SOCIO-POLITICAL NATURE OF DISASTER IMPACT: TORNADOES, FLOODS, AND EXTREME HEAT

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ABSTRACT

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Severe weather and climate events such as floods, heat waves, and tornadoes, are the most frequent and devastating extreme events among all types of natural disasters in the United States. Climate scientists predict that extreme weather phenomena are expected to increase in both frequency and intensity under ongoing global climate change. Given the anticipated growing risks and detrimental impacts on people of weather extremes, it is imperative to investigate past disaster incidents and uncover community characteristics that reflect vulnerability and resilience, in order to implement informed proactive policies to minimize future human impacts. To this end, my dissertation, titled "*Socio-Political Nature of Disaster Impact: Tornadoes, Floods, and Extreme Heat"* examines three types of extreme weather events in each of three chapters to investigate the determinants of community vulnerability to disasters and evaluate the life-saving benefits of disaster mitigation measures and practices.

Each of three chapters empirically examine tornadoes, floods, and extreme heat events at the subnational level – I consider the disaster experiences in about 3,100 counties in the contiguous United States. The integrated view of the physical, social, economic, and political elements of multi-faceted disaster vulnerability guides the empirical analyses. Each chapter employs different types of panel methods to address the county heterogeneity and potential simultaneity between governmental actions and disaster vulnerability – such as Poisson Fixed Effects (PFE), the Control-function(CF) approach within the Correlated Random Effects (CRE) framework, and the Random Trend Model (RTM).

Throughout the three chapters, I present evidence that people most vulnerable to disasters are those who have weaker economic and social bases; lower income, poverty, lower education, and poor housing quality increase disaster vulnerability. Also, I find that urbanization intensifies disaster vulnerability while learning from past experiences enhances communities' coping capacity. In the case of heatwaves, vulnerability is greater in counties with higher proportions of elderly, the very young, and non-white populations. Findings suggest that the socially isolated elderly and the elderly living in poverty are the most heat-vulnerable population sub-groups.

My dissertation pays special attention to the examination of the degree to which local government plays a role in reducing the potential disaster fatalities. The first chapter on tornadoes and the second chapter on floods shed light on the role of local government resources devoted to public safety, protection, and welfare in mitigating disaster fatalities. The second chapter on floods also provides a new evaluation of the role of the National Flood Insurance Program (NFIP) in preventing and reducing the loss of human life from flooding as an important *ex-ante* disaster management scheme. The third chapter provides significant evidence on the benefits of the government-initiated Heat Island Mitigation (HIM) measures in lowering heat intensity as well as reducing the loss of life from extreme heat.

Taken together, my research increases our understanding of the socio-political nature of the disaster vulnerability. Moreover, this study underscores the need for more proactive and precautionary public measures and policies to counter the potential harmful effects of the growing risk of weather extremes. Findings of this research may inform targeting efforts designed to protect and assist the most vulnerable populations and provide guidance to future disaster mitigation policies at the local, state and national levels.

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KEY TO ABBREVIATIONS

PFE	Poisson Fixed Effects
CF	Control Function
IV	Instrumental Variable
CRE	Correlated Random Effects
RTM	Random Trend Model
ZINB	Zero-Inflated Negative Binomial
NCEI	National Center for Environmental Information
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
CRED	Centre for Research on the Epidemiology of Disasters
FS	Fujita Scale
VSL	Value of a Statistical Life
FEMA	Federal Emergency Management Agency
NFIP	National Flood Insurance Program
SFHA	Special Flood Hazard Area
CRS	Community Rating System
NID	National Inventory of Dams
IPCC	Intergovernmental Panel on Climate Change
EPA	Environmental Protection Agency
HIM	Heat Island Mitigation
NDHS	Net Daily Heat Stress

INTRODUCTION

Severe weather and climate events such as floods, heat waves, and tornadoes, are the most frequent and devastating extreme events among all types of natural disasters in the United States. In 2017 alone, weather-related disasters caused more than $300 billion in total damages and 508 fatalities. Climate scientists predict that extreme weather phenomena are increasing in both frequency and intensity under ongoing global climate change. Given this trend, it is likely that the economic and human losses from these climatic events will be even greater in the coming decades. Notably, we have learned that natural disasters are not all “natural.” Evaluation of devastating natural disasters have revealed significant differentials in terms of impacts across different population segments, depending on socio-economic and political status. Given the anticipated growing risks and detrimental impacts of weather extremes, it is imperative to investigate past disaster incidents to uncover characteristics that make communities more or less vulnerable. Within this context, it is particularly important to examine the role of government in mitigating adverse impacts, in order to implement informed proactive policies to minimize potential losses and damages.

To this end, my dissertation, titled “*Socio-Political Nature of Disaster Impact: Tornadoes, Floods, and Extreme Heat”* examines three types of extreme weather events in each of three chapters to investigate the factors that make communities more or less vulnerable to disasters and to evaluate the life-saving benefits of disaster mitigation measures and practices. Thethree chapters empirically examine tornadoes, floods, and extreme heat events, respectively using subnational data – about 3,100 counties in the contiguous United States. The integrated view of the physical, social, economic, and political elements of multi-faceted disaster vulnerability guides the empirical analyses. Detailed disaster data are collected from National Center for Environmental Information (NCEI) of National Oceanic and Atmospheric Administration (NOAA). Major socio-economic, housing, and local government finance data at the county level available from U.S. Bureau of the Census are also used in the analysis. Each chapter employs different types of panel methods to address the county heterogeneity and potential simultaneity between government decisions and disaster risk – Poisson/Neg. Binomial Random Effects and Poisson Fixed Effects approach in the first chapter on tornados, the Control-function(CF) approach within the Correlated Random Effects (CRE) framework for the flood analysis, and the Random Trend Model (RTM) and Poisson Fixed Effects (PFE) approach in the third chapter on extreme heat. In addition, in the second and third chapters, the Zero-Inflated Negative Binomial model is applied to examine the original event data set in a Cross-Sectional-Time-Series structure with the over-dispersed non-negative count outcomes.

Throughout the three chapters, I present evidence that disaster-specific physical factors such as intensity, location, and timing of events, the built-environment as well as socio-economic characteristics such as demographic characteristics, income level, poverty, education, and housing quality determine the overall disaster fatalities. I consistently find that disaster-induced fatalities are greater in communities with weaker economic and social bases; lower income, poverty, and lower education increase disaster vulnerability. Housing quality is also a critical factor in explaining disaster-induced fatalities; living in mobile homes or rental homes increases vulnerability to climatic shocks. Urbanization intensifies disaster vulnerability. Also, results confirm the existence of learning effects from past experiences, where counties that suffered more disasters in the recent past tend to enhance their coping capacity against disasters and in turn are better able to mitigate the societal impacts. In the case of extreme heat, population composition is an important factor; heat vulnerability is greater in counties with higher proportions of elderly, young, and non-white populations. Findings suggest that the socially isolated elderly and the elderly living in poverty are the most heat-vulnerable population sub-groups. Notably, heightened heat vulnerability due to the growing elderly population is predicted to generate a two-fold increase in heat fatalities by 2030.

My analyses pay a special attention to the degree to which local government plays a role in reducing the potential disaster fatalities. The first chapter on tornadoes and the second chapter on floods shed lights on the role of local government resources devoted to public safety, protection, and welfare in mitigating disaster fatalities. The empirical analyses indicate that such local government expenditures appear to lead to better preparedness and faster responses to disaster events and improve overall safety/welfare of a community, thus reducing fatalities.

The second chapter on floods also provides a new analysis of the role of National Flood Insurance Program (NFIP) in reducing the loss of life from flooding as an important *ex-ante* disaster management scheme. Community participation in the NFIP program requires the participating communities to implement floodplain management requirements for flood risk and damage reduction. My findings provide an empirical evidence that flood-prone community participation help communities become more flood-resistant. My evaluation also shows that the life-saving benefits of the NFIP over the 20-year study period are estimated to be substantial enough to compensate for the program's deficits accumulated during the same period. Nevertheless, the program's current operational challenges and the public concerns regarding the fiscal soundness of the program necessitate a thoughtful reform of the NFIP, which must balance the affordability of flood insurance with financial solvency of the program. In this redesign process, the life-saving benefits of the disaster management of the NFIP ought to be taken into account.

In terms of extreme heat, the most relevant public efforts for heat mitigation and adaptation currently undertaken by state and local government are the government-initiated community Heat Islands Mitigation (HIM) activities (i.e. trees/vegetation, green/cool roofs, cool pavements). HIM strategies act primarily as heat-hazard mitigation measures by helping communities that are at higher risk of heat exposure to manage the fundamental meteorological risk of high temperatures. However, there has been no prior heat study that seeks to determine the extent to which government-initiated HIM measures have reduced heat-related fatalities. The third chapter provides new evidence on the benefits of HIM measures in terms of reducing heat intensity as well as reducing the loss of life from extreme heat. My estimate indicates that an additional measure that is locally implemented in a county is estimated to reduce annual deaths rate by 15.38 %.

Taken together, my research increases our understanding of the socio-political nature of the disaster vulnerability. Moreover, this study underscores the need for more proactive and precautionary public measures and policies to counter the potential harmful effects of the growing risk of weather extremes. Findings of this research may inform targeting efforts designed to protect and assist the most vulnerable populations and provide guidance to future disaster mitigation policies at the local, state and national levels.

CHAPTER 1

SOCIO-ECONOMIC DETERMINANTS OF TORNADO FATALITIES IN THE UNITED STATES: DIMENSIONS OF POVERTY, HOUSING QUALITY, AND GOVERNMENT

1.1 INTRODUCTION

Natural disasters such as tornadoes result in the significant loss of human life, as well as substantial economic damages. For example, in 2011 there were a record breaking 1,701 tornadoes in the United States resulting in 551 deaths (the most in the 62-year period for which we have records) and estimated total economic damages of over 28 billion U.S. dollars[1]. Given the recent demonstrations of the destructive power of tornado events and their largely unpredictable nature, improving our understanding of the factors that determine tornado-induced fatalities will help identify ways to potentially reduce losses. Surprisingly, to date there are relatively few studies that have empirically investigated the determinants of tornado impacts. This paper adds to this literature in several ways. First, this study considers a broader array of socio-economic factors that influence vulnerability. In particular, a range of alternative measures of poverty, including housing quality are considered. I also consider factors such as family structure as well as local government spending on emergency services.

As a prelude to full analysis, I find that counties with higher per capita income and per capita government spending on public safety and welfare have fewer deaths, whereas counties with greater income disparity and more female-headed households are more vulnerable to

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[1] NOAA National Climatic Data Center, State of the Climate: Tornadoes for Annual 2011, published online December 2011, retrieved on January 6, 2015 from http://www.ncdc.noaa.gov/sotc/tornadoes/2011/13.

tornadoes. Perhaps of most importance, housing quality as measured by mobile homes as a proportion of housing units is a critical factor in explaining tornado-induced fatalities. It might seem that tornado fatalities are simply a function of location – living in an area with a high risk of tornadoes increases the chances that one would die from a tornado. While this is certainly true, other factors are also at play. Blaikie et al. (1994) argue that *Disaster = Risk + Vulnerability,* where vulnerability depends on community and socio-economic variables in addition to location. Similarly, Cutter et al. (2003) discuss the interaction between social and biophysical vulnerabilities that determine overall place vulnerability. Overall, numerous scholars assert that underlying socio-economic factors such as poverty, access to social protection and security, as well inequalities with regard to gender, economic position, age, or race play an important role in determining disaster vulnerability (Aptekar and Boore 1990; Albala-Bertrand 1993, Cannon 1994, Blaikie et al. 1994; Cutter 1996; Enarson and Morrow 1998; Peacock et al. 1997; Morrow 1999).

A number of empirical studies of disasters sought to identify the major determinants of direct disaster impacts, where several focus on the role economic development plays in reducing disaster impacts using multi-national disaster data obtained from EM-DAT (Kahn 2005, Toya and Skidmore 2007, Stromberg 2007, Raschky 2008, Gaiha et al. 2013). Some of the above-mentioned studies evaluate the role of governmental conditions and structure, inequality, and education in determining disaster impacts. I build upon a study by Simmons and Sutter (2013), which uses U.S. county level tornado data from 1984-2007 to evaluate factors that determine vulnerability. They find that tornado characteristics such as timing, magnitude, and length are the major drivers of tornado-induced fatalities, but also find that economic and demographic factors such as education, race, community, and housing type are important. As discussed in detail below, this study expands on Simmons and Sutter (2013) by using data from a longer period of time as well as considering a broader array of potential factors and, importantly, accounting for potential interactions between tornado severity and the socio-economic factors that determine vulnerability.

Based on a conceptual framework where risk is considered to be a function of physical natural hazard characteristics as well as socially constructed factors, the present study uncovers a number of the socio-economic variables that make people and places more vulnerable to tornadoes. For the empirical examination, panel structured tornado data are used with observations at the sub-national level - 3,107 U.S. counties(excludes Alaska and Puerto Rico) over the 1980-2014 period. The detailed data on tornado events in U.S. counties are collected from NOAA, while socio-economic, housing, and local government fiscal data are obtained from U.S. Bureau of the Census. Taking into consideration that tornadoes are localized events as opposed to other more geographically dispersed disasters such as hurricanes, or earthquakes, the county level data (as opposed to aggregated national level data) allow us to more accurately identify and thus better understand the determinants of disaster vulnerability.

By identifying the factors influencing tornado-induced fatalities, with particular focus on which dimensions of poverty seem to contribute most, this study provides insight that will help policy makers to better prepare for future devastating events and reduce societal vulnerability to disasters. The following section offers a review of the empirical literature regarding the determinants of the impacts of natural disasters. Section 1.3 discusses tornado risks in the United States, and section 1.4 describes the underlying theoretical foundation for my analysis and introduces the primary hypotheses. Sections 1.5 and 1.6 present the empirical framework of the analysis and empirical results, respectively.

1.2 EMPIRICAL STUDIES ON THE DETERMINANTS OF DISASTER IMPACTS

While many sociologists, geographers and other social scientists have studied how social, economic, and political factors potentially affect a society's vulnerability to natural disasters (Aptekar and Boore 1990; Albala-Bertrand 1993, Cannon 1994, Blaikie et al. 1994; Cutter 1996; Enarson and Morrow 1998; Peacock et al. 1997; Morrow 1999), most of these studies are qualitative in nature in that they use subjective identification rather than quantitative methods to suggest statistical evidence.

In addition, economists have studied the economic impacts of natural disasters, estimating the economic consequences of significant disaster events. However, there are relatively few quantitative empirical studies that investigate the underlying determinants of disaster impacts. This literature review focuses on research that empirically examines the major factors associated with the disaster-induced losses.

Many of these studies focus on the relationship between income/wealth and disaster impacts. The overall argument is that economic development plays an important role in mitigating the disaster vulnerability of a society. One of the first studies to identify this relationship (Burton et al., 1993) compares the post-disaster responses of high-income and low-income countries and finds that the consequences of natural disasters such as drought, floods and tropical cyclones differ across countries not only by hazard, but also by income. Horwich (2000) draws a similar conclusion, arguing that the critical underlying factor in any economy’s response to disaster is its level of wealth. He explains that a rise in income will provide not only general safety but also improved protection from natural disasters.

Many of the more recent empirical studies that examine the determinants of disaster vulnerability have been cross-national and use disaster data obtained from EM-DAT[2]. For instance, Kahn (2005) uses this data source to examine the relationship between disaster-induced death and explanatory factors such as income, geography, and national institutions in the context of multiple types of natural disasters in 73 nations from 1980 to 2002. He finds that while a nation's level of development is not correlated with the number of natural disaster events it experiences, higher levels of development reduce disaster-induced deaths. Kahn estimates that an increase in per capita GDP from $2,000 to $14,000 results in a reduction in natural disaster deaths from 9.44 to 1.80 per million people per year. He also finds that democracies and nations with less income inequality suffer fewer deaths from disasters.

Toya and Skidmore (2007) expand on Kahn's (2005) investigation of the disaster-safety-development relationship by including other socio-economic measures. Specifically, they use disaster impact data from EM-DAT and several other sources for 151 countries over 44 years (1960-2003). Their study confirms that economic development as measured by per capita GDP is inversely correlated with both disaster deaths and damages. However, they also find that higher levels of educational attainment, greater openness, and a stronger financial sector are also associated with fewer deaths and less damage.

Other studies corroborate and expand on the cross-country link between economic development and disaster outcomes. For instance, Anbarci et al. (2005) in their study of earthquakes show that greater income inequality increases earthquake fatalities. Raschky (2008)

[2] Emergency Events Database EM-DAT that has been maintained by the Centre for Research on the Epidemiology of Disasters (CRED) contains essential core data on the occurrence and effects of mass disasters in the world from 1900 to present.

also shows that economic development reduces disaster fatalities and losses, but this relationship is nonlinear. Economic development decreases disaster losses but with a diminishing rate. Kellenberg and Mobarak (2008) find a similar relationship between economic development and disaster vulnerability with losses increasing at first and then declining as GDP rises. Raschky also incorporates a national government stability measure and finds that more stability is associated with fewer losses. Similarly, Stromberg (2007) finds that greater wealth and government effectiveness (World Bank, 2006) are associated with fewer disaster fatalities. Finally, Gahia et al (2013) find that poorer and larger countries suffered more disaster related fatalities, but that experience from past disasters and more resources targeted to disaster prevention and mitigation can dramatically reduce deaths.

One cross-country study that does not find a significant link between GDP/income inequality and disaster vulnerability is Brooks et al. (2005). In an effort to develop national-level indicators of vulnerability and present a set of socio-economic, political and environmental variables that correlate with mortality from disasters, they include many additional socio-economic factors beyond GDP into their analysis. They find that including factors such as sanitation, life expectancy, government effectiveness, and literacy are significant predictors of disaster fatalities, whereas GDP and income inequality are not. However, their significant factors may serve as proxies for GDP.

As noted earlier, most of the research discussed above incorporates multiple types of natural disasters across multiple countries and relies primarily on the multi-national EM-DAT data set as their source of information on disasters and their impacts. In contrast, this study focuses on a specific disaster type within a single country. As previously noted, the study most closely related to my study is that by Simmons and Sutter (2013); they employ detailed U.S.

county level tornado data from National Oceanic and Atmospheric Administration (NOAA) over the period 1984-2007 to examine the societal impacts of tornadoes. In this book, the authors examine the patterns in tornado casualties over time, by state and Fujita Scale rating, and provide a regression analysis on the potential determinants of tornado casualties. Using a Poisson estimation method, they show that not only do the elements of tornado hazards (timing, magnitudes, and length of incidence) determine tornado impacts, but that economic and demographic factors such as level of education, percentage of non-white and rural population, and percentage of mobile homes contribute to tornado vulnerability. However, the authors offered little evidence that income, poverty and income distribution were important determinants of disaster impacts. The present study extends this line of research by examining a wider range of potential socio-economic factors using U.S. county level data over the 1980-2014 period.

1.3 TORNADO RISK IN THE UNITED STATES

1.3.1 Tornado Frequency

As shown in Figure 1.1, the United States is the most tornado-prone country worldwide, with an average of 1,200 recorded tornado events each year. Canada is a distant second with around 100 tornadoes per year.[3] Focusing on the United States, the average annual number of tornadoes (all intensities) by state for years 1980-2014 is presented in Figure 1.2. The darker green area shown in Figure 1.2 spanning from Texas to South Dakota is called "Tornado Alley"[4] because of the disproportionately high frequency of tornadoes.

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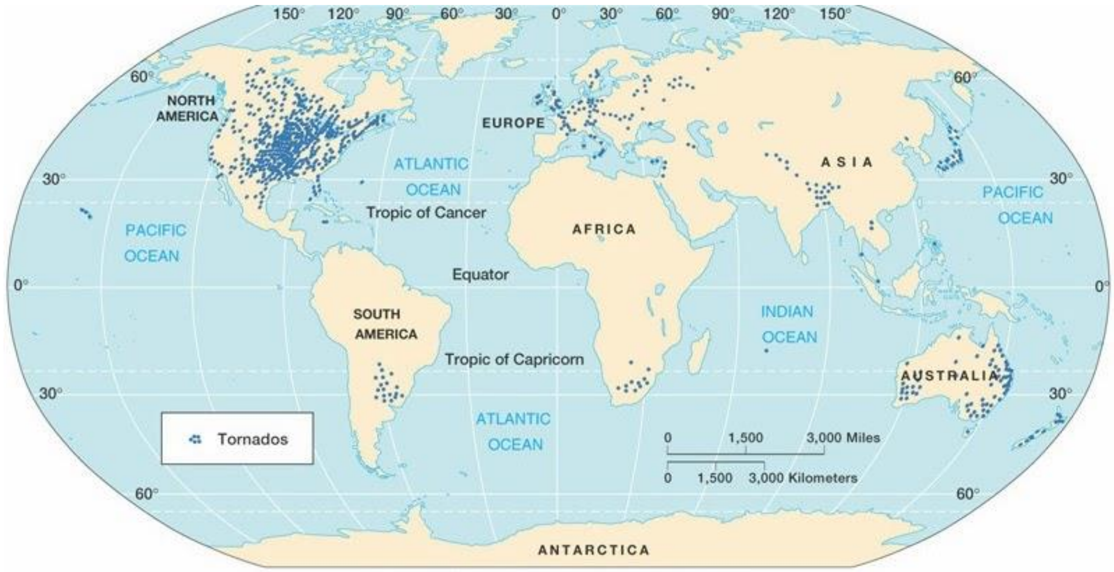
[3] NOAA National Climatic Data Center, U.S. Tornado Climatology, retrieved on November 6, 2014 from http://www.ncdc.noaa.gov/climate-information/extreme-events/us-tornado-climatology

[4] Although the boundaries of Tornado Alley are not clearly defined, for this analysis I define the states of Texas, Oklahoma, Kansas, Colorado, Nebraska, South Dakota, Iowa, Illinois, Missouri, and Arkansas as the Tornado Alley.

Figure 1.1: Global Tornado Activity



1.3.2 Tornado Intensity

In addition to tornado frequency, the magnitude and intensity of tornadoes are also important in determining impacts. According to National Climatic Data Center (NOAA), over the 1950 to 2010 time period the vast majority of tornadoes (about 77%) in the United States were categorized as weak (i.e., Fujita Scale[5] F0 or F1). Thus, nearly a quarter of tornadoes are classified as significant or strong/violent (F2 and above), with only 0.1% achieving F5 status (winds over 200 mph, resulting in near complete destruction of everything in its path). Given that, on average, about 1,200 tornadoes occur in the United States each year, about 276 will be classified as strong/violent, with perhaps one being F5. These strong/violent tornadoes account for the vast majority of tornado-induced fatalities and damage. For example, in May of 2013, a severe tornado produced catastrophic damage in Moore, Oklahoma and adjacent areas.

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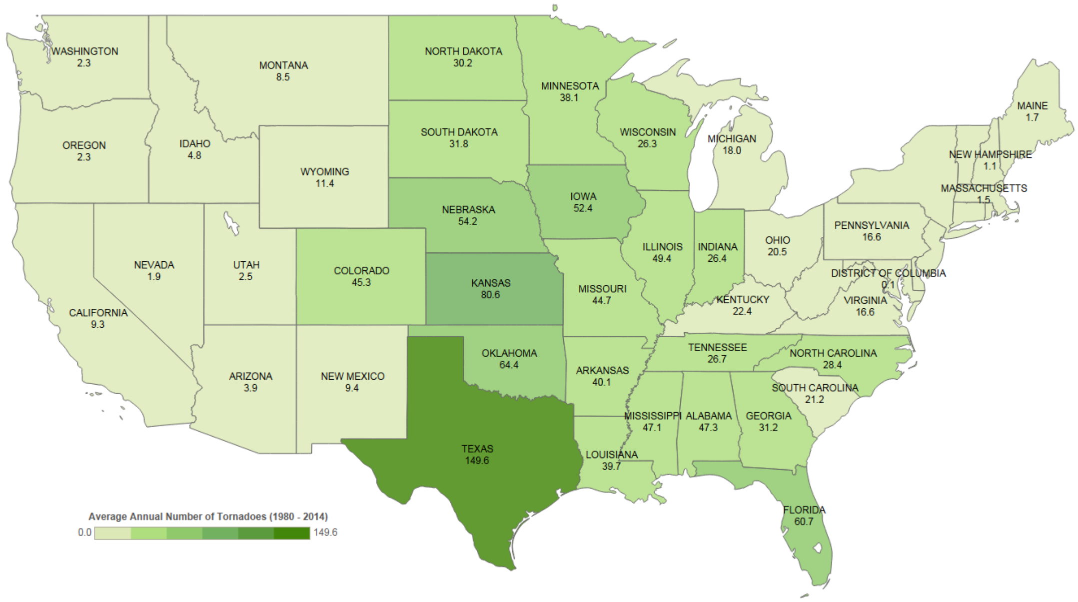
[5] Note that in 2007-2008 NOAA introduced and began using the Enhanced Fujita scale for measuring tornado intensity. I use the term Fujita scale throughout the paper since the majority of the data falls under this category.

Figure 1.2: Average Annual Number of Tornadoes during 1980-2014



This F5 rated tornado was the most deadly and devastating tornado of the year, claiming 24 lives and injuring 377 people. The tornado destroyed approximately 1,150 homes and caused more than $2 billion in damage (Insurance Journal, 2013). Another recent example is the tornado outbreak that occurred during April 25–28, 2011. This 4-day period included hundreds of tornadoes that struck communities across the southern plains and southeastern United States and was the largest and the deadliest tornado outbreak since formal record keeping began in 1950. In total, the National Weather Service (NWS) confirmed 351 tornadoes of which four were rated F5. In the four-day period 316 people died, more than 2,400 were injured, and economic damages totaled over $4.2 billion[6].

[6] National Oceanic and Atmospheric Administration. Service assessment: the historic tornadoes of April 2011. Silver Spring, MD: U.S. Department of Commerce, National Oceanic and Atmospheric Administration; 2011. Available at http://www.nws.noaa.gov/om/assessments/pdfs/historic_tornadoes.pdf.

1.4 DETERMINANTS OF TORNADO VULNERABILITY

1.4.1 Motivation

While it is clear that some places are simply more prone to tornadoes due to climactic reasons, this does not fully explain the differences in fatalities across the regions. For example, Figure 1.3 and 1.4 shows the differences between frequencies and fatalities of strong tornadoes.

Figure 1.3: Total Number of Strong/Violent Tornadoes (F2-F5), 1980-2014

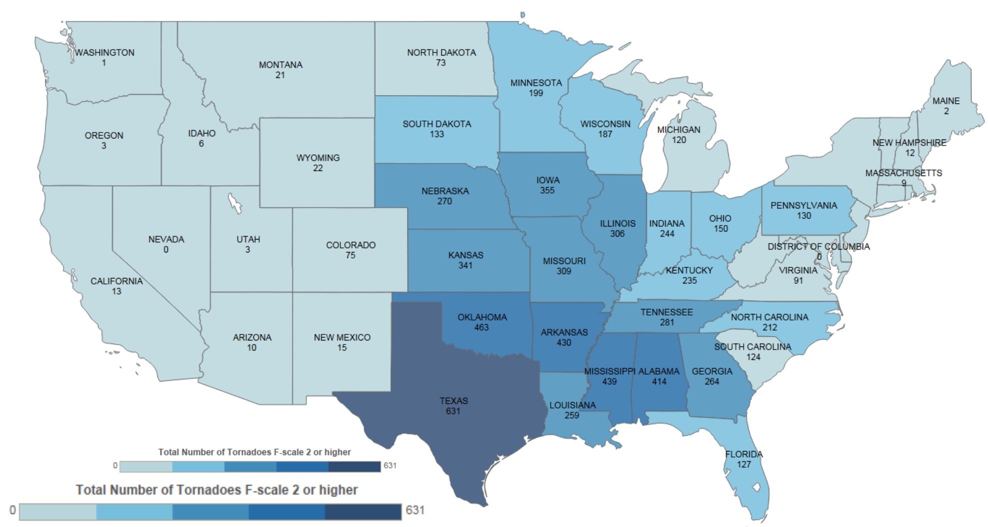
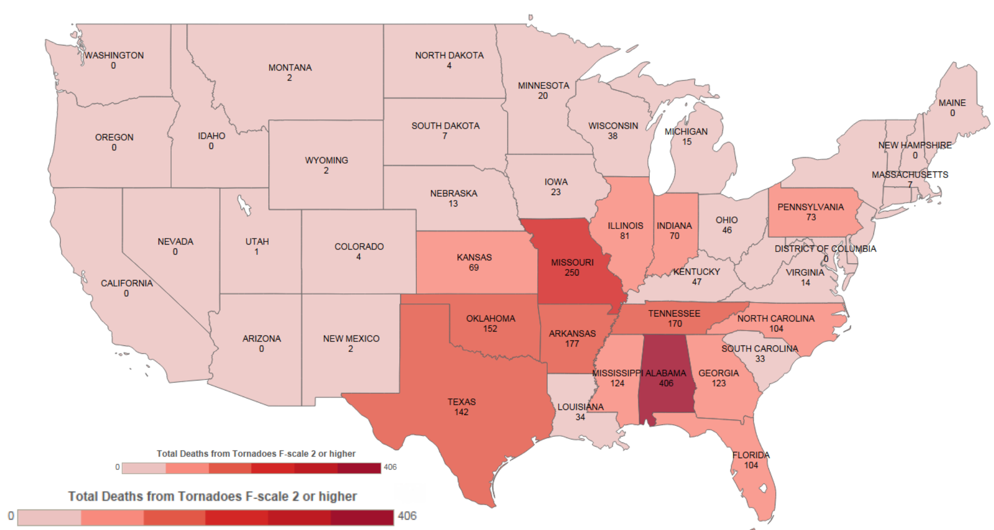


Figure 1.4: Total Number of Fatalities from Strong/Violent Tornadoes (F2-F5), 1980-2014



The map in Figure 1.3 presents the total number of F2 or higher rated tornadoes (strong/violent) over the period 1980 – 2014 by state, whereas the map in Figure 1.4 shows total fatalities from these tornadoes over the same period. As is clear, the areas with relatively high tornado fatalities do not necessarily match up with the areas with the highest tornado intensities. For example, though tornado activity is relatively modest in Missouri, this state experienced a relatively high number of fatalities per year. The present research is in part motivated by this observation. Note that these differences could be driven by many things including that there may have been a higher ratio of violent (F4 and F5) events in Missouri relative to say Texas. My analysis below takes this into account and yet I still find significant evidence that specific socio-economic factors appear to be, at least in part, driving these differences.

1.4.2 Conceptual Framework

As highlighted earlier, Cutter et al. (2003) discuss the possible interactions between social and biophysical vulnerabilities that determine overall place vulnerability. They explain that the hazard potential is either moderated or enhanced via a combination of geographic factors and the social fabric of the place. This social fabric can include a community's experience with hazards, and its ability to respond to, cope with, recover from, and adapt to hazards, which in turn are influenced by socio-economic status, demographics, and housing characteristics. In their model, disaster fatalities are largely determined by socio-economic factors that shape a community's vulnerability to disasters and in turn determine the impacts of disasters.

Similarly, Blaikie et al. (1994) note that vulnerability, in the disaster context, is a person's or group's "capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (p. 9). The group's disaster risk is determined purely exogenously by nature; however, a group's vulnerability against natural hazard is shaped by human components

(O'Keefe et al. 1976; Hewitt 1983). In the same vein, Cannon (1994) asserts that economic systems and class structures allocate income and access to resources, and this affects people's ability to cope with and recover from hazards. In general, it has been argued by many scholars that structural factors such as poverty, access to social protection and security, and inequalities with regard to gender, economic position, age, or race, cause or exacerbate vulnerability (Cannon 1994, Aptekar and Boore, 1990; Albala-Bertrand 1993, Enarson and Morrow 1998; Peacock et al., 1997; Morrow 1999). Fothergill et al. (2004) point out that disaster researchers increasingly use a "socio-political ecology of disasters" as a theoretical framework of their disaster research, conducting analyses of minority, gender, and inequality issues in the context of disasters.

1.4.3 Hypotheses on the Determinants of Tornado Vulnerability

Based on a conceptual framework where risk is considered to be a function of physically defined natural hazards and socially constructed vulnerability, this study seeks to identify key elements of tornado fatalities through empirical analysis using detailed data on tornado events and socio-economic data for 3,107 U.S. counties from 1980 through 2014. In addition to controlling for primary factors such as county population, lagged tornado frequency, and tornado magnitude (Fujita scale), I hypothesize that there are a number of demographic, socio-economic, housing, and governmental factors that may also play significant roles in determining tornado-induced deaths.

Income/Wealth and Income Distribution First, as one of the well-known determinants of disaster impacts. The robustness of the hypothesis is tested that the level of community's income/wealth plays significant role in vulnerability of disasters. Researchers such as Wildavsky (1988) contends that greater income and wealth translates to a safer society. Safety can be viewed as a natural product of a growing market economy since higher income places have a higher demand for safety and more resources to invest in risk reduction measures, which in turn leads to reduced vulnerability to disasters. The income/wealth hypothesis has been supported by many empirical studies (Kahn 2005, Toya and Skidmore 2007, Stromberg 2007, Raschky 2008, Gaiha et al. 2013). Note that these studies use cross-country data where GDP is used as a measure of income/wealth, whereas in this study, U.S. county per capita income is used.

In addition to per capita income, I also include the county top ten percentile income level and county poverty rates in my analysis as measures of income distribution. If income distributions are similar across all counties and over time, the top ten percentile income level measure should be closely correlated with per capita income. However, since income disparity in the United States has increased over the sample period and more so in some counties than others, I speculate that controlling for per capita income, the top ten percentile income variable will capture the role income disparity plays in determining disaster vulnerability.

Similarly, I hypothesize that societies with a higher concentration of poverty might encounter higher tornado-induced human losses. According to Fothergill et al. (2004), the poor in the United States are more vulnerable to natural disasters due to such factors as place and type of residence, building construction, access to information, low quality infrastructure, and social exclusion. Furthermore, Moore (1958) highlighted the relationship between socio-economic status and warning response, reporting that lower income groups were less likely to take the warnings of impending natural disasters seriously. Gladwin and Peacock (1997) reported in their study of warnings and evacuation for Hurricane Andrew that lower income people were less able and thus less likely to evacuate, mostly due to constraints placed by a lack of transportation and affordable refuge options. Similarly, an empirical study of natural disasters in Fiji, (Lal et al., 2009) finds evidence that the level of poverty (measured by the HDI) negatively affects disaster outcomes. The authors argue that those living in poverty are more sensitive to disasters because they have lower economic and social conditions; that is, they are unable to invest in adequate preparedness and risk reduction measures.

Gender and Female-Headed Households I also hypothesize that female-headed households are likely to be among the most vulnerable. According to the 2012 Census, families headed by a single adult are more likely to be headed by women, and these female-headed families are at greater risk of poverty and deep poverty; 30.2% of families with a female householder where no husband is present were poor and 16.9% were living in deep poverty. In addition, a study by Neumayer and Plumper (2007) suggests that for both social and physiological reasons, females are more vulnerable in disaster situations than men and therefore suffer higher mortality rates.

While this study attempts to shed light on the direct impacts of disasters on female-headed households, the vulnerability of female-headed households in a longer-run framework is highlighted in the literature. Researchers focusing on post-disaster outcomes indicate the degree of disaster impacts vary by gender not only in terms of direct physical loss, but also during the periods of emergency response, recovery, and reconstruction. For example, Blaikie et al. (1994) argue that women have a more difficult time during the recovery period than men, often due to sector-specific employment, lower wages, and family care responsibilities. Similarly, two years after Hurricane Andrew, thousands of poor families headed by minority women were still living in substandard temporary housing (Morrow and Enarson, 1996).

Human Capital The third hypothesis is that human capital as measured by percentage of population aged 25 and over holding a Bachelor's degree is one of the major characteristics defining social vulnerability. Several cross-country studies found significant correlations between level of educational attainment and reduced fatalities (see Skidmore et al., 2007). Education attainment is linked to the emergency decision-making process; education influences one's ability to understand warning information and perform evacuation or other necessary actions. Cutter et al. (2003) explain that while education is clearly linked to socio-economic status (higher educational attainment resulting in greater lifetime earnings), lower education may also constrain the ability to understand warning information and access to recovery information. Additionally, they argue that those with higher levels of education are more likely to choose safer locations and homes constructed with more durable materials, thus resulting in fewer fatalities.

In a recent study, Muttarak and Lutz. (2014) argue that education can directly influence risk perceptions, skills and knowledge and indirectly reduce poverty, as well as promote access to information and resources. These factors contribute to higher adaptive capacity and vulnerability reduction. The authors collect empirical evidence from a series of studies contained in a special issue aimed at investigating the role of education in vulnerability reduction; the authors provide consistent and robust findings on the positive impact of formal education in reducing vulnerability.

Housing Choice The fourth hypothesis is that communities with a higher proportion of households living in mobile homes or trailers will suffer increased levels of tornado casualties. Aptekar (1991) argues that it is more likely that disasters adversely affect those with lower socio-economic status largely because of the types of housing they occupy. Logically, people living in mobile homes are more vulnerable to natural events such as tornadoes because mobile homes typically have no foundation or basement and can more be easily destroyed. From 1996 to 2000, about half of tornado-induced deaths in the United States were in mobile homes[7], even though mobile homes accounted for less than 8% of the nation's housing during the same period, according to the National Oceanic and Atmospheric Administration and the U.S. Census Bureau. Historical data on tornado fatalities (1975-2000) tell us that the rate of death from tornadoes in mobile homes is about 20 times higher than that in site-built homes[7].

Table 1.1: Mobile Homes in the United States

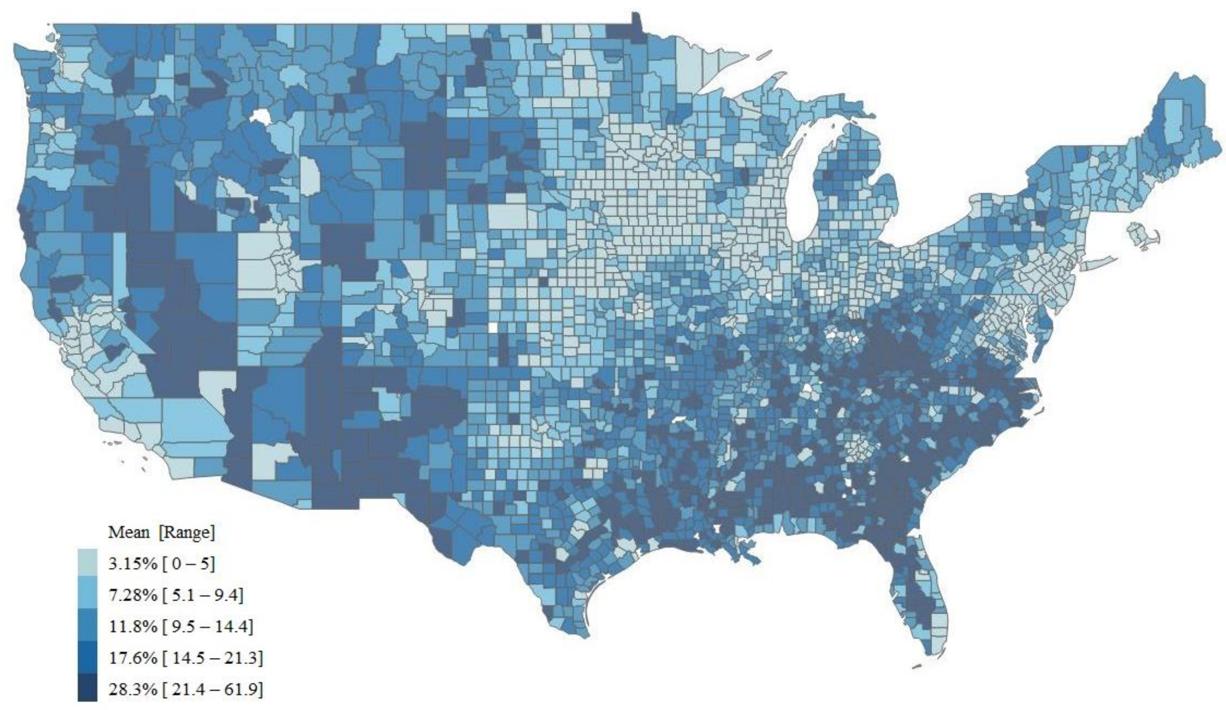
Year	Mobile Homes (%) in U.S. housing units	Total Mobile Homes in U.S. housing units	Total U.S. housing units
1950	0.7%	315,218	45,983,398
1960	1.3%	766,565	58,326,357
1970	3.1%	2,072,887	68,679,030
1980	5.1%	4,401,056	88,411,263
1990	7.2%	7,399,855	102,263,678
2000	7.6%	8,779,228	115,904,641
2010*	6.7%	8,684,414	130,038,080

Source: *U.S. Census Bureau, Housing and Household Economic Statistics Division*
*2010 data are estimates produced by American Community Survey while data for years 1950-2000 are from Decennial Census.

[7] Brooks, H., & Doswell III, C. A. (2001). A brief history of deaths from tornadoes in the United States. *Weather and Forecasting*, 1-9. http://www.nssl.noaa.gov/users/brooks/public_html/deathtrivia/

As shown in Table 1.1, the proportion of households living in mobile homes increased significantly since 1950. While the quality of these homes is probably higher than in the past, they still lack structural characteristics (e.g. foundations and basements) that make other types of construction more resistant to tornadoes. Importantly, mobile home living is very high in many rural counties across the Unites States. As shown in Figure 1.5, in 2010 many rural counties had more than a third of households living in mobile homes. The increase in the U.S. population living in mobile homes is likely to have important policy implications for disaster management in the context of tornadoes and other high wind events (Brooks 2001, Merrell et al. 2005, Kusenbach et al. 2010, Fothergill and Peek 2004, Schmidlin et al. 2009).

Figure 1.5: Proportion of Households Living in Mobile Homes, 2010



Local Government Investment My last hypothesis is that communities where local governments invest more resources in safety, protection and welfare will experience fewer fatalities. This type of expenditure number is not readily available, so I construct a measure of government spending on public safety and welfare by aggregating local government expenditures on fire/police protection and protective inspections/regulations and housing/ community development, and public welfare. Local government resources devoted to public safety services such as fire/police protection and protective inspection and regulation should lead to better preparedness and faster responses to disaster events, which, in turn, may play critical roles in reducing fatalities. It is also possible that allocating more resources to public welfare may reduce disaster vulnerability. In the context of local government, welfare services are not direct cash assistant (this comes from state government) but are for services like children's homes or payments to vendors for substance abuse treatment and the like.

1.5 EMPIRICAL ANALYSIS

1.5.1 Data Description

The county level panel data in the analysis consists of: (1) data on tornadoes from NOAA (1980-2014) used to develop detailed tornado information on locations, magnitudes and deaths, (2) data from U.S. Decennial census of population for the major socio-economic and housing factors in 3,107 counties from 1980 to 2010, and (3) local government fiscal data from the U.S. Census of Governments (1982 to 2012). Note that the Census of Population data are only available every ten years, whereas local government fiscal data are reported every five years (years ending in 2 or 7). Also, since, at the county level, the tornado data has many zero observations, the panel data is organized such that it contains county level tornado observations across seven time blocks between 1980-2014 (in five year intervals) : '80-84, '85-'89, '90-'94, ‘95-'99, '00-'04, '05-'09, '10-'14. The detailed tornado data are aggregated and rearranged to form county level observations and the tornado variables are averaged over each time block and are assigned middle years of each time block, 1982, 1987,…2012. Decennial census data for demographic and housing variables are interpolated to obtain data in 1982, 1987,.., 2012. Lastly, averaged tornado data and the interpolated census data are merged with the local government fiscal data. Overall, seven time-blocks are constructed for each of the 3,107 counties8. Thus, the unit of observation of this study is counties, not tornado event.

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[8] Given that county level socio-economic variables are only available every ten years, I use averaged tornado data in time intervals to avoid using interpolated data for all the socio-economic variables for all years except for years ending in 0, and interpolated government fiscal data for most time periods as well. By having a county as a unit of observation in this study, I am able to retain and explore a long-term variation in county socio-economic and government fiscal factors more accurately whose role in disaster events is the main interest of this study.

When I average tornado data across time blocks, I include only strong/violent tornadoes rated F2 or greater for the main analysis or, for the additional analysis F3 or greater. Accordingly, the dependent variable is the average number of deaths[9] caused by tornadoes rated F2-F5 (or F3-F5 in additional analysis). As noted earlier and shown in Table 1.2, most tornadoes are classified as F0 or F1 and those tornadoes commonly lead to very few deaths or do not claim lives at all. Since these types of tornadoes are effectively non-disasters, they are excluded for the analysis. As a result, county level panel data for my empirical estimation contains 2,120 counties that have experienced tornadoes of F2+ at least once over the study period. Table 1.2 presents the total number of tornadoes and resulting fatalities and injuries by F-scale over the years 1980-2014.

Table 1.2: Tornadoes and Resulting Impacts by Fujita-scale (1980-2014)*

	Tornado		Fatalities		Injuries	
F-scale	Obs.	%	Total	Avg.	Total	Avg.
F0	22,028	51.31	12	0.001	536	0.024
F1	11,977	27.90	128	0.011	3,945	0.329
F2	**3,907**	**9.10**	**330**	**0.084**	**8,427**	**2.157**
F3	**1,193**	**2.78**	**880**	**0.738**	**13,586**	**11.388**
F4	**301**	**0.70**	**869**	**2.887**	**13,055**	**43.372**
F5	**27**	**0.06**	**639**	**23.667**	**4,567**	**169.148**
Total	42934	100	2447	0.057	39877	0.929

* Only F2-F5 tornadoes are examined in this study.

[9] For example, a county A experienced two tornadoes each rated F2 and F0, having fatalities of 3 and 0 respectively, in a time block B, then county A in year B is assigned 3 for its average fatalities per tornadoes F2 or higher. I exclude and do not count F0 and F1 tornadoes when I generate *Avg. Fatalities_F2-F5* or *Avg.Fscale_F2-F5* variables.

1.5.2 Empirical Model

The dependent variable in this analysis is the average number of fatalities per tornado and thus, non-negative value. I employ Poisson model which properly treats the non-negative variables within the county level panel data framework (Wooldridge, 1991)[10]. Also, considering the large portion of zeros in the dependent variable, I repeat the analysis using a Negative Binomial model as a robustness check. In this study, many of the county socio-economic characteristics do not change much over time. Thus, there is little within-county variation for many of the explanatory variables. Given this, the fixed effects model is not necessarily preferred to random effects model.[11] In his multi-national disaster study, Kahn (2005) points out the presence of sluggish adjustment and long latency in economic development, which makes the inclusion of country fixed effects problematic. Taking the same stance as Kahn, I estimate the model using both random and fixed effects Poisson, but mainly discuss the random effects estimates.[12]

The regression analysis is characterized by the following equation:

$$E[Y_{jt}] = \exp(\beta X_{jt} + \rho G_{jt} + \gamma_1 Z_{1jt} + \gamma_2 Z_{2jt-1} + \delta D_j + \theta D_T + \alpha_j + \varepsilon_{jt})$$

where Y_{jt} is the average deaths per tornado in county j during time block t, $\boldsymbol{X_{jt}}$ is a vector of socio-economic and housing variables affecting deaths in county j at time t, G_{jt} is local government spending on public/safety, D_j is the dummy variable for Tornado Alley, Z_{ijt} is the average F-scale or the share of tornadoes of each F-scale levels (F2-F5) occurred in a county j at

[10] The dependent variable is an average value and can be non-integer. However, the Poisson (quasi-MLE) model is robust to distributional assumptions; it can be applied to any nonnegative outcome, either continuous or integer valued (Wooldridge, 1991).
[11] Wooldridge (2010) also discusses that when the key explanatory variables do not vary much over time, fixed effects methods can lead to imprecise estimates.
[12] The result of Fixed Effects Poisson is presented in the Appendix.

time t, Z_{jt-1} is the number of tornadoes in county j at time $t-1$, D_T represents a series of time indicator variables, α_j is a time-invariant effect for county j, and ε_{jt} is the unobservable error term. The detailed explanation for the variables in the model is provided in Table 1.3.

Table 1.3: List of dependent and explanatory variables in the model

Dependent Variable			
	Avg. Deaths from tornadoes		Y_{jt}
Explanatory Variables			
	Demographic	Log (Population size)	X_{ijt}
		Log (Land Area)	
		Percent of population over 65	
		Percent of population under 18	
		Percent of people aged 25 and over holding Bachelor's degree	
		Percent of female-headed households	
	Economic	Log (Per capita Income)	
		Log (Top 10 percentile income level)	
		Poverty rate	
	Housing	Percent of mobile homes in total housing units	
	Government	Log (Local government expenditures on public safety/welfare)	G_{it}
	Tornado	Magnitude of tornadoes (Avg. magnitude OR Percent of tornadoes of F2, F3, F4, and F5[13])	Z_{ijt}
		Lagged tornado frequency of F2+	
		Tornado alley	D_j
	Time Dummy	1987, 1992, 1997, 2002, 2007, 2012	D_T

Table 1.4 shows that over the 35 years from 1980 to 2014, a total of 5,428 tornadoes of F2 or greater occurred and caused 2,718 deaths and 39,635 injuries; 4,733 of these tornado events resulted in zero fatalities (Table 1.4). I aggregate tornado data into the aforementioned

[13] For a robustness check, I repeat my analysis using *the percent of tornadoes of each F-scale* among F2-F5 tornadoes that occurred (or among F3-F5 tornadoes for severe tornado analysis), instead of using the average F-scale as in my main analysis. The result is presented in Table 1.8.

five-year intervals and form a panel structure. The county level panel data for this study contains 4,757 county-year observations[14] with at least one strong/violent tornado rated F2 or higher and 1,016 observations had fatalities from those events. Using these data, I estimate equation (1) using a Poisson and Negative Binomial estimation procedures.

Table 1.4: Fatalities induced by Strong Tornadoes (F2-F5), 1980-2014*

Fatalities	Freq.	Percent
0	4,733	87.20
1-5	577	10.63
6-15	86	1.58
16-30	26	0.48
31-158	6	0.11
Total	5,428	100.00

* For this information, yearly tornado data from NOAA is used. However, this study exploits a panel data with county-year observations.

Eight specifications are estimated to test my hypotheses. The dependent variable is the average number of deaths per tornado (of Fujita Scale 2-5) in each county in a particular time block. Some of the socio-economic determinants are highly correlated with each other, which may result in multicollinearity. To address this possibility, I conduct preliminary analyses using more parsimonious model specifications as shown in columns (1) to (7) of Table 1.6 and 1.7. Each hypothesized potential determinant of tornado impacts – for example, poverty rate, education level, female-headed household, and mobile homes – are examined separately but with a consistent set of control variables. Given that many prior studies found income level to be one of the most important factors, per capita income is included in every specification. Government spending on public safety and welfare also appears in every specification because this is the only

[14] County-year observations without any experience of tornadoes of F2+ are excluded.

variable that represents the role of government, although government spending might be weakly related to the economic variables discussed above. The last specification includes all the poverty-related potential determinants, testing them in a single specification. In all specifications the following variables are included as controls: average tornado magnitude, population size, land area, percent of population over age 65 and under 18, lagged tornado frequency, and a categorical variable for counties located in the Tornado Alley region.

The EM-DAT data used in most of the prior studies discussed do not contain information on disaster magnitude on many of the recorded disaster events, so most studies using those data are unable to control for disaster magnitude. The tornado data from NOAA, however, does provide a magnitude measure for each tornado (F-scale), and thus I can more readily distinguish impacts on fatality due to disaster magnitude versus other explanatory variables I wish to explore. Specifically, I use the average magnitude of all tornadoes of F2-F5 that occurred in a particular county in a given period because the unit of observation of this study is counties, not tornado event.

Also, considering that Tornado Alley regions are more highly prone to tornadoes than other regions, I introduce a dummy variable in the model. ($D_j = 1$, if the county j is in this geographic region and $D_j = 0$, otherwise) along with lagged tornado frequency of F2-F5 (or F3-F5 in additional analysis on severe tornadoes). These variables allow us to test whether greater familiarity with this type of emergency makes the area more able to cope (e.g., building codes, population behavior during the event).

Table 1.5: County Summary Statistics

	Mean	Standard Deviation	Min	Max	Number of Obs.
Dependent Variables					
Avg. Tornado Deaths (F2-F5)	0.29	1.34	0	52.67	4757
Avg. Tornado Deaths (F3-F5)	0.77	2.45	0	52.67	1884
Independent Variables					
Avg. Fscale (F2-F5)	2.40	0.58	2	5	4757
Avg. Fscale (F3-F5)	3.25	0.44	3	5	1884
Pct Tornado of F2	68.03	42.78	0	100	4757
Pct Tornado of F3	24.50	39.31	0	100	4757
Pct Tornado of F4	6.95	22.91	0	100	4757
Pct Tornado of F5	0.53	5.76	0	100	4757
Lagged Freq. of F2-F5	0.58	0.96	0	9	4757
Lagged Freq. of F3-F5	0.20	0.53	0	5	1884
Tornado Alley Dummy	0.44	0.50	0	1	4757
Log (Land Area)	6.46	0.52	3.13	9.91	4757
Log (Population)	10.38	1.30	4.37	15.91	4757
Pct Over 65	14.01	3.93	3.06	35.99	4757
Pct Under 18	26.01	3.28	11.20	45.16	4757
Log (Per Capita Gov Expenditure on Public Safety & Welfare)	-1.55	0.70	-5.90	1.11	4757
Log (Per Capita Income)	9.79	0.25	8.80	10.93	4757
Log (Top 10% Income)	11.52	0.28	10.73	12.07	4757
Poverty Rate	15.97	6.90	0	58.18	4757
Pct BA Degree	15.04	6.90	4.12	55.35	4757
Pct Mobile Home	12.46	8.05	0.05	57.21	4757
Pct Female-Headed Household	10.54	4.30	2.88	35.46	4757

* Statistics are from observations with F2-F5 tornado experience that are used for the main regressions. For the additional regressions using severe tornadoes of F3-F5, only tornado statistics (Avg. Tornado Deaths, Avg. Fscale) are presented.

1.6 RESULTS

Table 1.6 and Table 1.7 presents the results of the regressions using F2 or higher tornado observations recorded in counties over 1980-2014 and a set of demographic, socio-economic, housing, and government fiscal factors as presented in Table 1.5. I mainly discuss the results of Random Effects Poisson and Negative Binomial[15] specifications here; however, the Fixed Effects specification estimates outcomes are provided in the Appendix for the interested reader.

Before discussing the primary findings as they relate to the hypotheses, consider the estimated effects of the control variables. The F-scale variable which is an indicator of the average magnitude of tornadoes within a given time period, has a strong association with the number of deathsin all specifications. As expected, the analysis confirms the magnitude of the tornado is a critical physical determinant of the tornado fatalities. The estimated coefficient of the average F-scale in column (8) in Table 1.7 implies that an increase in F-scale to the next level increases expected tornado fatalities by a factor of 4.21 ($\approx exp(1.437)$). Both lagged tornado frequency and tornado alley variables are estimated to be negatively correlated with fatalities in all specifications. Counties in tornado alley region who experience tornadoes relatively often are estimated to experience 13% ($\approx exp(-0.133) - 1$) lower fatalities than counties outside of the tornado-prone area, all other conditions being equal. This result supports the idea that there might be some kind of learning effects from risk history, where counties that suffered more tornado outbreaks tend to put more efforts to reduce their vulnerability and be better prepared for disasters and in turn, better able to mitigate the societal impacts. McEntire (2001) asserts that

[15] I discuss both Poisson and Neg. Binomial regressions results here, however, the likelihood ratio test of α (dispersion parameter) = 0 strongly rejects the null hypothesis that the errors do not exhibit overdispersion. Thus, the Poisson regression model is rejected in favor of its generalized version, the Neg. Binomial regression model. When explaining the estimated effects of explanatory variables, I refer to the results of Neg. Binomial model in Table 1.7.

beliefs and activities play a major role in the creation of vulnerabilities and past disaster lessons reduce future consequences.

As a measure of density, both county population and land area are included in logarithmic terms[16]. The results show that counties with greater populations and smaller land area experience more deaths when tornadoes strike - together implying the higher the density, the larger the tornado impacts. The estimates suggest that for two counties of equal land area, if one has 10 percent more population, the expected fatalities increase by 4 percent. Also, as a control, proportions of the population over the age of 65 and under 18 are included. In all estimates it is shown that counties with greater proportions of elder and young experience fewer fatalities. In my initial assessment I expected that these population groups would be more vulnerable rather than less. One possible explanation is the older people and families with children may be more risk averse and thus heed tornado warnings, thus reducing exposure. It could also be caused by higher proportions of these individuals being in environments (schools, retirement communities) where warnings are more easily distributed.

Let's now turn to the primary interest in the role that the various dimensions of poverty, and social vulnerability play in determining tornado impacts. I begin this portion of the discussion by considering the factors that align with my first hypothesis regarding the role of income/wealth in determining vulnerability.

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[16] Note that *Population Density=Population/Land Area*. Also*, Log(Density)=Log(Population)-Log(Land Area)*. Thus, the estimated coefficients of *Log(Population)* and *Log(LandArea)* variables are similar in magnitude but opposite in sign.

1.6.1 Richer Counties Experience Fewer Tornado-induced Deaths

Consistent with most other empirical studies, I find that per capita income is a key determinant of tornado-related deaths. The negative relationship between income and tornado fatalities is significant and robust in both Poisson and Negative Binomial models, indicating that higher county per capita income results in fewer tornado-induced fatalities. The estimated coefficient on the log of per capita income suggests that a one percent increase in county per capita income is expected to reduce tornado fatalities by one percent[17]. As Anbarci et al. (2005) and Kahn (2005) argued in their studies, it is also found in this study that income distribution (as measured by the top ten percentile income level) a significant factor. Holding other factors constant, per capita income and the poverty rate, higher top ten percentile income level means larger share of lower-middle income group, which indicates wider income disparity in the community. The estimates suggest that greater income inequality tends to exacerbate the impacts of disasters. In addition, controlling for income, the poverty rate is not a statistically significant factor. However, this result is largely due to multicollinearity as per capita income and the poverty rate are highly correlated. Consider the estimates in column 4 in both Table 1.6 and 1.7, where the poverty rate is included but not income per capita in the specification. In this regression we see that the poverty rate is positive and statistically significant as expected. The estimated coefficient in column 4 in Table 1.7 suggest that one percentage point increase in poverty rate is estimated to increase tornado fatalities by 3percent.

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[17] The estimated coefficients of log transformed variables can be interpreted as elasticities.

1.6.2 Human Capital Plays an Important Role in Reducing Tornado Vulnerability

The regression results indicate that human capital as measured by the proportion of the population aged 25 and over with a Bachelor (or higher) degree is also a significant determinant of tornado fatalities. As presented in specifications (5) and (8), the percent of bachelor degree holders is found to be negatively associated with the likelihood of deaths in disaster situations, though only statistically significant in specification (5). A one percentage point increase in the proportion of the Bachelor degree holder in a county is associated with 1.6 percent ($\approx exp(-0.016) - 1$)reduction in expected tornado fatalities. Educational attainment may be linked to emergency decision-making processes such as the ability to quickly comprehend warning information and perform evacuation or other necessary actions or to have work functions located inside, with more solid construction (e.g., office building versus pole barn). Thus, those with lower education attainment may be more vulnerable to disaster shocks. The estimated results are consistent with previous studies (e.g., Skidmore et al., 2007, Muttarak and Lutz, 2014). However, again, education and other economic variables such as income levels and poverty measures are highly correlated; thus, the insignificance of education in column (8) is likely the result of multicollinearity.

Table 1.6: Socio-economic Characteristics and Disaster Impacts
Poisson Random Effect Regressions Results

Dependent variable: *Deaths from F2-F5 tornadoes*

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fscale_F2+	1.551***	1.550***	1.553***	1.555***	1.550***	1.575***	1.554***	1.576***
	(0.061)	(0.061)	(0.061)	(0.060)	(0.061)	(0.060)	(0.061)	(0.061)
Lag_Tornado_F2+	-0.003	-0.005	-0.004	-0.003	-0.002	-0.003	-0.006	-0.006
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.046)	(0.045)	(0.046)
Tornado Alley	-0.461***	-0.457***	-0.454***	-0.467***	-0.432***	-0.213**	-0.421***	-0.206*
	(0.105)	(0.105)	(0.106)	(0.106)	(0.107)	(0.107)	(0.107)	(0.108)
Log(Land Area)	-0.039	-0.045	-0.037	-0.017	-0.018	-0.131	-0.016	-0.142
	(0.094)	(0.095)	(0.094)	(0.092)	(0.095)	(0.095)	(0.095)	(0.098)
Log(Population)	0.323***	0.322***	0.312***	0.260***	0.337***	0.443***	0.294***	0.432***
	(0.059)	(0.058)	(0.060)	(0.054)	(0.059)	(0.059)	(0.060)	(0.062)
Pct Over65	-0.044**	-0.034	-0.043**	-0.042**	-0.053**	-0.014	-0.039*	-0.001
	(0.020)	(0.022)	(0.020)	(0.020)	(0.022)	(0.019)	(0.020)	(0.024)
Pct Under18	-0.042**	-0.044**	-0.044**	-0.042**	-0.048**	-0.012	-0.047**	-0.011
	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)	(0.022)	(0.023)
Log(PerCapita GovtExp	-0.317***	-0.320***	-0.324***	-0.355***	-0.309***	-0.221**	-0.344***	-0.232**
onPublicSafetyWelfare)	(0.085)	(0.086)	(0.085)	(0.084)	(0.086)	(0.086)	(0.090)	(0.092)
Log (PerCapita Income)	-1.367***	-1.916***	-1.020**		-1.058***	-0.539	-1.013***	-1.041
	(0.304)	(0.527)	(0.489)		(0.357)	(0.336)	(0.391)	(0.854)
Log (Top 10% Income)		0.777						0.668
		(0.596)						(0.592)
Poverty Rate			0.010	0.030***				0.001
			(0.012)	(0.007)				(0.017)
Pct BA degree					-0.017*			0.008
					(0.010)			(0.013)
Pct Mobile home						0.053***		0.054***
						(0.007)		(0.008)
Pct Female-Headed							0.025	0.004
							(0.015)	(0.019)
Dummy 1987	0.377**	0.318	0.336*	0.225	0.352*	0.160	0.319	0.101
	(0.192)	(0.197)	(0.190)	(0.185)	(0.192)	(0.192)	(0.201)	(0.196)
Dummy 1992	0.278	0.204	0.198	-0.029	0.239	-0.133	0.154	-0.218
	(0.176)	(0.180)	(0.202)	(0.169)	(0.177)	(0.187)	(0.196)	(0.227)
Dummy 1997	0.718***	0.611***	0.605**	0.281	0.657***	0.179	0.544**	0.063
	(0.192)	(0.200)	(0.237)	(0.177)	(0.199)	(0.209)	(0.230)	(0.281)
Dummy 2002	0.973***	0.809***	0.839***	0.454***	0.909***	0.343	0.762***	0.169
	(0.204)	(0.230)	(0.252)	(0.170)	(0.207)	(0.222)	(0.251)	(0.308)
Dummy 2007	1.106***	0.868***	0.956***	0.548***	1.059***	0.469*	0.874***	0.222
	(0.215)	(0.266)	(0.279)	(0.196)	(0.219)	(0.242)	(0.277)	(0.354)
Dummy 2012	1.246***	0.921***	1.079***	0.645***	1.212***	0.619***	0.998***	0.285
	(0.220)	(0.307)	(0.288)	(0.204)	(0.224)	(0.237)	(0.276)	(0.380)
Constant	4.685	1.197	1.356	-8.350***	1.945	-5.603	1.275	-8.441
	(3.053)	(4.117)	(4.829)	(1.264)	(3.426)	(3.437)	(3.823)	(6.838)
No. of Observations	4,759	4,759	4,757	4,757	4,759	4,759	4,759	4,757
No. of Counties	2,121	2,121	2,120	2,120	2,121	2,121	2,121	2,120

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Socio-economic Characteristics and Disaster Impacts
Negative Binomial Random Effect Regressions Results

Dependent variable: *Deaths from F2-F5 tornadoes*

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fscale_F2+	1.408***	1.409***	1.411***	1.413***	1.407***	1.436***	1.409***	1.437***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Lag_Tornado_F2+	-0.005	-0.006	-0.006	-0.006	-0.003	-0.007	-0.007	-0.010
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Tornado Alley	-0.369***	-0.364***	-0.361***	-0.372***	-0.342***	-0.146	-0.327***	-0.133
	(0.094)	(0.094)	(0.094)	(0.094)	(0.095)	(0.097)	(0.097)	(0.099)
Log(Land Area)	-0.082	-0.086	-0.080	-0.059	-0.061	-0.159*	-0.056	-0.163*
	(0.087)	(0.087)	(0.087)	(0.086)	(0.088)	(0.087)	(0.088)	(0.091)
Log(Population)	0.315***	0.315***	0.304***	0.253***	0.326***	0.422***	0.283***	0.408***
	(0.049)	(0.049)	(0.050)	(0.044)	(0.049)	(0.050)	(0.052)	(0.054)
Pct Over65	-0.029*	-0.021	-0.028*	-0.027*	-0.038**	-0.001	-0.024	0.010
	(0.015)	(0.017)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)	(0.018)
Pct Under18	-0.038**	-0.041**	-0.039**	-0.036**	-0.044**	-0.009	-0.044**	-0.009
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)
Log(PerCapita GovtExp	-0.301***	-0.305***	-0.307***	-0.336***	-0.292***	-0.196***	-0.334***	-0.213***
onPublicSafetyWelfare)	(0.072)	(0.072)	(0.072)	(0.071)	(0.072)	(0.073)	(0.074)	(0.076)
Log (PerCapita Income)	-1.325***	-1.817***	-0.994**		-1.035***	-0.526*	-0.929***	-0.921
	(0.273)	(0.480)	(0.443)		(0.321)	(0.291)	(0.344)	(0.723)
Log (Top 10% Income)		0.685						0.490
		(0.551)						(0.549)
Poverty Rate			0.010	0.029***				-0.002
			(0.011)	(0.006)				(0.014)
Pct BA degree					-0.016*			0.007
					(0.009)			(0.011)
Pct Mobile home						0.050***		0.051***
						(0.006)		(0.007)
Pct Female-Headed							0.027*	0.010
							(0.014)	(0.017)
Dummy 1987	0.246*	0.194	0.211	0.109	0.220	0.047	0.176	-0.000
	(0.148)	(0.153)	(0.152)	(0.145)	(0.149)	(0.149)	(0.152)	(0.161)
Dummy 1992	0.185	0.121	0.108	-0.114	0.148	-0.199	0.044	-0.270
	(0.156)	(0.165)	(0.176)	(0.145)	(0.158)	(0.163)	(0.173)	(0.196)
Dummy 1997	0.627***	0.538***	0.519**	0.205	0.566***	0.107	0.429**	0.014
	(0.168)	(0.182)	(0.203)	(0.146)	(0.171)	(0.179)	(0.197)	(0.238)
Dummy 2002	0.869***	0.728***	0.743***	0.373**	0.808***	0.273	0.635***	0.132
	(0.182)	(0.214)	(0.225)	(0.153)	(0.185)	(0.195)	(0.220)	(0.275)
Dummy 2007	1.033***	0.827***	0.890***	0.494***	0.985***	0.406**	0.770***	0.209
	(0.177)	(0.243)	(0.234)	(0.153)	(0.180)	(0.193)	(0.225)	(0.307)
Dummy 2012	1.110***	0.826***	0.952***	0.532***	1.073***	0.506***	0.835***	0.245
	(0.176)	(0.289)	(0.243)	(0.155)	(0.178)	(0.191)	(0.229)	(0.349)
Constant	7.076***	4.094	3.873	-5.615***	4.539	-2.871	3.282	-4.697
	(2.730)	(3.641)	(4.349)	(1.012)	(3.098)	(2.993)	(3.383)	(5.977)
No. of Observations	4,759	4,759	4,757	4,757	4,759	4,759	4,759	4,757
No. of Counties	2,121	2,121	2,120	2,120	2,121	2,121	2,121	2,120

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

1.6.3 Mobile Homes Residents Experience More Tornado Fatalities

The fourth hypothesis is that mobile home living results in more tornado fatalities. The regression estimates in specifications (6) and (8) show that the percent of mobile homes in a county is positively related to tornado fatalities, and the estimates are robust. The results confirm that more mobile homes in a county results in greater vulnerability to tornadoes. The estimated coefficient implies that one percentage point increase in the proportion of mobile homes in total housing units is expected to increase tornado-related deaths by 5.2 percent ($\approx exp(0.051)$). Further, as noted earlier more households are choosing this type of housing arrangement over time, and thus vulnerability may be increasing. This finding may have important policy implications in the context of developing approaches to reduce tornado vulnerability. For example, mobile home parks could potentially provide common tornado shelter areas to be used in the event of a tornado watch or warning.

1.6.4 Female-Headed Households Are More Vulnerable to Tornadoes

The second hypothesis is that female-headed households are more vulnerable to tornadoes. This hypothesis is examined in specifications (7) and (8) in the Poisson and Negative Binomial models. These regressions show that female headed households and tornado-induced fatalities weakly have a positive correlation. The estimate in specification (7) shows that a one percentage point increase in the proportion of the female-headed households in a county is expected to increase tornado fatalities by 2.7 percent. It is implied that all else equal, places with more female-headed households are more vulnerable, perhaps because female-headed households have limited access to resources during high risk events. The result is consistent with the previous arguments by sociologists (Enarson and Morrow 1998; Enarson, Fothergill, and Peek 2006). However, the estimated effect only achieves significance in specification (8).

1.6.5 Government Spending in Public Safety Mitigates Losses from Tornadoes

Finally, I test the degree to which local government plays a role in reducing the potential tornado fatalities. The regression results show a significant and negative relationship between tornado fatalities and per capita government spending on public safety, protection, and welfare. Such local government expenditures appear to improve overall safety/welfare of a community, thus playing a role in mitigating citizens' vulnerability. For example, 10 percent increase in government per capita spending, which is $27.10 on average in my sample (in 2009 dollars), is estimated to have about 3 percent decrease in tornado-induced fatalities. Given the parameter estimate, if governments in each county had allocated 50% more funds to safety, protection, and welfare over the study period 1980-2014, 268 lives would have been saved from tornados[18]. However, considering the limited government resources available for public services, I offer an evaluation of whether it would be worthwhile for local government to allocate more funds to public safety, protection, and welfare, with the goal of reducing tornado fatalities. Specifically, I perform a straightforward cost-benefit analysis by comparing the amount of extra funds required to save a life in local governments from severe tornadoes with the benefit in terms of the value of life. On this benefit side, I follow the practice of giving an economic value to mortality - a value of a statistical life (VSL). The VSL that is currently being used in the U.S. government agencies when they appraise the benefits of regulations ranges from $8.2 to $9.5 million (in 2009 dollars) (Viscusi 2014). The cost-benefit comparison reveals that in order to save a life from severe tornado, each county would need to spend additional $508 per capita, on average, which is

[18] The expected number of lives that could have been saved by increasing per capita government expenditures by 50% has been calculated across all counties who had experienced FS2+ tornadoes over the study period and added up.

approximately $30 million in extra burden to local governments[19]. Altogether, it does not appear that increasing government expenditures is a cost-effective way of achieving tornado fatality reduction, even after taking into consideration that the life-saving benefit is just one component of the multiple benefits that may arise from such government spending. My empirical analysis suggests that general increase in government funds on public safety, protection, and welfare is linked to the goal of mitigating tornado impacts to some extent but the cost-benefit analysis reveals that it is not an effective policy scheme for mitigating tornado fatalities in most counties. In this regard, further research is needed to investigate to better target which set of public services provided by local governments most effectively mitigates the degree to which their citizens are exposed to tornadoes.

1.6.6 Additional Analyses

In Table 1.8, I present the results of additional analyses. The second set of regressions consist of four specifications: (1) and (2) use very strong tornadoes of Fujita-scale 3 or greater (F3-F5) in the same framework as in Table 1.6 and 1.7, and (3) and (4) exploit the magnitude of tornadoes in a different way compared to the main analysis presented in Table 1.6 and 1.7.

First two columns show Poisson and Negative Binomial regressions result for severe tornadoes rated F3 or higher. Focusing on the larger events reduces the number of tornado events

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[19] Let *Per Capita Gov Expenditure on Public Safety & Welfare* = G, *Avg. Fatalities per FS2+ tornado*= Y, and *Yearly fatalities from FS2+tornado*= D. The extra funds needed to save a life is calculated using the estimated relationship between G and Y where $\Delta Y/Y = \hat{\beta}\Delta G/G$ holds ($\hat{\beta}$ is the estimated coefficient of G), and the relationship $Y = D/$(Yearly No.FS2+ tornado). The expression $E(\Delta\hat{G})$ is derived such that $\Delta D = -1$ (i.e. yearly fatalities from FS3+ tornado decrease by one unit) using the sample mean ($\bar{D}$ and $\bar{G}$) from the observations with $D \geq 1$. I obtain $E(\Delta\hat{G})$ = $508, which implies if local governments that suffered at least one death every year from tornado increase per capita spending by $508, on average, one death would be avoided in each county every year. The average extra burden to local governments, $30M is obtained by multiplying county population by the per capita extra expenditure, $508.

by 3,907, leaving just 1,507 severe tornadoes. Thus, in my sample, only 1,245 counties are used for the analysis excluding those counties without any experience of tornadoes of F3+ during 1980-2014. The estimates reported in columns (1) and (2) in Table 1.8 are very consistent with those in Table 1.6 or 1.7 with the exception of a few differences. When I consider only the very strong and more destructive tornadoes, the significance of the estimated coefficients on some of the socio-economic variables disappears or weakens in magnitude. However, tornado vulnerability related variables such as Tornado Alley, lagged tornado frequencies, and population density measure take on greater importance, while the coefficient on the mobile home variable remains statistically significant and similar in magnitude compared to the estimation results using F2+ tornadoes. Taken together, these findings suggest that the stronger tornadoes extend vulnerability to a broader array of people in a community such that social-economic status becomes less important whereas the intensity of natural force and physical factors become more significant in determining vulnerability. In addition, the larger coefficients on tornado alley and lagged tornado frequencies compared to the estimate from F2+ tornadoes suggests that the previous experiences of severe disasters bring a stronger learning effect in case where the community is hit by a severe tornado.

Let's now turn to the result presented in columns (3) and (4) in Table 1.8. I perform an additional analysis as a robustness check to my main analysis, by including the fractions of tornadoes of each F-scale among F2 to F5 tornadoes (or among F3 to F5 in specification (4))[20] , instead of using the average F-scale variable. As shown in Table 1.2, tornadoes of different magnitudes can have widely differing degrees of impact. For instance, the average death from F5

[20] The fraction of F2 tornadoes (or F3 tornadoes in specification (4)) is a reference point.

tornadoes is 280 times larger than that of F2 tornadoes in my sample. In this additional analysis, I try to account for such differentiated impacts of each level of F-scale events. The results from the Poisson model[21] using tornadoes of F2+ and F3+ are presented in column (3) and (4), respectively. As expected, tornadoes of different levels of F-scale have largely different impacts on expected fatalities. The estimates in column (3) suggest that one percentage point increase in the share of F3 tornadoes (while having a one percentage point decrease in the share of F2 tornadoes instead) increases expected fatalities by 2 percent, F4 by 3 percent, and F5 by 6 percent. For instance, if we consider a worst-case scenario where the percent of F5 tornadoes changes from 0% to 100% with an F5 tornado occurrence in a county without any other tornado event, the county is expected to suffer 365 times ($\approx exp(100 * 0.059)$) as many fatalities as that from F2 tornadoes. After accounting for the magnitudes of tornadoes in a detailed way, I obtain results that are mostly similar to my main analysis. The estimation results in column (3) again demonstrate that housing quality, population density, income levels, and government spending on public safety and welfare are critical factors in determining tornado vulnerability.

[21] Due to a convergence difficulty in Negative Binomial estimation process, Poisson model is only employed for the estimation.

Table 1.8: Socio-economic Characteristics and Disaster Impacts Additional Regressions Results

Dependent variable	(1) Poisson *Deaths from F3+*	(2) Neg. Binomial *Deaths from F3+*	(3) Poisson *Deaths from F2+*	(4) Poisson *Deaths from F3+*
Fscale_F3+	1.508***	1.339***		
	(0.096)	(0.078)		
Pct F3 tornado			0.018***	
			(0.001)	
Pct F4 tornado			0.029***	0.011***
			(0.001)	(0.001)
Pct F5 tornado			0.059***	0.041***
			(0.004)	(0.004)
Lag_Tornado_F2+			-0.010	
			(0.045)	
Lag_Tornado_F3+	0.070	0.057		0.074
	(0.081)	(0.075)		(0.091)
Tornado Alley	-0.296**	-0.191*	-0.191*	-0.265**
	(0.125)	(0.109)	(0.107)	(0.125)
Log(Land Area)	-0.219*	-0.272***	-0.158	-0.146
	(0.124)	(0.102)	(0.099)	(0.124)
Log(Population)	0.459***	0.423***	0.411***	0.422***
	(0.076)	(0.061)	(0.061)	(0.075)
Pct Over65	0.017	0.033*	-0.006	0.004
	(0.027)	(0.020)	(0.023)	(0.028)
Pct Under18	-0.012	-0.015	-0.014	-0.033
	(0.027)	(0.022)	(0.023)	(0.029)
Log(Per Capita Govt Exp on	-0.232**	-0.195**	-0.199**	-0.227**
Public Safety & Welfare)	(0.113)	(0.089)	(0.089)	(0.111)
Log (PerCapita Income)	-1.282	-0.654	-0.783	-1.091
	(1.035)	(0.828)	(0.840)	(1.039)
Log (Top 10% Income)	1.073	0.526	0.404	1.069
	(0.713)	(0.608)	(0.586)	(0.773)
Poverty Rate	0.006	-0.000	0.003	0.008
	(0.020)	(0.016)	(0.017)	(0.020)
Pct BA degree	0.009	0.007	0.007	0.005
	(0.016)	(0.012)	(0.012)	(0.015)
Pct Mobile home	0.053***	0.053***	0.055***	0.048***
	(0.010)	(0.008)	(0.008)	(0.010)
Pct Female-Headed	-0.012	-0.001	0.003	-0.004
	(0.022)	(0.019)	(0.019)	(0.022)
Dummy 1987	-0.047	-0.351*	0.117	-0.069
	(0.255)	(0.194)	(0.197)	(0.258)
Dummy 1992	-0.419	-0.537**	-0.270	-0.456
	(0.274)	(0.221)	(0.227)	(0.278)
Dummy 1997	-0.126	-0.266	-0.006	-0.085
	(0.359)	(0.272)	(0.275)	(0.364)
Dummy 2002	0.054	-0.116	0.160	-0.067
	(0.372)	(0.316)	(0.307)	(0.383)
Dummy 2007	0.190	0.032	0.233	0.034
	(0.433)	(0.350)	(0.346)	(0.451)
Dummy 2012	-0.022	-0.023	0.216	-0.161
	(0.460)	(0.390)	(0.380)	(0.506)
Constant	-10.482	-7.880	-4.305	-6.849
	(8.154)	(6.672)	(6.713)	(8.433)
No. of Observations	1,884	1,884	4,757	1,884
No. of Counties	1,245	1,245	2,120	1,245

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

1.7 CONCLUSION

While tornado activity is exogenously determined by natural forces, it is also true that socio-economic factors are critical in determining vulnerability. This study seeks to uncover these underlying factors. To this end, I investigate the relationship between tornado fatalities and the potential determinants of tornado impacts within U.S. counties over the period from 1980 to 2014. Findings of the study enable us to identify which societal characteristics exacerbate or mitigate vulnerability to hazards, which in turn allow us to suggest policies that may help mitigate human losses from such events.

The empirical analysis of this study consistently demonstrates that income level is a crucial determinant of tornado fatalities; this finding is consistent with an array of previous studies, but this study offers more detail on how the various expressions of poverty may contribute to deaths. The analysis also suggests that income inequality is a significant factor that may exacerbate the impacts of disasters. Also, counties with higher poverty rate and more female-headed households tend to be more vulnerable, while the higher the education level, the lower the vulnerability. In general, households most affected by disasters are those with weaker economic and social bases. The information presented here may help to target the most vulnerable households and provide improved access to safety resources.

In addition, my analysis offers evidence that per capita government spending on public safety and welfare is negatively related to death tolls. This suggests that increased government spending in critical areas such as safety, protection, and welfare, reduce overall vulnerability within a community. For some counties with frequent tornado occurrences and higher fatality rates, extra funds on safety, protection, and welfare might mitigate the impacts and save lives effectively. However, a cost-benefit analysis that compares the estimated extra government expenditures required to save a life from severe tornado on average and a value of a statistical life (VSL) as a benefit reveals that generally increasing government funds on safety, protection, and welfare is not a cost-effective policy scheme for most local governments for reducing tornado fatalities. Nevertheless, it may be useful for policy makers to consider allocating resources on specific public services that improve safety and reduce tornado vulnerability. In this regard, further research is needed to investigate which particular public service provided by local government mitigates the degree to which their citizens are affected by tornadoes.

Another key finding is that the number of mobile homes in a county is critical factor in explaining tornado fatalities. This finding implies that housing quality is perhaps the most important factor in determining tornado vulnerability. Importantly, the proportion of households living in mobile homes has increased nearly three-fold since the 1970s, with much of this increase occurring between 1970 and 1980 (prior to the period of analysis). Though mobile homes offer a relatively inexpensive but comfortable housing alternative, it appears that this trend has made the United States more vulnerable to tornadoes over time. Given this trend and my findings, it is critical that federal, state and local policy makers consider alternatives to reduce vulnerability for those living in this type of housing arrangement. Policies aimed at strengthening the ability of mobile homes to withstand high winds and flying objects and more systematically require communal tornado shelters may be effective at reducing tornado fatalities. In particular, mobile homes are commonly classified and taxed as personal property placing lower tax burden to home owners. This tax advantage makes mobile home living economically more attractive, but at the same time the tax policy is in fact encouraging more people to live in housing that is more vulnerable to tornados. The external cost of being exposed to greater tornado risks may be ignored when households choose to live in mobile homes due to affordability. One potential policy scheme to internalize this social cost would have governments i) require communal shelters in mobile home parks and communities[22], ii) impose a higher tax rate to mobile homes where tornado shelter/safe room are unavailable, and iii) redirect the tax revenue raised from step ii) towards additional government funds for the local communities' safety/protection. In this way, local governments could broaden their tax base and target the revenue from that source to further mitigate human losses from future tornado events.

Overall, this study reveals which types of households tend to have more difficult time when disaster occurs, thus informing policies targeted at reducing tornado fatalities. More generally, addressing the root of the issue by improving the conditions of those with lower socio-economic status would reduce vulnerability over time. I expect that these findings will increase our understanding of the socio-economic nature of tornado impacts and enable decision-makers to improve mitigation efforts.

[22] There are communities that already require all mobile home parks to provide storm shelters for their residents, including the State of Minnesota, and some individual counties (e.g. Sedgwick County and Butler County in KS, St. Joseph County, MO, etc.)

APPENDIX

APPENDIX

Table 1.A1: Socio-economic Characteristics and Disaster Impacts—Poisson Fixed Effect Regressions Results

Dependent variable	*Deaths from F2+*	*Deaths from F3+*
Fscale_F2+	1.777***	
	(0.094)	
Lag_tornado_F2+	-0.030	
	(0.059)	
Fscale_F3+		1.774***
		(0.153)
Lag_tornado_F3+		0.042
		(0.099)
Log(Population)	0.253	-0.503
	(0.448)	(0.805)
Pct Over65	-0.046	-0.171
	(0.076)	(0.111)
Pct Under18	0.025	0.041
	(0.071)	(0.089)
Log(Gov Exp on Public Safety & Welfare)	-0.197	-0.189
	(0.206)	(0.283)
Log (PerCapitaIncome)	-3.375*	-3.846
	(1.963)	(2.694)
Log (Top 10% Income)	2.199**	1.835
	(1.011)	(1.397)
Poverty Rate	-0.084**	-0.070
	(0.038)	(0.053)
Pct BA degree	0.064	0.153
	(0.059)	(0.099)
Pct Mobile home	0.012	0.020
	(0.028)	(0.036)
Pct Female-Headed	-0.159*	-0.186
	(0.088)	(0.118)
Dummy 1987	0.471	0.498
	(0.312)	(0.405)
Dummy 1992	0.553	0.520
	(0.473)	(0.520)
Dummy 1997	0.616	0.677
	(0.686)	(0.780)
Dummy 2002	0.867	1.077
	(0.799)	(0.855)
Dummy 2007	0.786	1.091
	(0.881)	(0.959)
Dummy 2012	1.100	1.157
	(0.988)	(1.128)
No. of Observations	2,026	722
No. of Counties	629	288

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Though I do not offer a detailed discussion of the fixed effects estimates presented here, in general the statistical significance of the socio-economic variables is greatly reduced. Few of the variables are significant, but this is not too surprising given that within county changes over the 1980-2014 period are typically small for most of these variables. Note that in Table 1.A1 we observe a reversal of sign on most of socioeconomic variables except for income levels and government spending. However, those counterintuitive results are not robust as they are mostly insignificant in both columns (1) and (2). As noted by Kahn (2005) the fixed effects approach be problematic, given the presence of sluggish adjustment and long latency in economic development. Nevertheless, I present these estimates in Appendix for the interested reader.

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CHAPTER 2

FLOOD FATALITIES IN THE UNITED STATES: THE ROLES OF SOCIO-ECONOMIC FACTORS AND THE NATIONAL FLOOD INSURANCE PROGRAM

2.1 INTRODUCTION

Over the 20-year period from 1996-2015, a total of 107,743 floods resulted in 1,563 direct fatalities and over $167 billion in damages in the United States (US). Over the last 30 years floods kill an average of 84 people annually. Floods rank second in terms of resulting fatalities among the different types of life-threatening weather-related events; floods claimed more lives than high intensity disasters such as hurricanes or tornadoes. Importantly, climate scientists predict increases in climate variability and frequency of weather extremes in the coming years. Floods are no exception; Milly et al. (2002) find that the trend of increasing risk of significant floods was substantial during the twentieth century and their climate model suggests that the trend will continue.

Floods are one of the costliest natural hazard types in the United States, imposing a financial burden on a large number of households and communities. A large portion of property damage during massive hurricanes such as Katrina in 2005 and Harvey in 2017 were the result of flooding triggered by those storms. Given the lack of flood coverage in the private insurance market, the National Flood Insurance Act of 1968 established the National Flood Insurance Program (NFIP) to provide an insurance option priced below actuarial risk-based rates. However, the subsidized premiums of the insurance program have resulted in operating deficits. After a series of devastating hurricanes and superstorms since 2005 (e.g. Katrina, Rita, Sandy, Harvey, Maria, etc.), NFIP's debt level to the U.S. Treasury has increased substantially[23]. To improve the financial solvency of the program, government officials attempted to increase the policy premiums to match actuarial rates (Biggert-Waters Flood Insurance Reform Act of 2012), but due to the strong opposition by policy holders, the premiums were not increased to the level where claims can be paid without continuing to rely on federal subsidies[24]. There have been mounting concerns and criticisms over the fiscal sustainability of the program[25].

While the problems of the program have been debated, some of the beneficial components of the program have not been fully evaluated; to my knowledge no existing studies have empirically examined the NFIP *as a disaster management scheme*. It should be noted that the NFIP's mission includes providing government-funded coverage for floods as well as helping to guide and manage community implementation of floodplain management and mitigation practices. In disaster management, *ex-ante* hazard prevention and damage mitigation is at least as important as *ex-post* recovery efforts, but only the former can help to avert irreversible societal damages and fatalities. By design, the prevention and mitigation efforts of the NFIP are interconnected with the provision of flood insurance; the NFIP enables property owners in participating communities to purchase insurance in exchange for the *mandatory* implementation of floodplain management ordinances for flood risk and damage reduction. In this regard, I

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[23]. As of September 2017, the NFIP owes $24.6 billion to the U.S. Treasury. In October 2017, the Additional Supplemental Appropriations for Disaster Relief Requirements Act canceled $16 billion of NFIP's debt. As of February 2018, FEMA's debt is $20.5 billion.

[24] The Homeowner Flood Insurance Affordability Act (HFIAA) was enacted in 2014 and reinstated certain premium subsidies and slowed down certain premium rate increases that had been included in the Biggert-Waters Act.

[25] NFIP has been identified by U.S. Government Accountability Office (GAO) as "High-Risk" federal program since 2006 as a result of its substantial financial exposure and operational challenges.

hypothesize that the NFIP has played a substantial role in preventing and reducing the adverse impacts of floods through *ex-ante* flood risk management.

To explore and test the extent to which proactive disaster management practices regulated by the NFIP helps to reduce disaster impacts, I rely on the integrated view of the physical, social, economic, and political elements of disaster vulnerability. Lethal disasters in the United States such as the Loma Prieta Earthquake in 1989 in California, Hurricane Andrew in 1992, and Hurricane Katrina and Rita in 2005 and many other disasters reveal significant differential impacts across different population segments, depending on socio-economic and political status. That is, research is showing that natural disasters are not all “natural.” Consequently, the socio-political nature of disasters is increasingly the focus of attention in studies of disaster vulnerability.

Given that those with lower socio-economic status are more likely to experience the greatest impacts from natural hazards, I use a framework where the underlying social and institutional factors determine vulnerability to floods. To this end, I investigate the relationship between flood-induced fatalities and a wide range of vulnerability indicators such as demographic, socio-economic, and housing characteristics, as well as institutional factors. Considering that there might be a bi-directional process between the disaster-related government activities and disaster impacts, I test the endogeneity of institutional variables and implement the instrumental variable (IV) estimator by using the Control-function (CF) approach (Wooldridge, 2014). This study explores yearly flood events that occurred over the 1996 to 2015 period using US county level data. In my empirical analysis, I control for disaster-specific physical factors (e.g. timing, duration of the incidence) and area-specific environmental characteristics (e.g. urbanization, the number of dams, and past flood experiences) to assess the socio-economic and institutional factors that increase (or reduce) vulnerability to floods. Using county-year panel structured data, I employ the correlated random effects (CRE) framework combined with the Control-function approach, that allows unobserved county heterogeneity to be correlated with observed covariates (Wooldridge, 2010).

This study's contributions to the literature are as follows. First, my study provides a robust assessment of a broad array of structural and social components of disaster vulnerability, including urbanization, past flood experience, education, and housing quality, while controlling for the unique attributes of counties. Second, I examine the role of local government public safety and protection services in mitigating flood impacts, and I do so in a way that corrects for potential simultaneity bias by applying the IV method. Third, this study presents new evidence showing the National Flood Insurance Program (NFIP) has significantly reduced flood-related fatalities. The present study reveals range of factors that influence flood vulnerability, which can help local, state and national authorities to identify vulnerability “hotspots”. The analysis also shows the importance of the proactive mitigation measures and helps policymakers better prepare for future flood events.

2.2 LITERATURE REVIEW

2.2.1 Socio-political Nature of Disasters

In general, it has been argued by many scholars that structural, social, political factors such as poverty, access to social protection and security, and inequalities with regard to gender, economic position, age, or race, cause or exacerbate vulnerability (Aptekar and Boore 1990, Albala-Bertrand 1993, Cannon 1994, Blaikie et al. 1994, Cutter 1996, Peacock et al. 1997, Enarson and Morrow 1998, Morrow 1999). Blaikie et al. (1994) note that vulnerability, in a disaster context, is a person's or group's "capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard". While disaster risk is imposed exogenously by natural forces, the vulnerability of people to naturally occurring extreme events is influenced by human activity (O'Keefe et al. 1976, Hewitt 1983). Cannon (1994) asserts that people's ability to cope with and recover from hazards depends on economic systems and class structures that allocate resources and access to resources. Cutter et al. (2003) discuss the possible interactions between social and biophysical vulnerabilities that determine overall place vulnerability. In their model, disaster fatalities are largely determined by socio-economic factors that shape a community's disaster vulnerability; hazard potential is either moderated or enhanced via a combination of geographic factors and the social fabric of the place that are influenced by socio-economic status, demographics, and housing characteristics. With special attention to the institutional component, my study uses this conceptual framework where disaster risk is defined by the combination of bio-physical hazards of nature and societal vulnerability which is shaped by social conditions and structure.

2.2.2 Economic Development and Disaster Impacts

Most disaster studies addressing social vulnerability are qualitative in nature, but there are several quantitative empirical studies that investigate the major factors associated with the disaster-induced fatalities. The relationship between the level of economic development and disaster consequences are primary focus of this research. Burton et al. (1993) argue that the impacts of natural hazard (drought, floods, and tropical cyclones) vary across countries by income level. Similarly, Horwich (2000) asserts that higher income enables an increase in general safety of society as well as an improvement in protection against natural disasters. An economy's resilience and response to disasters are largely determined by its level of wealth.

More recent empirical studies on the determinants of disaster vulnerability use cross-country disaster data obtained from EM-DAT[26]. The work of Kahn (2005), Toya and Skidmore (2007), Strömberg (2007), Kellenberg and Mobarak (2008), Raschky (2008), and Gahia et al. (2013) examine the role of economic and institutional factors in determining disaster-induced fatalities. Kahn (2005) investigates the relationship between disaster deaths and income, geography, and institutions. He finds that disaster fatalities are negatively correlated with the level of development. Also, his research shows that democracies and nations with less income inequality tend to suffer fewer deaths from disasters. Another early study on the disaster-safety-development relationship is that of Toya and Skidmore (2007). Using disaster data from EM-DAT for 151 countries over 44 years (1960-2003) and other measures of socio-economic fabric, the study confirms that economic development as measured by per capita GDP is inversely correlated with both disaster deaths and damages.

Strömberg (2007) finds that greater wealth and government effectiveness are associated with fewer disaster fatalities. Raschky (2008) and Kellenberg and Mobarak (2008) find a nonlinear relationship between economic development and disaster impacts; economic development reduces disaster losses but with a diminishing rate. Also, Gahia et al. (2013) show that poorer and larger countries suffer more disaster related fatalities. Brooks et al. (2005) assess vulnerability to climate-related events by developing national-level indicators of vulnerability

[26] Emergency Events Database EM-DAT that has been maintained by the Centre for Research on the Epidemiology of Disasters (CRED) contains essential core data on the occurrence and effects of mass disasters in the world from 1900 to present.

and adaptive capacity. They find that socio-economic, political and environmental factors such as civil and political rights, life expectancy, government effectiveness and accountability, and literacy are significant predictors of disaster vulnerability.

2.2.3 Severe Weather Events in the United States and Disaster Vulnerability

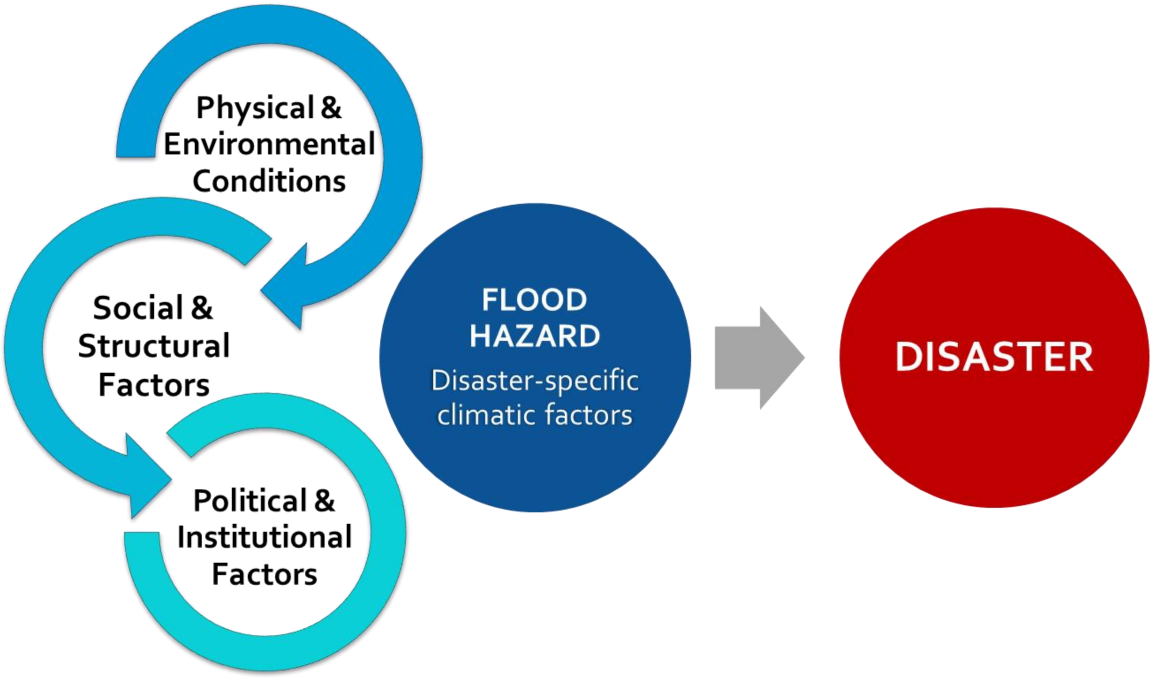
Unlike the abovementioned studies on multiple types of natural disasters across multiple countries using the EM-DAT data set, there are a few quantitative studies that discuss U.S. natural disasters and the role of various demographic, economic, and political factors. Addressing this research gap, my study focuses on U.S. county level flood events, within the context of socio-economic and political vulnerability. Most empirical studies on U.S. natural disasters examine flood, tornado, and hurricane events. Simmons and Sutter (2013) and Lim et al. (2017) use detailed U.S. county level tornado data from National Oceanic and Atmospheric Administration (NOAA) to examine the societal determinants of tornado vulnerability. Both studies show that the physical elements of tornado hazard (e.g. tornado intensity) and socioeconomic and demographic conditions of localities are key determinants of tornado fatalities. Simmons and Sutter (2013) find that education, percentage of non-white and rural population, and percentage of mobile homes are key factors. Lim et al. (2017) expand the findings of Simmons and Sutter (2013), showing that local governments can and do play a significant role helping to reduce fatalities. The study also finds that income inequality and various dimensions of poverty intensify societal vulnerability to tornadoes, and confirms the existence of learning effects from tornado risk history.

In terms of flooding, Zahran et al. (2008) analyze flood events in Texas counties from 1997-2001 to examine whether areas with higher concentration of socially vulnerable populations suffer greater fatalities from flood events. They construct an index of social vulnerability using measures of poverty, median income, and race. Their empirical analyses indicate the built-environment and social vulnerability significantly contribute to the degree to which localities are affected by flood events. They consider FEMA rating scores of Texas counties based on the Community Rating System (CRS) and show that FEMA premium discount provides incentives for flood mitigation, reducing the flood casualties. This study further extends and adds to the work of Zahran et al. (2008) by investigating the US nationwide flood vulnerability over the 20-year period with particular focus on the roles of institutional factors – NFIP and local government – in mitigating flood vulnerability.

2.3 CONCEPTUALIZING HUMAN AND ENVIRONMENTAL COMPONENTS OF FLOOD VULNERABILITY

Based on the conceptual framework where risk is considered to be a function of physically defined natural hazards and socially constructed vulnerability, I hypothesize that three key elements determine the degree of disaster impacts: i) disaster-specific climatic factors, ii) area-specific physical and environmental factors, and iii) socio-political conditions within communities. As shown in Figure 2.1, these three conditions together contribute to the overall place vulnerability to natural disasters. Although the third element of the disaster vulnerability is of my main interest, all three elements are integrated in order to conduct a robust examination of the socio-political determinants of flood-induced deaths.

Figure 2.1: Key Elements of Disaster Vulnerability



2.3.1 Disaster-specific Determinants of Flood Vulnerability

First, I control for disaster-specific factors, such as timing and the duration of the events. It is expected that the degree of disaster impacts would be different across the time of day when an event occurred. As in Simmons and Sutter (2011), each flood event is categorized by the time of day: overnight (12:00-5:59 AM), morning (6:00-11:59 AM), early afternoon (12:00-3:59 PM), late afternoon (4:00-7:59 PM), and evening (8:00-11:59 PM). The time of the day is related to the degree of vulnerability since people are better able to receive warnings, promptly respond, and take actions during the daylight hours. As a climatic element of flood vulnerability, I also control for the month of the flood event. One key factor is the duration of the event; the longer the exposure to the flood hazard, the more intense are the flood impacts.

2.3.2 Area-specific Physical and Environmental Determinants of Flood Vulnerability

I also incorporate area-specific characteristics that capture pre-existing physical and hydrological vulnerability to flood hazards. Those factors are the total number of dams (of all purposes) as well as those for flood control and storm water management located in a county, the percent of urban population, and the flood experience in the previous two years. Dams are constructed for various purposes, for example, water supply, irrigation, power generation, water flow control, and/or flood prevention, etc. In flood-prone areas, dams are constructed for the specific purpose of flood control and storm water management. The existence of such dams can aid controlling the flow of water during flood events. I thus hypothesize that the number of dam structures play a significant role in defining the area's hydrologic vulnerability to floods. It is expected that the risk of flooding would be lowered in a county if more dam structures are available for water flow management in flood situations.

Another important environmental condition related to flood vulnerability is the pattern of land use and land cover as a result of urbanization. The idea is that urban areas are more likely to be covered by building structures and paved surfaces, and as a result infiltration capacity of the land is greatly reduced, causing greater surface water runoff. Consequently, urbanization may magnify the risk of flooding (Hollis, 1975). The percent of population living in urban areas (including urbanized areas and urban clusters) in a county is included as a measure of urbanization in the empirical analysis.

In addition, the frequency of fatal floods (i.e. number of floods that resulted in one or more fatalities) in the previous two years are included as a measure of flood hazard history of the area. Flooding is one of the most frequent disaster types that occur in most U.S. counties, but most floods are not large-scale events nor deadly. Thus, frequently occurring small-scale flood events are not likely to alarm a community as a whole. However, significant events with fatalities are more likely to capture the attention of residents through local news and media about the dangers of floods and thus influence their perceptions and behaviors. Significant events may also stimulate local governments to increase efforts toward disaster prevention and management. In this regard, a community's past experiences with fatal floods and lessons learned may play a critical role in reducing vulnerability and the future consequences of floods (McEntire 2001).

2.3.3 Socio-political Determinants of Floods Vulnerability

I also hypothesize that demographic, socio-economic, housing, and institutional factors including the National Flood Insurance Program, are critical in shaping the overall vulnerability of people and places to disasters. Each key factor is discussed next.

Income The level of income within a community is a key factor that determines societal vulnerability to disasters. Communities with higher income and/or wealth have a greater demand for safety and can allocate more resources to safety and protective measures (Wildavsky, 1988). On the other hand, limited financial, physical, and social assets of the poor increase their susceptibility to disasters. The role of income (or wealth) and poverty in disaster contexts has been illustrated in many empirical studies (Kahn 2005, Toya and Skidmore 2007, Strömberg 2007, Raschky 2008, Lal et al. 2009, Gaiha et al. 2013, Lim et al. 2017). I hypothesize that communities with lower income level (or higher rates of poverty[27]) suffer greater flood-related fatalities. In this study, per capita income of U.S. counties is included as a measure of economic status.

[27] The correlation coefficient between poverty rate and per capita income level of county is -0.71. Two measures both represent economic status of counties from different angles but considering the strong correlation between two measures, I only include per capita income measure in the empirical analysis.

Education Level Prior disaster studies suggest that education level is closely linked with disaster vulnerability (Brooks et al. 2005; Cutter et al. 2003; Lim et al. 2017; Simmons and Sutter 2013; Skidmore et al. 2007; Muttarak and Lutz 2014). I include the share of Bachelor's degree holders among population aged 25+ in the estimation as a measure of education level of county population. Education enhances risk perception and promotes disaster preparedness against disasters (Hoffmann and Muttarak 2017), which are critical preconditions of disaster impact reduction at the individual level. More educated people who have better understanding of the hazard risks are more likely to take preventive measures and be better prepared for the shocks. Thus, I expect that counties with more educated population are less vulnerable in the face of flooding.

Housing Quality I also hypothesize that communities with a higher proportion of households living in mobile homes will suffer increased flood-induced fatalities. People living in mobile homes face greater vulnerability due to the structural features of mobile homes that typically have no foundation and are less able to withstand shocks. Moreover, a higher proportion of households living in mobile home implies greater vulnerability in a different context because lower cost mobile homes are often occupied by those who have relatively limited financial resources. Scholars argue that disasters adversely affect people in lower socio-economic status largely because of the types and quality of housing they occupy (Fothergill and Peak 2004). Similarly, minorities may be more likely to live in unsafe, substandard housing, and are thus at greater risk (Aptekar 1991, Phillips 1993, Pastor et al. 2006). For these reasons, a higher proportion of households living in mobile homes within a county indicates greater physical *and* socio-economic vulnerability of the community.

Local Government Investment I also examine the degree to which local government plays a role in protecting citizens from flood hazards. The idea is that more government resources allocated in safety, protection and welfare can increase overall safety of the localities and strengthen their ability to resist the impact of natural hazards, which can lead to the reduction in societal losses and damages. Lim et al. (2017) provide empirical evidence that local government expenditure on emergency services and community protection is a critical factor in reducing tornado impacts in the United States. Following Lim et al. (2017),I also test the role of local government in mitigating the flood impacts by constructing a measure of local government spending on public safety, protection, and welfare, which includes expenditures on fire/police protection and protective inspections/ regulations and housing/community development, and public welfare[28]. However, this type of government expenditure and the disaster occurrence may have a bi-directional relationship where frequent disaster events in a county would increase its spending on public safety, protection, and welfare. Acknowledging that such government expenditures may not be strictly exogenous, I apply two methods to address potential simultaneity. First, I construct a predetermined level of government expenditure by lagging the local government fiscal data, following the prior studies (Garcia-Mila and McGuire 1992, Cullen and Levitt 1999). The government fiscal data are reported every five years (in years ending in 2 and 7 within a decade), so I interpolate the expenditures (inflation-adjusted) and match the yearly data with flood event data set to reduce the possibility of capturing the reverse relationship between consequences of disasters and government activity. Second, I transform the original

[28] In the context of local government, welfare services are not direct cash assistant (this comes from state government), but are for services like children's homes or payments to vendors for substance abuse treatment and the like.

event data set into a county-year panel structured data and apply the instrumental variable (IV) estimator by using the Control-function approach (Wooldridge, 2014) within the Correlated Random Effects (CRE) framework.

National Flood Insurance Program Lastly, as the main concern of this study, I evaluate the role of National Flood Insurance Program (NFIP) in preventing and reducing the loss of human life from flooding through *ex-ante* floodplain management and mitigation efforts. The NFIP is a Federal program established by the U.S. Congress through the National Flood Insurance Act of 1968. The NFIP enables property owners in participating communities to purchase insurance (administered by the government) as financial protection against flood losses, in exchange for the implementation of floodplain management ordinances for flood risk and damage reduction. Participation is based on a cooperative agreement[29] between communities and the Federal Government. In order to participate in the NFIP, communities must meet (or exceed) the minimum floodplain management requirements, through building codes, zoning ordinances, subdivision regulations, health and safety codes, and stand-alone floodplain ordinances.

The Federal Emergency Management Agency (FEMA) manages the NFIP and oversees the identification and mapping[30] of flood-prone communities, reviews community adoption and implementation of land use regulation and construction standards, determines flood insurance

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[29] Once the flood hazard has been identified and an NFIP map has been provided to a community, the identified flood-prone community must assess its flood hazard and determine whether flood insurance and floodplain management would benefit the community's residents and economy.

[30] In support of the NFIP, FEMA identifies flood hazards nationwide and publishes flood hazard data such as Flood Hazard Boundary Maps (FHBMs), Flood Insurance Rate Maps (FlRMs), and Flood Boundary and Floodway Maps (FBFMs). These flood hazard data provided to the community by FEMA is the basis of community’s floodplain management regulations.

rates for different mapped zones of risk, provides flood insurance, and funds mitigation projects. The identification of flood hazards is an essential process as it creates an awareness of the hazard and provides communities with the information needed for land use planning, floodplain development, and for emergency management.

The 1994 NFIP amendment implemented through the National Flood Insurance Reform Act of 1994 directs FEMA to develop a standard form for determining whether the building or mobile home is located in the Special Flood Hazard Area (SFHA)[31]; in these areas for acquisition and/or construction of buildings, purchasing flood insurance as well as complying with specific building restrictions are *mandatory* as a condition of Federal or Federally related financial assistance. The floodplain management requirements within the SFHA are designed to prevent new development from increasing the flood threat and to protect new and existing buildings from anticipated flood events. The National Flood Insurance Reform Act of 1994 also strengthened the program by enacting a Community Rating System (CRS) that recognized and encouraged community floodplain management activities exceeding the minimum standards of the NFIP. With the CRS, the NFIP further incentivizes communities with discounts on flood insurance premiums to conduct mitigation and outreach activities that further increase safety and resilience of the area.

The NFIP also pays special attention to the vulnerability of mobile homes to flooding. FEMA P-85 titled *Protecting Manufactured Homes from Floods and Other Hazards* (second edition, initial edition of FEMA 85 published in 1985 and updated to FEMA P-85 in 2009)

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[31] Special Flood Hazard Area (SFHA), which is defined as an area of land that would be inundated by a flood having a 1 percent chance of occurring in any given year (also referred to as the base or 100-year flood). Development within the SFHA must comply with local floodplain management ordinances, which must meet the minimum Federal requirements.

provides guidance on foundation design and installation of mobile homes in floodplains; these guidelines are designed to make mobile homes less susceptible to floods (and other natural hazards). For example, the NFIP require manufactured homes located in Special Flood Hazard Areas be elevated and securely anchored to resist floatation, collapse, or lateral movement. FEMA's policy (as described in FEMA P-85) that addresses the vulnerability of mobile homes to natural hazards by establishing mandatory regulations and standards governing the mobile homes in hazard-prone areas contributes to the improvement in safety of mobile homes and the resilience of communities as a whole.

Risk-transfer mechanisms such as mandatory catastrophe insurance alleviate the impacts of natural hazards, reducing the burden of recovery and welfare losses (Kunreuther 1996, Luechinger and Raschky 2009). However, my hypothesis here is that by identifying flood hazards across the states and promoting and enforcing proper floodplain management and safety standards to mitigate future consequences of floods, NFIP plays a vital role in enhancing resilience and thus reduces vulnerability in flood-prone communities. To empirically evaluate the potential life-saving role of the program, a measure of the NFIP participation rate at the county level is constructed. Within-county participation rate is determined by the percent of communities (city, town or township, village)[32] within a county that entered in the program **at least *two* years before** the year when a flood event occurred. I use lagged participation rates

[32] The comprehensive list of the communities – city, town or township, village – within a county (or county equivalent) is from the list of subcounty governments that are used for local government finance/employment data, where municipal and township governments are identified by government type code 2 and 3, respectively.

because the implementation of the NFIP requirements would not take effect immediately in terms of enhancing overall safety of the community.[33].

2.4 EMPIRICAL ANALYSIS

2.4.1 Data Description

The analysis uses individual flood event data within U.S. counties over the 1996-2015 period[34]. Data on fatalities from floods in the United States are collected from NOAA National Centers for Environmental Information (NCEI)[35]. Detailed information on time, dates, and locations of the events are also provided. Major socio-economic, housing, and government expenditure data at the county level are collected from U.S. Bureau of the Census[36] and merged with the flood data. Detailed data on locations and built years of dams are from National Inventory of Dams (NID) published by U.S. Army Corps of Engineers. National Flood Insurance Program (NFIP) participation status of communities is from Federal Emergency Management Agency (FEMA). Table 2.1 presents the total number of various types of severe weather events in the United States and resulting fatalities and injuries by types of storm events during 1996-2015. At the county level, the total 175,863 storm events occurred over the period. Floods are the most frequent

[33] One might be concerned about reverse causality where greater flood impacts cause participation rates to increase. I performed the endogeneity tests for two institutional factors - the government expenditure on public safety, protection, & welfare and the NFIP participation rates. The test results suggest that only the government expenditure variable is endogenous and the predetermined NFIP participation rates are non-endogenous once I correct the simultaneity bias resulted from government expenditure variable. I thus, use instrumental variables methods to address the endogeneity of the government expenditure, taking the predetermined NFIP participation rates as exogenous.

[34] Note that flood events in 1996 and 1997 are only used for constructing the past 2-yr's flood experience of a county.

[35] Data source: www.ncdc.noaa.gov/data-access/severe-weather

[36] Decennial census data for demographic and housing variables, and local government expenditure data are interpolated/extrapolated to obtain yearly data over the study period (1996 – 2015).

disaster type; floods and flash floods account for 60% of the total climatic events in the United States. The next most frequent event type is the tornado with nearly 1,400 events per year. These storm events induced total of 7,342 deaths and 52,216 injuries over the last 20 years. Heat caused the highest number of fatalities, followed by tornadoes and flash flooding. In terms of the average fatality per event, rip currents recorded the highest deaths rate, with 0.7 fatalities per event. Tornadoes caused the largest number of injuries in total, whereas heat and excessive heat together recorded the highest number of injuries per event. This study focuses on flood-related fatalities37. County level flood frequencies and fatalities over the study period are presented in Figures 2.2 – 2.3.

Table 2.1: Fatalities and Injuries by Disaster Events, 1996 – 2015

	Frequency		**Fatalities**		**Injuries**	
Event Type[1]	Total	%	Total	Per event	Total	Per event
Flood	**39,893**	**22.7%**	**419**	**0.011**	**2,320**	**0.058**
Flash Flood	**67,850**	**38.6%**	**1,144**	**0.017**	**6,282**	**0.093**
Rip Current	807	0.5%	569	0.705	561	0.695
Hurricane[2]	162	0.1%	6	0.037	17	0.105
HurricaneTyphoon[2]	1,350	0.8%	86	0.064	921	0.682
Tornado	27,539	15.7%	1,680	0.061	23,089	0.838
Avalanche	427	0.2%	219	0.513	153	0.358
Heat	16,424	9.3%	1,966	0.120	8,956	0.545
Excessive Heat	5,897	3.4%	422	0.072	5,185	0.879
Debris Flow	429	0.2%	83	0.193	49	0.114
Lightning	15,085	8.6%	748	0.050	4,683	0.310
Total	**175,863**	**100%**	**7,342**	**0.042**	**52,216**	**0.297**

1. This study explores flood and flash flood events. The definition/determination of flood and flash flood are provided in Table 2.A1 in the Appendix.
2. The Hurricane/Typhoon category data only include fatalities, injuries, and damage amounts associated with wind damage (the other hazards are reported in their respective categories.).

[37] The historical storm data I have collected from NOAA contain injury data as well, however, the number of persons injured during flood events are not fully reported (whereas the number of persons killed by floods are extensively collected from various sources) and thus, county level injury data do not represent exact injury count. For this reason, I do not conduct empirical analysis using injury data.

Figure 2.2: Total Number of Floods by County, 1996-2015

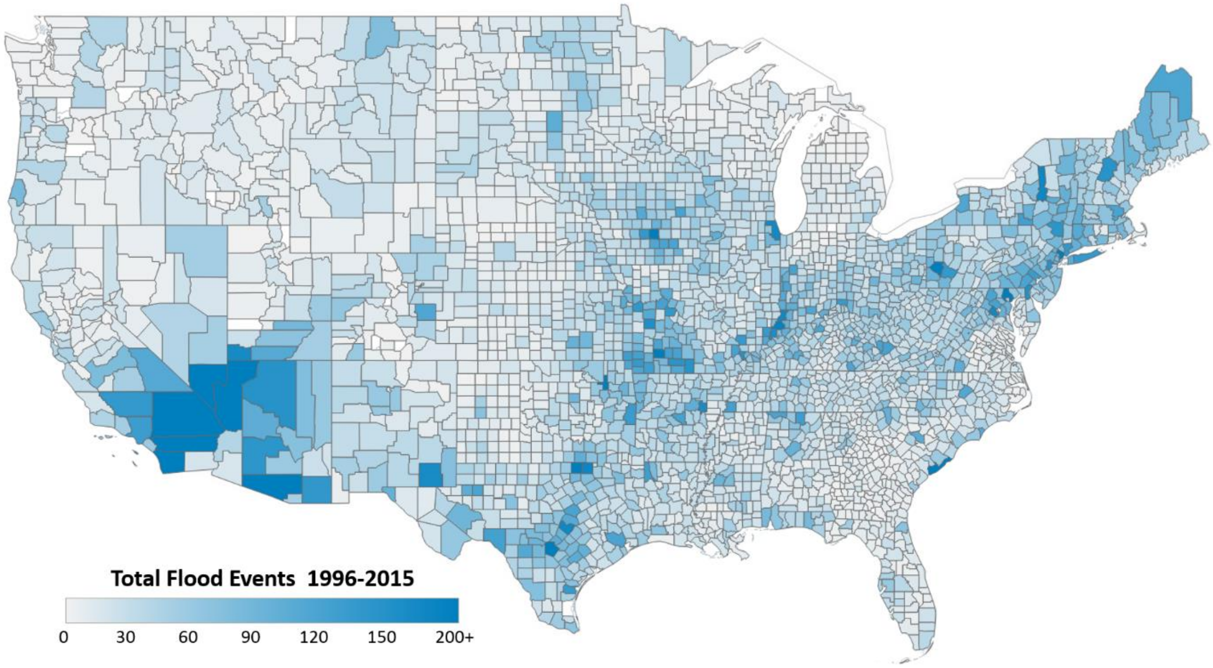
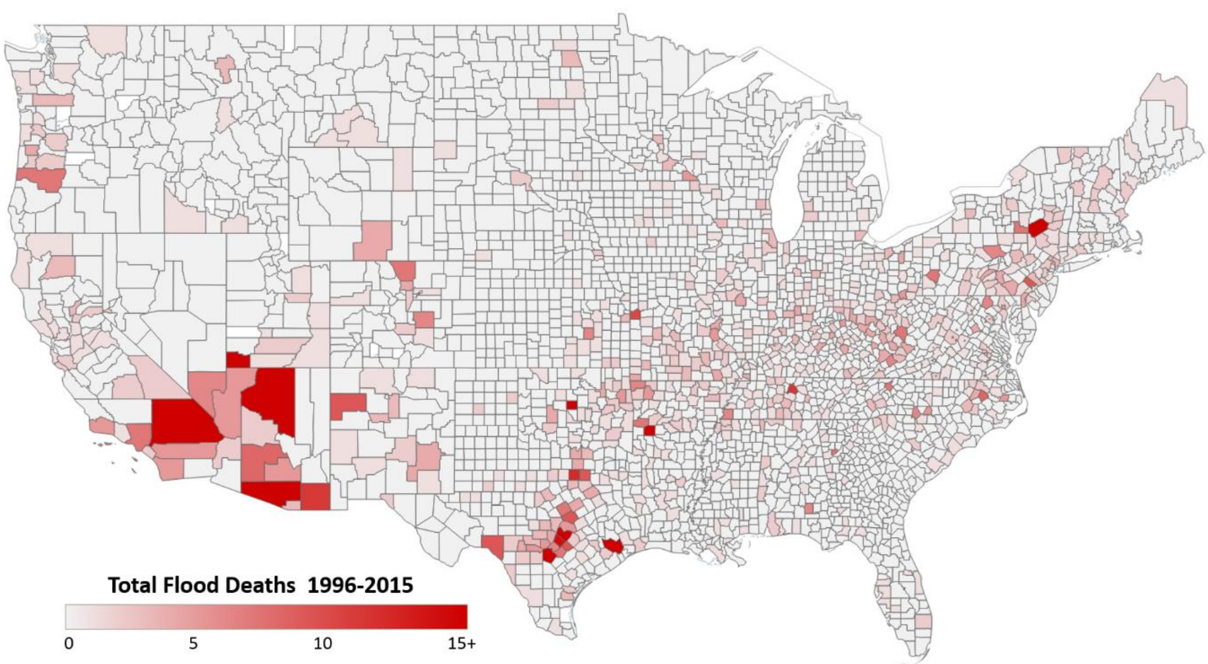


Figure 2.3: Total Deaths from Flood by County, 1996-2015



2.4.2 Empirical Model

2.4.2.1 Base Model

I first analyze the flood vulnerability preserving its original event data structure (also called Cross-Sectional-Time-Series), which contains observations of multiple cross-sectional units over multiple time periods. Note, however, that this data structure is different than a panel (or longitudinal) data structure because it can contain multiple observations of a unit in a year (e.g. +1 observations for a county in a specific year is possible if +1 flood events occurred within the county in that year). By retaining this original individual flood event data structure in this base model, the detailed information on each flood can be included.

The dependent variable is the number of fatalities caused from each flood event. Among total 107,708 flood events during the study period 1996-2015, only 1,067 events resulted in fatalities; for a large portion of observations, the dependent variable is zero. Thus, for the econometric analysis of the flood event data (to which conventional panel data methods cannot be applied), I employ Zero-Inflated Negative Binomial (ZINB) model which properly treats the non-negative count variables with the over-dispersion (excess zeros) problem (Long and Freese, 2006). Because of the distributional features of disaster-induced fatalities, ZINB model is increasingly employed in disaster studies (e.g. Kahn 2005, Zahran et al. 2008). In the ZINB model, the excess zeros are considered to be generated by a separate process from the count values and the excess zeros are modeled independently. The ZINB model combines binary Logit model for zero outcomes and Negative Binomial model for event-counts. The ZINB regression analysis is characterized by the following model:

(1) Log Likelihood:

$$\ln L = \sum_{j\in S} \ln\left[F(z_j\gamma) + \{1 - F(z_j\gamma)\}p_j^{1/\alpha}\right]$$
$$+\sum_{j\notin S}\left[\ln\{1 - F(z_j\gamma)\} + \ln\Gamma\left(\frac{1}{\alpha} + y_j\right) - \ln\Gamma(y_j + 1) - \ln\Gamma\left(\frac{1}{\alpha}\right) + \frac{1}{\alpha}\ln p_j + y_j\ln(1 - p_j)\right]$$

(2) $p_j = 1/\left[1 + \alpha\exp(x_j\beta)\right]$

(3) F : the inverse of the logit link

(4) S : the set of flood observations for which the outcome (y_j: death) is zero.

(5) z_j : Inflation variables for the binary Logit model predicting whether an observation is in the *always-zero* group where $\Pr(y_j = 0) = 1$

(6) x_j : Covariates for counts model (Negative Binomial)

In my empirical analysis, the covariates x_j for the count model of Negative Binomial include the following variables: $\boldsymbol{X_j}$, a vector of demographic and socio-economic characteristics, as well as institutional factors of the county that may determine fatalities of flood j, $\boldsymbol{F_j}$, the disaster specific characteristics, $\boldsymbol{E_j}$, a vector of physical and hydrologic characteristics of the county where the disaster j occurred. To control for the unobserved statewide heterogeneity, I also include state fixed effects along with year fixed effects. The detailed list of the explanatory variables in the ZINB analysis is provided in Table 2.2.

In addition, four key variables are selected from the explanatory variables to serve as inflation variables of ZINB model that determine the probability of being in the *always-zero* group: previous 2-year's flood experience, per capita income, the NFIP participation rate and per capita government expenditure on public safety/welfare. Each of these variables represent past flood history, socio-economic characteristics, and the institutional components of the affected areas, respectively.

Table 2.2: List of dependent and explanatory variables in the ZINB model

Dependent Variable			
	Deaths from each Flood event		$\boldsymbol{Y_j}$
Explanatory Variables			
	Event-specific	Begin time of the event: Overnight, Morning, Early Afternoon, Late Afternoon, Evening	$\boldsymbol{F_j}$
		Duration (days)	
		Season: Spring, Summer, Fall, Winter	
		Event Type: Flood, Flash Flood	
	Area-specific Environment	No. Dams in Total within a county (all purposes)	$\boldsymbol{E_j}$
		No. Dams for Flood Control and Storm Water Management	
		Percent of Urban Population	
		Past 2-year's Flood Experience	
	Demographic	Population Size	$\boldsymbol{X_j}$
		Percent of Population over 65	
		Percent of Population under 18	
	Socio-economic	Per capita Income*	
		Percent of Population over 25 with Bachelor's degree	
		Percent of Mobile Homes in Total Housing Units	
	Government	2yr-lagged NFIP Participation Rates within a County*	
		Lagged Per Capita Gov't Expenditure on Public Safety/Welfare*	
	Year Fixed Effects	Indicator variables for each year	T
	State Fixed Effects	Indicator variables for each state	S

* These factors serve as inflation variables of the ZINB model.

The hypothesized socio-economic characteristics and institutional components are examined with a set of control variables: i) population characteristics: county population size, percent of population over age 65 and under 18, ii) area-specific physical and environmental factors: the number of dams in total and for flood control, percent of urban population, and the previous 2-year's flood experience, and iii) event-specific climatic factors: begin time of the day and month of the event, duration of the incidence, and the type of the flood events. Summary statistics for all variables included in the ZINB analysis are presented in Table 2.3. The variable definitions and data sources are provided in Table 2.A2 in the Appendix.

Table 2.3: Summary Statistics of Variables in ZINB Model

	Mean	Standard Deviation	Min	Max	Number of Obs.
Dependent Variable					
Fatalities from individual event	0.014	0.188	0	20	97,416
Independent Variables					
Total No. Dams (all purposes)	32.879	39.091	0	331	97,416
No. Dams for Flood Control	6.228	14.675	0	230	97,416
Pct Urban population	50.773	31.526	0	100	97,416
Past 2-yr's Flood Experience	7.465	9.842	0	115	97,416
Ln(Population)	10.908	1.560	4.205	16.115	97,416
Pct Over65	14.068	3.631	2.148	43.641	97,416
Pct Under18	24.131	3.053	7.605	45.207	97,416
Pct Bachelor Degree	20.274	9.663	1.868	76.762	97,416
Pct Mobile home	11.878	8.662	0	61.29	97,416
Ln(Per Capita Income)	10.026	0.231	8.787	11.118	97,416
Lagged NFIP Participation Rates	62.937	32.366	0	100	97,416
Lagged Ln(Per Capita Gov Exp on Public Safety *in thousands*)	-0.949	0.678	-6.943	2.031	97,416
Duration (in days)	1.356	4.218	0	30.999	97,416
Flood	0.368	0.482	0	1	97,416
Flash Flood	0.632	0.482	0	1	97,416
Overnight	0.205	0.404	0	1	97,416
Morning	0.225	0.418	0	1	97,416
Early Afternoon	0.185	0.388	0	1	97,416
Late Afternoon	0.229	0.420	0	1	97,416
Evening	0.156	0.363	0	1	97,416
Spring	0.295	0.456	0	1	97,416
Summer	0.413	0.492	0	1	97,416
Fall	0.164	0.370	0	1	97,416
Winter	0.127	0.333	0	1	97,416

* Summary statistics of year dummies (1998-2015) and 50 state dummies that are included in the ZINB estimation are not presented here.

2.4.2.2 Instrumental Variable Model

As discussed above, disaster-related government activities might not be strictly exogenous, rather bi-directional. In consideration of the potential simultaneity bias, I implement the Poisson Instrumental Variable (IV) estimator by using the Control-function (CF) approach (Wooldridge, 2014) which accounts for both endogenous regressors and non-negative outcome variable. First, the endogeneity tests are performed for two institutional factors - the government expenditure on public safety, protection, & welfare and the NFIP participation rates. Both the robust Hausman test and CF-based Hausman test results[38] suggest that only the government expenditure variable is endogenous. I could not find evidence of the endogeneity of the predetermined NFIP participation rates. Hence, the instrumental variables methods is used to correct the endogeneity of the government expenditure, taking the predetermined NFIP participation rates as exogenous.

I consider two variables as an IV for the local government expenditure on public safety, protection & welfare. One is the number of government entities (e.g. city, town or township, village) within a county and the other is the ratio of the highest and the lowest (census tract level) effective tax rates for real estate within a county[39]. As the county government expenditures are aggregated values that include expenditures of all subdivisions located within the county, an increase in the number of governmental entities is likely to increase government spending.

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[38] For examining the endogeneity of the two institutional variables, I performed two tests. First, a test statistic is used, defined as the difference of two Sargan-Hansen statistics: one for the equation with the smaller set of instruments, where the suspect regressors are treated as endogenous, and one for the equation with the larger set of instruments, where the suspect regressors are treated as exogenous. This statistic is reported after *ivreg2* in Stata, which are robust to various violations of conditional homoskedasticity (Baum et al. 2007). Second, based on the Control-function approach, I carried out the regression-based Hausman tests of whether the suspected endogenous variables are actually endogenous (Wooldridge, 2014).

[39] Decennial Census and American Housing Survey data on the tract level aggregate real estate tax and the aggregate housing values are used to construct the effective tax rates of tracts.

However, changes in the number of local governmental entities is unlikely to have a direct impact on flood fatalities. A rationale for the use of the latter IV – the highest/lowest ratio of the effective tract property tax rates within a county – is that a greater difference in the effective tax rates within a county means higher inequality in property values and wealth as well as local government tax bases (and thus expenditures) within the county. Economic inequality and disproportionate police expenditures among nearby communities in a county might be a fostering ground for crime and generate negative spillovers across districts (Simon Hakim 1980; Furlong and Mehay 1981). The crime spillovers thus drive higher spending on public safety and protection within intra-county areas (Stephen Mehay 1977; Hakim et al. 1979;). However, the tax rate differentials within a county is unlikely correlated with flood fatalities. I formally test the validity of the two IVs by performing Weak identification test (Kleibergen-Paap Wald F statistic) and Overidentification test (Hansen J Statistic) as well as a regression-based correlation test between two IVs and the dependent variable (using Poisson CRE and Poisson FE). The tests of the validity of IVs I performed all suggest that the proposed instruments are reasonable.

To deal with the county heterogeneity while at the same time handling the endogeneity of the government spending, I adopt the correlated random effects (CRE) framework, combined with the CF approach that allows unobserved heterogeneity to be correlated with observed covariates (Wooldridge, 2010). For the application of CF in a CRE setting, county-year panel structured data is constructed. Some of the flood event specific details are averaged or aggregated by year (e.g. average deaths per flood, total duration of floods) while for event timing variables including time of the day and season, I generate shares of floods in each category by year (e.g. % of floods occurred in Spring, % of floods occurred in the morning, etc.). Summary statistics of the variables included in the Poisson IV (CF) model are presented in Table 2.4.

Table 2.4: Summary Statistics of variables in Poisson IV model

	Mean	Standard Deviation	Min	Max	Number of Obs.
Dependent Variable					
Annual Avg. Fatalities per flood	0.013	0.119	0	6	29,680
Explanatory Variables					
Total No. Dams (all purposes)	29.811	37.128	0	331	29,680
No. Dams for Flood Control	5.407	14.136	0	230	29,680
Ln(Population)	10.578	1.410	6.104	16.115	29,680
Pct Over65	14.291	3.725	2.148	43.641	29,680
Pct Under18	24.124	3.125	7.721	44.185	29,680
Past 2-yr's Fatal Flood Experience	0.059	0.263	0	5	29,680
Pct Urban Population	45.565	30.880	0	100	29,680
Pct Bachelor Degree	19.042	8.987	1.868	76.762	29,680
Pct Mobile home	12.844	8.882	0	59.950	29,680
Ln(Per Capita Income)	10.001	0.221	8.997	11.118	29,680
Lagged NFIP Participation Rates	62.096	32.057	0	100	29,680
Ln(Per Capita Gov Exp on Public Safety &Welfare *in thousands*)	-0.974	0.667	-7.488	1.501	29,680
Duration (in days)	4.408	15.924	0	476.572	29,680
Pct Flash Flood	0.656	0.410	0	1	29,680
Pct Flood	0.344	0.410	0	1	29,680
Pct Overnight floods	0.194	0.309	0	1	29,680
Pct Morning floods	0.217	0.322	0	1	29,680
Pct Early Afternoon floods	0.185	0.306	0	1	29,680
Pct Late Afternoon floods	0.240	0.340	0	1	29,680
Pct Evening floods	0.164	0.292	0	1	29,680
Pct Spring floods	0.298	0.387	0	1	29,680
Pct Summer floods	0.414	0.421	0	1	29,680
Pct Fall floods	0.154	0.305	0	1	29,680
Pct Winter floods	0.134	0.291	0	1	29,680
Instrumental Variables (IVs)					
Number of Subdivisions	14.118	14.454	1	151	29,680
H/L Ratio of Real Estate Tax Rates	2.392	4.893	1	131.746	29,680

* Summary statistics of year dummies (1998-2015) and the mean values of the explanatory variables for the Correlated Random Effects (CRE) estimation are not presented here.

2.5 RESULTS

2.5.1 Base Model Results from ZINB Estimation

I first present in Table 2.5 the estimates from the Zero-Inflated Negative Binomial (ZINB) model using individual flood events recorded at the scale of counties during 1996-2015[40]. The dependent variable is fatalities from each flood event. The determinants of flood fatalities are estimated with three specifications, controlling for state and year fixed effects in all specifications. As a part of ZINB model, the results of the logit model for predicting whether an observation is in the *always-zero* group are presented in columns (2), (4), and (6).

The key policy variable of interest, the NFIP participation rate, is introduced into the second and third specifications[41]. The estimated effects of the vulnerability factors on flood fatalities from specifications A, B, and C are largely consistent in direction but differ in magnitude once NFIP participation rate is included. In particular, comparing the specifications A and B, I find that the coefficients on income level and government expenditure variable decrease in magnitude as the NFIP variable is incorporated into the model. However, except for the per capita income, precision of the estimates of the other socio-economic factors and the government expenditure variable is low.

[40] Note that the previous 2-year's flood experience is incorporated as an explanatory variable and accordingly, flood observations in 1996 and 1997 are used as pre-sample data. Flood observations during 1998-2015, total 97,416 flood events are used in the estimation procedure.

[41] In specification C, I test whether the result is sensitive to a change in the choice of inflation variables for the first stage logit model and whether the inclusion of the lagged variable - previous flood experience (although it is not exactly a lagged dependent variable) causes any complications in the estimation process and leads to any notable changes in the estimates.

Table 2.5: Determinants of Flood Fatalities
Zero-Inflated Negative Binomial Regressions Results

	Model A		Model B		Model C	
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
: Deaths from Floods	**ZINB**	**Logit**	**ZINB**	**Logit**	**ZINB**	**Logit**
Overnight	-0.292**		-0.283**		-0.270**	
	(0.125)		(0.127)		(0.127)	
Morning	-0.363***		-0.344***		-0.336***	
	(0.117)		(0.120)		(0.119)	
Early Afternoon	-0.244**		-0.228*		-0.232*	
	(0.118)		(0.120)		(0.120)	
Late Afternoon	-0.409***		-0.394***		-0.387***	
	(0.114)		(0.116)		(0.116)	
Flash Flood	0.682***		0.703***		0.702***	
	(0.106)		(0.108)		(0.110)	
Spring	0.182**		0.193**		0.223**	
	(0.089)		(0.090)		(0.091)	
Fall	0.322***		0.333***		0.332***	
	(0.106)		(0.108)		(0.108)	
Winter	-0.182		-0.189		-0.136	
	(0.128)		(0.129)		(0.131)	
Duration_days	0.029***		0.030***		0.026**	
	(0.010)		(0.010)		(0.011)	
Total No. Dams (all purposes)	-0.004***		-0.005***		-0.005***	
	(0.002)		(0.002)		(0.002)	
No. Dams for Flood Control	0.008**		0.007**		0.007**	
	(0.003)		(0.003)		(0.003)	
PastFloodExperiences_2yr	-0.009	0.025**	-0.006	0.028**		
	(0.008)	(0.011)	(0.009)	(0.011)		
Pct BA Degree	-0.002		-0.002		-0.002	
	(0.010)		(0.010)		(0.010)	
Pct Mobile home	0.008		0.009		0.009	
	(0.008)		(0.009)		(0.009)	
Ln (Per Capita Income)	-1.734***	-2.975***	-1.679***	-2.817***	-1.591**	-2.904***
	(0.643)	(0.879)	(0.641)	(0.849)	(0.651)	(0.892)
Lagged NFIP Participation Rate		-0.018***	-0.011**	-0.026***	-0.011**	-0.026***
		(0.003)	(0.005)	(0.006)	(0.005)	(0.006)
Lagged ln(Govt Exp on Public	-0.141	-0.435	-0.053	-0.321	-0.037	-0.258
Safety, Protection & Welfare)	(0.290)	(0.332)	(0.281)	(0.316)	(0.295)	(0.340)
Constant	10.947*	31.743***	10.963*	30.930***	10.580	31.936***
	(6.486)	(9.048)	(6.409)	(8.669)	(6.513)	(9.152)
Observations	97,416	97,416	97,416	97,416	97,416	97,416

1. Cluster-adjusted robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10
2. The omitted categories are "*Evening*","*Summer*", and "*Flood*".
3. Logit estimation indicates that counties with less past experiences, higher income, higher NFIP participation rates, and more government expenditures on public safety are less likely to be in the *always-zero group*.
4. The estimates of several control variables (pct_elderly, pct_young, lnpopulation, pct_urban) and state and year fixed effects are not reported here.

Disaster-specific Determinants of Flood Fatalities As the estimations in the base model examine individual flood events within the original event data structure, the relationship between flood event-specific details and fatalities can be more precisely estimated. Estimation results demonstrate that event-specific factors such as duration, timing of the event, and flood types are key factors that affect the degree of flood impacts. As expected, a longer duration of flooding significantly relates to the number of deaths from flood events. The estimates also show that the degree of flood impact is different across the time of day when an event begins to occur. My analysis suggests that the impact of a flood tends to be greater when it occurs in the evening. Estimates also show that fatalities from flood events are higher in the fall season (Sep. to Nov.) – when the frequency of flooding is typically low and thus unexpected. Comparing to floods, flash floods are estimated to be deadlier.

Demand for Safety The base model result is consistent with the well-known argument that communities with higher income have a greater demand for safety and allocate more resources to safety and protective measures, mitigating societal vulnerability to disasters. My estimation results support the previous findings that the higher income is associated with the increase in safety against disasters. A negative association between income and flood fatalities is statistically and economically significant in all specifications. Moreover, I could also see a strong negative relationship between the NFIP participation rates and flood impact. The estimates from specification B and C indicate that flood-fatalities decrease by about 10.4%, on average, for a ten-percentage point increase in the within-county NFIP participation rate. The underlying mechanism is that a higher demand for safety against flooding within a community can be translated into the adoption of NFIP, promoting proper floodplain management and mitigation efforts, ultimately reducing flood fatalities.

The base model estimation using ZINB provides evidence for the role of income and the National Flood Insurance Program in mitigating flood vulnerability. However, I acknowledge that there are limitations in this estimation method. By retaining the original event data structure, panel methods that would allow us to deal with the county heterogeneity and the possible endogeneity of institutional factors could not be applied. Thus, the estimates here may not reflect the true relationships due to these issues, which I am not able to address in the current data configuration. In particular, the ZINB model exploits variation across counties, rather than the within-county, and hence, the estimates here may not be the basis of the causal inference. We proceed to the next subsection to discuss the bias-corrected results using the Instrumental Variable method in a CRE setting.

2.5.2 Instrumental Variable Model Results from IV Poisson CRE approach

I present in Table 2.6 the estimation results from the Poisson Instrumental Variable (IV) model using Control-function (CF) method, correcting the endogeneity of the government spending on public safety, protection, and welfare. I use two IVs -the number of local government entities and the highest/lowest ratio of the effective tract property tax rates within a county. I exploit the county-year panel data spanning from1996 to 2015[42], controlling for the county heterogeneity within the Correlated Random Effects (CRE) framework. I discuss in detail the results of the estimated relationship between flood fatalities and key explanatory variables such as area-specific characteristics, and socio-political vulnerability factors.

[42] I incorporate the previous 2-year's flood experience as an explanatory variable and accordingly, flood observations in 1996 and 1997 are used as pre-sample data.

Table 2.6: Determinants of Flood Fatalities
Poisson IV CF / CRE Estimates of Key Explanatory Variables

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	Poisson IV (CF) Correlated Random Effects Estimator			
Dependent Variable	**Model A**	**Model B**	**Model C**	**Model D**
: Avg Deaths per Floods	(1)	(2)	(3)	(4)
Duration_days	0.047***	0.057***	0.057***	0.055***
	(0.014)	(0.015)	(0.014)	(0.015)
Total No. Dams (all purposes)	0.080	0.134	0.151	0.153
	(0.138)	(0.142)	(0.142)	(0.141)
No. Dams for Flood Control	-0.173	-0.243	-0.260	-0.253
	(0.215)	(0.221)	(0.226)	(0.226)
Pct Urban Population	0.203***	0.240***	0.198***	0.210***
	(0.055)	(0.063)	(0.061)	(0.065)
Past 2-yr's Fatal Flood Experience	-6.138***	-6.754***	-6.756***	-6.680***
	(0.804)	(0.900)	(0.934)	(0.930)
Pct Mobile home	0.194***	0.207***	0.241***	0.241***
	(0.075)	(0.074)	(0.080)	(0.084)
Pct BA Degree		-0.316***	-0.383***	-0.380***
		(0.102)	(0.108)	(0.114)
Ln (Per Capita Income)			11.720***	11.821***
			(3.388)	(3.468)
Lagged NFIP Participation Rate	-0.029*	-0.028*	-0.024	
	(0.016)	(0.016)	(0.016)	
Ln (Govt Exp on Public Safety, Protection & Welfare)	-3.433	-4.487*	-4.698*	-6.804**
	(2.492)	(2.573)	(2.684)	(2.871)
Constant	-75.436*	-90.287**	-85.866**	-113.841**
	(38.667)	(39.916)	(41.212)	(44.3742)
Exogeneity Test (p-value)	0.069	0.031	0.032	0.005
Observations	29,680	29,680	29,680	29,680

1. Cluster-adjusted robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10
2. The unit of observation is a county-year. U.S. counties with more than one flood experience in a given year are included.
3. The estimation results not reported here are the first stage Control-function, the mean values of regressors for CRE, and the control variables estimates. The full results are available upon request.

Area-specific Physical and Environmental Determinants of Flood Fatalities A set of area-specific environmental and hydrologic characteristics of the affected area is considered such as past 2-year's fatal flood experience and the number of dams in total and for flood control. The negative correlation between previous flood fatalities and current flood deaths implies that communities' resilience to disasters increases through learning from their past experiences. The results of all specifications consistently demonstrate that learning effects from risk history play an important role in increasing the coping capacity of communities, thus reducing disaster fatalities in areas that recently experienced lethal flooding.

Contrary to the strong positive estimates from the ZINB model, the number of dams for flood control variable now has a negative coefficient (although insignificant with p-value of 0.24 in specification 4). In the ZINB model, the positive coefficient of the number of dams for flood control appears to capture the positive correlation, rather than a causal relationship, between the level of flood risk and the number of structures for flood control. However, once I control for county heterogeneity and handle the endogeneity issue in the IV/CRE model, the estimates presumably reveal a causal relationship. An increase in the availability of dams for flood management helps localities prevent massive water flow into human settlements, thus reducing the risks of life-threatening floods. Also, the positive coefficients of the percent urban population suggests the urbanization worsens the flood impacts. One explanation for the greater flood vulnerability of more urbanized counties is that paved surfaces and concentrated building structures tend to reduce infiltration capacity of the land and consequently intensify flood risk.

Socio-political Determinants of Floods Fatalities In addition to the environmental and hydrologic factors of flood vulnerability, my findings reveal a significant role of socio-economic and political factors in determining flood impacts. First, I find that the education attainment, measured by the share of Bachelor's degree holders among population aged 25+, is closely linked with the flood vulnerability. The results indicate that counties with a higher proportion of educated people experience fewer flood-related fatalities. This result is consistent with the findings of previous empirical disaster studies (Brooks et al. 2005; Lim et al. 2017; Simmons and Sutter 2013; Skidmore et al. 2007; Muttarak and Lutz 2014). Higher education level is associated with enhanced risk perception and proper disaster preparedness and responses. More educated people may have better understanding of the hazard risks and thus are likely to be better prepared for shocks, thus reducing disaster vulnerability.

I also examine the degree to which housing quality, as measured by the percent of mobile homes in the county, is closely linked to flood vulnerability. The estimations in Table 2.6 show a robust and significant result; the estimates of mobile homes are positive with statistical significance. The result confirms that housing quality is one of the more important determinants of flood impacts. Mobile homes are increasingly filling a demand for affordable housing across the states; from 2006 to 2015 nearly half of new manufactured homes were shipped to the seven coastal states in the South region (Texas, Louisiana, Mississippi, Alabama, Florida, South Carolina, and North Carolina). Greater vulnerability of those living in mobile homes suggests important policy implications for disaster management and community vulnerability assessment (Fothergill and Peek 2004, Merrell et al. 2005, Schmidlin et al. 2009, Kusenbach et al. 2010, Lim et al. 2017).

Notably, once the IV method is applied to deal with the simultaneity between government resource allocation decision and disaster risk, I obtain a statistically significant evidence that local government spending in public safety, protection, and welfare plays a role in helping to mitigate human losses from floods. For example, a five percent increase in government spending is expected to reduce flood fatalities by about 20 percent. Consistent with the previous findings from an analysis of tornado impacts by Lim et al. (2017), it appears that overall safety of a county can be enhanced through local government public safety and protection services.

Contrary to the results of the base model, once I correct the simultaneity bias and control for the unobserved heterogeneity, I find a positive relationship between income level and flood fatalities. The difference in the estimated results is first attributed to the fact that ZINB estimator mostly explains the variation across the cross-sectional units, while the CRE method exploit within variation. we should also note that income level/wealth can in fact influence flood outcomes through various pathways, including those that are already taken into account – education level, location and housing choices, as well as local government resource availability for emergency management and disaster mitigation. For instance, in the first stage Control-function estimation, the per capita income is estimated to be a dominant and significant factor of government expenditure decision. Thus, these pathways by which income translates to increased safety are included in the estimation, effectively capturing the effect of individual and community level attitudes and efforts for safety and preparedness against flood within a county. Controlling for these other factors, the positive coefficient on income may reflect the idea that growing income translates to increased housing in higher amenity areas such as near water where flooding risk is higher.

The Role of NFIP on Floods Fatalities We now discuss the results of the main policy variable of this study – the role of National Flood Insurance Program (NFIP) – in helping communities become more aware of and better prepare for the risks of floods, and avoid the adverse impacts. The NFIP participation rate is consistently estimated to have a statistically significant negative effect in both the ZINB and the IV Poisson estimations, while the magnitude of the effect is relatively larger in the IV estimation. In particular, the estimates from specification C indicate that flood-fatalities are reduced by about 24% on average if the within-county NFIP participation rate increases by ten percentage point, whereas the estimated effect in the ZINB model was about a 10% reduction in fatalities. Biases from the simultaneity and county heterogeneity may account for the differences in magnitude of effects and statistical precision between the two model specifications.

Comparing the column 3 and 4, we observe that the coefficient on the government spending on safety, protection, and welfare greatly rise in absolute magnitude once the NFIP variable is excluded from the model. The enhanced resilience and increased safety of the place enabled by the implementation of NFIP are instead captured by the local governments' efforts for public safety and protection services. One possible explanation for this result is that local government resources allocated to public safety and protection, and compliance with the flood mitigation measures required by the NFIP work towards the same goal of improved flood safety. Thus, when the NFIP participation rates are incorporated to explain the variability of flood fatalities, the explanatory power of the local government variable is reduced. The change in the estimated effect of this key institutional factor further highlights the importance of taking into consideration the role of NFIP when analyzing the flood vulnerability.

Post-estimation: Hypothetical NFIP Participation Rates and Predicted Fatalities

The average within-county participation rate was 27% in 1980 and doubled to 54% by 1990. During the study period from 1996-2015, the average participation rate has risen by 12% from 57% to 69%. To calculate the effect of the flood program in terms of saving lives, I predict the change in fatality rates using the estimation results of model 3 in Table 2.6. I also compute the predicted outcome of several hypothetical cases: i) the participation rate had not grown at all from 1996 to 2015 in any county, remaining at the same rate as in 1996 for the whole study period, ii) the participation rates were 20% lower for all counties, iii) 30% lower, and iv) the participation rates were 50% lower (to reflect a NFIP participation rates of about zero). A comparison of the predicted death rates in various scenarios and the actual flood deaths is presented in Table 2.7.

Table 2.7: Predicted Death Counts by NFIP Participation Rates and the Total Value of Lives Saved during 1996-2015

	Prediction			**Valuation**
NFIP Participation Rates	Death Rate[1]	Expected Total Death[2]	Difference[3] : no. lives saved	Value of Lives Saved[4]
In-Sample	.0137	1,563		
Hypothetical Cases				
Remain at 1996 level	.0155	1,814	**251**	**$ 2.26 billion**
Lower by 20% [5]	.0213	2,442	**879**	**$ 7.92 billion**
Lower by 30% [5]	.0254	2,972	**1,409**	**$ 12.68 billion**
Lower by 50% [5]	.0359	4,327	**2,764**	**$ 24.87 billion**

1. Death rate indicates the county-year average of predicted deaths per flood event.
2. The actual number of total flood occurrence in the U.S. counties during 1996-2015 is used for calculation.
3. The difference is between each hypothetical case and in-sample prediction. This indicates the potential loss of lives prevented by NFIP.
4. The value of a statistical life used in calculation is $9 million (Viscusi, 2014)
5. The standard deviation of the NFIP participation rate is 32.37% and the yearly averages range from 53% to 69%.

Each row in Table 2.7 indicates the predicted death rates (i.e. fatality per flood event) and expected total death counts from floods by in-sample or hypothetical NFIP participation rates. Following the practice of giving an economic value to mortality – a value of a statistical life (VSL), I also perform a straightforward calculation of the benefit of the NFIP in saving lives from floods. The VSL that is currently being used in the U.S. government agencies when they appraise the benefits of regulations ranges from $8.2 to $9.5 million (in 2009).

Table 2.7 shows that the predicted deaths increase as the NFIP participation rates fall. If the NFIP participation rate had not risen and remained at the 1996 level for 20 years for all counties, we would have suffered 251 more fatalities from flood events during the 1996-2015 period. The estimated value of lives saved due to the expanded adoption and implementation of the program since 1996 across the nation is $2.26 billion. Moreover, the impact would be greater if every counties' participation rates were reduced by 20% relative to the actual rate; the calculations suggest that the same number of flood events would have resulted in additional 879 deaths during the period. For the last scenario - the NFIP participation rates were close to zero – my calculations indicate that we would have experienced 2,764 more deaths from floods during the 1996 to 2015 period, implying that the program has helped prevent flood-induced fatalities, which is valued at $25 billion – about the program's current debt level. Overall, my findings provide evidence that flood-prone communities become more flood-resistant due to the enforcement of floodplain management requirements of the NFIP, and in turn, the loss of human life induced by flooding is reduced in high flood risk areas across the United States.

2.6 CONCLUSION

While floods are exogenously determined by climatic and environmental factors, this study shows that socio-economic and institutional factors are critical in determining vulnerability. This paper seeks to uncover the underlying factors that make people and places more vulnerable to floods in the United States. To this end, I investigate the relationship between flood fatalities and the potential human and institutional components of disaster impacts within US counties over the 1996 to 2015 period. The study findings enable us to identify the societal characteristics and government factors that exacerbate or mitigate vulnerability to hazards and the extent to which different population groups are disproportionally affected by floods. This in turn allows us to suggest policies that may help mitigate human losses from such events.

The empirical analysis in this paper demonstrates that people most affected by disasters like floods are primarily those who have weaker economic and social bases, those who are less educated and have limited risk perception and preparedness, and those who are living in homes less resistant to shocks.   People living in mobile homes are at greater risk due to the structural vulnerability of mobile homes as well as due to the lower socio-economic status. Another key finding is that urbanization and past disaster experience are critical components of flood vulnerability. The analysis using IV method shows that increased government spending in critical areas such as safety, protection, and welfare, is associated with reduced overall community vulnerability to floods.

Above all, this paper provides new evaluation of the life-saving role of National Flood Insurance Program. To my knowledge, this is the first empirical study that presents evidence that the National Flood Insurance Program has played a vital role in reducing flood fatalities. My findings suggest that the benefits of the NFIP in terms of saving lives over the 20-year study period are estimated to be substantial enough to compensate for the program's deficits that were accumulated during the same period. Nevertheless, the program's current operational challenges and the public concerns regarding the fiscal soundness of the program necessitate a thoughtful reform of the NFIP, which must ensure a balance between the affordability of flood insurance and the financial solvency of the program. In this redesign process, the benefits of the proactive disaster management of the NFIP ought to be taken into account.

Overall, this study reveals which population subgroups are most vulnerable to flooding in the United States, as well as local and federal government public actions that serve to reduce vulnerability. Generally, these findings increase our understanding of the socio-political nature of disaster impacts, enable decision-makers to better prepare for and respond to pending catastrophic events, and guide mitigation efforts at the local, state and national levels.

APPENDIX

APPENDIX

Table 2.A1: Determination of Flood-category Events

Determination by Event Type
Flood
Any high flow, overflow, or inundation by water which causes damage. In general, this would mean the inundation of a normally dry area caused by an increased water level in an established watercourse, or ponding of water, that poses a threat to life or property. If the event is considered significant, it should be entered into *Storm Data*, even if it only affected a small area. Urban and small stream flooding commonly occurs in poorly drained or low-lying areas. These are types of areal flooding and are to be recorded as Flood events, not Heavy Rain.
Flash Flood
A life-threatening, rapid rise of water into a normally dry area beginning within minutes to multiple hours of the causative event (e.g., intense rainfall, dam failure, ice jam). Ongoing flooding can intensify to the shorter-term flash flooding in cases where intense rainfall results in a rapid surge of rising flood waters. Every Flash Flood event that occurred and meets the criteria will be logged in *Storm Data*, regardless of whether or not a flash flood warning was issued.

Source: National Weather Service Instruction 10-1605 (MARCH 23, 2016) Operations and Services Performance, Storm Data Preparation. (http://www.nws.noaa.gov/directives/)

Table 2.A2: Variable Definitions and Sources

VARIABLE	DEFINITION	SOURCE
Flood Fatalities	Direct deaths from a flood-category event	NOAA NCEI*
Overnight	Begin time of a flood event is 12:00-5:59 AM	NOAA NCEI*
Morning	Begin time of a flood event is 6:00-11:59 AM	NOAA NCEI*
Early Afternoon	Begin time of a flood event is 12:00-3:59 PM	NOAA NCEI*
Late Afternoon	Begin time of a flood event is 4:00-7:59 PM	NOAA NCEI*
Evening	Begin time of a flood event is 8:00-11:59 PM	NOAA NCEI*
Jan – Dec	Begin month of a flood event	NOAA NCEI*
Flood	Type of a flood event is "Flood"	NOAA NCEI*
Flash Flood	Type of a flood event is "Flash Flood"	NOAA NCEI*
Duration_days	Duration of a flood event in days	NOAA NCEI*
Total No. Dams (all purposes)	Total number of dams within a county regardless of the main purposes of dams	US Army Corps of Engineers
No. Dams for Flood Control	Total number of dams within a county for flood control and storm water management	US Army Corps of Engineers
Previous 2-yr's Flood Experience	County level flood fatalities in the previous two years	NOAA NCEI*
Pct NFIP Participating Communities_Lag	Percent of communities (city, town, village) within a county that entered in the National Flood Insurance Program at least *two* years prior to a flood event	FEMA National Flood Insurance Program (NFIP)
Pct Urban Population	Percent of the county population living in urban areas (= urbanized areas and urban clusters)	US Census: Geography
Ln (Population)	County population in natural logarithm	US Census: Population
Pct Over 65	Percent of population 65 years old and over	US Census: Population
Pct Under18	Percent of population 18 years old and under	US Census: Population
Pct BA degree	Percent of people aged 25 and over holding Bachelor's degree	US Census: Population
Pct of Mobile Homes	Percent of mobile/manufactured homes in housing units	US Census: Housing
Ln (Per Capita Income)	County Per Capita Income which is derived by dividing the total income of a county by its total population in natural logarithm.	US Census: Income
Ln (Per Capita Gov't Expenditure on Public Safety &Welfare)	Local government spending (in thousands, 2009 $) on public safety, protection, and welfare in natural logarithm, which includes expenditures on fire/police protection, protective inspections/ regulations, housing/community development, public welfare	US Census: Local Government Finances

* NOAA NCEI: National Oceanic and Atmosphere Administration National Center for Environmental Information

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CHAPTER 3

GROWING HEAT VULNERABILITY OF AGING SOCIETY:

THE POTENTIAL ROLE OF HEAT ISLAND MITIGATION MEASURES

3.1 INTRODUCTION

Heat waves are the deadliest type of natural hazard among all weather extremes in the United States. Every year, more than 1,000 heat events occur, causing an average of 131 deaths during the last twenty years. However, according to National Center for Health Statistics (NCHS) (Kochanek *et al.* 2011), excess heat exposure actually contributed to a far greater number of deaths (directly and indirectly) – 658 deaths per year on average during the years 1999-2009. The risk of extreme heat has been elevated in many regions of the world including the United States as extreme weather phenomena is increasing in both frequency and magnitude under the global climate change (Greenough, 2001; Beniston and Stephenson, 2004). The observed and predicted shifts in the variability and intensity of weather extremes that are driven by climate change, such as heat waves, flooding, droughts, and tornadoes have been substantially discussed in many scientific studies (Meehl and Tabaldi, 2004; Milly *et al.*, 2002; IPCC, 2013; Strader *et al.*, 2017). With regard to heat hazard, Meehl and Tabaldi (2004) and IPCC (2013) predict the future heat waves in North America will occur more frequently with greater intensity and longer duration.

Increasing outbreaks of stronger weather extremes in recent decades and the gloomy predictions about climate change and future weather extremes triggered policy efforts and community actions for mitigation and adaptation (Morss et al., 2011; Gago et al., 2013). Most relevant heat-related actions currently undertaken by state and local government in the United

States are the community-based “Heat Island” reduction activities (U.S. Environmental Protection Agency (EPA), 2008) [43]. Heat Island reduction measures include Trees and Vegetation, Green Roofs, Cool Roofs, Cool Pavements; these strategies are implemented through demonstration projects (e.g. green roof installation), incentive programs (e.g. tax abatement or rebate), urban forestry and community tree planting programs (e.g. Million Trees Initiative in LA, NYC, Denver, etc.), and outreach and education programs. The primary goal of the community Heat Islands reduction measures is to lower a populated area’s elevated surface/atmospheric temperatures. Thus, Heat Island reduction actions serve as an important heat hazard mitigation measure by limiting temperature rise of the areas at risk.

Given the life-threatening consequences of extreme heat events and the predicted increase in the heat-related risks in the coming years, understanding the concept of heat vulnerability and examining the impacts of heat events are increasingly of significant interest to scholars from various disciplines. Epidemiologists, sociologists, and geographers have discussed heat vulnerability by examining the excess mortality due to high temperatures in certain areas (Bell *et al.*, 2008; Huang *et al.*, 2011**;** Loughnan *et al.*, 2014; Sheridan *et al.*, 2003; Stafoggia *et al.*, 2006; Uejio et. al., 2011). Some studies examine the impact of an extreme heat event as a case study (Klinenberg, 1999; Browning *et al.*, 2006). Another large set of studies focuses on the construction and/or evaluation of a heat vulnerability index for a certain region in the United States (Aubrecht *et al.* 2013; Harlan *et al.*, 2006; Harlan *et al.*, 2013; Hondula *et al.*, 2012; Johnson *et al.*, 2012; Reid *et al.*, 2009). However, none of the previous studies empirically

[43] Total 172 statewide or community level actions database are publicly available from the U.S. Environmental Protection Agency (EPA) website https://www.epa.gov/heat-islands/heat-island-community-actions-database

address the role of heat mitigation actions initiated by state/local governments in reducing heat vulnerability.

Consolidating the prior findings and knowledge on disaster vulnerability from multiple disciplines, this study constructs an integrative perspective toward the climatic, built-environmental, socio-economic elements of disaster vulnerability. Fundamental notion of this integrative framework is that heat vulnerability of a community is defined and shaped not only by physical and meteorological characteristics of hazard itself, but also, equally importantly, by various human components such as built-environmental conditions, population characteristics, and socio-economic factors. Within this framework, I empirically address the dynamics of heat vulnerability by analyzing an important linkage and interaction between heat hazard mitigation/adaptation efforts and heat vulnerability.

The empirical analysis involves a modeling of two critical phases of heat vulnerability dynamics. For the first-phase *Heat Hazard Mitigation* model, I use county-year panel structured data for years 1998 – 2011 to evaluate the role of Heat Island reduction measures in mitigating heat hazards intensity at county scale. I employ the Random Trend Model that allows for both the level effect of county heterogeneity and county-specific time trend. In the second-phase *Heat Vulnerability – Fatality Model*, I examine all heat and excessive heat events over 1996 to 2011 periods in the counties of United States to analyze a wide range of meteorological and anthropogenic determinants of heat-induced fatalities at local scales. The Zero-Inflated Negative Binomial (ZINB) model that properly treats the non-negative count variables with the excess zeros problem is employed for the estimation with state and time fixed effects. Lastly, I perform a direct estimation of the effects of Heat Island Mitigation (HIM) measures on heat fatalities, using the Poisson Fixed Effects estimator, controlling for the unobserved attributes of counties.

This study adds to the existing literature and fills in important research gaps. First, I apply an integrative conceptual framework of disaster vulnerability to model U.S. nationwide local scale heat vulnerability. Second, I synthesize U.S. trends of an aging population and deepening poverty with my estimates to predict the expected increase in heat-induced fatalities over the next few decades due to the growth of the most heat-vulnerable population segment in the United States. Third, I take into consideration government-initiated Heat Island mitigation actions and analyze their role in lowering temperatures across U.S. counties and further make a quantitative inference about a mediated effect of HIM measures on heat-induced fatalities by combining the results of the first and second phase models, as well as by using a direct estimation result.

Findings of this study are as follows. The two-phase analysis finds that due to the long-lasting and synergistic effects of the Heat Island Mitigation (HIM) measures, the heat intensity lowering benefit of such measures are accumulated and thus, counties with more mitigation actions are progressively less vulnerable to extreme heat than counties with fewer activities. The Poisson FE results indicate that an additional measure that is locally implemented in a county reduces annual deaths rate (deaths per heat event) by 15.83 %. Notable findings from the second-phase heat fatality model are as follows. Urbanization measured by the urban population density tends to increase the adverse impacts of heat waves, leading to more fatalities. My analysis confirms that higher income reduces vulnerability to heat waves, while poverty intensifies it. I also find that several housing related factors are critical predictors of heat wave vulnerability; living in mobile homes or rental homes heightens disaster vulnerability. Also, population composition is important; heat vulnerability is greater in counties with higher proportions of elderly, young, and non-white populations. Findings suggest that the socially isolated elderly and the elderly living in poverty are the most heat-vulnerable population sub-groups. Notably, the heightened heat vulnerability due to the growth of the elderly population is predicted to generate a two-fold increase in heat fatalities by 2030.

The rest of this paper is organized as follows. In the next two sections, the risk of extreme heat in the U.S. and the community Heat Island mitigation actions are discussed in detail. In Section 3.4 and 3.5, I review the literature and present the conceptual framework. In Section 3.6, the empirical methodology and the data are described. In the Section 3.7, I discuss the results and draw a quantitative inference. Section 8 concludes the paper.

3.2 RISK OF EXTREME HEAT IN THE U.S.

Heat waves are not as destructive as other types of natural hazards such as hurricanes or tornadoes, however, extreme heat is by far the deadliest type of hazard among all weather extremes in the United States. Heat waves put a lot of stress on the body, and can lead to serious health conditions, such as heat exhaustion, heat stroke, which could result in death. They can also exacerbate underlying health problems. Every year, more than 1,000 heat events occur, causing hundreds of deaths and even more heat-related illnesses. Over the last twenty years, heat resulted in an average of 131 direct deaths each year (NWS). However, a National vital statistics report from National Center for Health Statistics (NCHS) (Kochanek *et al.* 2011) showed that during 11 years from 1999 to 2009, extreme heat exposure resulted in 7,233 deaths in total (658 per year) where it was an underlying cause for about 70% of the deaths and a contributing factor for remaining 30%. Notwithstanding heat-induced illnesses and injuries, 658 direct plus indirect fatalities are far greater than the number of deaths that are primarily and directly resulted from incidents of extreme heat. This manifests that the extent to which extreme heat adversely affect people's health and lives could widely vary across individuals – one might die from heat even with a relatively low level of heat exposure, perhaps, because of one's own health conditions.

Figure 3.1: Heat Index Chart

Temperature (°F)

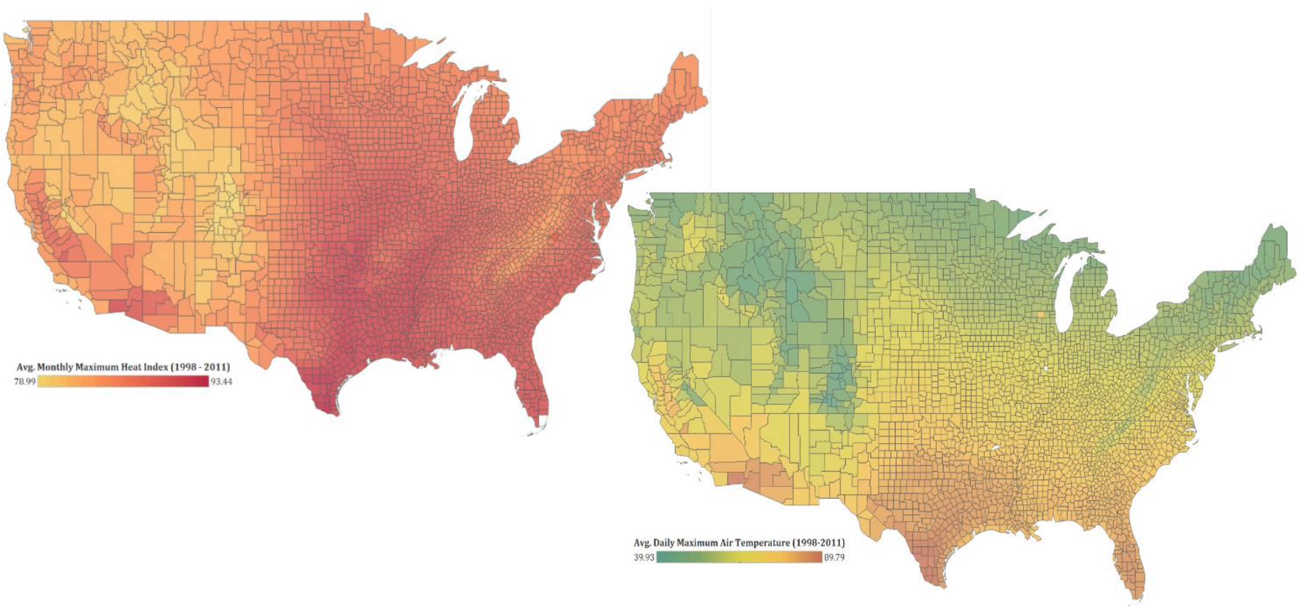
Relative Humidity (%)	80	82	84	86	88	90	92	94	96	98	100	102	104	106	108	110
40	80	81	83	85	88	91	94	97	101	105	109	114	119	124	130	136
45	80	82	84	87	89	93	96	100	104	109	114	119	124	130	137	
50	81	83	85	88	91	95	99	103	108	113	118	124	131	137		
55	81	84	86	89	93	97	101	106	112	117	124	130	137			
60	82	84	88	91	95	100	105	110	116	123	129	137				
65	82	85	89	93	98	103	108	114	121	128	136					
70	83	86	90	95	100	105	112	119	126	134						
75	84	88	92	97	103	109	116	124	132							
80	84	89	94	100	106	113	121	129								
85	85	90	96	102	110	117	126	135								
90	86	91	98	105	113	122	131									
95	86	93	100	108	117	127										
100	87	95	103	112	121	132										

Likelihood of Heat Disorders with Prolonged Exposure or Strenuous Activity

Caution | Extreme Caution | Danger | Extreme Danger

Source: National Oceanic Atmospheric Administration (NOAA) National Weather Service (NWS) Heat Index Chart. http://www.nws.noaa.gov/om/heat/heat_index.shtml

Figure 3.2: Summertime Average Maximum Heat Index vs. Daily Maximum Temperature (1998-2011)



Source: Authors' own illustration. ***Data***: NLDAS Daily Air Temperatures and Heat Index, CDC

Before discussing the heat waves and their human impact, it is important to correctly understand the definition and related measures of heat event. Like the Fujita-scale for tornadoes, there is a Heat Index measure for heat waves. The U.S. National Oceanic and Atmospheric Administration National Weather Service (NOAA NWS) defines the Heat Index (in Figure 3.1) as "a subjective measure of what it feels like to the human body when relative humidity is factored into the actual air temperature[44]." It implies that heat events result from a combination of high temperatures and high humidity. Figure 3.2 compares the average daily maximum Heat Index (= apparent temperature) and the average daily maximum temperature. It clearly shows the temperature alone cannot explain the risk of heat across the regions in the United States. Compared to dry hot areas in the West regions such as Nevada, Utah, New Mexico states, humid regions in the Midwest and Eastern U.S. have relatively higher Heat Index values. An excessive heat event or a heat event are announced to occur (and reported in *NOAA Storm Events Database*[45]) whenever Heat Index values meet or exceed locally/regionally established excessive heat warning or heat advisory thresholds, respectively. The definition/determination of heat and excessive heat are provided in Table 3.A1 in the Appendix.

Figures 3.3 and 3.4 show the average frequency and average fatality of extreme heat events by state in the contiguous United States over the 20 years from 1996 to 2015, respectively. In general, most heat waves occur in southern part of the country including western regions, and the Great Plains. The areas in the west of the Rocky Mountains exhibit high temperature, however, as both temperature and humidity are factored in to constitute a heat event, dry hot

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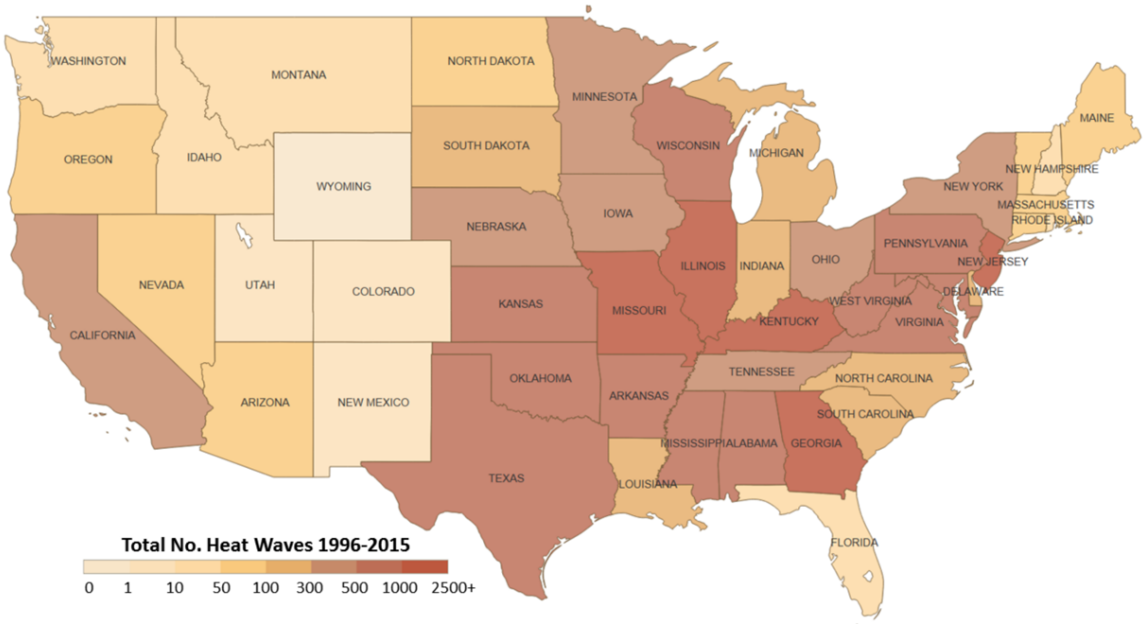
[44] "Heat and Extremely Hot Weather" from National Oceanic and Atmospheric Administration National Weather Service (NOSS NWS). Retrieved from https://www.weather.gov/phi/heat.

[45] *Storm Events Database* managed by NOAA's National Centers for Environmental Information (NCEI) is available at https://www.ncdc.noaa.gov/stormevents/ftp.jsp.

areas in the west regions such as Wyoming, Utah, Colorado states rarely have heat events. Among all states, Missouri, Illinois, New Jersey, Georgia, and Kentucky are the top five states that experienced most frequent extreme heat events, whereas the top five states with the highest death tolls are Illinois, Pennsylvania, Texas, Missouri, and Nevada. It is shown that human impacts of extreme heat hazard are not proportionally distributed across the regions depending on the frequency of the heat waves. The disparity between two maps hints at the importance of societal and human components in shaping disaster vulnerability and determining adverse impacts.

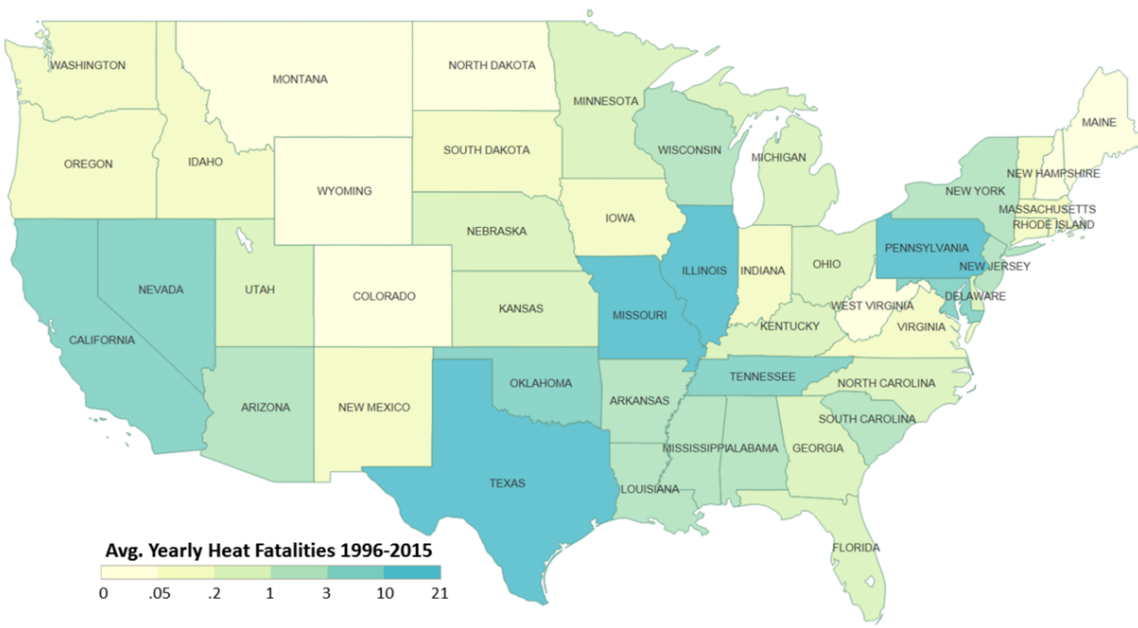
Moreover, there are mounting concerns about the risk of heat waves in the United States; scientific predictions find that the future heat events will become more devastating with an increase in magnitude and frequencies of extreme heat phenomena (Greenough, 2001; Beniston and Stephenson, 2004). A scientific study (Meehl and Tabaldi, 2004) predicts future heat waves in North America will become "more intense, more frequent, and longer lasting". Also, the fifth assessment report of the UN Intergovernmental Panel on Climate Change (IPCC) summarizes predictions from climate models as follows: "it is '*virtually certain'* that there will be more frequent hot and fewer cold temperature extremes over most land areas as global mean temperatures increase and it is *'very likely'* that heat waves will occur with a higher frequency and duration". The observed and anticipated increase in risk of heat waves and their silent yet catastrophic impact draw considerable attention from scholars in various disciplines as well as policy makers and the media, becoming a global public concern. In the following sections, I discuss the U.S. state and local government activities to mitigate the growing risk of heat hazard (section 3.3) and briefly review multi-disciplinary literature on disaster vulnerability (section 3.4).

Figure 3.3: Total Number of Heat Waves by State (1996-2015)



***Source**:* Authors' own illustration. **Data**: National Centers for Environmental Information (NCEI)

Figure 3.4: Heat-Induced Fatalities per Year by State (1996-2015)



***Source**:* Authors' own illustration. **Data**: National Centers for Environmental Information (NCEI)

3.3 COMMUNITY HEAT ISLAND MITIGATION ACTIONS

Increasing outbreaks of stronger weather extremes in recent decades and the gloomy predictions about climate change and future weather extremes triggered policy efforts and community actions for mitigation and adaptation. Most relevant heat-related actions currently undertaken by state and local government in the United States are the community-based “Heat Islands” reduction activities[46]. The primary goal of the community Heat Islands measures is to lower the developed area’s elevated surface/atmospheric temperatures, which thereby reduces the risk of heat waves. Under the Heat Islands phenomena, annual mean air temperature of a city with one million or more people can be 1.8 to 5.4°F warmer than air in surrounding areas (EPA, 2008). The main causes of Urban Heat Islands are reduced vegetation (i.e. more dry and impervious surfaces), materials used to build urban infrastructures (which reflect/shed less and absorb/store more of the sun’s energy), urban geometry (which affect wind flow, energy absorption, radiation), and anthropogenic heat emission (all the energy used for human activities). Increased temperature due to the Heat Islands have considerable impacts on human life, such as detrimental effect on health, added risk of heat waves, impaired water quality, and other adverse impacts on environment. (EPA, 2008)

Growing interest and concern among communities regarding the Heat Island effect have enabled development and implementation of Heat Island reduction strategies by state and local governments in recent decades. The Heat Island mitigation actions (currently active or completed) are listed by the U.S. Environmental Protection Agency (EPA). Communities use

[46] Total 172 statewide or community level actions are publicly available at the U.S. Environmental Protection Agency (EPA) website https://www.epa.gov/heat-islands/heat-island-community-actions-database

four main measures to reduce the urban Heat Islands problem: i) Trees and Vegetation ii) Green Roofs, iii) Cool Roofs, iv) Cool Pavements. Such strategies are implemented through voluntary or policy mechanisms. Voluntary mechanisms include demonstration projects (e.g. green roof installation), incentive programs (e.g. tax abatement or rebate), urban forestry and community tree planting programs (e.g. Million Trees Initiative in LA, NYC, Denver, etc.), and outreach and education programs. Policy mechanisms involve procurement, ordinances, and standards such as building/zoning code, tree and landscape ordinances, green building programs and standards, as well as comprehensive community plans and design guidelines for Heat Island reduction.

Table 3.1: Heat Island Mitigation Actions List by Initiation Year (1985-2017)

	Trees & Vegetation	**Cool Roofs**	**Green Roofs**	**Cool Pavements**	**Others (HVI, etc.)**	
Years			**WITHIN-COUNTY ACTIONS**			Total
1985 - 1989	2	0	0	0	0	2
1990 - 1994	2	1	0	0	0	3
1995 - 1999	4	2	3	1	1	11
2000 - 2004	19	9	10	8	0	46
2005 - 2009	35	19	18	23	1	96
2010 - 2014	22	19	15	15	0	71
Total	**84**	**50**	**46**	**47**	**2**	**229**
Years			**STATEWIDE ACTIONS**			Total
1995 - 1999	0	1	0	0	0	1
2000 - 2004	2	2	1	0	0	5
2005 - 2009	3	3	1	0	1	8
2010 - 2014	6	2	2	3	0	13
Total	**11**	**8**	**4**	**3**	**1**	**27**

***Source**:* Authors' own calculation. **Data** : "Heat Island Community Actions Database" from the U.S. Environmental Protection Agency (EPA) website: https://www.epa.gov/heat-islands/heat-island-community-actions-database.

Table 3.1 present total number of community and statewide Heat Island mitigation measures by types of strategies and by years from 1985 to 2014. During this period, total 229 within-county and 27 statewide strategies have been initiated. Except for completed demonstration projects (e.g. green roof installation), most of them have been active since initiated. The number of Heat Island mitigation adoptions and implementations substantially increased from early 2000s as communities became more aware of the Heat Island problem and harmful effects of the elevated temperatures. The trees and vegetation measure has been the most popular strategy of all, followed by cool roofs. About half of the strategies have been implemented through policy mechanisms such as building/zoning codes, ordinances, programs and standards. The other half have been carried out voluntarily through incentive programs, demonstration projects, and outreach/education.

Heat Islands mitigation measures address the root causes of the growing heat vulnerability by modifying and reducing the long-term likelihood and prevalence of heat risk. Heat Island mitigation strategies help communities manage the fundamental meteorological risk of high temperature, thus acting primarily as “heat-hazard mitigation”. For instance, we might not be able to prevent tornadoes or hurricanes from happening (we instead dedicate our disaster efforts to minimize harmful consequences through anticipation, preparedness, disaster warning, post-disaster relief, etc.), however, heat events can be potentially averted and thus negative impacts to people can be avoided if we devote our efforts to “cool down” at-risk communities. Given this context, I hypothesize and test the notion that communities that implement Heat Islands mitigation measures exhibit a lower Heat Index values (i.e. apparent temperature) and in turn, become less vulnerable to heat hazards relative to communities that do not. More details on the heat hazard mitigation model are presented in section 3.5.

3.4 LITERATURE REVIEW

Given the life-threatening consequences of extreme heat events and the predicted increase in the heat-related risks in the coming years, understanding the concept of heat vulnerability and examining the impacts of heat events are increasingly of significant interest to scholars from various disciplines. Previous studies on heat waves from a disaster vulnerability perspective have been mostly conducted by epidemiologists, sociologists, or geographers. These studies are primarily interested in the temperature-mortality relationship; they use daily all-cause mortality of the study area to find factors that can explain the increase in mortality during (and in the aftermath of) heat waves. Some studies discuss heat vulnerability by examining the excess mortality due to high temperature of certain areas in the U.S. (Huang *et al.*, 2011**;** Sheridan *et al.*, 2003; Uejio et. al., 2011), or in international context (Bell *et al.*, 2008; Loughnan *et al.*, 2014; Stafoggia *et al.*, 2006). Others discuss the impact of a large heat event as a case study (Klinenberg, 1999; Browning *et al.*, 2006). Another large set of studies focuses on the construction and/or evaluation of a heat vulnerability index for a certain region in the United States (Aubrecht *et al.* 2013; Harlan *et al.*, 2006; Harlan *et al.*, 2013; Hondula *et al.*, 2012; Johnson *et al.*, 2012; Reid *et al.*, 2009)[47].

However, this study takes a different analytical approach. I examine every individual heat event and the resulting direct deaths that occurred across the United States at county scale for many years. This study differs from previous studies in several respects. First, societal outcomes of the heat waves modeled are structurally different – previous heat studies use all-cause mortality while this study uses direct heat-induced fatalities. As a result of using all-cause

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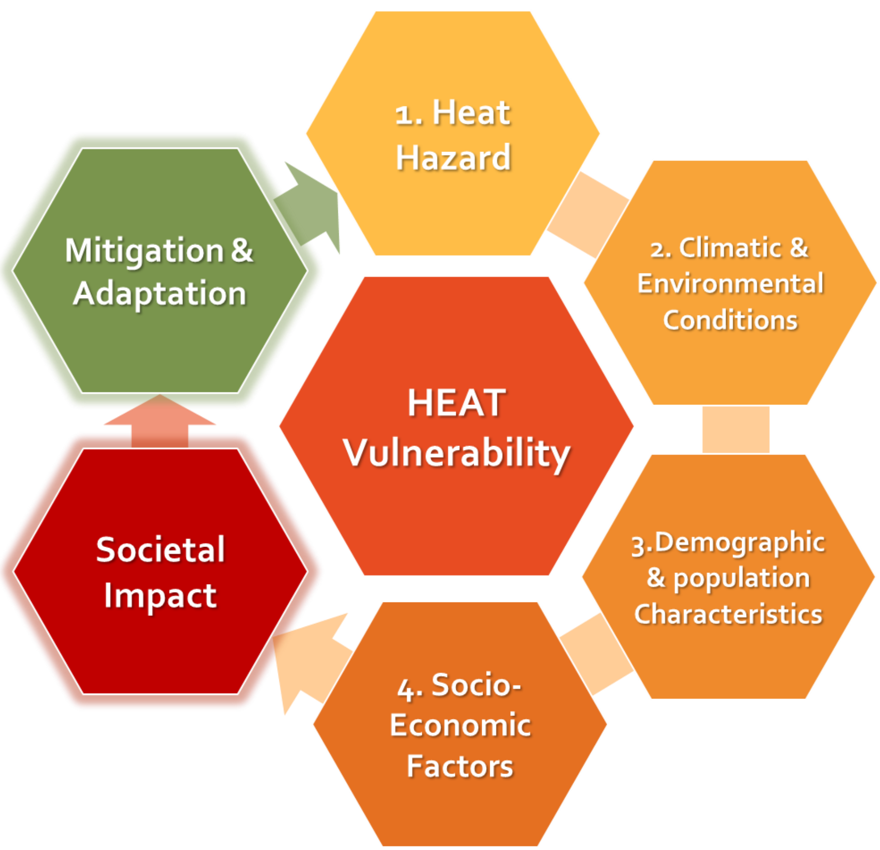
[47] Previous studies on heat vulnerability index for areas within the United States are only introduced.

mortality, it is not obvious in those studies whether the factors found to be significantly contributing to the mortality indicate true “heat” vulnerability factors, or just those associated with general mortality. Often, the interpretation of these relationships was left to the discretion of the authors. Second, epidemiological studies apply case-oriented approaches, thus their findings are often not comparable to each other and not easily generalizable across different spatial or temporal contexts. The present paper constructs a model of U.S. nationwide heat fatalities at local scales, utilizing both spatial and temporal variations while controlling for state fixed effects. Finally, none of the previous studies empirically address political and institutional aspects, whereas I seek to identify the role of community-based heat mitigation actions initiated by state/local governments in reducing heat vulnerability. However, in both strands of the heat study literature, the importance of social vulnerability components in defining overall place vulnerability to heat are emphasized. Building upon the findings of previous heat studies, I construct an integrative conceptual framework of heat vulnerability in the next subsection.

3.5 CONCEPTUALIZING MULTI-FACETED HEAT VULNERABILITY

Devastating natural disasters to date have revealed significant differentials in terms of impacts across different population segments, depending on socio-economic and political status. Numerous social scientists argue that underlying socio-economic factors such as poverty, access to social protection and security, as well inequalities with regard to gender, economic position, age, or race play an important role in determining disaster vulnerability (Aptekar and Boore 1990; Albala-Bertrand 1993, Cannon 1994, Blaikie et al. 1994; Cutter 1996; Enarson and Morrow 1998; Peacock et al. 1997; Morrow 1999). Over the last decade, a body of empirical disaster studies have emerged that acknowledge the multi-faceted nature of disaster vulnerability and use socio-political ecology of disasters as a conceptual framework of their empirical models (Brooks et al., 2005; Donner, 2007; Lim et al. 2017; Uejio et al., 2011; Zahran et al., 2008). In general, this strand of literature highlights socio-economic conditions that exacerbate or alleviate disaster impacts, while some of them are paying a greater attention to political and institutional components in defining disaster vulnerability (Brooks et al., 2005; Lim et al. 2017). In international context, a set of multiple-disaster studies focuses on the relationship between economic development and disaster impacts, demonstrating the role of economic and institutional factors in determining disaster-induced fatalities (Kahn, 2005; Toya and Skidmore, 2007; Strömberg, 2007; Kellenberg and Mobarak, 2008; Raschky, 2008; Gaiha et al., 2013).

Figure 3.5: Conceptualizing Multi-Faceted Heat Vulnerability



Consolidating the prior findings and knowledge on disaster vulnerability from multiple disciplines, this study applies an integrative view of the climatic, built-environmental, socio-economic, and institutional elements of disaster vulnerability for more comprehensive appreciation of heat vulnerability and more robust identification of heat risk factors. To facilitate the understanding of the important linkages and interactions among various components, a conceptual framework of the heat vulnerability model is illustrated in Figure 3.5. As shown in the figure, disaster vulnerability of a community is multi-faceted; it is defined and shaped not only by physical and meteorological characteristics of hazards, but also by various human components such as built-environmental conditions, population characteristics, and socio-economic factors.

Each of three arrows in Figure 3.5 indicate important interactions and relationships among components, which this study is primarily interested in and attempts to empirically address. The first arrow that connects four key elements that shape "Heat Vulnerability" and points to the "Societal Impact" shows that societal outcomes of extreme heat hazards are determined and influenced by the key elements of heat vulnerability. My main analysis investigates this relationship to identify underlying societal and environmental factors that determine heat-induced fatalities and use the estimation results to predict future outcomes. The second arrow that connects "Societal Impact" and "Adaptation & Mitigation", pointing to the latter, indicates a short-run societal and political pressure for public actions and initiatives for heat mitigation, as a reaction to the negative consequences of heat hazard. In the longer-term, the public efforts on structural hazard mitigation and adaptation, such as the abovementioned Heat Island reduction strategies, will modify and ameliorate heat vulnerability by fundamentally reducing the risk of heat hazard the society faces. This linkage is indicated by the green arrow pointing to the "Heat Hazard" – the first element of heat vulnerability. Each major components of heat vulnerability and how they are empirically incorporated in my analysis are discussed in detail in the following subsections.

3.5.1 Major Components of Heat Vulnerability

Based on the conceptual framework presented in Figure 3.5, I propose that major components that define and modify overall vulnerability to heat hazards are i) heat hazard profile, ii) climatic and environmental conditions, and iii) demographic and socio-economic characteristics. In addition, I consider institutional efforts for mitigation and adaptation as an external component of heat vulnerability that influences and interacts with heat vulnerability.

Heat Hazard Profile The heat hazard profile includes event-specific physical and meteorological aspects of a heat event. I consider factors such as timing of the incidence (time of day, season of the year when an event occurred), type of the heat event (excessive heat or heat), and Heat Index value of the month an event occurred. Previous study on tornadoes (Simmons and Sutter, 2011) control for the time of day by categorizing it into overnight (12:00-5:59 AM), morning (6:00-11:59 AM), early afternoon (12:00-3:59 PM), late afternoon (4:00-7:59 PM), and evening (8:00-11:59 PM), and show that disaster impacts could differ depending on the timing of an incidence. I also include indicator variables for the seasons (Spring, Summer, Fall, and Winter) as a control variable. One of the most critical meteorological factors in my model is the Heat Index (also known as apparent temperature) that measures the intensity of heat hazard. The intensity of a heat event is approximated by the average maximum Heat Index value of the month the event occurred. Previous epidemiologic heat studies find the positive correlation between the temperature and all-cause mortality (Hajat and Kosatky, 2010). Although my study examines the direct fatalities resulting from a heat event (instead of all-cause mortality) as an outcome measure, it is expected that a similar or even stronger positive relationship holds between the heat index (apparent temperature) and heat-induced fatalities.

Climatic and Environmental Conditions Heat vulnerability is also shaped by characteristics of the place exposed to extreme heat hazard. I take into consideration area-specific risk factors such as climatic and meteorological conditions of the area (annual average temperature, annual average of max. air temperature) and built-environmental conditions (urbanization, population density). If a heat event occurs in a community that is not accustomed to the extreme high temperature and heat hazards, the impact of the heat stressor can be deadlier. In this regard, the annual average air temperature and the average max. air temperature are included in my model. In addition, as discussed in section 3.3, the Heat Island effects magnify the heat vulnerability of the urban population due to the urban structures and land use pattern with less vegetated surfaces compared to rural areas. Considering that the urbanization is an important heat risk factor that would exacerbate the adverse impacts of heat waves, I include the urban population density in the model as a measure of urbanization of counties[48].

Demographic & Socio-Economic Characteristics As previously discussed, impacts of extreme weather events on different population segments can significantly vary depending on their social and economic characteristics. Those who are more vulnerable in societal context are more susceptible to harm in the event of extreme heat. Based on the previous findings from

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[48] As an alternative measure of the urbanization, *the percent of urban population* was also considered. However, due to the strong correlation between *the percent of urban population* and *the population size* (correlation coefficient = 0.84), I incorporate *the urban density,* controlling for the *population size* in the empirical analysis.

studies on heat or other types of natural disasters, I stress that population composition, poverty, income level, as well as housing related factors are key aspects that shape heat vulnerability and influence societal outcomes.

In the heat vulnerability model, *demographic composition* such as the proportion of young and elderly population, and the proportion of non-white are considered. Many epidemiological studies have previously shown the differences in heat mortality risk by age where the elderly and children tend to suffer a greater health impact from heat stress due to their limited ability to thermoregulate (Åström et al., 2011; Kovats and Hajat, 2008). Race or ethnicity are another key factor that must be taken into account when modeling disaster vulnerability. Prior disaster studies have elucidated that disaster effects vary by race and ethnicity across all the phases of disasters due to factors such as language barriers, housing patterns, community isolation, and social and economic disparities (Fothergill et. al.,1999; Hansen et al., 2013).

We also incorporate several *socio-economic factors* that are key indicators of population vulnerability. I consider economic status of communities measured by county per capita income and poverty rate. A core interest for research in the economics of natural disasters literature is how the level of economic development, or wealth, affects the disaster impacts (Kahn, 2005; Toya and Skidmore, 2007; Strömberg, 2007; Kellenberg and Mobarak, 2008; Raschky, 2008; Gaiha et al., 2013). These studies find in general, a negative relationship between income and disaster consequences – mostly, disaster fatalities – and explain that the wealthier countries have a higher demand for safety where economic resources they possess enable them to employ precautionary measures to mitigate disaster risk. On the other hand, some studies address the higher vulnerability of people who are economically insecure or living below poverty line (Lal et al., 2009; Lim et al., 2017). Lim et al. (2017) find a disproportionate concentration of poor people at greater tornado risk areas, as well as how various dimensions of poverty aggravate vulnerability of people to tornadoes. Heat-episode case studies find that majority of the victims of the Midwest heat disaster in 1980 and Chicago heat waves in 1995 were low-income groups (Fothergill and Peek, 2004; Klinenberg, 1999).

A last set of human components factored in to my heat vulnerability model is *housing-related factors* – the share of renter occupied housing units and the share of mobile homes among all housing units. Previous studies discuss that people who are living in a low-cost, affordable housing are exposed to greater risks of hazards due to the substandard quality of housing they occupy (Aptekar 1991, Phillips 1993, Pastor et al. 2006). Both housing factors are closely linked with structural and socio-economic vulnerability of people to natural hazards. Cutter et al. (2003) explain that housing ownership and mobile homes are one of the most important predictors of social vulnerability. Recent disaster studies (Lim et al. 2017; Simmons and Sutter, 2013) provide consistent empirical evidence that places with more mobile homes or renter occupied homes suffer greater human losses from natural disasters.

Extension: Poverty + Aging Society Many heat studies find the elderly are one of the most vulnerable group of people to heat stress. The elderly is more vulnerable to heat due to their increased physiological susceptibility, but from the social vulnerability perspective, elders are at greater risk in that they are more likely socially isolated, having no one available to help them in disaster situation (Klinenberg, 1999). Furthermore, senior poverty is another serious issue that aggravates vulnerability of the elderly. Economic insecurity among senior households increased from 27 percent to 36 percent over the period 2004 – 2008 (Meschede et al., 2011). In this trend, setting aside the increasing heat risks in the coming years, the heat vulnerability of the United States that is characterized by two key risk factors – aging and poverty combined – is anticipated only to increase if the trends continue and no actions are taken.

To identify the growing heat vulnerability of the United States given the expected substantial growth of older population and deepening poverty among them, my empirical analysis factors in senior poverty and elderly isolation along with a wide range of heat vulnerability factors and discusses implications to our society. In particular, I utilize the results of the empirical analysis along with the projected trend in elderly population growth, to make a prediction about the future heat vulnerability of the United States and anticipated detrimental consequences – measured by the expected increase in heat-induced fatalities – over the next few decades, due to the growth of the most heat-vulnerable population segment in the United States.

3.5.2 Institutional Efforts for Mitigation and Adaptation

Lastly, I introduce another facet of growing importance in heat vulnerability framework – heat mitigation and adaptation efforts. I consider government-initiated efforts and interventions for mitigation and adaptation as an external component that influences and interacts with heat vulnerability. Many scientific simulation or experimental studies have been carried out to assess the microclimate cooling benefits of the Heat Island measures such as cool roofs (Rosenzweig et al., 2009; Synnefa et al., 2008), trees and vegetation (Perini and Magliocco, 2014; Tan et al., 2016), and cool pavements (Akbari et al., 2001; Synnefa et al., 2011). However, there has been no prior heat study that seeks to find to what extent the government-initiated Heat Island mitigation measures (discussed in section 3.3) can enhance societal outcomes of heat hazard. To fill this significant gap in the literature, I construct a two-phase model in which the first-phase model estimate whether communities that implement Heat Islands mitigation measures exhibit lower Heat Index values than communities that do not. Using the Heat Index measure as an *intermediary variable*, I combine the result from the first-phase Heat Index model with the second-phase estimation result of heat fatality analysis. I also conduct a direct estimation of the effect. My analyses enable us to evaluate the role of the Heat Island mitigation activities in reducing extreme heat risk and to identify a mediated effect Heat Island mitigation measures have on heat-induced fatalities.

3.6 EMPIRICAL ANALYSIS

My empirical analysis involves modeling two critical phases of heat vulnerability dynamics. Each model is discussed in detail in the following subsections.

3.6.1 First-Phase: Heat Hazard Mitigation Model

Heat hazards are caused and magnified by human activities, but they can be also weakened and ameliorated by human efforts. The first-phase model evaluates the role of Heat Islands reduction measures in mitigating heat hazards at county scale. Factors that are known to increase heat hazards include anthropogenic heat emissions, urbanization, climatic conditions, and geographic locations (EPA, 2008). Considering these contributing factors to heat hazards, the first-phase Heat Hazard model is conceptualized in the following equation:

$$\boldsymbol{Heat\ Hazard_{it}} = \mathrm{f}(\text{Anthropogenic Heat}_{it}, \text{Urbanization}_{it}, \textbf{Mitigation}_{\boldsymbol{it-2}}, \text{Climatic conditions}_{it}\ |\boldsymbol{c_i}, \boldsymbol{g_i t}, \lambda_t) \quad (1)$$

$$\text{where}\quad \boldsymbol{c_i} = \text{unobserved county fixed effects,}$$
$$\boldsymbol{g_i} = \text{county} - \text{specific linear trend}$$
$$\boldsymbol{\lambda_t} = \text{time fixed effects}$$

For the dependent variable of the first-phase model, the Heat Index (also known as apparent temperature) is used as a measure of the intensity of heat hazards. Specifically, the maximum for monthly average of daily max. A Heat Index measuring the most devastating summertime heat hazard that pose the greatest threat to people is examined. I hypothesize that community efforts for heat hazard mitigation through various “cooling” measures would lower the risk of the deadly heatwaves. I also explore alternative specifications using different measure of heat hazard. The number of heat wave days[49] based on i) daily maximum Heat Index and ii) Net Daily Heat Stress (NDHS) are used as an alternative measure of the intensity of heat hazards.

Considering the long-lasting effects of heat mitigation strategies (planting trees & vegetation, use of cool materials for roofs and pavements), I construct a county-year Heat Island Mitigation (HIM) Actions variable that indicates a *cumulative* number of the Heat Island reduction strategies that have been implemented in a county by the given year. I then group counties by the number of mitigation measures they have been implementing. Importantly, as the realization of the heat-hazard-lowering effects of the HIM measures may not be immediate, I use 2-year lagged values of the HIM Actions variables. In the regression model, three types of Heat Island Mitigation Actions variable are incorporated in each three specifications: a) an indicator variable that represents whether any Heat Island mitigation actions have been adopted (=1) or not, b) a continuous variable for the total number of actions, c) multiple group indicator variables that are constructed based on the number of mitigation actions taken (0, 1, 2-3, 4+). The number of measures of 0, 1, 2-3, 4+ are specifically used to group counties in order to have a sufficient

[49] The number of heat wave days is computed at the county level, the totals show the number of heat wave days per county per year. When the geographic area spans more than one county, an extreme heat event is counted for each county where measurable observations that met the heat event definition occurred. (National Climate Assessment, 2015. *Extreme Heat Events: Heat Wave Days in May - September for years 1981-2010*)

number of observations for each group indicators in the regression[50].

I use county-year panel structured data to estimate the heat-hazard-lowering effect of Heat Island mitigation measures and employ the Random Trend model, controlling for time fixed effects as well. The Random Trend Model (RTM) explicitly allows for two sources of heterogeneity – the level effect, c_i, and the county-specific linear trend, g_i (Wooldridge, 2010). In the FE estimation, the unobserved effect is set to have the same partial effect on the heat hazard in all time periods. However, the length of the time dimension of my panel data (1998-2011) is relatively long, during which each county could presumably have its own specific time trend. Allowing for this possibility, the Random Trend Model is estimated. We first difference the equation (2) to eliminate the level effect, c_i, and then apply the FE to the first differenced equation (3) to remove a trend effect, g_i.

By employing the Random Trend Model, I can control for the geographic location and many other area-specific physical factors that are related to heat hazard, such as proximity to large water bodies and mountainous terrain but are rarely changes over time (i.e. time-invariant county traits and characteristics, c_i) as well as county-specific trends that could affect the intensity of heat hazard (g_i)[51] . In addition, naturally occurring meteorological temporal variations over time that are common to all counties over the periods are absorbed by a vector of

[50] In earlier years, there are very limited number of counties that adopted any HIM measures. For example, prior to 2006, counties with 2 HIM measures make up less than 1% of total observation.

[51] For example, a well-known factor of Urban Heat Island – urban growth – is expected to be captured by the county trend effects. A continuing urbanization trends are found nation-wide, but the rate of the urban growth may vary across the counties. However, the county level urban population data are only available decennially. The interpolation method is commonly used in practice to treat the decennial data to obtain a monotonic interpolation of data, i.e. a linear trend. I include the urbanization measure in the FE specification (Table 3.A2) but do not in the RTM specification, as the trend effect g_i in the RTM would capture county-specific urbanization trends that influence the heat hazard intensities.

the time-fixed effects, $\boldsymbol{\lambda_t}$. Thus, any global or macro-scale trend of heat intensity, such as global warming trend, would be captured by the year fixed effects while a meso-scale heat trend would be controlled for by the county-specific time trend.

$$\boldsymbol{HI_{it}} = c_i + g_i t + \boldsymbol{\beta_1 M_{it-2}} + \beta \cdot X_{it} + \boldsymbol{\lambda_t} + u_{it} \qquad t = 3, \dots, T \qquad (2)$$

$$\Delta \boldsymbol{HI_{it}} = \qquad g_i + \boldsymbol{\beta_1} \Delta \boldsymbol{M_{it-2}} + \beta \cdot \Delta X_{it} + \Delta \boldsymbol{\lambda_t} + \Delta u_{it}, \quad t = 4, \dots, T \qquad (3)$$

Annual air temperatures and monthly Heat Index data for years 1998-2011 are collected from North America Land Data Assimilation System (NLDAS) at CDC WONDER online database. Heat Wave Days data are from National Climate Assessment (NCA) at CDC WONDER. The statewide or community-wide Heat Island mitigation actions data are collected from Environmental Protection Agency (EPA). Table 3.2 shows a list of the dependent variable and explanatory and control variables included in the Heat Hazard Mitigation model.

Table 3.2: List of Variables in the Heat Hazard Mitigation Model

Dependent Variable			**Source**
	Max. for Monthly Average Heat Index Value (°F) of year t (t=1998-2011)	$\boldsymbol{HI_{it}}$	NLDAS
	Heat Wave Days Based on Daily Max. Heat Index or Net Daily Heat Stress		NCA
Explanatory/Control Variables			
Heat Island Mitigation Actions	Lagged Heat Island Mitigation Status (Yes=1, No=0)	$\boldsymbol{M_{it-2}}$	EPA
	Lagged Total No. of Heat Island Mitigation Actions		EPA
	Group Indicators (Lagged No. of actions: 0, 1, 2-3, 4+)		EPA
Climatic Conditions	Annual Average of Max. Daily Air Temperature (°F)	$\boldsymbol{X_{it}}$	NLDAS
	Annual Average of Min. Daily Air Temperature (°F)		NLDAS
Population	County Population Size		U.S.Census
County FE	Time-invariant County Traits and Characteristics.	c_i	
FE Trend	County-specific Linear Trend	g_i	
Time FE	A set of Year Indicators (1998 – 2011)	$\boldsymbol{\lambda_t}$	

To understand the Heat Island Mitigation Actions adoption status across counties depending on the vulnerability to heat events, I present Table 3.3 that shows the average heat fatalities (as a measure of heat vulnerability) by Heat Island Mitigation Actions adoption status (binary; adopted or not) and by county metropolitan categories (metro, metro & micro, and all). Differences in rows by adoption status in Table 3.3 suggests that counties that experience more human losses from heat are more likely to adopt heat mitigation strategies. This correlation indicates that there is an immediate societal and political pressure for public actions and initiatives for heat mitigation, as a reaction to the negative consequences of heat hazard. It explains the interrelationship depicted in the red arrow in the heat vulnerability framework diagram (Figure 3.5) that connects "Societal Impact" and "Mitigation & Adaptation", pointing to the latter. Across the columns of Table 3.3, we can compare mitigation adoption status ('%' column) and average heat fatalities ('Avg.' column) by county metropolitan categories. It shows that more urbanized counties suffer greater societal impacts from heat exposure and thus, they are more likely to put forth an effort into heat mitigation.

Table 3.3: Heat Vulnerability and Heat Island Mitigation Actions by Metropolitan Status

Heat Island Mitigation Actions Adoption Status	Direct Fatalities Resulted from Heat Events (1996 – 2010)								
	Metro + Micro + Rural			**Metro + Micro**			**Metropolitan only**		
	Avg.	Obs.	%	Avg.	Obs.	%	Avg.	Obs.	%
No Actions taken	0.031	39,128	84%	0.050	22,190	82%	0.074	13,879	80%
1 or more Actions	0.094	7,447	16%	0.146	4,705	18%	0.196	3,461	20%
Total	0.041	46,575	100%	0.067	26,895	100%	0.098	17,340	100%

Note: 3,015 county observations for 15 years from 1996-2010 consist of the total observation of 46,575.
Source*:* Authors' own calculation. **Data**: EPA *Heat Island Community Actions Database* and NCEI *Storm Events Database*.

3.6.2 Second-Phase: Heat Vulnerability – Fatality Model

Based on the Heat Vulnerability framework discussed in section 3.4, I examine all heat and excessive heat events that occurred over the 1996 and 2011 period in the contiguous United States using county level data in the second-phase Heat Fatality analysis. Data on individual heat events in the United States are collected from NOAA National Centers for Environmental Information (NCEI)[52]. In the NCEI S*torm Events Database,* each entry for individual heat events has detailed information on time, dates, locations of the events, as well as (direct and indirect) fatalities. Each heat event is matched with the county meteorological characteristics. Annual air temperatures and monthly Heat Index data for years 1996-2011 from North America Land Data Assimilation System (NLDAS) are used. County demographic, socio-economic, and housing data are collected from U.S. Bureau of the Census[53] and merged with the heat data. Note that the unit of observation of this study is individual heat event at the scale of counties. Thus, some counties may appear in the data set multiple times in a certain year but may not in a different year (so-called time-series-cross-sectional *event data* structure).

The dependent variable in the main analysis is the number of fatalities directly resulted from individual heat events. Among total 12,779 heat events during the study period 1998 – 2011, only 849 events resulted in fatalities; for a large portion of observations, the dependent variable is zero. Thus, for the econometric analysis of the main model, I employ Zero-Inflated Negative Binomial (ZINB) model which properly treats the non-negative count variables with the over-dispersion (excess zeros) problem (Long and Freese, 2006). Because of the

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[52] Data source: www.ncdc.noaa.gov/data-access/severe-weather

[53] Decennial census data for years 1990 and 2000, and American Community Survey data for year 2015 are used for demographic and housing variables. They are interpolated to obtain yearly data over the study period 1996 – 2011.

distributional features of disaster-induced fatalities, ZINB model is increasingly employed in disaster studies (e.g. Kahn 2005, Zahran et al. 2008). In the ZINB model, the excess zeros are considered to be generated by a separate process from the count values and the excess zeros are modeled independently. The ZINB model combines binary Logit model for zero outcomes and Negative Binomial model for event-counts. The ZINB regression analysis is characterized by the following model:

(a) Log Likelihood:

$$\mathrm{lnL} = \sum_{j \in S} \ln \left[F(\boldsymbol{z_j}\gamma) + \{1 - F(\boldsymbol{z_j}\gamma)\} p_j^{\frac{1}{\alpha}} \right]$$

$$+ \sum_{j \notin S} \left[\ln\{1 - F(\boldsymbol{z_j}\gamma)\} + \ln\Gamma\left(\frac{1}{\alpha} + y_j\right) - \ln\Gamma(y_j + 1) - \ln\Gamma\left(\frac{1}{\alpha}\right) + \frac{1}{\alpha}\ln p_j + y_j \ln(1 - p_j) \right]$$

(b) $p_j = \frac{1}{[1+\alpha \exp(\boldsymbol{x_j}\boldsymbol{\delta})]}$

(c) F : the inverse of the logit link

(d) S : the set of heat observations for which the outcome (y_j: death) is zero.

(e) $\boldsymbol{z_j}$: Inflation variables for the binary Logit model predicting whether an observation is in the *always-zero* group where $\Pr(y_j = 0) = 1$

(f) $\boldsymbol{x_j}$: Covariates for counts model (Negative Binomial)

In the empirical analysis, the covariates $\boldsymbol{x_j}$ for the count model of Negative Binomial include the following variables: $\boldsymbol{C_j}$, a vector of demographic, socio-economic, and housing characteristics of the county that influence fatalities of heat j; $\boldsymbol{K_j}$, meteorological disaster-specific characteristics of individual heat event j; $\boldsymbol{E_j}$, a vector of climatic and environmental characteristics of the county where the disaster j occurred. My data set is in a time-series-cross-section structure and thus, the empirical estimation can exploit both cross-sectional & cross-temporal variations. State fixed effects are included to control for unobserved statewide heterogeneity. Time fixed effects are also included. As the inflation variables of ZINB model, four key variables are selected from the explanatory variables to serve that determine the probability of being in the *always-zero* group: annual average daily air temperature, annual average of max daily air temperature, metropolitan status, and per capita income. Each of these variables represent the affected area's climate normal, urbanization, and socio-economic status, respectively. The detailed list of the variables included in the analysis is provided in Table 3.4.

Using the same notations specified in Table 3.2 and 3.4, I summarize two regression equations as follows:

Heat Hazard Mitigation Model

$$E(HI_{it}|M, X, c, g, \lambda) = c_i + g_i t + \beta_1 M_{it-2} + \boldsymbol{\beta} \cdot \boldsymbol{X_{it}} + \boldsymbol{\lambda_t} \tag{4}$$

Heat Vulnerability – Fatality Model

$$E(y_{jt}|\boldsymbol{x}) = \exp(\boldsymbol{x_{jt}\delta}) \cdot [1 - Pr(y = 0)] = \exp(\boldsymbol{x_{jt}\delta}) \cdot \left[1 - \frac{\exp(\boldsymbol{z_{jt}\gamma})}{1+\exp(\boldsymbol{z_{jt}\gamma})}\right] \tag{5}$$

$$\text{where} \quad \exp(\boldsymbol{x_{jt}\delta}) = \exp(\delta_0 + \delta_1 HI_{jt} + \boldsymbol{\delta} \cdot \boldsymbol{x_{jt}} + \boldsymbol{T_t} + \boldsymbol{S_j})$$

Once the regressions results are obtained, I combine the result from the first-phase Heat Index model (equation (4)) with the second-phase estimation result of heat fatality analysis (equation (5)), using the Heat Index measure as an intermediary variable. Mediated effect of heat mitigation actions (M_{it}) on heat fatalities (y_{it}) is then derived from the product of two estimates, $\delta_1 \cdot \beta_1$. Given the sign of coefficient β_1 to be negative and δ_1 to be positive, for one unit increase in variable M_{it}, the expected heat fatalities decrease by $(1 - \exp(\delta_1 \cdot \beta_1))\%$ on average, holding all other variables constant.

Table 3.4: List of Variables in the Heat Fatality Model

Category	Variable	Symbol	Source
Dependent Variable			**Source**
	Direct Deaths from Heat	$\boldsymbol{y_j}$	NCEI
Explanatory/Control Variables			
Heat Hazard Profile	Begin Time of the event : Overnight, Morning, Early Afternoon, Late Afternoon, Evening	$\boldsymbol{K_j}$	NCEI
	Season : Spring, Summer, Fall, Winter		NCEI
	Event Type : Heat, Excess Heat		NCEI
	Monthly Average of Daily Maximum Heat Index (°F)		NLDAS
Climatic & Environmental Conditions	Annual Average of Daily Air Temperature (°F)	$\boldsymbol{E_j}$	NLDAS
	Annual Average of Max. Daily Air Temperature (°F)		NLDAS
	Population Size		Census
	Urban Population Density (per 1,000 m^2)		Census
Demographic Composition	Percent of Non-White	$\boldsymbol{C_j}$	Census
	Percent of the Young (under 18)		Census
	Percent of the Elderly (over 65)		Census
	Percent of the Elderly Living Alone		Census
Economic Factors	Poverty Rate among Elderly		Census
	Per capita Income		Census
	Poverty Rate		Census
Housing Factors	Percent of Renter Occupied Housing Units		Census
	Percent of Mobile Homes in Total Housing Units		Census
Time FE	Year Indicator Variables	$\boldsymbol{T_t}$	
State FE	Indicator Variables for U.S. States	$\boldsymbol{S_j}$	
Inflation Variables of ZINB logit model			
Climate	Annual Average of Daily Air Temperature (°F)	$\boldsymbol{z_j}$	NLDAS
	Annual Average of Max. Daily Air Temperature (°F)		NLDAS
Urbanization	Metropolitan Status (Metro=1, Micro=0, Rural=-1)		Census
Economic Status	Per capita Income		Census

3.6.3 Heat Island Mitigation Actions and Heat Fatality: A Direct Estimation

I also attempt to estimate a direct effect of HIM measures on heat fatalities, using the Poisson Fixed Effects estimator, controlling for the time-invariant unobserved heterogeneity of counties that might be correlated with the area's susceptibility to heat. For the application of the panel method, I transform the heat event data, which is also called Cross-Sectional-Time-Series data, into county-year panel structured one. The dependent variable is now the number of fatalities *per heat event* which is no longer integer valued and still has an overdispersion problem due to the excess zeros. However, Poisson Fixed Effects (quasi-MLE) estimator is fully robust to any distributional failure and serial correlation (Wooldridge, 1991). In this analysis, I primarily focus on the effect of the Heat Island Mitigation measures on heat fatalities, controlling for the meteorological factors, demographic characteristics, and per capita income level of counties along with county fixed effects and time fixed effects. Summary statistics for all variables included in the first-phase, second-phase, and the direct effect analysis are presented in Table 3.5.

Table 3.5: Summary Statistics

	Mean	Standard Deviation	Min	Max	Obs. No.
First-Phase Random Trend Model					
Max. for Monthly Avg. Max. Heat Index (°F)	94.45	6.09	78.40	111.02	40168
Heat Island Mitigation Status (=1 if yes)	0.164	0.37	0	1	40168
Total No. of Heat Island Mitigation Actions	0.218	0.60	0	11	40168
No. of Mitigation Actions: 0 (=1 if yes)	0.836	0.37	0	1	40168
No. of Mitigation Actions: 1 (=1 if yes)	0.132	0.34	0	1	40168
No. of Mitigation Actions: 2-3 (=1 if yes)	0.028	0.16	0	1	40168
No. of Mitigation Actions: 4+ (=1 if yes)	0.004	0.06	0	1	40168
Annual Avg. of Max. Daily Temperature (°F)	65.31	8.99	40.84	89.79	40168
Annual Avg. of Min. Daily Temperature (°F)	47.11	7.66	22.71	72.01	40168
Population (in thousands)	91.73	295.33	0.055	9818.61	40168
Heat Wave Days Based on Daily Max Heat Index	7.36	6.75	0	52	43414
Heat Wave Days Based on Net Daily Heat Stress	6.62	6.93	0	51	43414
Second-Phase ZINB Model					
Direct Heat Fatalities	0.13	1.30	0	93	15050
Monthly Avg. of Max. Heat Index (°F)	96.91	6.16	78.80	111.02	15050
Annual Avg. of Max. Daily Temperature (°F)	67.00	7.02	44.36	89.04	15050
Annual Avg. of Daily Temperature (°F)	57.65	6.21	36.07	77.41	15050
Ln (Population)	10.69	1.54	5.70	16.09	15050
Urban Population Density per 1000m^2	1.63	1.92	0	69.47	15050
Metro Status (Metro=1, Micro=0, Rural=-1)	0.12	0.91	-1	1	15050
Ln (Per capita Income)	10.01	0.23	9.23	11.03	15050
Poverty Rate	14.75	6.60	2.56	46.09	15050
Percent of the Young (under 18)	24.38	2.66	13.88	41.66	15050
Percent of the Elderly (over 65)	14.94	3.68	1.95	34.03	15050
Percent of the Elderly Living Alone	4.31	1.29	0.36	11.08	15050
Poverty Rate among Elderly	11.02	4.86	0	40.87	15050
Percent of Non-White	16.96	16.35	0.47	89.22	15050
Percent of Renter Occupied Housing	27.59	8.13	10.16	80.09	15050
Percent of Mobile Homes	11.46	8.58	0	59.36	15050
Excessive Heat	0.25	0.44	0	1	15050
Heat	0.75	0.44	0	1	15050
Overnight	0.20	0.40	0	1	15050
Morning	0.42	0.49	0	1	15050
Early Afternoon	0.04	0.19	0	1	15050
Late Afternoon	0.01	0.07	0	1	15050
Evening	0.20	0.40	0	1	15050
Spring	0.04	0.20	0	1	15050
Summer	0.91	0.29	0	1	15050
Fall	0.05	0.21	0	1	15050
Winter	0.00	0.04	0	1	15050
Poisson FE Heat Fatality Model					
Annual Heat Fatalities per Heat Event	0.47	1.92	0	35	1585
No. of Heat Island Mitigation Actions_All	0.22	0.83	0	11	1585
No. of Heat Island Mitigation Actions_Local	0.08	0.59	0	11	1585
Heat Wave Days Based on Daily Max Temp.	11.40	11.20	0	65	1585
Annual Avg. of Max. Daily Temperature (°F)	67.12	6.72	49.93	84.95	1585
Annual Avg. of Min. Daily Temperature (°F)	49.11	5.20	35.63	68.91	1585
Population (in thousands)	395.20	833.40	2.20	9737.96	1585
Percent Urban Population	67.01	28.98	0	100	1585
Percent of the Elderly (over 65)	12.68	3.29	3.64	22.24	1585
Ln (Per capita Income)	10.08	0.24	9.35	10.92	1585

3.7 RESULTS

3.7.1 First-Phase: Heat Hazard Mitigation Model

Table 3.6 presents the estimates from the Random Trend Model (RTM)[54] for the first phase Heat Hazard Mitigation Model. I test if community efforts for heat mitigation through various Heat Island mitigation measures would lower the risk of the deadly heatwaves. Two types of measures for heat hazard intensity are used – the Heat Index measure (i.e. the maximum for monthly average of daily max. Heat Index) in columns (1) – (3) and the number of Heat Wave Days in columns (4) and (5). In particular, the number of Heat Wave days based on daily maximum Heat Index (column 4) and Net Daily Heat Stress (NDHS) (column 5) are examined as an alternative measure to the Heat Index.

Three specifications are estimated to investigate the role of community Heat Island mitigation (HIM) actions on the Heat Index. In column (1), an indicator variable for Heat Island mitigation adoption status is incorporated to identify the expected change in heat hazard intensity by comparing the Heat Index values (apparent temperature) pre- and post- adoption. The result shows that counties that have initiated any mitigation strategies experience .697°F lower apparent temperature, on average, compared to the period they had not implemented any HIM. In column (2), I estimate a slope relationship between the number of Heat Island mitigation measures and the Heat Index values. It is found that one unit increase in the number of actions taken for heat hazard reduction is estimated to lower the heat index values by .258°F.

[54] I also estimate alternative specifications using the FE approach that allows only a level effect, but not a county-specific time trend. The result is presented in Table 3.A2 in the Appendix. However, Wooldridge Test (2002) indicates that these FE models suffer from the presence of serial correlation, supporting the choice of the Random Trend Model with cluster-robust standard errors.

Table 3.6: Heat Hazard Model: The Role of Heat Island Mitigation Actions
Panel Fixed Effects & Random Trend Model Results

	(1)	(2)	(3)	(4)	(5)
	RTM_HI 1	**RTM_HI 2**	**RTM_HI 3**	**RTM_HD 1**	**RTM_HD 2**
Dependent Variable	Heat Index	Heat Index	Heat Index	Heat Days by Heat Index	Heat Days by Heat Stress
HIM Status_lag	-0.697***				
	(0.102)				
No. of HIM Actions_lag		-0.258***			
		(0.063)			
1 HIM Actions Group_lag			-0.685***	-1.664***	-1.958***
			(0.105)	(0.247)	(0.256)
2-3 HIM Actions Group_lag			-0.896***	-2.809***	-2.632***
			(0.185)	(0.444)	(0.383)
4+ HIM Actions Group_lag			-1.932***	-3.994***	-3.942***
			(0.295)	(1.496)	(1.313)
Population (in thousands)	0.018***	0.017***	0.018***	0.006	0.012
	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)
Annual Avg of Max Daily Temp	0.545***	0.546***	0.545***	1.959***	1.719***
	(0.011)	(0.011)	(0.011)	(0.034)	(0.036)
Annual Avg of Min Daily Temp	0.016	0.014	0.014	-1.241***	-1.197***
	(0.018)	(0.017)	(0.017)	(0.044)	(0.041)
Constant	0.241***	0.240***	0.244***	0.945***	0.947***
	(0.005)	(0.005)	(0.005)	(0.012)	(0.011)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
County-Specific Time Trend	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared : within	0.434	0.434	0.434	0.405	0.397
Number of Counties	3,093	3,093	3,093	3,101	3,101
Observations	40,168	40,168	40,168	43,414	43,414

1. Cluster (County)-adjusted Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10
2. The omitted category for the group indicators in columns (1), (3), (4), and (5) is "*Non-adoption (zero-actions) group*"
3. The estimates of time fixed effects are not reported here.

The specification **RTM_HI 3** in column (3) include multiple group indicator variables instead, that represent different levels of heat mitigation efforts. The results imply that temperature lowering effects of mitigation measures are non-linear; adopting additional mitigation activities have a greater beneficial effect on lowering apparent temperatures. The estimated effect of implementing 4 or more mitigation measures is substantial; a county can lower the apparent temperature by 1.93°F, on average, by implementing 4 or more HIM measures. However, the HI-lowering effect implied by the linear relationship in column (2) is approximately, 1.36°F, given that the average number of HIM actions among counties in *4+ actions group* is 5.27. Also, the difference in the temperature lowering effects between *1 actions group* and *2-3 actions group* is - 0.21°F, meaning that a county is expected to have a further decrease in heat intensity by an average of 0.21°F by adopting one or two extra HIM measures (i.e. moving from *1 actions group* to *2-3 actions group*). The difference further increases to -1.04°F if a county's adoption status changes from *2-3 actions group* to *4+ actions group*. The estimated relationship confirms the long-lasting and sustainable nature of the heat mitigation measures that enables the environmental benefits to accumulate and synergistic effects to arise.

I find consistent results using a set of alternative specifications where the measure of heat hazard intensity used as an outcome variable is the number of Heat Wave Days. The Random Trend Model specification as described in equation (3) with the alternative dependent variables is estimated. As shown in column (4) and (5), the estimation results suggest that counties with more Heat Island Mitigation actions experience fewer Heat Wave Days. For example, the Heat Wave Days decrease by 1.66 or 1.96 days on average (depending on the measure used to define the Heat Wave Days), if a county initiates HIM activities by adopting a measure for mitigation. The Heat Wave Days further decrease as a county implements more HIM strategies; the difference between coefficients on *1 action group* and *2-3 actions group* dummies indicates that the reduction in Heat Wave Days for additional measure is 0.67 – 1.14 days. The estimates suggest that the first HIM measure implemented in a county has the largest marginal effect (1.66 – 1.96), and the marginal effects of additional measures decrease, but still having a significant hazard-reduction effect. The estimated effects of HIM actions on Heat Wave days using *HIM status indicator* and *the number of HIM measures* are presented in Table 3.A3.

3.7.2 Second-Phase: Heat Vulnerability – Fatality Model

Table 3.7 presents the estimates from the Zero-Inflated Negative Binomial models using heat events recorded at the scale of counties during 1998-2011. The dependent variable is direct fatalities from each heat event. Due to the high correlation among socio-economic variables, I estimate specification 1 as a base model and additionally introduce the poverty rate variable in specification 2, elderly poverty rate in specification 3, and percent elderly living alone in specification 4. Specification 2 and 3 connect the issue of poverty and the resulting increase in heat vulnerability whereas specification 3 and 4 highlights the implications of aging society in the context of the heat vulnerability dynamic. As a part of ZINB model, the results of the logit model for predicting whether an observation is in the always-zero group are presented in the lower panel of Table 3.7.

Heat Hazard Profile First, consider the results of the heat hazard profile variables. A measure of the intensity of a heat event, the Heat Index level, is found to be one of the most crucial meteorological elements of heat hazard that determine the level of societal impacts. The results from all four specifications demonstrate that a significant positive relationship holds between the Heat Index and the heat-induced fatalities. An increase in the maximum daily Heat Index value by one degree (F) would lead to 12% more heat fatalities on average. Timing of the event variables are also estimated to affect the degree of heat impacts. The societal outcome of a heat event is greater when it begins to occur during late afternoon hours (4:00-7:59 PM). This is perhaps because higher temperatures at night in urban areas (due to the impeded release of heat absorbed during daytime in urban areas) may further increase the nighttime atmospheric temperatures and exacerbate the impacts of extreme heat on human health.

Table 3.7: Heat Vulnerability – Fatalities Model
Zero-Inflated Negative Binomial Regressions Results

	Zero Inflated Negative Binomial Model (ZINB)			
Dependent Variable	(1)	(2)	(3)	(4)
Direct Heat Fatalities	Specification 1	Specification 2	Specification 3	Specification 4
Monthly Avg. Max Heat Index(°F)	0.110***	0.110***	0.115***	0.110***
	(0.017)	(0.017)	(0.017)	(0.017)
Annual Avg. of Daily Temp. (°F)	-0.319***	-0.333***	-0.351***	-0.307***
	(0.104)	(0.098)	(0.108)	(0.098)
Annual Avg. of Max. Daily Temp.(°F)	0.220**	0.230***	0.245***	0.206**
	(0.087)	(0.084)	(0.090)	(0.083)
Ln (Population)	0.932***	0.927***	0.946***	0.953***
	(0.083)	(0.082)	(0.083)	(0.084)
Urban Population Density (per 1000m^2)	0.072***	0.067***	0.050**	0.069***
	(0.022)	(0.021)	(0.020)	(0.020)
Percent Young	0.086**	0.087***	0.074**	0.083**
	(0.034)	(0.033)	(0.033)	(0.033)
Percent Elderly	0.103***	0.094***	0.092***	
	(0.027)	(0.028)	(0.028)	
Percent Elderly Living Alone				0.292***
				(0.068)
Poverty Rate among Elderly			0.065***	
			(0.021)	
Poverty Rate		0.038*		
		(0.021)		
Ln (Per capita Income)	-1.003*	-0.290	-0.146	-0.899
	(0.537)	(0.644)	(0.607)	(0.551)
Percent Non-White	0.016***	0.012**	0.010*	0.014***
	(0.005)	(0.006)	(0.006)	(0.005)
Percent Renter Occupied Housing	0.021*	0.013	0.019	0.013
	(0.012)	(0.013)	(0.012)	(0.012)
Percent Mobile Homes	0.029*	0.028*	0.027	0.032*
	(0.017)	(0.016)	(0.016)	(0.018)
Excessive Heat	0.001	0.012	0.007	-0.002
	(0.141)	(0.141)	(0.141)	(0.141)
Overnight	-0.373**	-0.361**	-0.376**	-0.375**
	(0.166)	(0.165)	(0.166)	(0.166)
Morning	-0.293**	-0.289**	-0.292**	-0.289**
	(0.123)	(0.122)	(0.123)	(0.122)
Late Afternoon	0.324	0.331	0.313	0.339
	(0.222)	(0.220)	(0.218)	(0.225)
Evening	0.258	0.258	0.236	0.278
	(0.538)	(0.538)	(0.548)	(0.540)

Table 3.7 (cont'd)

	(1)	(2)	(3)	(4)
Spring	0.143	0.120	0.119	0.151
	(0.307)	(0.304)	(0.304)	(0.306)
Fall	0.328	0.329	0.345	0.321
	(0.340)	(0.332)	(0.336)	(0.337)
Winter	-12.981***	-12.353***	-13.236***	-12.935***
	(0.750)	(0.727)	(0.695)	(0.733)
Constant	-15.679**	-22.801***	-24.725***	-16.117**
	(6.596)	(7.865)	(7.654)	(6.937)
State Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
	Logit Inflation Model			
Annual Avg. of Max. Daily Temp.(°F)	2.433**	2.441***	2.391**	2.482***
	(0.987)	(0.854)	(1.057)	(0.877)
Annual Avg. of Daily Temp. (°F)	-2.947***	-2.953***	-2.898**	-3.004***
	(1.110)	(0.967)	(1.189)	(0.988)
Metropolitan Status	1.001	1.043	0.915	1.118
	(1.145)	(0.986)	(1.192)	(0.977)
Ln (Per capita Income)	-10.807*	-11.154**	-10.639	-11.082**
	(6.363)	(5.337)	(7.048)	(5.523)
Constant	110.309*	113.500**	108.592*	112.755**
	(58.628)	(49.431)	(64.827)	(51.001)
Observations	15,050	15,050	15,050	15,050

1. Cluster (County)-adjusted Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10
2. The omitted category for the begin time is "*Early Afternoon*".
3. The omitted category for the season is "*Summer*".
4. The omitted category for event type is "*Heat*"
5. The estimates of state FE and year FE are not reported here.

Climatic and Environmental Conditions Our estimates confirm that climatic and environmental characteristics of the place are another important facet of heat vulnerability. The negative coefficient of the average daily air temperature suggests that counties in warmer climates tend to be less sensitive to heat as they are more likely accustomed to high temperatures. However, among counties with the same average temperature, those with the higher maximum daily temperatures may suffer greater heat-related fatalities. The result shows that susceptibility to heat hazards not only depends on the normal climate conditions of the area but also on the area's meteorological variability (e.g. daily temperature range). Consistent with the previous findings from heat studies, the level of urbanization is an important heat risk factor. I find that more populated counties experience higher risk of life-threatening extreme heat. Also, urban concentration magnifies the risk of heat by aggravating Heat Island effects. The estimates imply that if urban density (per 1,000 m^2) rises by its standard deviation (SD) (≈ 2), a 15% increase in heat fatalities would result.

Demographic & Socio-Economic Characteristics Our analysis provides statistically and economically significant evidence in support of the "socio-political nature of disasters" argument – those who are more vulnerable in societal context are more susceptible to harm in the event of disasters. First, I ascertain that *demographic composition* factors, such as the proportion of young and elderly population, and the proportion of non-white, constitutes essential facet of population heat vulnerability. Most of all, age is a key factor, in particular, the elderly population is estimated to have higher chance to be a victim of heat waves. The heat vulnerability model estimates that one percentage point increase in the share of elderly population is associated with 11% increase in heat fatalities (specification 1).

The relationship between heat vulnerability and the socially isolated elderly is notable, who are characterized by greater physiological and societal vulnerabilities. The estimate in specification 4 implies that our society would suffer an average of 34% more heat fatalities if isolated elderly people comprise one additional proportion of total population. The substantially greater heat vulnerability as a result of a growing share of socially isolated elderly is attributable to the individual vulnerability of elderly and population characteristics of aging society as a whole.

It is also found that different race groups experience disproportionate disaster impacts. Counties with more non-white population have greater fatalities from heat. One SD (≈ 16) increase in the share of the non-white population is associated with 17% - 30% greater heat fatalities, depending on the model specifications. Because vulnerability of certain race/ethnicity groups are highly linked with their socio-economic status (Hansen et al., 2013), the estimated effect of the percent non-white variable decreases once I include poverty measures in specification 2 and 3.

Our analyses suggest that *socio-economic factors* are among the many essential factors contributing to heat vulnerability. First, my results support the idea that the economic level has a negative relationship with disaster consequences, which has been echoed by many disaster studies and vulnerability literature. This relationship holds in case of extreme heat, as well. Naturally occurring hazards do not discriminate among people thus, the likelihood of disaster occurrence is purely random. However, those with more economic resources can utilize their wealth to prevent the worst consequences of and better respond to heat hazards. People living below poverty line, on the other hand, are at a greater risk, as they possess limited financial, physical, and social assets, which limits their coping capacity. One percentage point increase in poverty rates leads to 4% increase in fatalities, whereas a one SD (≈ 7) increase results in 30% increase in fatalities.

A combination of two vulnerability factors - aging coupled with poverty - is considered in specification 3. One percentage point increase in senior poverty rates is estimated to result in 7% more heat fatalities. Comparing with the estimated effect of unit change in population poverty rate (4% increase in fatalities), we infer that among the people living in poverty, elderly people have higher susceptibility to harm from heat hazards. Note that this is only a partial effect of senior poverty rates where other variables – including the share of elderly population – are held constant. To further investigate the growing heat vulnerability on account of aging population, I calculate the effect based on the projected growth in elderly population and elderly poverty rates; i) the national share of elderly in the study period is 12.3%[55] (14-year average) and is projected to rise to 20.3% by 2030 and 21% by 2040, and ii) 1 out of 10 elderly lived in poverty during 1990-2014 (10.34%, 25 year average) (U.S. Census Bureau, 2014). The population projections indicate that the share of elderly will rise by 8 percentage points by 2030 and 8.7 percentage points by 2040, from 12.3%. Using these statistics, the predicted increase in heat fatalities for years 2030 and 2040 are estimated. I use the result of the specification 3 in Table 3.7 for prediction, assuming the poverty rates among elderly will remain the same at the average rate of 10.34% in 2030 and 2040[56]. As shown in Table 3.8, I find that the heightened heat vulnerability due to the growth of the elderly is predicted to generate a two-fold increase in heat fatalities by 2030 and 2.23-fold increase by 2040, relative to the average fatalities during the study period (1998-2011). The heat vulnerability of the United States is predicted to substantially increase in the coming decades as the most heat-vulnerable group of people is going to comprise a growing share of the population.

Table 3.8: Increase in Heat Fatalities
Given the Projected Growth of the Elderly Population in 2030 and 2040

Year	Population aged 65+		65+ Population Growth		**Yearly Heat Fatalities**[2]		
	Share	Number[1]	Δ Share	Δ Number[1]	Pct Δ	Avg Deaths/yr	Δ Deaths
1998-2011	12.3%	35,945				142	
2030	20.3%	72,774	8 %	36,829	**209 %**	**297**	**155**
2040	21%	79,719	8.8 %	43,774	**223 %**	**317**	**175**

1. Numbers in thousands.
2. The predicted heat fatalities are calculated using the estimation result of the specification 3 in Table 3.7. Note that the predicted changes are average partial effects of the *Pct Elderly* variable, with all other variables being held constant.

[55] 12.3% is the national level statistics while my sample mean of 14.94% in Table 3.5 is the mean of county level Pct Elderly with some counties are included multiple times for the computation of mean values.

[56] I am primarily interested in the projected increase in heat fatalities in relation with the growth in elderly in this calculation while considering the poverty rates among them. However. due to the assumption of *Ceteris paribus* of multiple regression, the coefficient of *Pct Elderly* in specification 3 means a partial effect of increase in *Pct Elderly,* holding other variables including the elderly poverty rates constant. Assuming the poverty rates among elderly will remain the same, I estimate the predicted increase in heat fatalities as a result of the aging population using the result in specification 3.

Consider next the result of *housing-related factors*. The results show that housing ownership is closely related with heat vulnerability. One SD (≈ 8) increase in the share of renter occupied housing unit is associated with 16% increase in heat fatalities (specification 3). Also, consistent with the previous findings on the vulnerability of mobile homes (Lim et al. 2017; Simmons and Sutter, 2013), my empirical analyses show that mobile homes are a significant heat risk factor. For one SD (≈ 9) increase in the share of mobile homes in total housing stock, heat fatalities are expected to increase by 26%. It might be the structural vulnerability of mobile homes which are typically of lower quality than traditional homes in terms of inefficient cooling systems and/or insufficient insulation and windows, which make people living in mobile homes more vulnerable to extreme heat. My results also highlight greater vulnerability of the residents to heat who have limited financial resources and may have no other choice but to live in lower cost rental housing or mobile homes.

3.7.3 Heat Island Mitigation Actions and Heat Fatality

3.7.3.1 First and Second Phase Models Combined: A Mediated Effect

As illustrated in section 3.6, I combine the result from the first-phase Heat Index model (equation (4)) with the second-phase estimation result of the heat fatality analysis (equation (5)) to derive a mediated effect of heat mitigation actions on heat fatalities. Using the estimated coefficients from three specifications (columns 1, 2, 3) in Table 3.6 and a coefficient of the Heat Index variable from specification 1 in Table 3.7, I compute the mediated effects on heat fatalities and present them in Table 3.9. Findings are as follows[57]. First, counties in the Heat Island

[57] Even though my findings provide evidence on the negative causality between the heat mitigation measures and the heat fatalities (where a positive statistical correlation is found between heat mitigation measures and the heat hazard as shown in Table 3.3), I acknowledge that one should be cautious in interpreting the magnitude of the effects.

mitigation adoption group experience an average of 7.38 % less heat fatalities than those in non-adoption group. It is also found that one additional measure for heat hazard reduction reduces heat fatalities by 2.8 % on average. However, due to the long-lasting and synergistic effects of the heat mitigation measures, the temperature lowering benefit of such measures are accumulated and thus, counties with more mitigation actions are progressively less vulnerable to extreme heat than counties with less activities. It is shown in the lowest panel of Table 3.9 that counties in the *1 action group* suffer 7.26 % fewer heat fatalities, compared to the non-adoption status, while counties in *2-3 actions group* experience 9.39 % fewer heat fatalities. The fatality reducing effects increase progressively if a county has taken 4 or more actions for Heat Island mitigation. The mediated effect analysis shows that counties in *4+ actions group* could avoid a great deal of fatal consequences of extreme heat events due to their efforts and dedication to heat mitigation. They could reduce heat fatalities by almost 20 % compared to the non-adoption group.

Table 3.9: The Mediated Effect of Heat Mitigation Actions on Heat Fatalities

		Estimated Coefficients	**Effects on Fatalities**
		$\hat{\delta}_1$ and $\hat{\beta}_1$	$(1-\exp(\hat{\delta}_1 \cdot \hat{\beta}_1))\%$
Heat Fatality Model	**Mediator variable**		
	Monthly Avg. Max Heat Index(°F)	$\hat{\delta}_1$ = +0.110***	
Heat Hazard Model	Specification 1		
	Heat Island Mitigation Adoption Status[1]	$\hat{\beta}_{1d}$ = -0.697***	**7.38 % Reduction** (vs. non-adoption)
	Specification 2		
	No. of Heat Island Mitigation Actions	$\hat{\beta}_{1n}$ = -0.258***	**2.80 % Reduction** (for one additional action)
	Specification 3		
	1 Mitigation Actions Group[1]	$\hat{\beta}_{11}$ = -0.685***	**7.26 % Reduction**
	2-3 Mitigation Actions Group[1]	$\hat{\beta}_{12}$ = -0.896***	**9.39 % Reduction**
	+4 Mitigation Actions Group[1]	$\hat{\beta}_{13}$ = -1.932***	**19.15 % Reduction**

1. The reference group for these group indicator variables is non-adoption (zero-actions) group.
2. *** means p-values <0.01

3.7.3.2 A Direct Estimation of the Effect

I also perform a direct estimation of the effect of Heat Island Mitigation (HIM) measures on heat fatalities, using the Poisson Fixed Effects estimator, controlling for the unobserved heterogeneity of counties. I use county-year panel structured data with deaths per heat event as a dependent variable. In section 3.6.1, the HIM measures are found to have significant heat lowering effects. In section 3.6.2, using the Heat Index as *an intermediary variable,* I show that how HIM measures influence the heat outcomes. To identify the effect of heat mitigation efforts on fatalities, I only include the HIM variables as a regressor along with controls, excluding the *intermediary variable* – the Heat Index measure. However, it is still important to capture the changes in heat fatalities due to the naturally occurring variations in heat hazard over the period that might not be explained by other annual max/min temperatures nor by the HIM variable. Thus, I include the days in which the county max air temperature[58] reached or exceeded the 95th percentile of daily max temperature in May – September period, along with other meteorological conditions.

The results of the direct estimation of the effects of HIM actions on heat fatalities using the Poisson Fixed Effects are presented in columns (2) – (3) in Table 3.10. The Random Effects model results are provided in columns (4) – (5) as a robustness check. I find a statistical evidence that the more HIM measures a county has implemented, the smaller the heat fatalities in that county. However, the difference between the estimated effects of the number of all HIM measures shown in column (2) and the effects of the number of locally implemented measures (i.e. non-statewide activities) in column (3) implies that the heat-vulnerability reducing benefits

[58] The heat days measure is closely related with the Heat Index but it only accounts for the temperature component of extreme heat, but not the humidity component.

of HIM activities can differ depending on the spatial-scale and the main agents of HIM implementation. The results indicate that community-based, local government initiated HIM actions have larger effects on heat fatality reduction. An additional measure that is locally implemented in a county is estimated to reduce annual deaths rate (deaths per heat event) by 15.38 %. The estimated direct effect is much larger than the mediated effect that is identified in the prior subsection (in Table 3.9).

Table 3.10: A Direct Estimation of the Effect of Heat Island Mitigation Actions on Heat Fatalities – Poisson FE and RE Model Key Results

Dependent Variable	(1)	(2)	(3)	(4)	(5)
Direct Heat Fatalities	**Poisson FE**	**Poisson FE**	**Poisson FE**	**Poisson RE**	**Poisson RE**
Monthly Avg. Max Heat Index(°F)	0.193***				
	(0.040)				
No. of HIM Actions_lag (All)		-0.044		-0.106	
		(0.065)		(0.066)	
No. of HIM Actions_lag_(Non-Statewide)			-0.167*		-0.180**
			(0.088)		(0.092)
Heat Wave Days (based on Max Temp)		0.017	0.017	0.010	0.011
		(0.011)	(0.011)	(0.008)	(0.008)
Population (in thousands)	0.000	0.001	0.001	0.001***	0.001***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
Pct Urban Population	0.053	0.053	0.042	0.027***	0.027***
	(0.045)	(0.045)	(0.045)	(0.006)	(0.006)
Ln (Per capita Income)	-1.875	-2.422	-3.456	-1.313**	-1.333**
	(2.458)	(2.843)	(2.812)	(0.555)	(0.558)
Constant				4.465	4.715
				(5.999)	(6.017)
Number of Counties	304	272	272	1,906	1,906
Observations	1,746	1,585	1,585	6,635	6,635

1. Cluster (County)-adjusted Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10
2. The omitted category for the group indicators in columns (2) and (3) is "*Non-adoption (zero-actions) group*"
3. The estimates of meteorological and demographic control variables, and time fixed effects are not reported here.

3.8 CONCLUSION

Under the ongoing climate change, the frequency and intensity of extreme heat events are predicted to increase. Given the devastating consequences of heat events and the growing risks of extreme heat, it is critical to identify the major determinants of heat vulnerability to minimize potential human losses. My analysis reveals a multi-faceted nature of the heat vulnerability; event-specific heat hazard profiles, meteorological, climatic and environmental conditions, as well as, various socio-economic and housing factors are critical in determining heat vulnerability. The findings suggest that a trend of an aging population and continuing urbanization combined with the projected increase in heat risks will aggravate the adverse consequences of extreme heat to society. The heightened heat vulnerability due to the growth of the elderly population is predicted to generate a two-fold increase in heat fatalities by 2030.

Importantly, this study provides an evidence on the benefits of the community Heat Island mitigation measures in lowering temperatures and further, reducing the loss of life from extreme heat events. Under the anticipated increase in societal vulnerability of the United States to heat hazard, the findings of this study underscore the need for more proactive and precautionary public measures and regulations to counterbalance the harmful effects of heat hazard. In this regard, a key area of further research is to closely examine each type of strategies for Heat Island mitigation and evaluate their life-saving benefits against extreme heat events from the cost-benefit perspective. Overall, findings of this study increase our understanding of the socio-political nature of heat wave impacts and inform targeting efforts designed to protect and assist the most vulnerable populations.

APPENDIX

APPENDIX

Table 3.A1: Determination of Heat and Excess Heat

Determination of a Heat category event in NWS *Storm Data*
Heat
A period of heat results from the combination of high temperatures (above normal) and relative humidity. A Heat event occurs and is reported in Storm Data whenever heat index values meet or exceed locally/regionally established heat advisory thresholds. Fatalities or major impacts on human health occurring when ambient weather conditions meet heat advisory criteria are reported using the Heat event. If the ambient weather conditions are below heat advisory criteria, a Heat event entry is permissible only if a directly-related fatality occurred due to unseasonably warm weather, and not man-made environments.
Excess Heat
Excessive Heat results from a combination of high temperatures (well above normal) and high humidity. An Excessive Heat event occurs and is reported in *Storm Data* whenever heat index values meet or exceed locally/regionally established excessive heat warning thresholds. Fatalities (directly-related) or major impacts to human health that occur during excessive heat warning conditions are reported using this event category. If the event that occurred is considered significant, even though it affected a small area, it should be entered into *Storm Data*.

Source: National Weather Service Instruction 10-1605 (MARCH 23, 2016) Operations and Services Performance, Storm Data Preparation. (http://www.nws.noaa.gov/directives/)

Table 3.A2: Heat Hazard Model: The Role of Heat Island Mitigation Actions Alternative Specifications: Fixed Effects OLS

Dependent Variable	(1)	(2)	(3)
Max. for Monthly Avg. of Daily Max. Heat Index (°F)	FE Specification 1	FE Specification 2	FE Specification 3
HIM Adoption Status_lag	-0.238***		
	(0.050)		
No. of HIM Actions_lag		-0.201***	
		(0.024)	
1 HIM Actions Group_lag			-0.158**
			(0.068)
2-3 HIM Actions Group_lag			-0.278***
			(0.057)
4+ HIM Actions Group_lag			-1.961***
			(0.235)
Percent Urban Population	0.006**	0.007**	0.006*
	(0.003)	(0.003)	(0.003)
Population (in thousands)	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)
Annual Avg. of Max. Daily Temp.(°F)	0.691***	0.689***	0.685***
	(0.010)	(0.010)	(0.010)
Annual Avg. of Min. Daily Temp.(°F)	-0.138***	-0.140***	-0.139***
	(0.015)	(0.015)	(0.015)
Constant	55.514***	55.665***	55.878***
	(0.649)	(0.649)	(0.654)
County Fixed Effects	Yes	Yes	Yes
County-Specific Time Trend	No	No	No
Time Fixed Effects	Yes	Yes	Yes
R-squared : within	0.542	0.542	0.543
Number of Counties	3,091	3,091	3,091
Observations	43,250	43,250	43,250

1. Cluster (County)-adjusted Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10
2. The omitted category for the group indicators in columns (1) and (3) is "*Non-adoption (zero-actions) group*"
3. The estimates of time fixed effects are not reported here.

Table 3.A3: Heat Hazard Model: The Role of Heat Island Mitigation Actions Random Trend Model Using Heat Wave Days as an Alternative DV

	(1)	(2)	(3)	(4)
	RTM_HD 3	**RTM_HD 4**	**RTM_HD 5**	**RTM_HD 6**
Dependent Variable	Heat Days by Heat Index	Heat Days by Heat Index	Heat Days by Heat Stress	Heat Days by Heat Stress
HIM Adoption Status_lag	-1.744***		-2.005***	
	(0.240)		(0.249)	
No. of HIM Actions_lag		-0.756***		-0.991***
		(0.168)		(0.169)
Population (in thousands)	0.007	0.006	0.013	0.011
	(0.010)	(0.010)	(0.009)	(0.010)
Annual Avg of Max Daily Temp	1.954***	1.959***	1.716***	1.722***
	(0.035)	(0.035)	(0.036)	(0.036)
Annual Avg of Min Daily Temp	-1.240***	-1.245***	-1.197***	-1.203***
	(0.044)	(0.044)	(0.041)	(0.041)
Constant	0.938***	0.932***	0.942***	0.938***
	(0.011)	(0.012)	(0.011)	(0.012)
County Fixed Effects	Yes	Yes	Yes	Yes
County-Specific Time Trend	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
R-squared : within	0.405	0.405	0.397	0.396
Number of Counties	3,101	3,101	3,101	3,101
Observations	43,414	43,414	43,414	43,414

1. Cluster (County)-adjusted Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10
2. The omitted category for the group indicators is "*Non-adoption (zero-actions) group*"
3. The estimates of time fixed effects are not reported here.

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