the country affected back on track. Despite this, they do not affect GDP growth in the same way. Natural disasters lead to lower GDP growth, while terrorist attacks do not affect growth. Further, the results here show that not all types of natural disasters have a negative effect on GDP growth and not all types of terrorist attacks have no significant effect on GDP growth. Among natural disasters, floods and storms lead to lower GDP growth, while earthquakes result in no significant change in GDP growth. Examining transnational terrorism and domestic terrorism shows that it is domestic terrorism that leads to a decline in GDP growth.

Evaluating the channels through which these specific natural disasters and terrorist attacks affect GDP growth further reveals the difference between each of these events. Disruption of infrastructure in the aftermath of floods is evident through increased non-military expenditures. Domestic terrorist attacks lead to increased military expenditures, suggesting that countries attempt to implement security measures to make their citizens feel more secure. It also experiences a countering decline in non-military expenditures suggesting a shift in government expenditures.

Examining the effects of disasters separately for developed and emerging economies brings to the forefront the inadequacy of emerging economies to absorb the shock of natural disasters and terrorist attacks. It is evident from the results presented that developed nations are better able to absorb the shock of the different types of terrorist attacks as well as natural disasters. Although emerging economies are able to absorb the shock of transnational and domestic terrorist attacks, the shock of a flood or a storm leads to a fall in GDP growth. Examining the channels through which these incidents affect growth in emerging economies sheds some light on the disaster relief needs of these countries. The results show that floods affect GDP growth through higher non-military government expenditure. Hence, floods affect growth not only through destruction and loss of human life, but also through increased government expenditures. Storms on the other hand affect growth through loss of human life.

3.8 Tables

Table 3.1: Summary Statistics

	All	Developed	Emerging
GDP Growth	0.0189	0.0216	0.0176
	(0.0484)	(0.0380)	(0.0528)
Capital Formation (% of GDP)	22.34	23.93	21.55
	(7.246)	(5.954)	(7.688)
Trade Openness (% of GDP)	75.43	88.01	69.20
	(49.31)	(65.34)	(37.48)
Government Consumption (% of GDP)	15.75	18.48	14.39
	(5.859)	(4.748)	(5.884)
Military Expenditures (% of GDP)	2.523	2.994	2.269
	(2.344)	(3.114)	(1.743)
Educational Attainment	18.74	28.95	13.68
	(15.80)	(14.69)	(13.76)
Population growth	0.0164	0.00921	0.0199
	(0.0132)	(0.0139)	(0.0112)
Polity 2	3.068	7.279	0.982
	(7.018)	(5.877)	(6.589)
Terror (Deaths per thousand)	0.00141	0.000512	0.00190
	(0.00698)	(0.00253)	(0.00844)
Transnational Terror (Deaths per thousand)	0.000672	0.000497	0.000779
	(0.00504)	(0.00246)	(0.00610)
Domestic Terror (Deaths per thousand)	0.00114	0.000168	0.00159
	(0.00565)	(0.000948)	(0.00677)
Natural Disaster (Deaths per thousand)	0.0123	0.00132	0.0170
	(0.139)	(0.00729)	(0.166)
Flood (Deaths per thousand)	0.00276	0.000603	0.00344
	(0.0306)	(0.00181)	(0.0350)
Earthquake (Deaths per thousand)	0.0334	0.00396	0.0416
	(0.260)	(0.0176)	(0.294)
Storm (Deaths per thousand)	0.00654	0.000526	0.0109
	(0.0919)	(0.00118)	(0.120)
N	4600	1524	3076
Countries	125	41	84

mean coefficients; sd in parentheses

The table reports the pooled average of the variables for an unbalanced panel of countries spanning from 1970 to 2015. The number of observations for military expenditures are 4293 for the full sample, 1509 for the developed countries sample, and 2784 for the emerging countries sample.

Table 3.2: Large Event Definition

	Killed per thousand inhabitants of a country
Transnational Terrorism	0.0002
Domestic Terrorism	0.0005
Floods	0.0016
Earthquake	0.0010
Storms	0.0011

The table reports the deaths per thousand inhabitants of a country at the 75 percentile of the World pooled distribution from 1970 to 2015.

Table 3.3: Number of Events

	All	Developed	Emerging
Terror	532	97	435
	(91)	(22)	(69)
Transnational Terrorism	359	104	255
	(78)	(19)	(59)
Domestic Terrorism	396	40	356
	(80)	(16)	(64)
Disaster	589	60	529
	(92)	(18)	(74)
Flood	445	31	414
	(89)	(12)	(77)
Earthquake	130	17	113
	(39)	(6)	(33)
Storm	266	55	211
	(68)	(20)	(48)

Overall No. of instances that result in accumulated deaths greater than the 75 percentile of the world pooled deaths between due to a specific type of event that a country experiences in a given year with No. of Countries that have experienced these instances in parenthesis. This data spans from 1970 to 2015.

Table 3.4: Estimation of Growth Model

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.2468		-0.2474	
	(0.2344)		(0.2343)	
$Transnational_{it}$				-0.1684
				(0.4771)
$Domestic_{it}$				-0.3046*
				(0.1766)
$NaturalDisaster_{it}$		-0.0200*	-0.0201*	
		(0.0115)	(0.0115)	
$Flood_{it}$				-0.1415***
				(0.0525)
$Earthquake_{it}$				-0.0050
				(0.0088)
$Storm_{it}$				-0.0316***
				(0.0116)
$ln(GDP)_{it-1}$	-0.0446***	-0.0440***	-0.0444***	-0.0446***
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
$ln(Education)_{it}$	-0.0034	-0.0034	-0.0034	-0.0035
	(0.0023)	(0.0024)	(0.0023)	(0.0024)
$Populationgrowth_{it}$	-0.5574***	-0.5518***	-0.5566***	-0.5611***
	(0.1757)	(0.1779)	(0.1758)	(0.1757)
$ln(G/GDP)_{it-1}$	-0.0164***	-0.0166***	-0.0165***	-0.0164***
	(0.0059)	(0.0060)	(0.0060)	(0.0059)
$ln(I/GDP)_{it-1}$	0.0153***	0.0153***	0.0152***	0.0154***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
$ln(trade)_{it-1}$	0.0325***	0.0325***	0.0324***	0.0322***
	(0.0066)	(0.0065)	(0.0065)	(0.0065)
$Polity_{it}$	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is GDP growth, the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75^{th} percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.5: Estimation of Investment Model

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.5623		-0.5629	
	(0.9709)		(0.9704)	
$Transnational_{it}$				-0.6917
				(1.5246)
$Domestic_{it}$				-0.4620
				(0.9924)
$NaturalDisaster_{it}$		-0.0226	-0.0227	
		(0.0679)	(0.0679)	
$Flood_{it}$				0.2322
				(0.1736)
$Earthquake_{it}$				-0.0372
				(0.0862)
$Storm_{it}$				-0.0453
				(0.0637)
$ln(GDP)_{it-1}$	0.1234**	0.1243**	0.1236**	0.1239**
	(0.0582)	(0.0578)	(0.0582)	(0.0582)
$ln(Education)_{it}$	0.0838***	0.0836***	0.0838***	0.0839***
	(0.0286)	(0.0286)	(0.0286)	(0.0287)
$Populationgrowth_{it}$	3.8487***	3.8609***	3.8494***	3.8575***
	(1.3860)	(1.4004)	(1.3861)	(1.3981)
$ln(G/GDP)_{it-1}$	-0.0803	-0.0806	-0.0804	-0.0807
	(0.0499)	(0.0499)	(0.0499)	(0.0498)
$ln(trade)_{it-1}$	0.2754***	0.2755***	0.2753***	0.2755***
	(0.0586)	(0.0586)	(0.0586)	(0.0587)
$Polity_{it}$	0.0058**	0.0058**	0.0058**	0.0058**
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is the natural log of Investment (% of GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75^{th} percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.6: Estimation of Military Expenditures Model

	(1)	(2)	(3)	(4)
$Terror_{it}$	4.5426**		4.5438**	
	(1.7983)		(1.7995)	
$Transnational_{it}$				2.5037
				(2.8195)
$Domestic_{it}$				5.9780***
				(1.4995)
$NaturalDisaster_{it}$		0.0363	0.0377	
		(0.0459)	(0.0476)	
$Flood_{it}$				-0.0027
				(0.1094)
$Earthquake_{it}$				0.0962
				(0.0718)
$Storm_{it}$				-0.1199
				(0.0845)
$ln(GDP)_{it-1}$	-0.0585	-0.0653	-0.0590	-0.0593
	(0.0699)	(0.0703)	(0.0699)	(0.0696)
$ln(Education)_{it}$	0.0281	0.0295	0.0281	0.0276
	(0.0350)	(0.0346)	(0.0350)	(0.0351)
$Populationgrowth_{it}$	-2.5075	-2.5826*	-2.5093	-2.4086
	(1.6146)	(1.5416)	(1.6145)	(1.5377)
$ln(I/GDP)_{it-1}$	0.0491	0.0467	0.0493	0.0494
	(0.0404)	(0.0409)	(0.0405)	(0.0405)
$ln(trade)_{it-1}$	-0.0712	-0.0729	-0.0711	-0.0703
	(0.0464)	(0.0467)	(0.0464)	(0.0462)
$Polity_{it}$	-0.0103***	-0.0105***	-0.0103***	-0.0102***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75th percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.7: Estimation of Non-Military Government Expenditures Model

	(1)	(2)	(3)	(4)
$Terror_{it}$	-1.3663		-1.3672	
	(1.1349)		(1.1350)	
$Transnational_{it}$				0.4564
				(1.7980)
$Domestic_{it}$				-2.6764*
				(1.5396)
$NaturalDisaster_{it}$		-0.0264	-0.0269	
		(0.0437)	(0.0435)	
$Flood_{it}$				0.1943**
				(0.0767)
$Earthquake_{it}$				-0.0421
				(0.0552)
$Storm_{it}$				-0.0559
				(0.0341)
$ln(GDP)_{it-1}$	0.0505	0.0527	0.0508	0.0512
	(0.0655)	(0.0655)	(0.0656)	(0.0656)
$ln(Education)_{it}$	0.0114	0.0110	0.0114	0.0119
	(0.0275)	(0.0274)	(0.0275)	(0.0276)
$Populationgrowth_{it}$	-1.8774	-1.8540	-1.8761	-1.9632
	(1.4011)	(1.3965)	(1.4014)	(1.3903)
$ln(I/GDP)_{it-1}$	-0.0450	-0.0443	-0.0451	-0.0456
	(0.0412)	(0.0412)	(0.0412)	(0.0412)
$ln(trade)_{it-1}$	0.1537***	0.1541***	0.1536***	0.1527***
	(0.0537)	(0.0537)	(0.0537)	(0.0536)
$Polity_{it}$	0.0123***	0.0124***	0.0123***	0.0123***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of non-military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75$^{\text{th}}$ percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.8: Estimation of Growth Model for Developed and Emerging Economies

	(1) Developed	(2) Emerging	(3) Developed	(4) Emerging
$Terror_{it}$	-0.2188	-0.1601		
	(0.2731)	(0.2196)		
$Transnational_{it}$			-0.1962	-0.2040
			(0.3665)	(0.4913)
$Domestic_{it}$			-0.2171	-0.1349
			(0.6969)	(0.1907)
$NaturalDisaster_{it}$	-0.0177	-0.0183		
	(0.1067)	(0.0114)		
$Flood_{it}$			-1.5256	-0.1384**
			(1.1181)	(0.0543)
$Earthquake_{it}$			0.0655	-0.0033
			(0.1228)	(0.0084)
$Storm_{it}$			-0.7545	-0.0296**
			(0.8613)	(0.0147)
$ln(GDP)_{it-1}$	-0.0412***	-0.0470***	-0.0424***	-0.0472***
	(0.0068)	(0.0077)	(0.0067)	(0.0078)
$ln(Education)_{it}$	-0.0001	-0.0054*	0.0001	-0.0056*
	(0.0041)	(0.0032)	(0.0041)	(0.0032)
$Populationgrowth_{it}$	-1.0078***	-0.1146	-1.0003***	-0.1124
	(0.1658)	(0.2939)	(0.1658)	(0.3008)
$ln(G/GDP)_{it-1}$	-0.0435***	-0.0140**	-0.0446***	-0.0138**
	(0.0079)	(0.0065)	(0.0078)	(0.0065)
$ln(I/GDP)_{it-1}$	0.0108	0.0104*	0.0109	0.0106*
	(0.0156)	(0.0058)	(0.0156)	(0.0057)
$ln(trade)_{it-1}$	0.0460***	0.0354***	0.0459***	0.0352***
	(0.0101)	(0.0075)	(0.0101)	(0.0075)
$Polity_{it}$	0.0003	-0.0003	0.0002	-0.0003
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
N	1524	3076	1524	3076

Standard errors in parentheses

The dependent variable in this table is GDP growth, the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75^{th} percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.9: Estimation of Investment Model for Developed and Emerging Economies

	(1) Developed	(2) Emerging	(3) Developed	(4) Emerging
$Terror_{it}$	0.0001	-0.6575		
	(2.8617)	(1.0531)		
$Transnational_{it}$			2.7722	-1.8156
			(1.8111)	(1.3963)
$Domestic_{it}$			-11.1333	0.1141
			(10.3188)	(1.0973)
$NaturalDisaster_{it}$	-0.1317	0.0234		
	(0.3192)	(0.0594)		
$Flood_{it}$			1.4107	0.2195
			(6.7210)	(0.2164)
$Earthquake_{it}$			-0.2076	-0.0012
			(0.1909)	(0.0738)
$Storm_{it}$			-1.4438	0.0533
			(3.3587)	(0.0749)
$ln(GDP)_{it-1}$	0.1817**	0.1012	0.1823**	0.1019
	(0.0726)	(0.0724)	(0.0734)	(0.0725)
$ln(Education)_{it}$	-0.0500	0.0520	-0.0493	0.0520
	(0.0339)	(0.0344)	(0.0338)	(0.0345)
$Populationgrowth_{it}$	1.2174	6.2978**	1.1877	6.4015**
	(1.3918)	(2.4370)	(1.3796)	(2.4401)
$ln(G/GDP)_{it-1}$	-0.4028***	-0.0223	-0.4036***	-0.0223
	(0.0953)	(0.0508)	(0.0949)	(0.0507)
$ln(trade)_{it-1}$	0.1443**	0.3104***	0.1426**	0.3112***
	(0.0690)	(0.0694)	(0.0692)	(0.0695)
$Polity_{it}$	0.0088**	0.0010	0.0088**	0.0010
	(0.0039)	(0.0029)	(0.0040)	(0.0029)
N	1524	3076	1524	3076

Standard errors in parentheses

The dependent variable in this table is the natural log of Investment (% of GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75th percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.10: Estimation of Military Expenditures Model for Developed and Emerging Economies

	(1) Developed	(2) Emerging	(3) Developed	(4) Emerging
$Terror_{it}$	0.2383	4.7051**		
	(1.3472)	(1.9235)		
$Transnational_{it}$			0.7619	2.6458
			(1.2672)	(2.9895)
$Domestic_{it}$			-1.6236	6.0345***
			(8.0118)	(1.5867)
$NaturalDisaster_{it}$	0.6616	0.0490		
	(0.9728)	(0.0476)		
$Flood_{it}$			-6.4852	-0.0352
			(3.8971)	(0.1230)
$Earthquake_{it}$			0.8738	0.1069
			(0.9739)	(0.0696)
$Storm_{it}$			4.4278	-0.0934
			(4.6314)	(0.0949)
$ln(GDP)_{it-1}$	0.0613	-0.0553	0.0580	-0.0553
	(0.0554)	(0.1049)	(0.0555)	(0.1046)
$ln(Education)_{it}$	0.0098	-0.0020	0.0094	-0.0027
	(0.0512)	(0.0409)	(0.0512)	(0.0411)
$Populationgrowth_{it}$	-1.3231	-2.7018	-1.2984	-2.5146
	(1.2331)	(2.8218)	(1.2349)	(2.6791)
$ln(I/GDP)_{it-1}$	-0.1224*	0.0509	-0.1209*	0.0506
	(0.0647)	(0.0468)	(0.0634)	(0.0469)
$ln(trade)_{it-1}$	0.0872	-0.0879	0.0857	-0.0869
	(0.1080)	(0.0539)	(0.1074)	(0.0538)
$Polity_{it}$	-0.0164**	-0.0105**	-0.0166***	-0.0105**
	(0.0061)	(0.0041)	(0.0061)	(0.0041)
N	1509	2784	1509	2784

Standard errors in parentheses

The dependent variable in this table is the natural log of Military Expenditures (% of GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75^{th} percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 3.11: Estimation of Non-Military Government Expenditures Model for Developed and Emerging Economies

	(1) Developed	(2) Emerging	(3) Developed	(4) Emerging
$Terror_{it}$	1.6202	-0.8521		
	(1.3598)	(1.2502)		
$Transnational_{it}$			2.6717	0.4505
			(1.6164)	(2.3876)
$Domestic_{it}$			-3.3418	-1.7121
			(3.5050)	(1.3584)
$NaturalDisaster_{it}$	-0.1191	-0.0378		
	(0.4927)	(0.0512)		
$Flood_{it}$			-3.7749	0.2538***
			(3.1579)	(0.0926)
$Earthquake_{it}$			0.1603	-0.0645
			(0.2719)	(0.0648)
$Storm_{it}$			-15.2554***	-0.0487
			(4.1464)	(0.0350)
$ln(GDP)_{it-1}$	-0.0443	0.0515	-0.0518	0.0516
	(0.1360)	(0.0613)	(0.1348)	(0.0614)
$ln(Education)_{it}$	0.0472	0.0314	0.0491	0.0322
	(0.0346)	(0.0364)	(0.0342)	(0.0365)
$Populationgrowth_{it}$	-5.0335***	-0.2981	-4.9816***	-0.4158
	(1.4863)	(2.0229)	(1.4899)	(2.0354)
$ln(I/GDP)_{it-1}$	-0.2384**	-0.0015	-0.2374**	-0.0016
	(0.1125)	(0.0406)	(0.1121)	(0.0406)
$ln(trade)_{it-1}$	-0.1303	0.1999***	-0.1303	0.1994***
	(0.0967)	(0.0612)	(0.0968)	(0.0612)
$Polity_{it}$	0.0175**	0.0136***	0.0172**	0.0136***
	(0.0072)	(0.0038)	(0.0072)	(0.0038)
N	1509	2784	1509	2784

Standard errors in parentheses

The dependent variable in this table is the natural log of Non-Military Expenditures (% of GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 75^{th} percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Chapter 4 The Path to Recovery in the Wake of Terrorist Attacks

4.1 Introduction

Terrorist attacks, both transnational and domestic, aim to cause the most damage on the economies of their target countries by damaging human capital, physical capital and economic institutions. These incidents can be fatal to businesses by obstructing regular operations. In addition, literature reveals that terrorist attacks increase uncertainty leading to decreased foreign direct investment (FDI) (Abadie and Gardeazabal, 2008; Enders and Sandler, 1996). For developing countries, FDI is a crucial source of financing. Examining the response of growth and its disaggregated industrial, service, and agricultural sector value added component can help quantify the effect that terrorism has on growth through obstruction to the normal operation of businesses. For this purpose, in this chapter, I examine the mean response of GDP growth along with its disaggregated industrial, service, and agricultural sector components in the aftermath of transnational as well as domestic terrorist attacks. Utilizing a panel VAR methodology, I find that GDP growth experiences no significant change due to the number of deaths per thousand inhabitants of a country caused by transnational terrorist attacks. Similarly, fatalities per thousand inhabitants of a country caused by domestic terrorist attacks also lead to no significant change to GDP growth. Examining the effects of transnational and domestic terrorism by the disaggregated sectoral growth shows that there is no significant change in the growth rate of either industrial, service, or agricultural sector due to casualties caused by transnational or domestic terrorist attacks.

Studies in the past have focused on a specific incident or a broad range of transnational as well as domestic terrorist attacks. Studies on a broad range of transnational terrorist attacks have found that transnational terrorist attacks negatively influence growth (Blomberg et al., 2004; Gaibulloev and Sandler, 2009, 2011). Blomberg et al. (2004) use a structural VAR model to examine the effects of transnational terrorism on GDP growth and their channels. They find that transnational terrorism has a negative effect on growth. Gaibulloev and Sandler (2009) examine the long run effects and the transmission channels of transnational terrorism on growth using a standard growth model. They focus on Asian countries in this study. Gaibulloev and Sandler (2011) use the same methodology to examine the long run growth effects of transnational as well as domestic terrorist attacks in Africa. They find that transnational terrorism negatively affects growth, while domestic terrorism has no significant effect on growth. Gaibulloev and Sandler (2008), on the other hand find a decline in growth due to domestic terrorist attacks in Western Europe. Thus studies have found heterogeneous effects of transnational and domestic terrorist attacks. Gaibulloev and Sandler (2011) also suggest various reasons for the difference in response of growth to transnational and domestic terrorist attacks affect. They contend that since domestic terrorist attacks occur more frequently than transnational terrorist attacks, people and businesses accept domestic terrorism as part of their daily routine creating the perception of a persistent shock in case of domestic terrorism. They argue that countermeasures for domestic terrorism does not require additional border security and offensive operations in foreign countries and are therefore cheaper to implement. Studies by Abadie and Gardeazabal (2008) and Enders and Sandler (1996) that are focused on transnational terrorism have found that they have a negative effect on foreign direct investment which is an important source of savings for developing countries. Furthermore, the threat of transnational terrorism may curb the inflow of foreign aid. Hence following the example of previous studies, I distinguish between transnational and domestic terrorist attacks and find that there are no differences in the way that growth and its components respond to these different types of terrorism for this sample of countries. The literature predominantly focuses on the long run effects of terrorism on GDP growth. A study by Abadie and Gardeazabal (2003) utilizes synthetic control methodology to evaluate the incidents in the Basque region of Spain and find that these attacks led to a 10% loss in GDP per capita during the 1980's and 1990's. Although the literature is comprehensive, it fails to distinguish between the dynamic response of GDP growth to transnational and domestic terrorist attacks.

Studies have also focused on investigating the channels through which these incidents affect growth by examining some of the traditional factors of growth like investment and government spending (Blomberg et al., 2004; Gaibulloev and Sandler, 2008, 2009, 2011). Several studies show that increased uncertainty due to terrorism, both transnational and domestic, reduces investment and foreign direct investment (Abadie and Gardeazabal, 2003, 2008; Enders and Sandler, 1996; Bandyopadhyay et al., 2013). Studies have also found differences in the channels through which domestic and transnational terrorism may influence growth. Blomberg et al. (2004) observe that transnational terrorism leads to redirection of resources from investment spending to government expenditures. Gaibulloev and Sandler (2008) find that transnational terrorist attacks lead to decreased investment while domestic terrorist attacks cause governments to redirect spending towards security and away from more growth enhancing public and private investments. This chapter adds to this body of literature by focusing on the disaggregated value added components of GDP as a channel through which transnational and domestic terrorism may affect growth.

Instances like the IRA attacks on London's financial district at the Baltic Exchange on April 10, 1992 resulted in $800 million in lost business (Gaibulloev and Sandler, 2009). This would suggest that domestic terrorist attacks also increase the cost of doing business because of higher wages, larger insurance premiums, and greater security expenditures. Destroyed infrastructure leads to business disruption. Each of these factors are relevant even for transnational terrorism. Gunasekar et al. (2018)

find that India experienced a decline in tourism in the wake of the 2008 Mumbai transnational terrorist attacks. This too suggests a decrease in business activity. Examining the effect of transnational and domestic terrorism on industrial, service and agricultural value added components of growth can shed some light on the extent to which business activity is affected.

The effect of transnational and domestic terrorist attacks on business activities may vary based on developed and emerging countries. This would reflect in the response of GDP growth and its disaggregated components. Studies about transnational and domestic terrorist attacks have observed this differential effect on growth in developed and emerging countries (Gaibulloev and Sandler, 2009, 2011). They find that developed economies are adept at counter-acting the negative effects of transnational and domestic terrorist attacks, while emerging economies experience some adverse effects. Additionally, a decline in foreign direct investment due to terrorism can be far more fatal for emerging economies. I therefore also focus my investigation into the path of growth and the sectoral channels through which these destructive events affect growth on emerging economies separately. I find that emerging economies experience no significant effects due to the casualties of transnational and domestic terrorist attacks.

4.2 Data

4.2.1 Definition of Terrorism, Transnational Terrorism, and Domestic Terrorism

Terrorism is broadly defined as the use of violence and intimidation in order to gain political or social leverage. A feature of terrorism is that it usually circumvents democratic processes by threatening the citizens of the target country. Hence the objective behind the violence goes beyond the victims of the incident. Another aspect of terrorism is that it is initiated by either individuals or groups. Terrorism includes state-sponsored terrorism, where a state provides assistance by providing a safe-haven, financing, or information. However, it does not include a state employing violence against its own citizens. This definition is similar to the one defined by the U.S. Department of State (2003: xii): 'terrorism means premeditated, politically motivated violence against non-combatant targets by sub-national groups or clandestine agents, usually intended to influence an audience'.

Enders et al. (2011) classify terrorism as domestic terrorism and transnational terrorism. Domestic terrorism is home grown and affects only the host country, institutions, citizens, property, and policies. The venue, target, and victims, and event initiators are from the same country. An example of terrorism is the bombing and shooting in Norway on July 22, 2011 which killed 77 people. As per the definition of terrorism and domestic terrorism, most terrorist incidents enacted for the purpose of independence are classified as a domestic terrorist attack. For instance, terror attacks by Sikh extremists in India during the Khalistan movement in 1984 would be classified as domestic terror incidents. This would include the assassination of former Prime Minister Indira Gandhi by Sikh extremists in New Delhi, India on October 31, 1984. Transnational terrorism concerns more than one country. For instance, international skyjacking or the mailing of a letter bomb to another country constitutes transnational terrorism. The shootings and hostage situation in Mumbai, India on November 26, 2008 is one such example. Another example is the shooting down of a Russian airline in Egypt on October 31, 2015. In each instance there was involvement of individuals from different countries, either as victims, as perpetrators or both.

4.2.2 Data Description

The World Bank's World Development Indicators (WDI) provides data for the macroeconomic indicators that I use for my analysis. I use the following annual data from the WDI: (1) GDP per capita, (2) industry, value added, (3) services, value added,

(4) agriculture, value added, (5) gross fixed capital formation as a share of GDP, (6) government expenditure as a share of GDP. World Bank Analytical Classification groups countries based on their income into high, upper middle, lower middle, and low income countries. Using these data, I classify upper middle, lower middle, and low income countries in 2015 as emerging economies.

The data on terrorism is obtained from Global Terrorist Database (GTD). This dataset includes violent incidents that are instigated by individuals or groups. The dataset also requires that two out of the following three conditions be met for an incident to be classified as a terrorist attack: (1) the incident was aimed at achieving a political, economic, religious, or social goal; (2) it was intended to strong arm or be a message to individuals other than the victims; and (3) it violated International Humanitarian Law. GTD includes data on domestic as well as transnational terrorist attacks. However, it does not distinguish between the two. For this reason, I follow the steps outlined by Enders et al. (2011) to distinguish between domestic and transnational terrorist attack. The steps are as follows:

1. Remove any event that does not satisfy conditions defined by the GTD dataset as a terrorist attack.

2. Exclude events that have been flagged as doubtful by the dataset.

3. The next steps identify transnational terrorist incidents from among the remaining observations

    a) GTD reports the nationality of three victims. If the nationality of at least one of these reported victims is different from the target country reported by GTD, flag the observation as a transnational terrorist attack.

    b) Diplomatic targets like foreign emissaries, embassies, consulates, and diplomatic staff, families, and property along with non-government organizations (NGO) that are mostly multinational in nature are considered transnational targets. GTD identifies the target type. If an incident targets a diplomatic entity, or an NGO, the incident is considered transnational.

c) If the incident targets a U.S. entity outside of the USA or an international entity like the UN, the incident is classified as a transnational terror attack.

d) GTD reports U.S. specific information like fatalities, hostages, wounded etc. If these reports indicate that one of these U.S specific events may be involved outside of the USA, flag the incident as a transnational terror attack.

e) In case of hijackings or kidnappings, GTD reports the country in which this incident concluded or if there was a diversion. If this country is different from the origin country flag the event as a transnational incident.

f) GTD also identifies incidents as having international ideologies or geography. In addition to the above steps described by Enders et al. (2011), I distinguish these incidents as transnational terrorist attacks.

4. From among the observations that have not been flagged as transnational, an incident that has information missing about the nationality of the victims, or the target type is considered uncertain. Also incidents that are missing information regarding U.S. fatalities, wounded, hijackings, or ransoms are considered uncertain. I drop these uncertain events.

5. The remaining incidents that are not marked as transnational are identified as domestic terrorist incidents.

A concern with terrorist attacks is that they could be endogenous to economic factors. Although studies have failed to show any influence of development indicators on terrorism, several studies find that ethno-religious diversity, increased state repression, political volatility are good predictors of terrorism (Piazza, 2007; Abadie, 2006; Crenshaw, 1981). Studies also show that socio-economic conditions play a part in the circumstance from which terrorists originate. They suggest that an individual may feel disadvantaged in the face of extreme economic inequality resulting in him turning to violence to change the status quo (Gurr, 1970; Blomberg, Hess and Weerapana, 2004). A cycle of violent behavior can lead an individual to believe that the opportunity cost of terrorism is low and the payout is higher relative to his current occupation. Lai (2007) finds that the contrary case of high income levels along with low levels of income inequality result in lower levels of terrorism production. Studies have also suggested that quality of economic institutions and trade openness are other socio-economic factors that have a negative impact on the generation of terrorists (Basuchoudhary and Shughart, 2010; Kurrild-Klitgaard, Justesen, and Klemmensen, 2006). Literature extensively shows that economic factors play a key role in the creation of terrorists. The creation of terrorists and the decision to undertake a terrorist act as described by literature is based on pre-existing scoio-economic conditions. Hence it can be assumed that transnational and domestic terrorism are predetermined relative to the economic variables being examined here.

The final dataset consists of an unbalanced panel of annual data for 109 countries spanning from 1970 to 2015. This includes 71 emerging economies[1]. Table 4.1 presents the summary statistics of the macroeconomic variables as well as the average fraction of the population that has died due to transnational and domestic terrorist attacks. The table shows that the average GDP growth over the period of 1970 to 2015 is 2.17%. It also illustrates that growth in emerging economies of 2.28% exceeds the growth of the entire sample suggesting higher growth than developed economies. A similar pattern can be observed in industrial, service and agricultural sector growth in emerging economies. The summary statistics reveal that on average 0.0001 people per thousand inhabitants of a country die due to transnational terrorist attacks whereas

[1]The list of the countries can be found in the appendix.

domestic terrorist attacks leads to higher fatalities of 0.0004 per thousand inhabitants of a country. For the full sample, as well as developed and emerging economy sub-samples, the data reveals that there have been more incidents of domestic terrorism than transnational terrorism. The data shows that the likelihood of a developed economy in the sample experiencing a transnational terrorist attack is 32.3% while the likelihood of an emerging economy experiencing one is 36.3%. This suggests that a developed economy is as likely to experience a transnational terrorist attack as an emerging economy. Whereas for domestic terrorist attacks the data reveals that emerging economies are more likely to experience a domestic terrorist attack with a probability of 47.5% compared to developed economies where the probability of an attack is 35.7%.

4.3 Methodology

Consider the following panel VAR with panel fixed effects:

$$y_{i,t} = \Phi_1 y_{i,t-1} + \alpha_i + \delta_t + \varepsilon_{i,t} \tag{4.1}$$

where, $i = 1,\ 2,\ \cdots,\ N$ is the country index and the time index for country i is $t = -1,\ 0,\ 1,\cdots,\ T_i$. α_i is the country fixed effect and δ_t is the time fixed effect. I assume the error structure in the above equation to be homogeneous, such that. $E(\varepsilon_{i,t}\varepsilon_{i,t}^{'}) = \omega$ for all i and t. I also assume that the errors are independent across time and countries, i.e. $E(\varepsilon_{i,s}\varepsilon_{i,t}^{'}) = 0, s \neq t$, and $E(\varepsilon_{i,s}\varepsilon_{j,t}^{'}) = 0$, for any s and t where $i \neq j$.

$y_{i,t}$ is a 5×1 vector of variables that include (1) domestic terrorist attacks, (2) transnational terrorist attacks, (3) the growth rate of fixed capital formation as a share of GDP, (4) the growth rate of government consumption expenditures as a share of GDP and (5) either growth rates of real GDP per capita, real industrial sector value added per capita, real service sector value added per capita, or real agricultural sector value added per capita.

$$y_{i,t} = \begin{bmatrix} Domestic\ terrorism_{i,t} \\ Transnational\ terrorism_{i,t} \\ Capital\ formation_{i,t} \\ Government\ consumption_{i,t} \\ GDP\ /\ Industry\ /\ Service\ /\ Agri.\ growth_{i,t} \end{bmatrix}$$

The transnational and domestic terrorist attack variables are the natural log of the number of deaths per thousand inhabitants that occurred due each in country i in time t. Due to the censored nature of these two variables, the results of the above estimation might be biased. In case of censured models, consistent estimators can be obtained using restricted maximum likelihood estimators as described by Kilian and Vigfusson (2009). Even though, I do not implement this estimation method here, I plan to do so in future research.

Nickell (1981) shows that the panel fixed effect estimator for a dynamic model with a fixed and small T is inconsistent. However, if the errors are serially uncorrelated, the first difference transformation can be consistently estimated by instrumenting lagged differences and levels of $y_{i,t}$ (Anderson and Hsiao, 1982). I use the second and third lags of the dependent variables as instruments.

Based on the vast growth literature (Barro, 1991; Barro and Sala-i-Martin, 2003; Mankiw, Romer and Weil, 1992; among others), I include some determinants of growth as one of the dependent variables. The order of the variables for the purpose of determining the orthogonal impulse response is as mentioned above. Using past literature as a basis, I assume that the terror variables affect the macroeconomic indicators contemporaneously, however macroeconomic indicators do not affect the terror variables contemporaneously (Blomberg et al., 2004). I assume that domestic terrorist attacks can affect transnational terrorist attacks contemporaneously and not vice versa[2]. Within the macroeconomic variables, I assume that GDP growth is affected by the remaining macroeconomic variables as well as the terror variables contemporaneously. I further assume that growth in investment as a share of GDP affects growth in government expenditures as a share of GDP contemporaneously[3]. I cluster the standard errors at the country level and use a 1000 Monte Carlo simulation draws to plot the confidence intervals of the cumulative orthogonal impulse responses. Holtz-Eakin et al. (1988) note that the pooling of multiple panels has the advantage of relaxing the time stationarity assumption. They also state that the presence of an explosive process may lead to difficulty in interpreting the model. For ease of interpretation, I conduct a series by series unit root test using DF-GLS, augmented Dickey Fuller test and Phillips-Perron test on the macroeconomic indicator levels as well as their growth rates. Table 4.2 reports the results of these tests. The test results for log levels show that we fail to reject the null of a unit root for the vast majority of the series. For this reason, I use log differences of the macroeconomic variables.

I estimate the moment and model selection criteria (MMSC) that are analogous to the Akaike information criteria (MAIC), Bayesian information criteria (MBIC), and the Hannan-Quinn information criteria (MQIC) along with Hansen's (1982) J statistic of over-identifying restrictions to identify the appropriate lag structure. Table 4.3 reports these statistics. In the table, p represents the lags for the dependent variable. Since Hansen's (1982) J statistic of over-identifying restrictions is smaller for two lags, I estimate my models with two lags. For consistency and to simplify interpretation across estimations, I use the same number of lags for all of the models.

[2]To test the robustness of this assumption I reverse the order of transnational and domestic terrorist attacks and find that the results are similar to the base case.

[3]I test the robustness of this assumption by reversing this order. I find that the results are basically the same as the base case.

4.4 The Path of the Economy in the Aftermath of Terrorism

Figure 4.1 illustrates the cumulative orthogonal impulse response of GDP growth, government consumption expenditures and investment to a one standard deviation shock to the number of fatalities per thousand inhabitants caused by transnational and domestic terrorist attacks. The shaded area represents the 90% confidence intervals. The results show that the cumulative effect of the number of deaths due to transnational terrorism on growth is insignificant for the horizon under analysis. These findings are at odds with the findings of Gaibulloev and Sandler (2009, 2011) and Blomberg et al. (2004) who find that transnational terrorist attacks lead to lower GDP growth. The difference in results could be due to difference in the sample period, geography, or methodology. Investigating potential channels through which transnational terrorist attacks drives the effect on GDP growth shows that government expenditures as well as investment experience no change following a transnational terrorist attack.

The figure also reveals an insignificant effect on GDP growth due to fatalities caused by domestic terrorist attacks. Although these findings are in accordance with findings of Gaibulloev and Sandler (2011) who find that domestic terrorism in Africa has no significant effect on GDP growth though their coefficient expresses negative growth, they are contrary to findings of Gaibulloev and Sandler (2008). Gaibulloev and Sandler (2008) find that that domestic terrorism in Western Europe leads to lower GDP growth. Exploring the response of government expenditures and investment to domestic terrorism reveal that these indicators also experience no significant change. The results reported in figure 4.1 show a similar response of GDP growth in the aftermath of the two types of terrorist attacks. This suggests that the reasons illustrated by Gaibulloev and Sandler (2011) for the difference in response to the transnational and domestic terrorist attacks may not necessarily hold. While the estimation results suggest the effect of transnational and domestic terrorism on GDP growth is insignificant, aggregation across different sectors might mask variation in the responses across different industries. After all, terrorist attack tend to occur more often in areas where manufacturing and services are the main economic activities. Examining the value added growth rates of the different sectors in the aftermath of domestic terrorism sheds some light on the sectors through which GDP growth is negatively affected.

Figure 4.2 plots the cumulative response of industrial sector value added growth to fatalities caused by transnational and domestic terrorist attacks. The figures show that a one standard deviation shock to the number of fatalities per thousand inhabitants of a country due to transnational terrorism leads to no significant change in industrial sector growth. Further the figure reveals that a one standard deviation shock to the number of deaths per thousand inhabitants of a country due to domestic terrorist attacks also does not lead to any significant change in the growth rate of the industrial sector.

Figure 4.3 graphs the cumulative response of growth in service sector to casualties of transnational and domestic terrorist attacks. The results show that, in the aftermath of a one standard deviation shock to the number of deaths per thousand inhabitants of a nation due to transnational terrorism, service sector growth experiences no significant change. Similarly, a one standard deviation shock to the number of fatalities per thousand habitant of a country due to domestic terrorist attacks has no significant effect on service sector growth.

Figure 4.4 plots the cumulative response of growth in the agricultural sector in the aftermath of casualties cause by transnational and domestic terrorist attacks. The figures illustrates that agricultural sector growth experiences no significant change due to a one standard deviation increase in fatalities per thousand people of a country due to transnational terrorist attack. Casualties due to domestic terrorism too, exhibit no adverse effects on the growth of the agricultural sector.

The above results show that the response of GDP growth and its disaggregated value added sector growth to the number of deaths per thousand inhabitants of a country due to transnational and domestic terrorist attacks does not vary. The insignificant change to economic growth illustrates that on average, countries have adjusted to the frequent occurrence of these events within a year. Additionally, the variable of transnational and domestic terrorist attack measures the intensity of the fatalities that an event causes, however, the data reveals that not all incidents cause casualties. These incidents are not accounted for in the analysis. Furthermore, although the intensity measure of transnational and domestic terrorist attacks accounts for the number of deaths this may have a very small effect economic growth, specifically when the number of deaths is a very small fraction of the total population of a country. This measure also fails to account for damages to physical capital which may play a larger role in disruption of regular business operations.

4.4.1 Emerging Economies

An important source of financing for emerging economies is through foreign direct investment (FDI). Studies by Abadie and Gardeazabal (2008) and Enders and Sandler (1996) have found that terrorism has a negative effect on foreign direct investment. For this reason, it is important to examine the response of GDP growth and its disaggregated value added sectors in emerging economies to transnational and domestic terrorism. I define emerging economies as countries that are classified as upper middle, lower middle, and low income in 2015.

Figure 4.5 graphs the cumulative response of GDP growth, government consumption expenditures and investment to the number of fatalities per thousand inhabitants caused by transnational and domestic terrorism in emerging economies. The figure shows that a one standard deviation shock to the number of fatalities per thousand inhabitants of a country due to transnational terrorist attacks leads to no significant change in GDP growth of emerging countries for the entire duration of analysis.

A one standard deviation shock to the number of deaths per thousand inhabitants of a country due to domestic terrorist attacks also results in no significant change in GDP growth for the duration of the analysis. The estimated responses suggest that the response of GDP growth to the deaths caused by transnational and domestic terrorist attacks is not different in emerging countries. Investigating potential channels through which transnational and domestic terrorist attacks drive the effect on GDP growth in emerging economies shows that government expenditures as well as investment experience no change following a transnational or domestic terrorist attack.

Although examining the response of GDP growth in emerging economies reveals that they cause no significant harm to the economy of an emerging economy, aggregation across different sectors might mask variation in the responses across different industries. Figure 4.6 graphs the cumulative response of industrial sector growth to the number of fatalities per thousand inhabitants of a country due to these different types of terrorist incidents in emerging economies. These figures show that a one standard deviation shock to the number of deaths per thousand inhabitants of a country due to transnational terrorist attacks has no significant effect on growth in the industrial sector. Additionally, the industrial sector growth experiences no significant change due to a one standard deviation shock to the number of casualties per thousand inhabitants of a country caused by domestic terrorist attacks in an emerging country. Figure 4.7 plots the cumulative response of service sector growth in emerging economies to a one standard deviation shock to the number of deaths per thousand inhabitants of a country due transnational and domestic terrorist attacks. In emerging countries, the service sector experiences no significant change due to a one standard deviation shock to the number of fatalities per thousand inhabitants of a country caused by transnational terrorist attacks. A similar insignificant change in service sector growth is observed due to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by a domestic terrorist attack.

Figure 4.8 graphs the cumulative response of agricultural sector growth to the number of deaths per thousand inhabitants of a country due to the two types of terrorist attacks in an emerging economy. These results illustrate that agricultural growth remains unaffected by a one standard deviation shock to the number of fatalities per thousand inhabitants of a country due to both transnational and domestic terrorist attack throughout the horizon being examined.

Examining the data fo emerging countries shows that the economy of emerging countries like that of the entire sample experience no adverse effects of the deaths caused by transnational and domestic terrorist attacks. The results reaffirm that the response of economies does not vary based on transnational and domestic terrorism for this sample of countries.

4.5 Alternative Specifications and Robustness Checks

I consider a number of alternate specifications to ensure the robustness of the main results presented above. First, I consider estimation of the above model with different ordering of the terrorism variables. The cumulative response of the GDP growth to transnational and domestic terrorist attacks estimated with the assumption that transnational terrorism affects domestic terrorism, but not vice versa is illustrated in figure A.7. This shows that the path of the cumulative response is similar for transnational as well as domestic terrorist attacks. Figures A.8 to A.10 graph the results for growth in different sectors. These results illustrate similar response as the base case for transnational and domestic terrorist attacks.

Next, I examine the robustness of the ordering of investment as a share of GDP and government expenditures as a share of GDP by reversing their order. Figures A.11 to A.14 present the cumulative response of GDP growth and the growth in its disaggregated sector under this specification. The results show that the cumulative responses to transnational and domestic terrorist attacks remain basically unchanged relative to the benchmark throughout the horizon of analysis.

Overall, the results from the above robustness checks suggest that the cumulative response to domestic and transnational terrorism observed in the base case are not sensitive to the originally defined specification.

4.6 Key Findings

The deaths caused by transnational and domestic terrorist attacks have no statistically significant effect on GDP growth within a year. Examining the effects on the government and investment component of GDP reveals that these components are also unaffected by the deaths caused by the two types of terrorist attacks. Further, examining the effects of fatalities due to transnational and domestic terrorist attacks on the disaggregated value added sectoral growth shows no significant change in either the industrial, services, or agricultural sectors. These results suggest that the response of the economy to the casualties of transnational terrorist attacks is not different from that of the casualties of domestic terrorist attacks.

4.7 Tables

Table 4.1: Summary Statistics

	All	Emerging
GDP Growth	0.0217	0.0228
	(0.0432)	(0.0464)
Industrial Growth	0.0205	0.0240
	(0.0707)	(0.0733)
Service Growth	0.0258	0.0271
	(0.0474)	(0.0525)
Agricultural Growth	0.00455	0.00571
	(0.0784)	(0.0744)
Capital Formation Growth	0.00306	0.00612
	(0.131)	(0.148)
Government Consumption Growth	0.00225	0.00246
	(0.110)	(0.127)
Transnational Terrorist Attack	0.000146	0.000141
	(0.00126)	(0.000942)
Domestic Terrorist Attacks	0.000456	0.000625
	(0.00291)	(0.00345)
N	2707	1881
Countries	109	71

Note: The table reports the pooled average of the variables for an unbalanced panel of countries spanning from 1970 to 2015. The standard deviations are reported in parenthesis.

Table 4.2: Unit Root Tests of Economic Indicators

	Levels			First Difference		
	DF-GLS	ADF	PP	DF-GLS	ADF	PP
Investment	14	17	17	84	90	90
	(109)	(109)	(109)	(109)	(109)	(109)
Government Consumption	16	24	24	94	97	97
	(109)	(109)	(109)	(109)	(109)	(109)
GDP Growth	8	8	8	78	85	85
	(109)	(105)	(105)	(109)	(109)	(109)
Industry Growth	9	16	16	83	86	86
	(109)	(108)	(108)	(109)	(109)	(109)
Services Growth	7	11	11	75	82	82
	(109)	(104)	(104)	(109)	(109)	(109)
Agricultural Growth	36	23	23	104	104	104
	(109)	(109)	(109)	(109)	(109)	(109)

Note: Overall No. of Countries that reject unit root with total No. of Countries in parenthesis. Significance level is at 10%

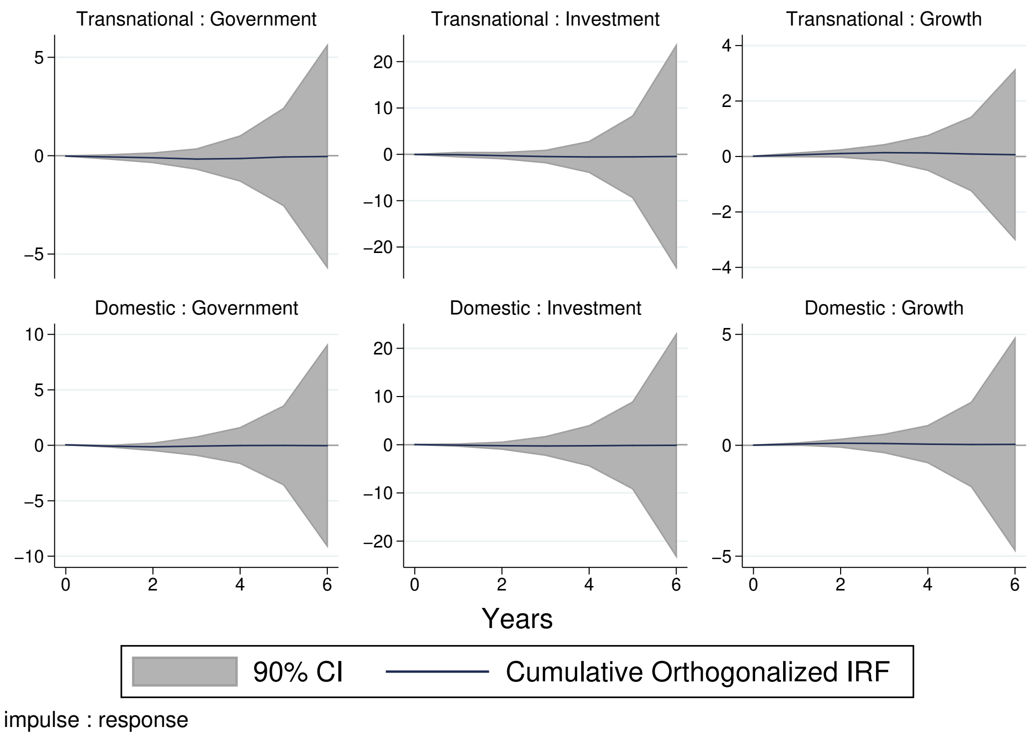
Table 4.3: Information Criteria for Lag Structure

		Number of Lags	
		p=1	p=2
All	MAIC	**-63.38702**	-32.54955
	MBIC	**-347.3265**	-174.5193
	MQIC	**-167.2332**	-84.47264
	J	36.61298	**17.45045**
Emerging Countries	MAIC	**-71.67993**	-36.43285
	MBIC	**-338.2002**	-169.693
	MQIC	**-170.883**	-86.03439
	J	28.32007	**13.56715**

Note: The table reports the model selection criteria estimates analogous to Akaike infomration criteria (MAIC), Bayesian information criteria (MBIC), Hannan-Quinn information criteria (MQIC) for the panel VAR model, and Hansen's (1982) J statistic of over-identifying restrictions. p represents the number of lags of the dependent variables to include in the model. The model uses two, three and four lags of the dependent variables as instruments for the calculation of these information criteria estimates.

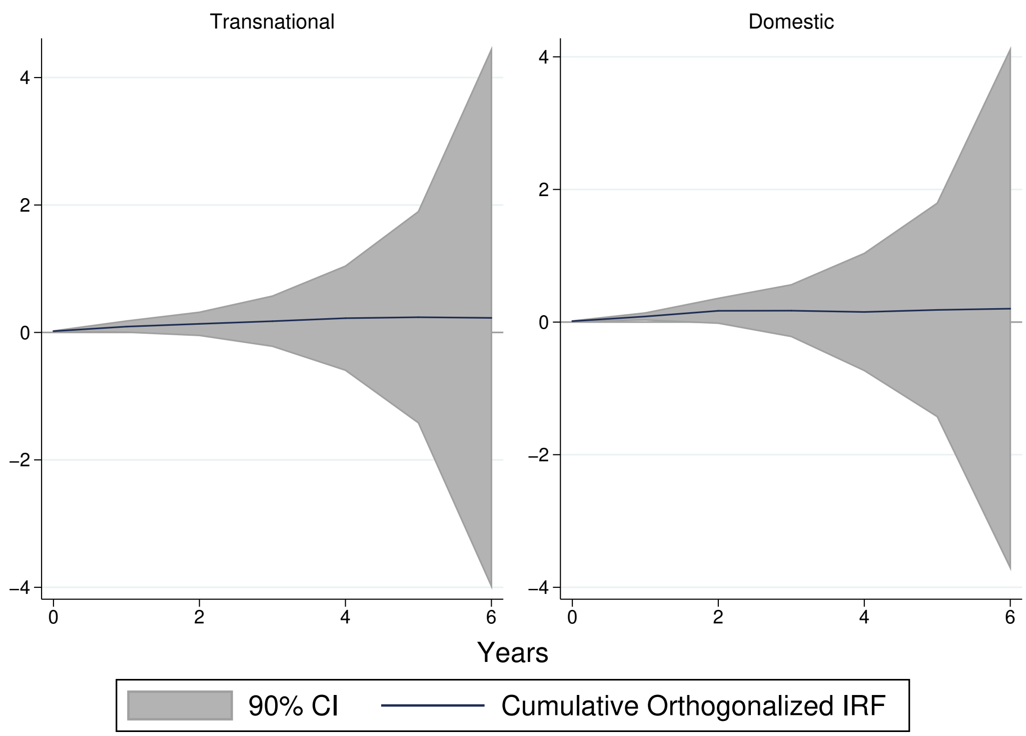
4.8 Figures

Figure 4.1: Cumulative Response of GDP Growth, Government Consumption, and Investment



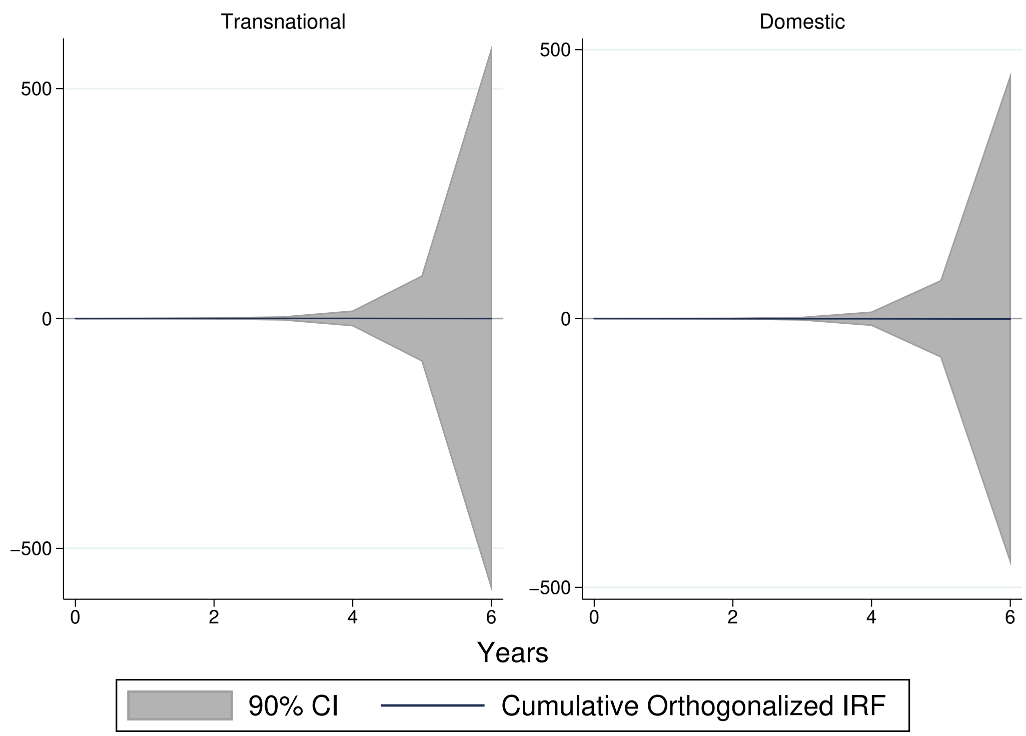
Note: The figures plot the cumulative impulse response of government consumption expenditures, investment, and GDP growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The top panel plots the response to transnational terrorism and the lower panel plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Figure 4.2: Cumulative Response of Industrial Sector Growth



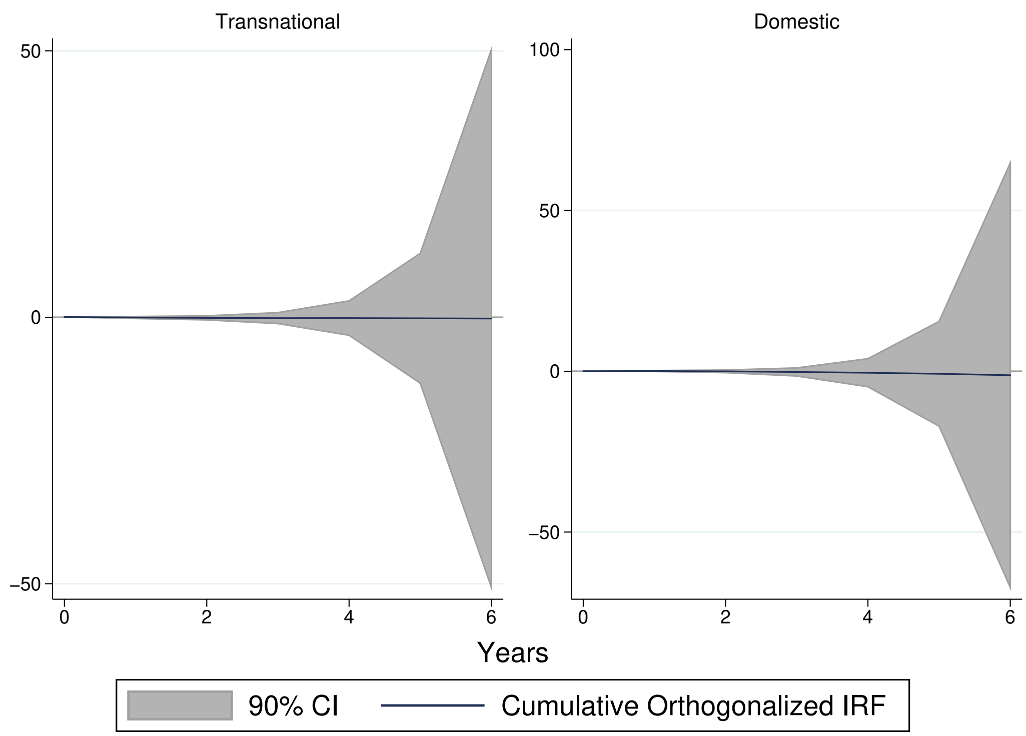
Note: The figures plot the cumulative impulse response of industrial sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Figure 4.3: Cumulative Response of Service Sector Growth



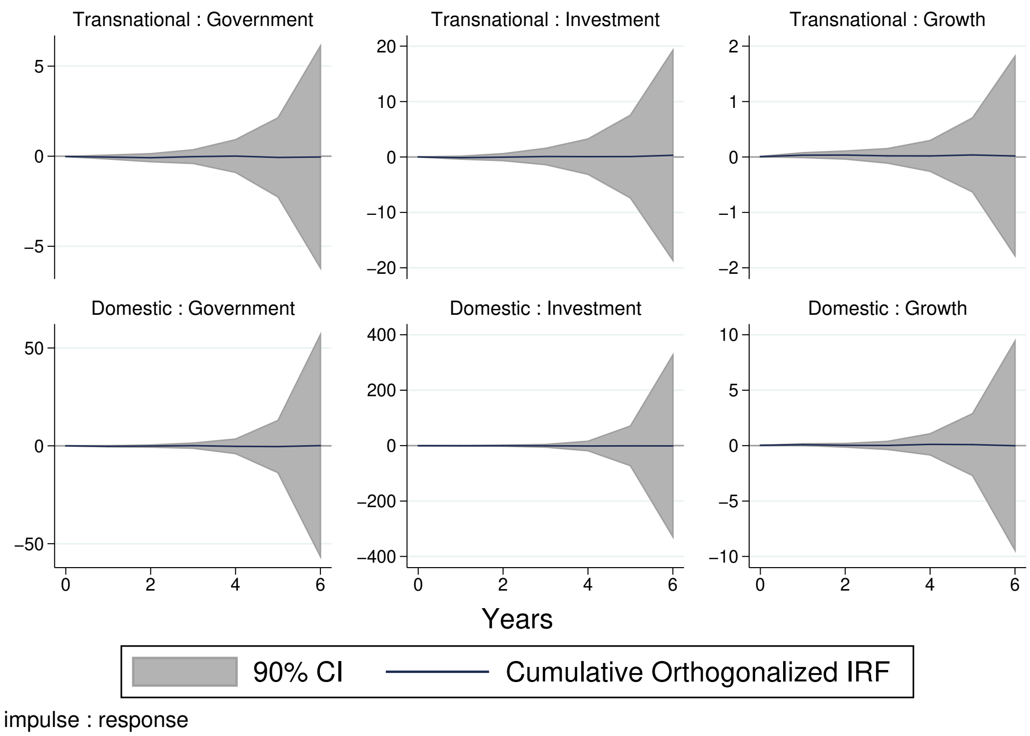
Note: The figures plot the cumulative impulse response of service sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Figure 4.4: Cumulative Response of Agricultural Sector Growth



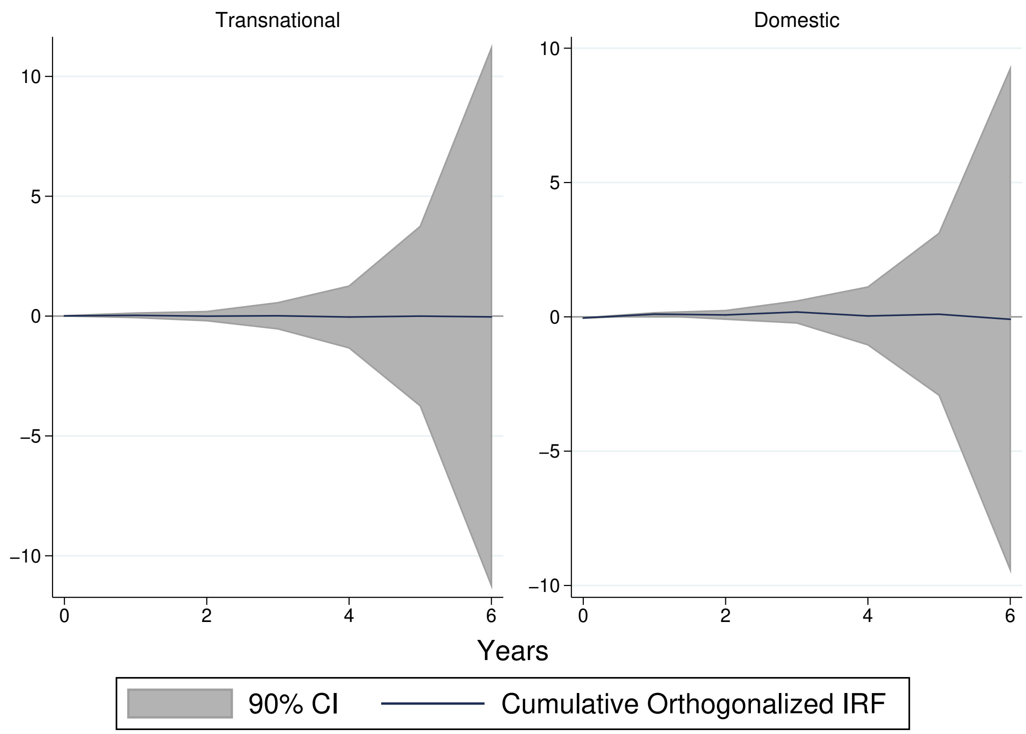
Note: The figures plot the cumulative impulse response of agricultural sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Figure 4.5: Cumulative Response of GDP Growth, Government Consumption, and Investment in Emerging Economies



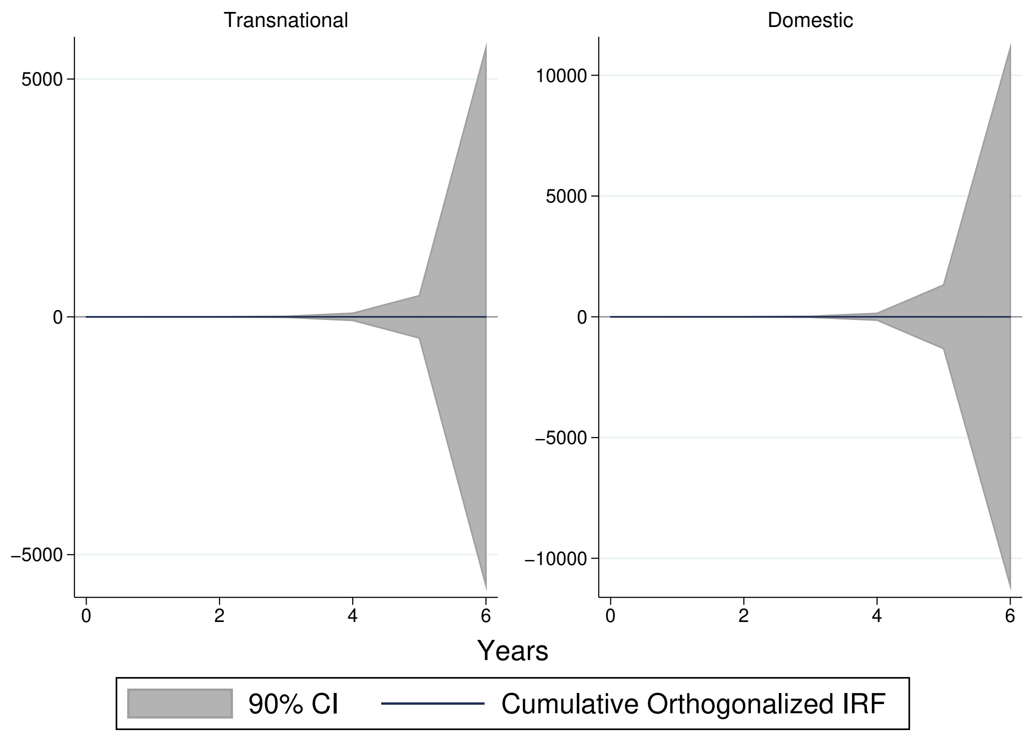
Note: The figures plot the cumulative impulse response of government consumption expenditures, investment, and GDP growth of emerging economies to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The top panel plots the response to transnational terrorism and the lower panel plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Figure 4.6: Cumulative Response of Industrial Sector Growth in Emerging Economies



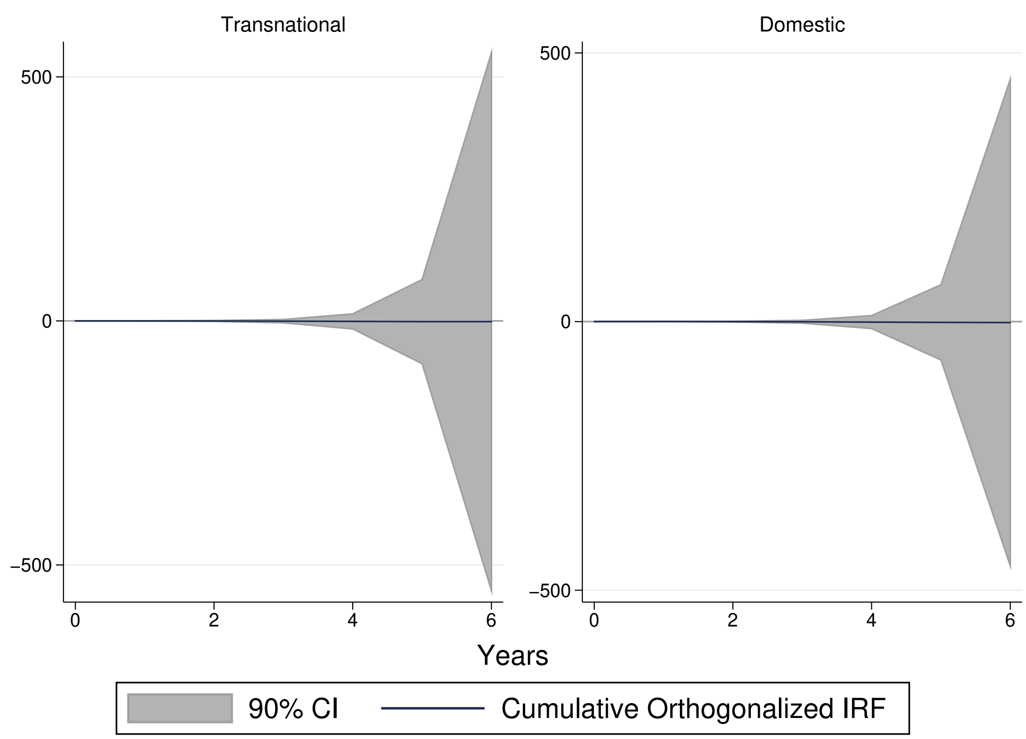
Note: The figures plot the cumulative impulse response of industrial sector growth in emerging economies to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Figure 4.7: Cumulative Response of Service Sector Growth in Emerging Economies



Note: The figures plot the cumulative impulse response of service sector growth in emerging economies to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Figure 4.8: Cumulative Response of Agricultural Sector Growth in Emerging Economies



Note: The figures plot the cumulative impulse response of agricultural sector growth in emerging economies to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval.

Appendix A

A.1 Chapter 1 Appendix

A.1.1 Data Appendix

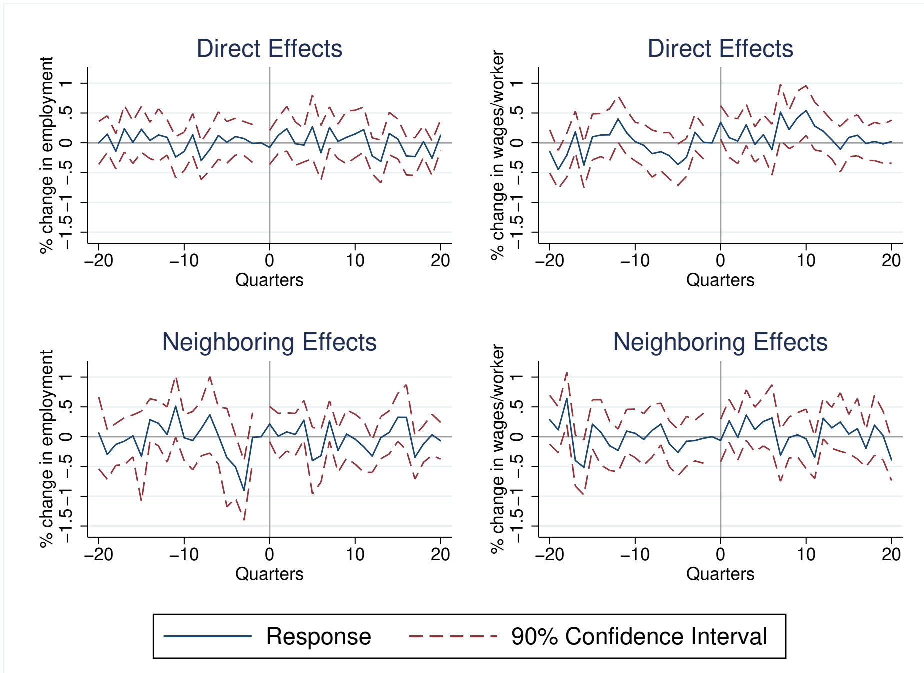
A.1.1.1 Definitions and Sources

Table A.1: Definitions and Sources of the Variables

Variable	Definitions	Source
Employment	Total number of peopled employed in a county	Bureau of Labor Statistics' Quarterly Census of Employment and Wages
Wages per worker	Total wages paid to all the employed in a county divided by the total number of people employed in the same county	Bureau of Labor Statistics' Quarterly Census of Employment and Wages
Violent tornadoes	Tornadoes classified as EF-4 and EF-5	National Oceanic and Atmospheric Administration's Storm Events Database
Large tornadoes	Tornadoes classified as EF-2 and higher	National Oceanic and Atmospheric Administration's Storm Events Database

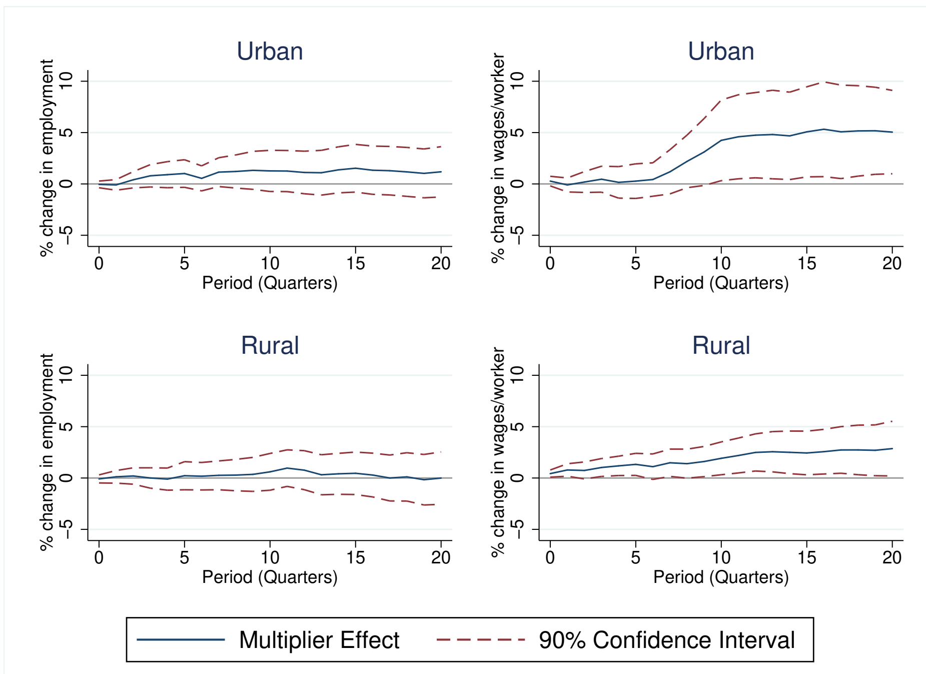
A.1.2 Robustness Checks

Figure A.1: Effect of violent tornadoes on labor market outcomes (all industries) - (20 lags)



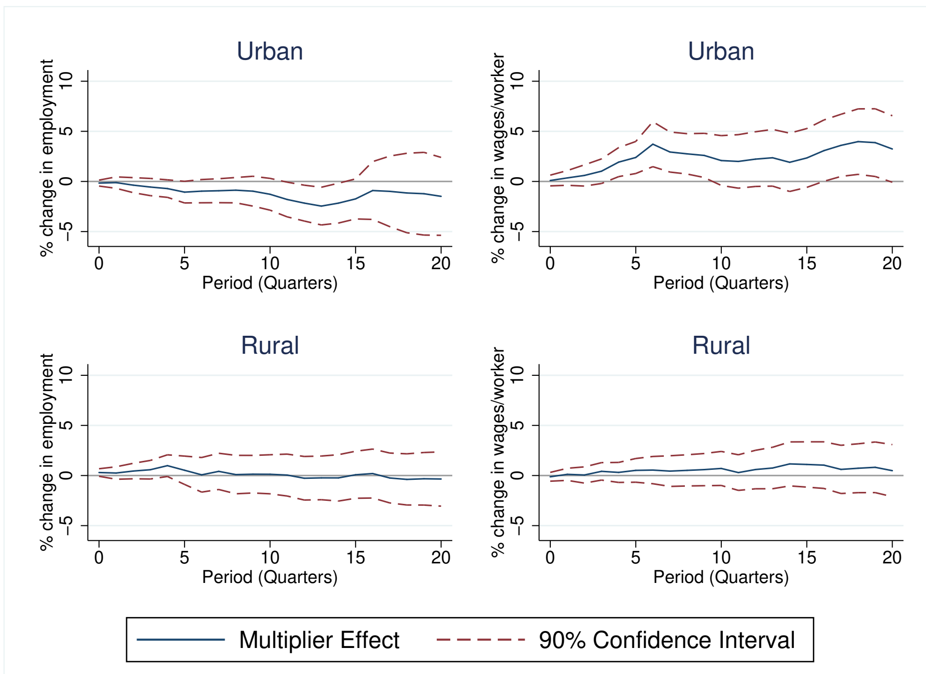
Note: The solid line plots the response of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the direct effects and the lower panel plots the neighboring effects

Figure A.2: Multiplier effect of violent tornadoes on labor market outcomes (all industries) of directly affected urban and rural counties - (20 lags)



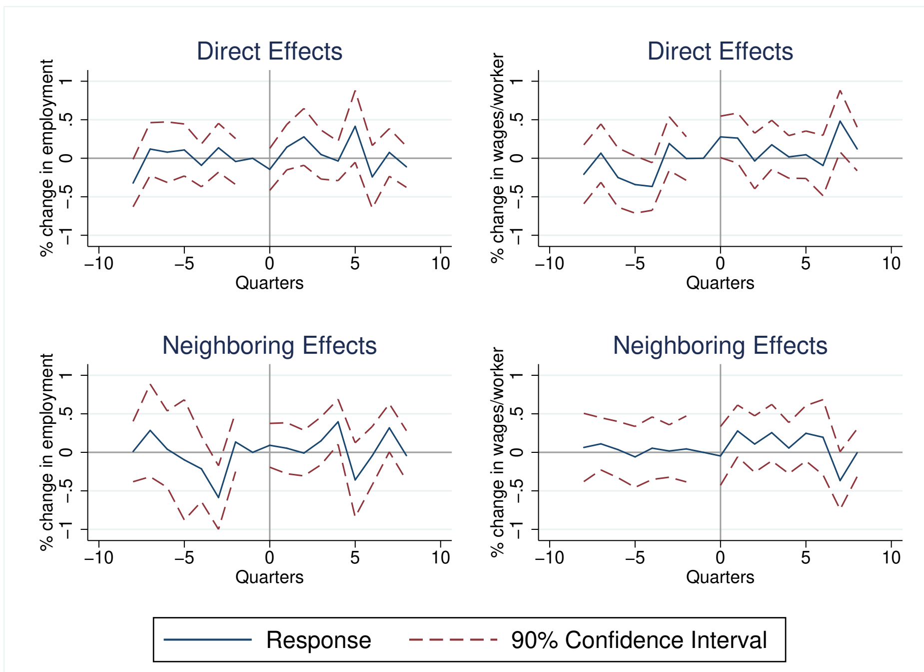
Note: The solid line plots the multiplier effect of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the effect on Urban counties and the lower panel plots effects for Rural counties

Figure A.3: Multiplier effect of violent tornadoes on labor market outcomes (all industries) of neighboring urban and rural counties - (20 lags)



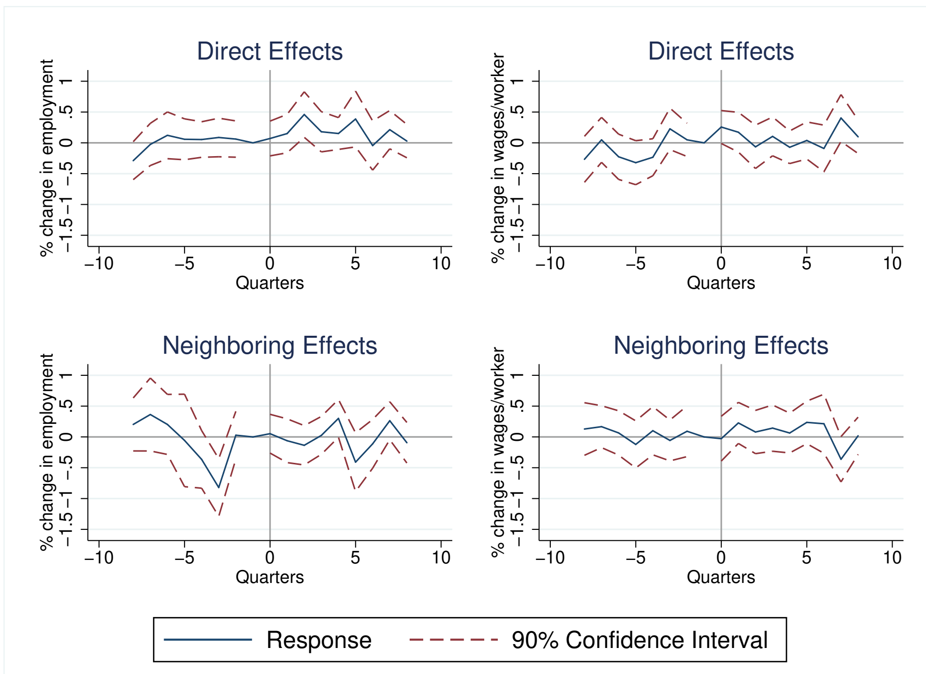
Note: The solid line plots the multiplier effect of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the effect on Urban counties and the lower panel plots effects for Rural counties

Figure A.4: Effect of violent tornadoes on labor market outcomes (all industries) - Midwest and Southern Regions



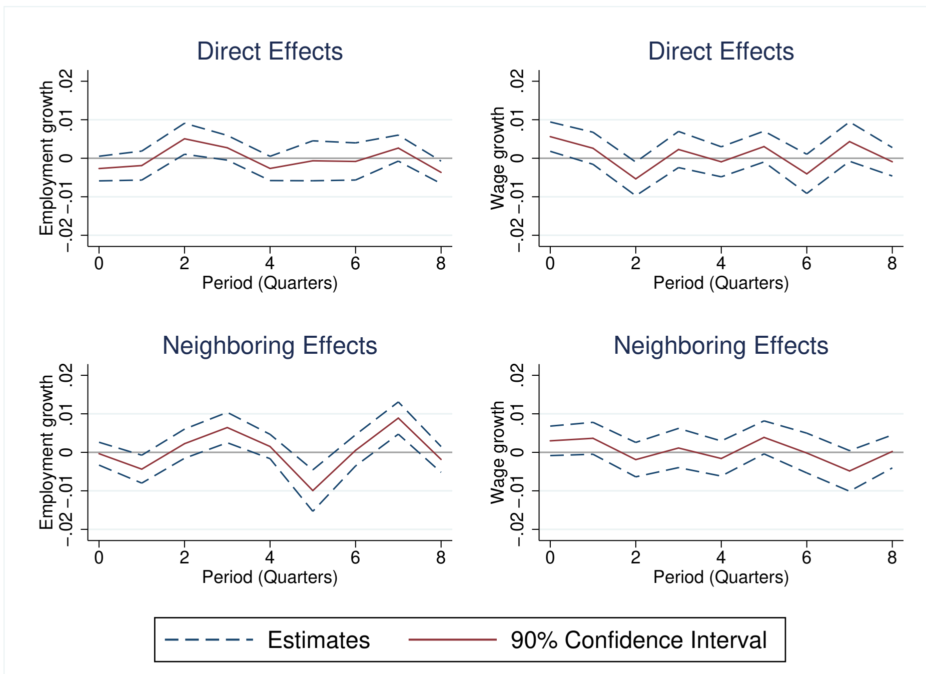
Note: The solid line plots the response of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the direct effects and the lower panel plots the neighboring effects

Figure A.5: Effect of violent tornadoes on labor market outcomes (all industries) - Pooling



Note: The solid line plots the response of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the direct effects and the lower panel plots the neighboring effects

Figure A.6: Effect of violent tornadoes on labor market outcomes (all industries) - Local Projection



Note: The solid line plots the response of employment or wages per worker. The dotted line plots the 90% confidence interval. The top panel illustrates the direct effects and the lower panel plots the neighboring effects

A.2 Chapter 2 Appendix

A.2.1 Data Appendix

Although the Global Terrorist Database (GTD) includes data on both domestic and transnational terrorist attacks, it does not identify them separately. For this reason, I follow Enders et. al (2011) to distinguish between domestic and transnational terrorist attack from the GTD database as follows:

1. Exclude events that do not satisfy the three conditions defined by the GTD dataset as a terrorist attack.
2. The dataset flags some incidents as doubtful. Remove these events.
3. The next five steps identify transnational terrorist incidents from among the remaining observations
   a) GTD reports the nationality of three victims. If the nationality of even one of these victims is different from the target country reported by GTD, identify the observation as a transnational terrorist attack.
   b) Foreign emissaries, embassies, consulates, and diplomatic staff, families, and property along with non-government organizations (NGO) that are mostly multinational in nature are considered diplomatic entities. Based on the target type identified by GTD, an incident targeting a diplomatic entity, or an NGO is considered transnational.
   c) If GTD identifies that an incident targeted a U.S. entity outside of the USA or an international entity like the UN, classify that incident as a transnational terror attack.
   d) U.S. specific information like fatalities, hostages, wounded etc. are reported separately by GTD. If these reports indicate that a U.S specific

event may have occurred outside of the USA, identify the incident as a transnational terror attack.

e) GTD reports the concluding country of hijackings or kidnappings. It also specifies if there was a diversion. If this country is different from the origin country the event is a transnational incident.

f) In addition to the above steps described by Enders et al. (2011), I identify incidents that the GTD database discerns as having international ideologies or geography as transnational terrorist incidents.

4. Any incident from among the observations that have not been identified as transnational, that has information missing about the nationality of the victims, or the target type is considered uncertain. Also incidents that are missing information about U.S. fatalities, wounded, hijackings, or ransoms are considered uncertain. I drop these uncertain incidents.

5. Any incident that has not been identified as transnational or uncertain is classified as a domestic terrorist incident.

A.2.1.1 Definitions and Sources

Table A.2: Definitions and Sources of the Variables

Variable	Definitions	Source
GDP per capita	The real GDP per capita in US dollars	World Bank's World Development Indicators
I/GDP (Gross fixed capital formation as a share of GDP)	This measure includes land improvements, equipment purchases, and construction of infrastructure, buildings - private and public.	World Bank's World Development Indicators

Military Expenditures as a share of GDP	This measures includes expenditures on armed forces, paramilitary fores, and military space activities. It includes expenses on military research and developmet, military aid, and personnel expenditures. It however, does not include expenditures for previous military activities.	World Bank's World Development Indicators
G/GDP (Government Consumption Expenditures as a share of GDP)	This includes all government expenditures for purchases of goods and services. It also includes employee wages and national defense and security expenditures. However, it excludes military expenditures that would be considered part of government capital formation	World Bank's World Development Indicators
Non-military expenditures as a share of GDP	This is government consumption expenditure as a share of GDP minus military expenditures as a share of GDP	
Population	This is the total population of a country	World Bank's World Development Indicators
Educational attainment	This variable is the percentage of population that has completed a secondary education.	Barro and Lee (2013)

Polity 2	This variable is the polity2 score reported by the Polity IV dataset. It scores a country based on democratic or autocratic status.	Polity IV
Natural disasters	Disasters that have been identified as floods, storms, or earthquake	Emergency Disaster Database (EM-DAT)
Terrorist attacks	Violent incidents perpetrated by individuals or groups for a political or religious reason.	Global Terrorism Database (GTD)
Transnational terrorist attacks	Terrorist incidents that involve more than one country. The country of victims, and/or perpetrators can vary. The target country could also be different from the country where the incident occurred.	Global Terrorism Database (GTD)
Domestic terrorist attacks	Terrorist incidents that involve only one country. The victims, target, and the perpetrators are from the same country.	Global Terrorism Database (GTD)

A.2.2 List of Countries

Developed Countries:

Australia, Austria, Bahrain, Belgium, Canada, Chile, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Republic of Korea, Kuwait, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Saudi Arabia, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States, Uruguay.

Emerging Countries:

Afghanistan, Albania, Algeria, Argentina, Armenia, Bangladesh, Benin, Bolivia, Botswana, Brazil, Bulgaria, Burundi, Cambodia, Cameroon, Central African Republic, China, Colombia, Democratic Republic of Congo, Republic of Congo, Costa Rica, Cuba, Dominican Republic, Ecuador, Egypt, El Salvador, Eswatini (Swaziland), Fiji, Gabon, Gambia, Ghana, Guatemala, Guyana, Honduras, India, Indonesia, Islamic Republic of Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Lao People's Democratic Republic, Lesotho, Liberia, Libya, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Niger, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Romania, Russian Federation, Rwanda, Senegal, Sierra Leone, South Africa, Sri Lanka, Sudan, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Uganda, Ukraine, Venezuela, Vietnam, Zimbabwe.

A.2.3 Robustness Check

Table A.3: Estimation of Growth Model (Non-Linear Specification)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.6590*		-0.6592*	
	(0.3729)		(0.3693)	
$Terror_{it}^2$	4.2931*		4.2849*	
	(2.3787)		(2.3516)	
$Transnational_{it}$				-0.5798
				(0.7655)
$Transnational_{it}^2$				4.0024
				(3.7866)
$Domestic_{it}$				-0.5655
				(0.5510)
$Domestic_{it}^2$				3.5397
				(4.8365)
$NaturalDisaster_{it}$		-0.0465***	-0.0465***	
		(0.0161)	(0.0162)	
$NaturalDisaster_{it}^2$		0.0130***	0.0129***	
		(0.0045)	(0.0045)	
$Flood_{it}$				-0.6042*
				(0.3444)
$Flood_{it}^2$				0.4251
				(0.2700)
$Earthquake_{it}$				-0.0293*
				(0.0175)
$Earthquake_{it}^2$				0.0086*
				(0.0047)
$Storm_{it}$				-0.0073
				(0.0247)
$Storm_{it}^2$				-0.0041
				(0.0094)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is GDP growth, the data spans from 1970 to 2015. The variables of interest are the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms and the square of the intensity. The intensity measure is the number of deaths per thousand caused by an event.The controls included in the specification are initial GDP per capita, educational attainment, population growth, polity 2 score, investment, government consumption.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.4: Estimation of Growth Model (Robustness Check - Dummy Variable)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.0007		-0.0007	
	(0.0031)		(0.0031)	
$Transnational_{it}$				0.0004
				(0.0033)
$Domestic_{it}$				-0.0018
				(0.0036)
$NaturalDisaster_{it}$		-0.0054*	-0.0054*	
		(0.0027)	(0.0027)	
$Flood_{it}$				-0.0024
				(0.0028)
$Earthquake_{it}$				-0.0012
				(0.0055)
$Storm_{it}$				-0.0032
				(0.0028)
$ln(GDP)_{it-1}$	-0.0443***	-0.0446***	-0.0446***	-0.0446***
	(0.0058)	(0.0057)	(0.0058)	(0.0058)
$ln(Education)_{it}$	-0.0034	-0.0034	-0.0034	-0.0035
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
$Populationgrowth_{it}$	-0.5545***	-0.5525***	-0.5542***	-0.5568***
	(0.1766)	(0.1775)	(0.1762)	(0.1749)
$ln(G/GDP)_{it-1}$	-0.0165***	-0.0165***	-0.0165***	-0.0165***
	(0.0060)	(0.0060)	(0.0060)	(0.0060)
$ln(I/GDP)_{it-1}$	0.0154***	0.0154***	0.0155***	0.0155***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
$ln(trade)_{it-1}$	0.0325***	0.0323***	0.0323***	0.0323***
	(0.0065)	(0.0065)	(0.0065)	(0.0066)
$Polity_{it}$	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is GDP growth, the data spans from 1970 to 2015. The variables of interest are the dummy variables of terrorism, transnational terrorism, domestic terrorism, natural disasters, floods, earthquake, and storms. The dummy variable takes the value one if the number of deaths in a country in a given year due to a certain type of event exceeds 75 percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.5: Estimation of Investment Model (Robustness Check - Dummy Variable)

	(1)	(2)	(3)	(4)
$Terror_{it}$	0.0173		0.0172	
	(0.0223)		(0.0223)	
$Transnational_{it}$				0.0196
				(0.0202)
$Domestic_{it}$				0.0078
				(0.0259)
$NaturalDisaster_{it}$		0.0069	0.0067	
		(0.0118)	(0.0118)	
$Flood_{it}$				0.0223
				(0.0151)
$Earthquake_{it}$				0.0024
				(0.0144)
$Storm_{it}$				0.0171
				(0.0237)
$ln(GDP)_{it-1}$	0.1259**	0.1245**	0.1263**	0.1277**
	(0.0582)	(0.0579)	(0.0583)	(0.0582)
$ln(Education)_{it}$	0.0831***	0.0836***	0.0831***	0.0827***
	(0.0287)	(0.0286)	(0.0287)	(0.0284)
$Populationgrowth_{it}$	3.9037***	3.8596***	3.9029***	3.9039***
	(1.3964)	(1.4003)	(1.3965)	(1.3926)
$ln(G/GDP)_{it-1}$	-0.0809	-0.0804	-0.0808	-0.0799
	(0.0497)	(0.0500)	(0.0497)	(0.0498)
$ln(trade)_{it-1}$	0.2763***	0.2759***	0.2765***	0.2775***
	(0.0585)	(0.0586)	(0.0585)	(0.0585)
$Polity_{it}$	0.0058**	0.0058**	0.0058**	0.0057**
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is the natural log of Investment (% of GDP), the data spans from 1970 to 2015. The variables of interest are the dummy variables of terrorism, transnational terrorism, domestic terrorism, natural disasters, floods, earthquake, and storms. The dummy variable takes the value one if the number of deaths in a country in a given year due to a certain type of event exceeds 75 percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.6: Estimation of Military Expenditures Model (Robustness Check - Dummy Variable)

	(1)	(2)	(3)	(4)
$Terror_{it}$	0.0979***		0.0978***	
	(0.0358)		(0.0358)	
$Transnational_{it}$				0.0576*
				(0.0324)
$Domestic_{it}$				0.0915***
				(0.0337)
$NaturalDisaster_{it}$		0.0064	0.0054	
		(0.0106)	(0.0109)	
$Flood_{it}$				0.0104
				(0.0141)
$Earthquake_{it}$				0.0196
				(0.0187)
$Storm_{it}$				-0.0035
				(0.0152)
$ln(GDP)_{it-1}$	-0.0545	-0.0643	-0.0541	-0.0530
	(0.0703)	(0.0704)	(0.0703)	(0.0701)
$ln(Education)_{it}$	0.0260	0.0295	0.0259	0.0265
	(0.0351)	(0.0346)	(0.0351)	(0.0350)
$Populationgrowth_{it}$	-2.3382	-2.5824*	-2.3397	-2.3209
	(1.5274)	(1.5409)	(1.5268)	(1.5165)
$ln(I/GDP)_{it-1}$	0.0457	0.0463	0.0456	0.0444
	(0.0404)	(0.0409)	(0.0404)	(0.0402)
$ln(trade)_{it-1}$	-0.0681	-0.0726	-0.0678	-0.0652
	(0.0460)	(0.0467)	(0.0460)	(0.0458)
$Polity_{it}$	-0.0105***	-0.0105***	-0.0105***	-0.0106***
	(0.0034)	(0.0035)	(0.0035)	(0.0034)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the dummy variables of terrorism, transnational terrorism, domestic terrorism, natural disasters, floods, earthquake, and storms. The dummy variable takes the value one if the number of deaths in a country in a given year due to a certain type of event exceeds 75 percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.7: Estimation of Non-Military Government Expenditures Model (Robustness Check - Dummy Variable)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.0385*		-0.0386*	
	(0.0200)		(0.0200)	
$Transnational_{it}$				-0.0281
				(0.0189)
$Domestic_{it}$				-0.0214
				(0.0241)
$NaturalDisaster_{it}$		0.0092	0.0096	
		(0.0113)	(0.0113)	
$Flood_{it}$				-0.0013
				(0.0138)
$Earthquake_{it}$				0.0230
				(0.0153)
$Storm_{it}$				0.0152
				(0.0160)
$ln(GDP)_{it-1}$	0.0483	0.0530	0.0490	0.0485
	(0.0659)	(0.0654)	(0.0659)	(0.0659)
$ln(Education)_{it}$	0.0124	0.0109	0.0123	0.0121
	(0.0275)	(0.0275)	(0.0276)	(0.0275)
$Populationgrowth_{it}$	-1.9508	-1.8576	-1.9535	-1.9381
	(1.3909)	(1.3961)	(1.3908)	(1.3904)
$ln(I/GDP)_{it-1}$	-0.0439	-0.0444	-0.0441	-0.0436
	(0.0411)	(0.0412)	(0.0412)	(0.0410)
$ln(trade)_{it-1}$	0.1523***	0.1548***	0.1529***	0.1526***
	(0.0537)	(0.0539)	(0.0539)	(0.0541)
$Polity_{it}$	0.0124***	0.0124***	0.0123***	0.0124***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of non-military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the dummy variables of terrorism, transnational terrorism, domestic terrorism, natural disasters, floods, earthquake, and storms. The dummy variable takes the value one if the number of deaths in a country in a given year due to a certain type of event exceeds 75 percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.8: Estimation of Growth Model (Robustness Check - All Events)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.2486		-0.2492	
	(0.2353)		(0.2352)	
$Transnational_{it}$				-0.1675
				(0.4770)
$Domestic_{it}$				-0.3040*
				(0.1769)
$NaturalDisaster_{it}$		-0.0197*	-0.0198*	
		(0.0114)	(0.0114)	
$Flood_{it}$				-0.1397***
				(0.0511)
$Earthquake_{it}$				-0.0050
				(0.0088)
$Storm_{it}$				-0.0314***
				(0.0116)
$ln(GDP)_{it-1}$	-0.0446***	-0.0440***	-0.0444***	-0.0446***
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
$ln(Education)_{it}$	-0.0034	-0.0034	-0.0034	-0.0035
	(0.0023)	(0.0024)	(0.0023)	(0.0024)
$Populationgrowth_{it}$	-0.5575***	-0.5518***	-0.5566***	-0.5612***
	(0.1757)	(0.1779)	(0.1758)	(0.1758)
$ln(G/GDP)_{it-1}$	-0.0164***	-0.0166***	-0.0165***	-0.0164***
	(0.0059)	(0.0060)	(0.0060)	(0.0059)
$ln(I/GDP)_{it-1}$	0.0153***	0.0153***	0.0152***	0.0154***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
$ln(trade)_{it-1}$	0.0325***	0.0325***	0.0324***	0.0322***
	(0.0066)	(0.0065)	(0.0065)	(0.0065)
$Polity_{it}$	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is GDP growth, the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.9: Estimation of Investment Model (Robustness Check - All Events)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.5325		-0.5331	
	(0.9754)		(0.9749)	
$Transnational_{it}$				-0.6933
				(1.5240)
$Domestic_{it}$				-0.4162
				(0.9928)
$NaturalDisaster_{it}$		-0.0204	-0.0205	
		(0.0680)	(0.0680)	
$Flood_{it}$				0.2424
				(0.1662)
$Earthquake_{it}$				-0.0370
				(0.0862)
$Storm_{it}$				-0.0443
				(0.0636)
$ln(GDP)_{it-1}$	0.1234**	0.1243**	0.1236**	0.1239**
	(0.0582)	(0.0578)	(0.0582)	(0.0582)
$ln(Education)_{it}$	0.0838***	0.0836***	0.0838***	0.0839***
	(0.0286)	(0.0286)	(0.0286)	(0.0287)
$Populationgrowth_{it}$	3.8494***	3.8608***	3.8500***	3.8594***
	(1.3865)	(1.4004)	(1.3866)	(1.3981)
$ln(G/GDP)_{it-1}$	-0.0804	-0.0806	-0.0805	-0.0807
	(0.0499)	(0.0499)	(0.0499)	(0.0498)
$ln(trade)_{it-1}$	0.2754***	0.2755***	0.2753***	0.2755***
	(0.0586)	(0.0586)	(0.0586)	(0.0587)
$Polity_{it}$	0.0058**	0.0058**	0.0058**	0.0058**
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is the natural log of Investment (% of GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.10: Estimation of Military Expenditures Model (Robustness Check - All Events)

	(1)	(2)	(3)	(4)
$Terror_{it}$	4.5403**		4.5415**	
	(1.8030)		(1.8042)	
$Transnational_{it}$				2.5224
				(2.8238)
$Domestic_{it}$				5.9648***
				(1.4972)
$NaturalDisaster_{it}$		0.0360	0.0373	
		(0.0459)	(0.0477)	
$Flood_{it}$				-0.0127
				(0.1044)
$Earthquake_{it}$				0.0962
				(0.0717)
$Storm_{it}$				-0.1204
				(0.0845)
$ln(GDP)_{it-1}$	-0.0585	-0.0653	-0.0590	-0.0593
	(0.0699)	(0.0703)	(0.0699)	(0.0696)
$ln(Education)_{it}$	0.0280	0.0295	0.0280	0.0276
	(0.0350)	(0.0346)	(0.0350)	(0.0351)
$Populationgrowth_{it}$	-2.5082	-2.5826*	-2.5100	-2.4098
	(1.6148)	(1.5416)	(1.6147)	(1.5383)
$ln(I/GDP)_{it-1}$	0.0490	0.0467	0.0492	0.0493
	(0.0404)	(0.0409)	(0.0405)	(0.0405)
$ln(trade)_{it-1}$	-0.0712	-0.0729	-0.0710	-0.0703
	(0.0464)	(0.0467)	(0.0464)	(0.0462)
$Polity_{it}$	-0.0103***	-0.0105***	-0.0103***	-0.0102***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.11: Estimation of Non-Military Government Expenditures Model (Robustness Check - All Events)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-1.3714		-1.3723	
	(1.1389)		(1.1389)	
$Transnational_{it}$				0.4396
				(1.7934)
$Domestic_{it}$				-2.6945*
				(1.5440)
$NaturalDisaster_{it}$		-0.0278	-0.0282	
		(0.0436)	(0.0434)	
$Flood_{it}$				0.1841**
				(0.0746)
$Earthquake_{it}$				-0.0423
				(0.0552)
$Storm_{it}$				-0.0556
				(0.0343)
$ln(GDP)_{it-1}$	0.0505	0.0527	0.0508	0.0511
	(0.0655)	(0.0655)	(0.0656)	(0.0656)
$ln(Education)_{it}$	0.0115	0.0110	0.0115	0.0119
	(0.0275)	(0.0274)	(0.0275)	(0.0276)
$Populationgrowth_{it}$	-1.8773	-1.8540	-1.8759	-1.9633
	(1.4013)	(1.3965)	(1.4016)	(1.3903)
$ln(I/GDP)_{it-1}$	-0.0449	-0.0443	-0.0451	-0.0455
	(0.0412)	(0.0412)	(0.0412)	(0.0412)
$ln(trade)_{it-1}$	0.1537***	0.1541***	0.1536***	0.1527***
	(0.0537)	(0.0537)	(0.0537)	(0.0536)
$Polity_{it}$	0.0123***	0.0124***	0.0123***	0.0123***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of non-military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.12: Estimation of Growth Model (Robustness Check - 90th percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.2685		-0.2692	
	(0.2363)		(0.2362)	
$Transnational_{it}$				-0.1676
				(0.4770)
$Domestic_{it}$				-0.3210*
				(0.1770)
$NaturalDisaster_{it}$		-0.0194*	-0.0195*	
		(0.0114)	(0.0114)	
$Flood_{it}$				-0.1423***
				(0.0526)
$Earthquake_{it}$				-0.0054
				(0.0090)
$Storm_{it}$				-0.0315***
				(0.0115)
$ln(GDP)_{it-1}$	-0.0446***	-0.0440***	-0.0444***	-0.0446***
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
$ln(Education)_{it}$	-0.0034	-0.0034	-0.0034	-0.0035
	(0.0023)	(0.0024)	(0.0023)	(0.0023)
$Populationgrowth_{it}$	-0.5576***	-0.5518***	-0.5568***	-0.5615***
	(0.1757)	(0.1779)	(0.1757)	(0.1757)
$ln(G/GDP)_{it-1}$	-0.0164***	-0.0166***	-0.0165***	-0.0164***
	(0.0059)	(0.0060)	(0.0060)	(0.0059)
$ln(I/GDP)_{it-1}$	0.0153***	0.0153***	0.0152***	0.0153***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
$ln(trade)_{it-1}$	0.0325***	0.0325***	0.0324***	0.0322***
	(0.0066)	(0.0065)	(0.0065)	(0.0065)
$Polity_{it}$	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is GDP growth, the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 90th percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.13: Estimation of Investment Model (Robustness Check - 90th percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.6477		-0.6486	
	(0.9651)		(0.9644)	
$Transnational_{it}$				-0.6651
				(1.5226)
$Domestic_{it}$				-0.5604
				(0.9806)
$NaturalDisaster_{it}$		-0.0254	-0.0256	
		(0.0678)	(0.0679)	
$Flood_{it}$				0.1992
				(0.1974)
$Earthquake_{it}$				-0.0385
				(0.0863)
$Storm_{it}$				-0.0458
				(0.0637)
$ln(GDP)_{it-1}$	0.1233**	0.1244**	0.1235**	0.1238**
	(0.0582)	(0.0578)	(0.0582)	(0.0582)
$ln(Education)_{it}$	0.0838***	0.0836***	0.0838***	0.0839***
	(0.0286)	(0.0286)	(0.0286)	(0.0287)
$Populationgrowth_{it}$	3.8474***	3.8610***	3.8483***	3.8535***
	(1.3845)	(1.4004)	(1.3846)	(1.3983)
$ln(G/GDP)_{it-1}$	-0.0803	-0.0806	-0.0805	-0.0808
	(0.0499)	(0.0499)	(0.0499)	(0.0498)
$ln(trade)_{it-1}$	0.2754***	0.2755***	0.2752***	0.2755***
	(0.0586)	(0.0586)	(0.0586)	(0.0587)
$Polity_{it}$	0.0058**	0.0058**	0.0058**	0.0058**
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is the natural log of Investment (% of GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 90th percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.14: Estimation of Military Expenditures Model (Robustness Check - 90th percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	4.3307**		4.3321**	
	(1.7199)		(1.7214)	
$Transnational_{it}$				2.4260
				(2.7838)
$Domestic_{it}$				5.8545***
				(1.4620)
$NaturalDisaster_{it}$		0.0336	0.0352	
		(0.0454)	(0.0475)	
$Flood_{it}$				-0.0045
				(0.1060)
$Earthquake_{it}$				0.0985
				(0.0730)
$Storm_{it}$				-0.1188
				(0.0842)
$ln(GDP)_{it-1}$	-0.0591	-0.0653	-0.0596	-0.0597
	(0.0700)	(0.0703)	(0.0699)	(0.0696)
$ln(Education)_{it}$	0.0283	0.0295	0.0283	0.0278
	(0.0350)	(0.0347)	(0.0350)	(0.0351)
$Populationgrowth_{it}$	-2.5146	-2.5825*	-2.5164	-2.4141
	(1.6102)	(1.5416)	(1.6102)	(1.5364)
$ln(I/GDP)_{it-1}$	0.0490	0.0466	0.0492	0.0493
	(0.0404)	(0.0409)	(0.0405)	(0.0405)
$ln(trade)_{it-1}$	-0.0714	-0.0729	-0.0713	-0.0705
	(0.0464)	(0.0467)	(0.0464)	(0.0462)
$Polity_{it}$	-0.0103***	-0.0105***	-0.0103***	-0.0102***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 90th percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.15: Estimation of Non-Military Government Expenditures Model (Robustness Check - 90$^{\text{th}}$ percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-1.3047		-1.3057	
	(1.1247)		(1.1248)	
$Transnational_{it}$				0.5603
				(1.8183)
$Domestic_{it}$				-2.7806*
				(1.5453)
$NaturalDisaster_{it}$		-0.0248	-0.0253	
		(0.0439)	(0.0436)	
$Flood_{it}$				0.2150**
				(0.0827)
$Earthquake_{it}$				-0.0455
				(0.0550)
$Storm_{it}$				-0.0577*
				(0.0335)
$ln(GDP)_{it-1}$	0.0506	0.0527	0.0510	0.0512
	(0.0655)	(0.0655)	(0.0656)	(0.0656)
$ln(Education)_{it}$	0.0114	0.0110	0.0114	0.0119
	(0.0275)	(0.0274)	(0.0275)	(0.0276)
$Populationgrowth_{it}$	-1.8753	-1.8540	-1.8740	-1.9693
	(1.4002)	(1.3965)	(1.4005)	(1.3887)
$ln(I/GDP)_{it-1}$	-0.0449	-0.0443	-0.0451	-0.0456
	(0.0412)	(0.0412)	(0.0412)	(0.0411)
$ln(trade)_{it-1}$	0.1538***	0.1542***	0.1537***	0.1527***
	(0.0537)	(0.0537)	(0.0537)	(0.0536)
$Polity_{it}$	0.0123***	0.0124***	0.0123***	0.0123***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of non-military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 90$^{\text{th}}$ percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.16: Estimation of Growth Model (Robustness Check - 99$^{\text{th}}$ percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.1996		-0.2004	
	(0.1944)		(0.1945)	
$Transnational_{it}$				-0.1694
				(0.4830)
$Domestic_{it}$				-0.1351
				(0.1167)
$NaturalDisaster_{it}$		-0.0163	-0.0163	
		(0.0115)	(0.0115)	
$Flood_{it}$				-0.1421**
				(0.0546)
$Earthquake_{it}$				0.0014
				(0.0065)
$Storm_{it}$				-0.0268**
				(0.0133)
$ln(GDP)_{it-1}$	-0.0444***	-0.0441***	-0.0442***	-0.0444***
	(0.0058)	(0.0058)	(0.0058)	(0.0058)
$ln(Education)_{it}$	-0.0034	-0.0034	-0.0034	-0.0036
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
$Populationgrowth_{it}$	-0.5532***	-0.5520***	-0.5526***	-0.5535***
	(0.1768)	(0.1780)	(0.1768)	(0.1782)
$ln(G/GDP)_{it-1}$	-0.0165***	-0.0166***	-0.0166***	-0.0164***
	(0.0060)	(0.0060)	(0.0060)	(0.0059)
$ln(I/GDP)_{it-1}$	0.0153***	0.0153***	0.0152***	0.0154***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
$ln(trade)_{it-1}$	0.0325***	0.0325***	0.0325***	0.0323***
	(0.0065)	(0.0065)	(0.0065)	(0.0065)
$Polity_{it}$	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is GDP growth, the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 99$^{\text{th}}$ percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.17: Estimation of Investment Model (Robustness Check - 99th percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.6348		-0.6354	
	(0.6514)		(0.6513)	
$Transnational_{it}$				-1.5044
				(1.1683)
$Domestic_{it}$				0.2332
				(0.8485)
$NaturalDisaster_{it}$		-0.0135	-0.0138	
		(0.0696)	(0.0696)	
$Flood_{it}$				0.2419
				(0.1663)
$Earthquake_{it}$				-0.0465
				(0.0948)
$Storm_{it}$				-0.0612
				(0.0560)
$ln(GDP)_{it-1}$	0.1236**	0.1242**	0.1237**	0.1242**
	(0.0580)	(0.0578)	(0.0579)	(0.0579)
$ln(Education)_{it}$	0.0837***	0.0836***	0.0838***	0.0837***
	(0.0286)	(0.0286)	(0.0286)	(0.0287)
$Populationgrowth_{it}$	3.8576***	3.8605***	3.8579***	3.8968***
	(1.3887)	(1.4003)	(1.3888)	(1.3979)
$ln(G/GDP)_{it-1}$	-0.0804	-0.0806	-0.0805	-0.0806
	(0.0499)	(0.0499)	(0.0499)	(0.0498)
$ln(trade)_{it-1}$	0.2754***	0.2756***	0.2753***	0.2760***
	(0.0586)	(0.0586)	(0.0586)	(0.0587)
$Polity_{it}$	0.0058**	0.0058**	0.0058**	0.0058**
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
N	4600	4600	4600	4600

Standard errors in parentheses

The dependent variable in this table is the natural log of Investment (% of GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 99th percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.18: Estimation of Military Expenditures Model(Robustness Check - 99^{th} percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	1.9240*		1.9261*	
	(1.1550)		(1.1542)	
$Transnational_{it}$				1.9569
				(2.3849)
$Domestic_{it}$				2.2001*
				(1.1752)
$NaturalDisaster_{it}$		0.0442	0.0450	
		(0.0476)	(0.0483)	
$Flood_{it}$				-0.0341
				(0.0859)
$Earthquake_{it}$				0.0984
				(0.0807)
$Storm_{it}$				-0.0931
				(0.0741)
$ln(GDP)_{it-1}$	-0.0631	-0.0654	-0.0637	-0.0638
	(0.0701)	(0.0703)	(0.0700)	(0.0698)
$ln(Education)_{it}$	0.0291	0.0295	0.0291	0.0288
	(0.0347)	(0.0346)	(0.0347)	(0.0348)
$Populationgrowth_{it}$	-2.5802	-2.5827*	-2.5821	-2.5680*
	(1.5706)	(1.5417)	(1.5706)	(1.5414)
$ln(I/GDP)_{it-1}$	0.0476	0.0467	0.0478	0.0481
	(0.0407)	(0.0409)	(0.0407)	(0.0407)
$ln(trade)_{it-1}$	-0.0725	-0.0729	-0.0724	-0.0730
	(0.0466)	(0.0467)	(0.0466)	(0.0468)
$Polity_{it}$	-0.0104***	-0.0105***	-0.0104***	-0.0104***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 99^{th} percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.19: Estimation of Non-Military Government Expenditures Model (Robustness Check - 99$^{\text{th}}$ percentile)

	(1)	(2)	(3)	(4)
$Terror_{it}$	-0.7494		-0.7510	
	(1.1589)		(1.1589)	
$Transnational_{it}$				0.4544
				(1.9115)
$Domestic_{it}$				-1.8673
				(1.8170)
$NaturalDisaster_{it}$		-0.0326	-0.0329	
		(0.0429)	(0.0428)	
$Flood_{it}$				0.1611**
				(0.0677)
$Earthquake_{it}$				-0.0392
				(0.0580)
$Storm_{it}$				-0.0698*
				(0.0362)
$ln(GDP)_{it-1}$	0.0517	0.0528	0.0522	0.0522
	(0.0654)	(0.0655)	(0.0654)	(0.0655)
$ln(Education)_{it}$	0.0112	0.0110	0.0112	0.0116
	(0.0275)	(0.0274)	(0.0275)	(0.0275)
$Populationgrowth_{it}$	-1.8556	-1.8539	-1.8541	-1.9066
	(1.4020)	(1.3965)	(1.4023)	(1.3960)
$ln(I/GDP)_{it-1}$	-0.0446	-0.0443	-0.0448	-0.0452
	(0.0412)	(0.0412)	(0.0412)	(0.0412)
$ln(trade)_{it-1}$	0.1540***	0.1542***	0.1540***	0.1536***
	(0.0536)	(0.0537)	(0.0537)	(0.0535)
$Polity_{it}$	0.0124***	0.0124***	0.0123***	0.0124***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
N	4293	4293	4293	4293

Standard errors in parentheses

The dependent variable in this table is the natural log of non-military expenditures (% GDP), the data spans from 1970 to 2015. The variables of interest are the natural log of the intensity measure of transnational terrorism, domestic terrorism, floods, earthquake, and storms. The intensity measure is the number of deaths per thousand caused by an event when it exceeds the 99$^{\text{th}}$ percentile of the worlds pooled distribution of deaths caused by that event.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

A.3 Chapter 3 Appendix

A.3.1 Data Appendix

A.3.1.1 Definitions and Sources

Table A.20: Definitions and Sources of the Variables

Variable	Definitions	Source
GDP per capita	The real GDP per capita in US dollars	World Bank's World Development Indicators
Industry, value added per capita	Industry, value added in constant US dollars divided by the population	World Bank's World Development Indicators
Service, value added per capita	Services, value added in constant US dollars divided by the population	World Bank's World Development Indicators
Agriculture, value added per capita	Agriculture, value added in constant US dollars divided by the population	World Bank's World Development Indicators
I/GDP (Gross fixed capital formation as a share of GDP)	This measure includes land improvements, equipment purchases, and construction of infrastructure, buildings - private and public.	World Bank's World Development Indicators

G/GDP (Government Consumption Expenditures as a share of GDP)	This includes all government expenditures for purchases of goods and services. It also includes employee wages and national defense and security expenditures. However, it excludes military expenditures that would be considered part of government capital formation	World Bank's World Development Indicators
Terrorist attacks	Violent incidents perpetrated by individuals or groups for a political or religious reason.	Global Terrorism Database (GTD)
Transnational terrorist attacks	Terrorist incidents that involve more than one country. The country of victims, and/or perpetrators can vary. The target country could also be different from the country where the incident occurred.	Global Terrorism Database (GTD)
Domestic terrorist attacks	Terrorist incidents that involve only one country. The victims, target, and the perpetrators are from the same country.	Global Terrorism Database (GTD)

A.3.1.2 List of Countries

Emerging Countries:

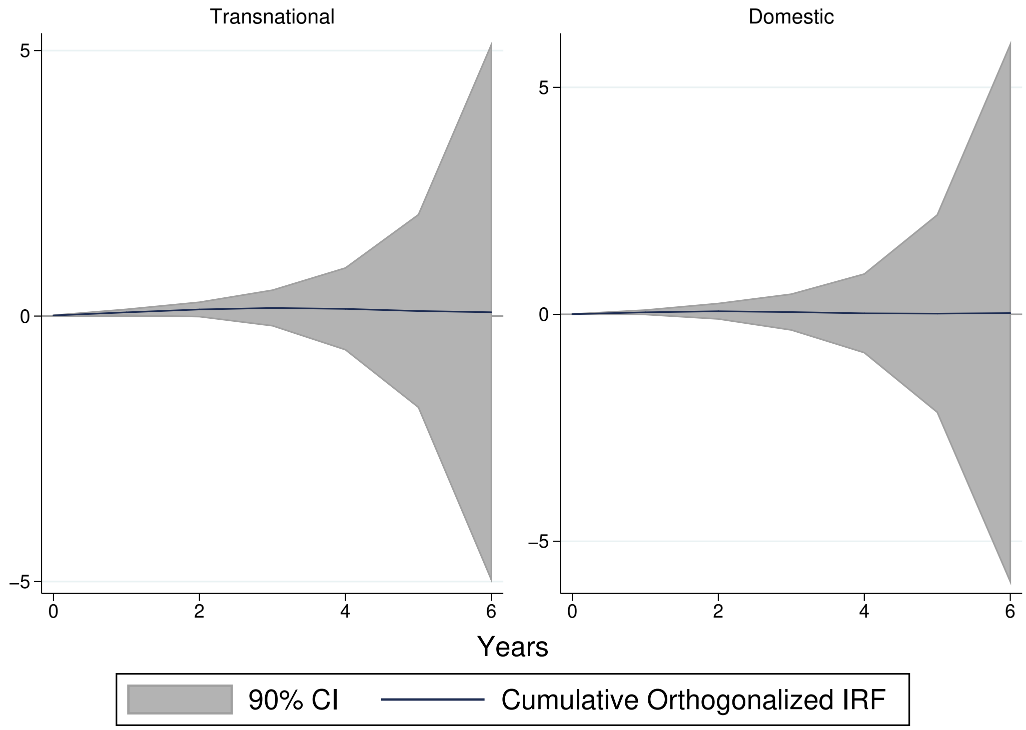
Albania, Algeria, Angola, Azerbaijan, Bangladesh, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Comoros, Costa Rica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Swaziland, Gabon, Ghana, Guatemala, Guinea, India, Indonesia, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Liberia, Madagascar, Malawi, Malaysia, Mali, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Pakistan, Panama, Paraguay, Peru, Philippines, Romania, Senegal, Serbia, Sierra Leone, Sri Lanka, Sudan, Tajikistan, Tanzania, Thailand, Timor-Leste, Tunisia, Turkey, Uganda, Ukraine, Vietnam, West Bank and Gaza.

Remaining Countries:

Australia, Austria, The Bahamas, Belgium, Brunei Darussalam, Chile, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Luxembourg, Netherlands, Norway, Poland, Portugal, Saudi Arabia, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States, Uruguay.

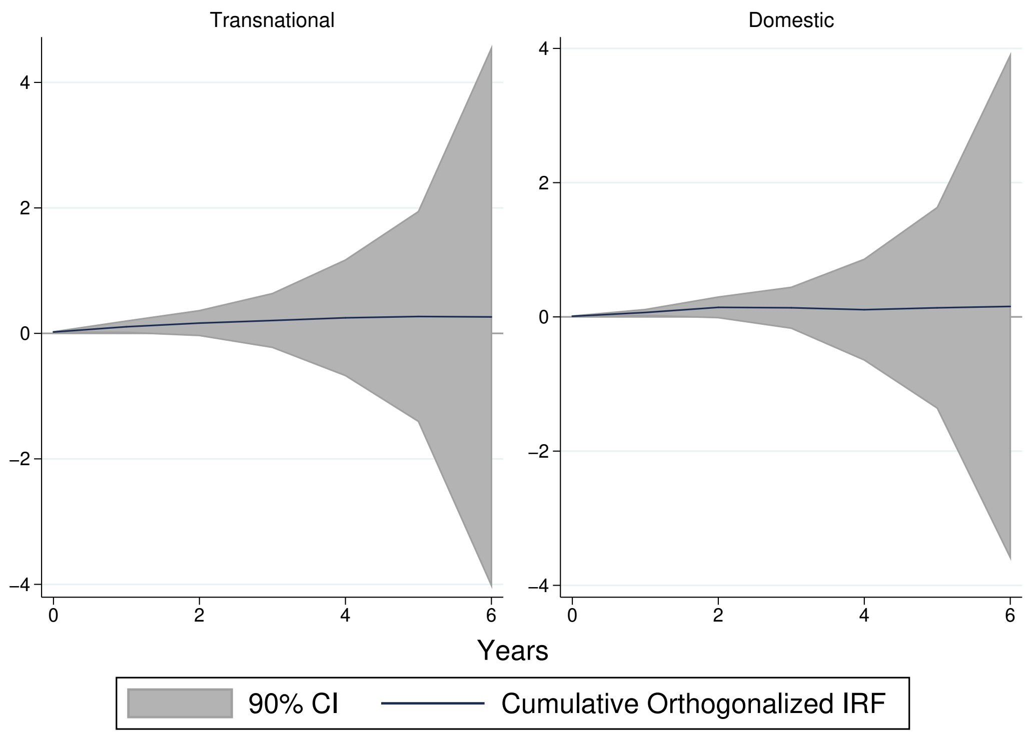
A.3.2 Robustness Check

Figure A.7: Cumulative Response of GDP Growth (Terrorism Variable Ordering)



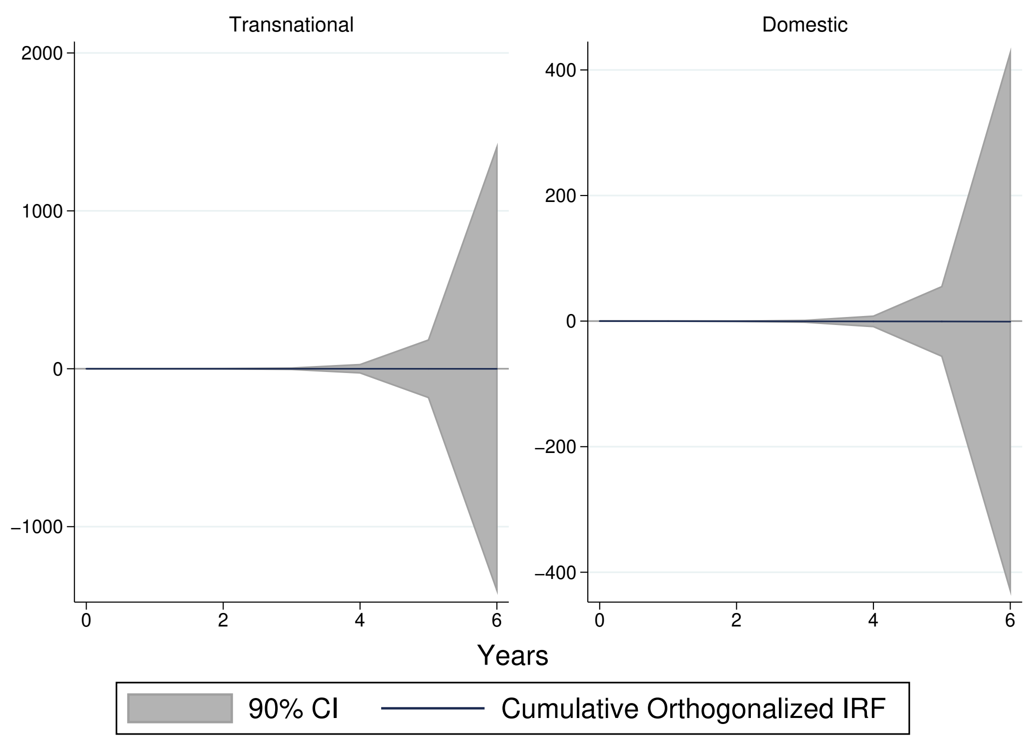
Note: The figures plot the cumulative impulse response of GDP growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of the terrorism variables to transnational terrorism and then domestic terrorism.

Figure A.8: Cumulative Response of Industrial Sector Growth (Terrorism Variable Ordering)



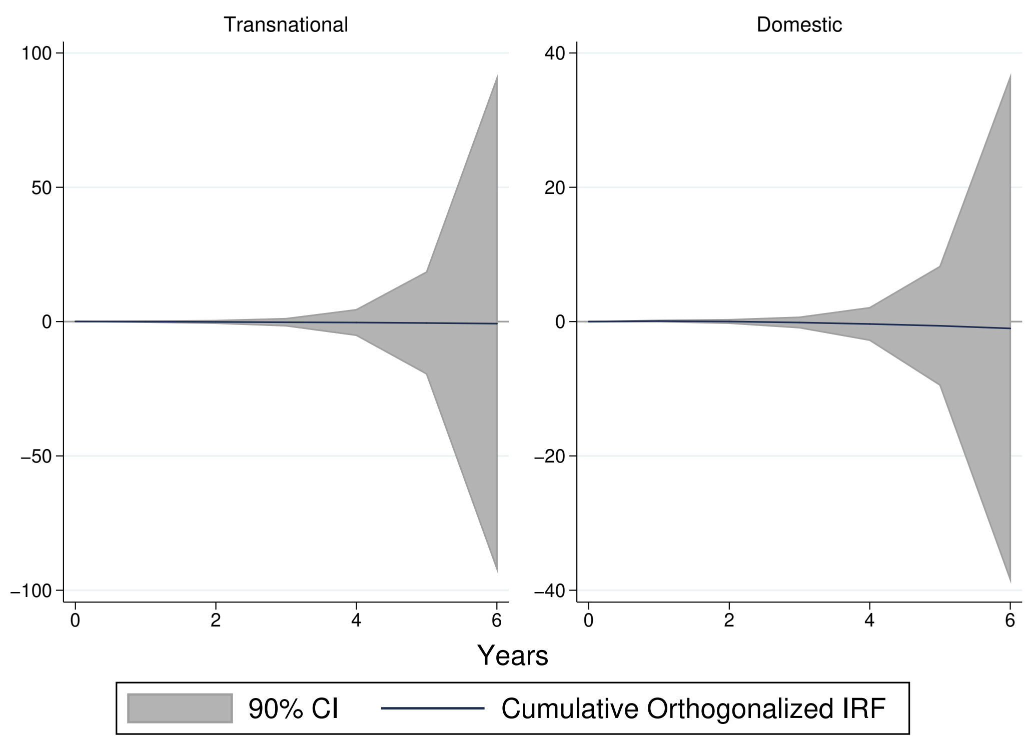
Note: The figures plot the cumulative impulse response of industrial sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of the terrorism variables to transnational terrorism and then domestic terrorism.

Figure A.9: Cumulative Response of Service Sector Growth (Terrorism Variable Ordering)



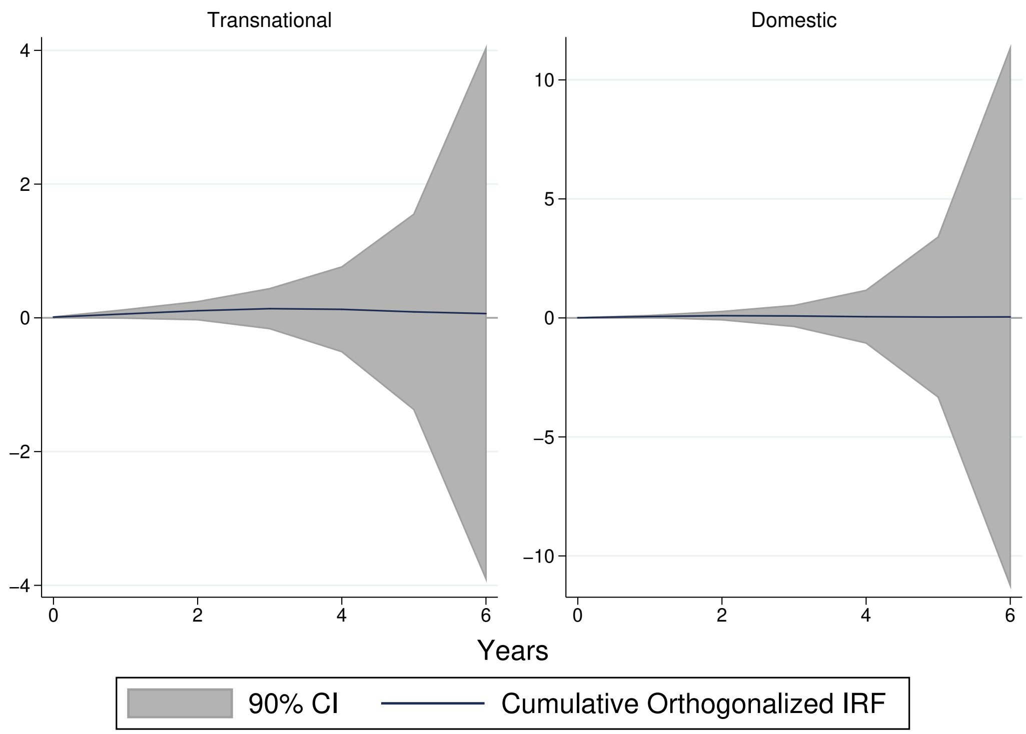
Note: The figures plot the cumulative impulse response of service sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of the terrorism variables to transnational terrorism and then domestic terrorism.

Figure A.10: Cumulative Response of Agricultural Sector Growth (Terrorism Variable Ordering)



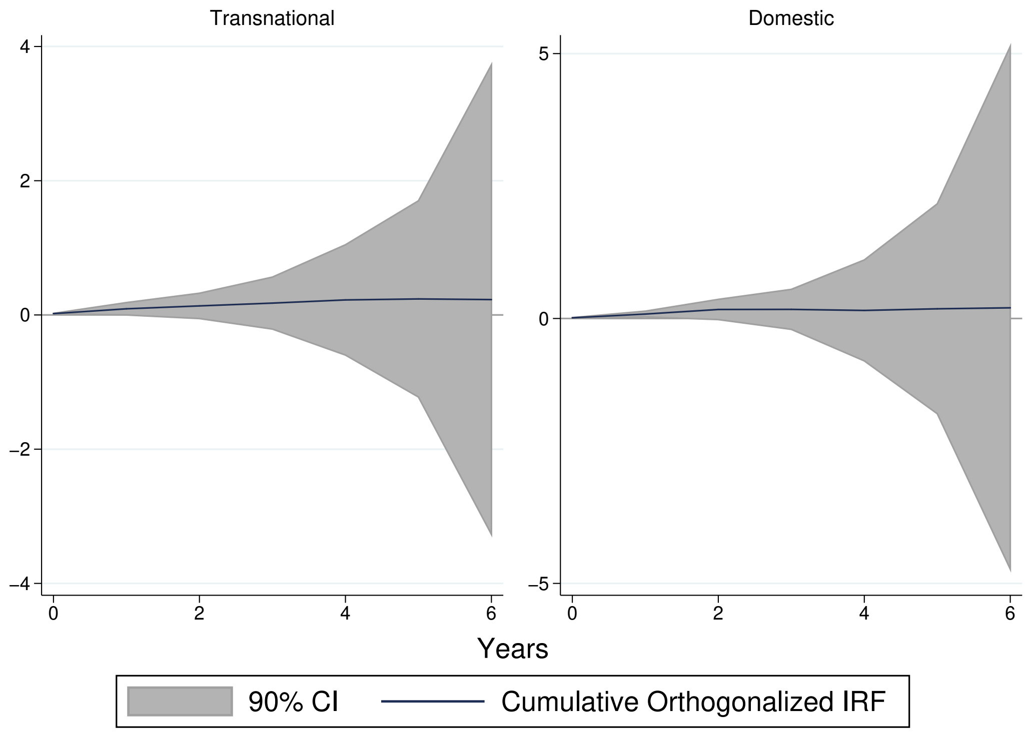
Note: The figures plot the cumulative impulse response of agricultural sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of the terrorism variables to transnational terrorism and then domestic terrorism.

Figure A.11: Cumulative Response of GDP Growth (Macroeconomic Variable Ordering)



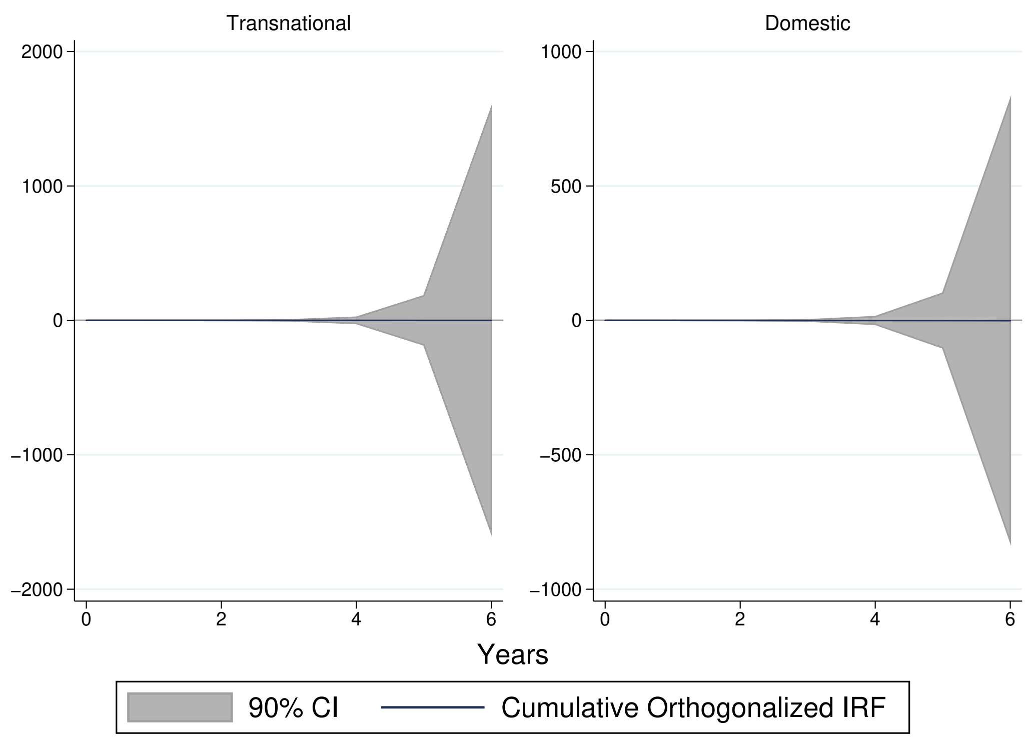
Note: The figures plot the cumulative impulse response of GDP growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of capital formation and government consumption to government expenditures and then capital formation.

Figure A.12: Cumulative Response of Industrial Sector Growth (Macroeconomic Variable Ordering)



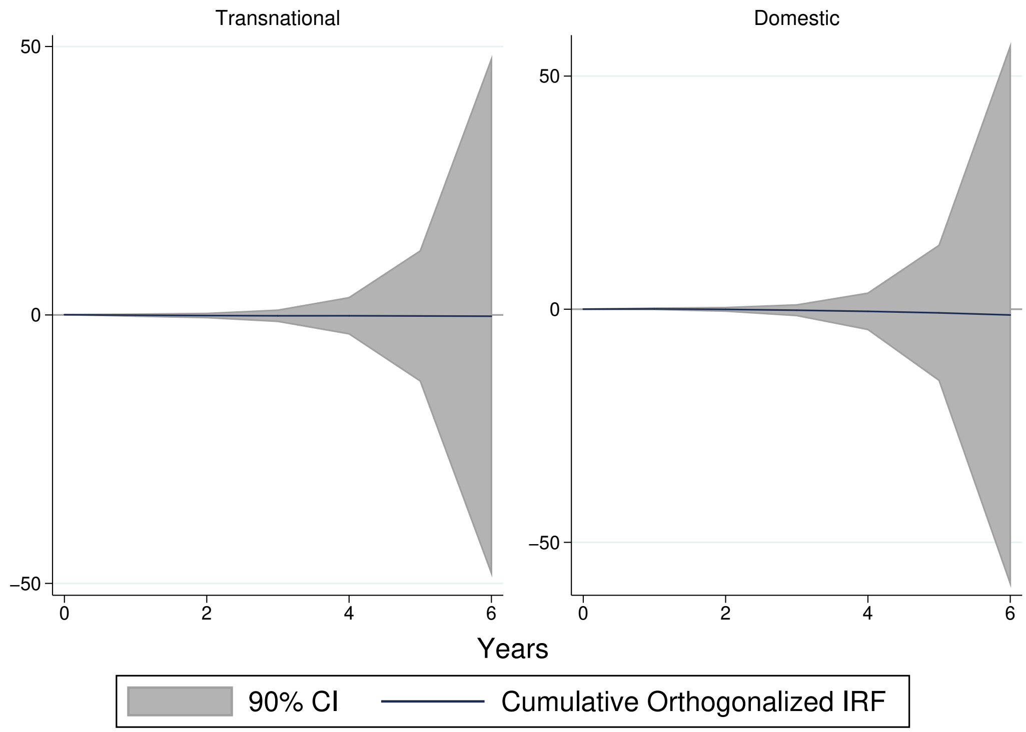
Note: The figures plot the cumulative impulse response of industrial sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of capital formation and government consumption to government expenditures and then capital formation.

Figure A.13: Cumulative Response of Service Sector Growth (Macroeconomic Variable Ordering)



Note: The figures plot the cumulative impulse response of service sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of capital formation and government consumption to government expenditures and then capital formation.

Figure A.14: Cumulative Response of Agricultural Sector Growth (Macroeconomic Variable Ordering)



Note: The figures plot the cumulative impulse response of agricultural sector growth to a one standard deviation shock to the number of deaths per thousand inhabitants of a country caused by transnational and domestic terrorist attacks. The figure on the left plots the response to transnational terrorism and the figure on the right plots the response to domestic terrorism. The solid line plots the response while the shaded region represents the 90% confidence interval. This figure reverses the order of capital formation and government consumption to government expenditures and then capital formation.

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