DISSERTATION

LONGITUDINAL AND GEOGRAPHIC ANALYSIS OF THE RELATIONSHIP BETWEEN NATURAL DISASTERS AND CRIME IN THE UNITED STATES

Submitted by

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ABSTRACT

LONGITUDINAL AND GEOGRAPHIC ANALYSIS OF THE RELATIONSHIP BETWEEN NATURAL DISASTERS AND CRIME IN THE UNITED STATES

Natural disasters and crime are ubiquitous in the United States. The public generally views the social disorder associated with disaster events as criminogenic—that is, disasters somehow foster opportunistic criminal behavior. Scientific investigation into the relationship between disaster and crime is more nuanced—and at times has produced contradictory and inconsistent findings.

This dissertation research explores the relationship between disaster and crime in the continental United States to investigate the question of whether disasters of different magnitudes and/or types differentially affect crime rates. I employ three sociological theories to inform the analyses. First, sociology of disaster researchers, using the therapeutic community hypothesis, have long asserted that disasters *reduce* criminal activity both during and after the event. Second, criminologists using social disorganization theory assert that disaster may *increase* the likelihood and occurrence of crime. Third, researchers using routine activity theory suggest that disaster may *increase* or *decrease* criminal activity, depending on how a disaster restructures formal and informal mechanisms of social control, and criminal opportunity.

To investigate this question, I use geographic and longitudinal analyses of 14 years of county-level data on socio-demographic predictors of crime, crime rates, and disaster impacts. I statistically model 11 different categories of crime and impacts from

12 different disaster types using geographic information systems, hierarchical linear modeling, and geographically weighted regression. In general, findings indicate that higher crime rates are associated with larger disaster magnitudes. The effect is not consistent for all categories of crime investigated in this research. Findings also indicate that certain types of disasters have a differential effect on crime outcomes, independent of disaster magnitude. This research and results represent the first county-level geographic and longitudinal analysis of disaster and crime for the United States.

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CHAPTER ONE: INTRODUCTION

I. Introduction

The number of recorded natural disasters—and subsequent focus of researchers and the public on these events—has increased markedly over the last fifteen years. Recent research highlights rising economic costs (Lott, Smith, Houston, and Shein 2011; Pielke, Gratz, Landsea, Collins, Saunders, and Musulin 2008) and human tolls (Bourque, Siegel, Kano, and Wood 2006; Zahran, Peek, and Brody 2008) associated with natural disasters (Cutter and Emrich 2005). Although loss estimates vary widely (Cutter and Emrich 2005; Mileti 1999a), the National Oceanic and Atmospheric Administration (NOAA) recently estimated that human causalities and direct monetary costs of major[1] weather disasters in the past 30 years averaged over 760 deaths and in excess of $24 billion annually (Lott et al. 2011). Future human and economic costs associated with natural disasters are likely to increase as population growth and demographic shifts toward hazardous regions—such as coastal areas—increase U.S. vulnerability to natural disasters (Changnon, Pielke, Changnon, Sylves, and Pulwarty 2000; van der Vink, Allen, Chapin, Crooks, Fraley, Krantz, Lavigne, LeCuyer, MacColl, Morgan, Ries, Robinson, Rodriquez, Smith, and Sponberg 1998)

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[1] This report defined "major" weather disasters as those distinct events exceeding $1 billion in overall damages/costs. These figures are thus conservative estimates of the overall cost of weather-related events. This estimate also excludes geophysical events such as landslides, wildfires, and earthquakes.

Tornadoes, hurricanes, floods, wildfires, earthquakes and other natural events are clearly wide reaching in their effects. That natural disasters upset routine community functioning suggests that patterns of crime activity may also be affected by such events. Disasters have long been considered social laboratories for examining the effects of disruption of social order on individual and collective behavior (Barton 1963; Barton 1969; Drabek 1986; Prince 1920). Early disaster researchers recognized the importance of documenting patterns of crime after disaster events (Prince 1920), and contemporary researchers continue to request systematic investigations of crime and disaster (Harper and Frailing 2010).

The public generally views the social disorder associated with disaster events as criminogenic—that is, disasters somehow foster opportunistic criminal behavior (Fischer 2008). Concurrently, media outlets present crime as ubiquitous in the aftermath of disaster (Johnson, Dolan, and Sonnett 2011; Tierney, Bevc, and Kuligowski 2006; Wiltenberg 2004). Scientific investigation into the relationship between crime and disasters, however, is more nuanced—and at times has produced contradictory results. For example, research has shown that although some types of crime, such as domestic violence, are likely to increase (Curtis, Miller, and Berry 2000; Enarson 1999; Fothergill and Peek 2004; Zahran, Shelley, Peek, and Brody 2009), disasters may decrease the likelihood of other crime types, such as property crime (Zahran et al. 2009).[2] This dissertation research seeks to interrogate these disparate findings by examining the following core research question: *Do natural disasters of different types and magnitudes differentially affect crime outcomes in the United States?*

[2] Other research has show that the origin of a disaster also matters in conditioning crime outcomes. For example, hate crimes have increased post-9/11 (Peek 2011), as have fraud cases in the wake of technological disasters (Gill, Picou, and Ritchie 2010).

I draw on three sociological theories to investigate the relationship between disaster and crime. Similar to empirical research documenting patterns of criminal activity and disaster, theoretical approaches to the core research question likewise offer contradictory predictions regarding the relationship between disasters and crime. First, sociology of disaster researchers, using the therapeutic community hypothesis (Barton 1963; Fritz 1961), have long asserted that disasters *reduce* criminal activity both during and after the event (Quarantelli and Dynes 1970). Second, criminologists using social disorganization theory (Shaw and McKay 1942; Thomas and Znaniecki 1918) assert that disasters may *increase* the likelihood and occurrence of crime (Harper and Frailing 2010). Third, researchers using routine activity theory (Cohen and Felson 1979) suggest that disaster may *increase* or *decrease* criminal activity, depending on how a disaster restructures the usual mechanisms of social control and criminal opportunity (Cromwell, Dunham, and Lanza-Kaduce 1995).

II. Research Questions and Methodological Design

Although the question of the effect of disaster on crime continues to inform a number of research projects, there is a lacuna in the disaster and crime literature that uses data for the entire U.S. and analyzes it both spatially and longitudinally. The purpose of the present research is to investigate whether natural disasters of different types[3] and

[3] Natural disaster types, sometimes referred to as natural hazards, include: avalanches, coastal surf, droughts, earthquakes, flooding, fog, hail, heat, hurricanes/tropical storms, landslides, lightning, severe storms/thunder storms, tornadoes, tsunamis, volcanoes, wildfires, wind, and winter weather. During the study period, there were no volcanic eruptions in the continental United States. In Chapter 3, I combine a number of these disaster types to facilitate analysis.

magnitudes[4] differentially affect the occurrence and frequency of violent and property crime in both geographic space and over time. With this purpose in mind, the primary goals of the research include: (1) identifying patterns of property and violent crimes before and after natural disaster events of different types and magnitudes; (2) utilizing spatial data to investigate relationships among geography, natural disasters, and crime across the entire United States; (3) investigating community characteristics that increase or decrease the likelihood that violent and property crime will be committed following natural disaster; and (4) improving knowledge regarding the likelihood and character of post-disaster crime for researchers, practitioners, and policy makers.

The following specific research questions guide the project:

- Does a disaster's magnitude and/or type influence aggregate crime rates?
- Does a disaster's magnitude and/or type influence rates of violent crime?
- Does a disaster's magnitude and/or type influence rates of property crime?

Because the research utilizes national, spatial, and longitudinal data at the county level, all research questions implicitly explore: (1) whether disasters affect long-term trends in crime patterns, and (2) whether patterns of crime and disaster are spatially clustered. Approaches to answering the research questions were informed by theories of disaster and crime, which are detailed in Chapter 2.

This research employed data from a variety of sources in order to address the above research questions. These sources included: the FBI Uniform Crime Report (UCR) data, available from the U.S. Department of Justice; Law Enforcement Management and Administrative Statistics (LEMAS) data from the U.S. Department of Justice; data from

[4] The magnitude of a disaster is often equated to direct economic losses and/or fatalities and injuries (e.g. Mileti 1999; Cutter and Emrich 2005). In this dissertation, I consider the magnitude in reference to these measures and assume a level of social disruption as a component of a disasters size.

the National Center for Charitable Statistics (NCCS); disaster impact data from the Spatial Hazard Events and Losses Database (SHELDUS) at the Hazards and Vulnerability Research Institute at the University of South Carolina; Presidential disaster declaration data from the Federal Emergency Management Agency (FEMA); U.S. Census county-level data and TIGER/line shape files; demographic data from the National Cancer Institute Surveillance Epidemiology and End Results (SEER); and U.S. Bureau of Economic Analysis, Department of Commerce, county-level data.

Using this secondary data on crime, natural disasters, and theoretically relevant socio-demographic control variables, the research statistically modeled county-level crime rates for the continental United States.[5] Statistical procedures used in the analysis included multiple regression, geographically weighted regression, and hierarchical linear modeling (HLM). The analysis and presentation of the findings were augmented using Geographic Information Systems (GIS) spatial analyses.

III. Defining Natural Disaster

Defining disaster is a necessary step in the process of social research into disaster impacts (Perry and Quarantelli 2005; Quarantelli 1998). A commonly used definition is from Fritz (1961):

> *…an event, concentrated in time and space, in which a society, or a relatively self-sufficient subdivision of a society, undergoes severe danger and incurs such losses to its members and physical appearances that the social structure is disrupted and the fulfillment of all or some of the essential functions of the society is prevented.* (655)

[5] Methodological restrictions for spatial analyses required the spatial units to be contiguous for the study area. This excludes the U.S. states of Hawai'i and Alaska (see Getis and Ord 1992).

Though such a definition admittedly carries structural functionalist paradigmatic baggage (c.f. Gilbert 1998; Hewitt 1998; Perry 1998), the Fritz definition allows the discussion of pre- and post- disaster conditions by considering disaster as an "event." Further, the disaster event disrupts societal arrangements and essential functions within the social structure, and human activity following a disaster may be considered a reflexive adjustment to the disruption created by the event (Bates and Peacock 1989; Mileti 1980; Mileti 1999b).

In the context of natural disasters, these disruptive events are often associated with environmental extremes. A sociological interpretation of a disaster as "natural" recognizes that disaster results from the intersection of the environmental event with other social systems. As Mileti (1999) notes of natural disaster, "rather than stemming from unpredictable events, [natural disasters] are the predictable result of interactions among three major systems: the physical environment, which includes hazardous events; the social and demographic characteristics of the communities that experience them; and the buildings, roads, bridges, and other components of the constructed environment" (3). Mileti's (1999) observation that natural disasters stem from the intersection of hazardous events, the built environment, and society underscores the approach to understanding natural disasters used in this research. Specifically, natural disasters and their effects are not simply the result of nature, but reflect society's culturally manufactured vulnerability to environmental extremes (c.f. Alagona 2006; Weisner, Blaikie, Cannon, and Davis 2004).

An additional consideration when defining a natural disaster is identifying the impacted parties. Central to both the Fritz (1961) and Mileti (1999) statements on disaster is the notion of the affected community. As Dynes (1998) observes, the social unit of community represents "the universal form of social life and response" to disaster (109). Communities possess the spatial, temporal, and organizational elements that are stressed, transformed, or eliminated during and after natural disasters. As such, the community actively engages in the creation of vulnerability to environmental extremes and is the primary locus of response to natural disasters and the disruption they create.

To summarize, in this research, a natural disaster is conceived of as an event, with both spatial and temporal dimensions that is the result of the intersection of socially manufactured community vulnerability to environmental extremes. The event creates conditions whereby normal community functioning is transformed or stressed by the creation of physical and social disruption. The occurrence of the natural disaster represents an opportunity to explore the effects of physical and social disruption on crime in the community.

IV. Outline of the Dissertation

This dissertation is organized around the specific research questions discussed earlier in this chapter—how disaster types and magnitudes influence the geographic and temporal distribution of violent and property crime rates. Chapter 2 provides an overview of relevant theoretical orientations, offers a clarification of how each theoretical approach is related to the research questions, introduces hypotheses derived from each theoretical orientation, and reviews empirical findings related to the predicted outcomes of these three orientations. I also note how each theory arrives at alternative explanations of crime patterns following disaster.

Chapter 3 offers a detailed overview of the study's methodological design. I begin with a brief description of the data collection and analysis phases, followed by a justification of the county as the unit of analysis and a discussion of the variables, their empirical operators, and the sources for these data. Next, I discuss the data sets, their contents, and the data re-coding procedures I employed. I follow that with a description of the statistical modeling procedures used in the research, and conclude by reiterating the hypotheses to be tested.

In Chapter 4, I begin my analysis by using the study's data to describe:

- the setting of the study in terms of the geographic distribution of natural disaster types;
- the temporal distribution of natural disasters and their types;
- the geographic distribution of index,[6] violent, and property crime rates;
- the empirical relationship between time and index, violent, and property crime.

In Chapter 5, I use Hierarchical Linear Modeling and Geographically Weighted Regression to test explicit hypotheses regarding the natural disaster magnitudes, and their effects on all *index crime*, *property crime*, and *violent crime*. Using relevant controls I test explicit hypotheses derived from each of the three theoretical orientations—the therapeutic community, social disorganization, and routine activity. I conclude the chapter with a brief discussion of the key findings.

Chapter 6 includes a summary of the findings and a discussion of their relevance to theoretical and methodological advances in the study of crime and disaster. I acknowledge of the limitations of the study and consider how future research might build

[6] Index crime refers to all crimes, property and violent, reported in the UCR data set. These are considered "Part I" offenses by the Federal Bureau of Investigation (James 2008).

on the findings revealed in this research. I conclude by highlighting the relevance of the study's findings to researchers, policy-makers, disaster management personnel, emergency service providers, and criminal justice professionals.

CHAPTER TWO: BACKGROUND AND THEORETICAL PERSPECTIVES

I. Introduction

This chapter offers an overview of the theoretical and empirical literature germane to the research questions proposed. Specifically, this chapter provides first, a discussion of three dominant theoretical approaches to the research question; second, a review of empirical evidence related to these theoretical orientations; and third, an introduction of the theory-informed variables of interest to be used in this study and outlines associated hypotheses.

II. Theoretical Approaches to Disaster-Related Crime

Three theoretical orientations are typically used to explain the effect of disaster on crime. First, Fritz's (1961) therapeutic community hypothesis predicts that when a disaster strikes, community members engage in altruistic behavior and norms of reciprocity increase. With these conditions, it is hypothesized that crime rates will *decrease* in the aftermath of disaster. The second orientation draws on theories of social disorganization (Park, Burgess, and McKenzie 1925; Shaw and McKay 1942; Thomas and Znaniecki 1918) and predicts an *increase* in criminal activity following disasters. The third orientation utilizes the routine activity theory of crime (Cohen and Felson 1979; Felson and Cohen 1980) and predicts that *increases* or *decreases* in criminal activity following disasters may occur and are conditioned by the level of guardianship, availability of suitable targets, and supply of motivated offenders in a community. Below, I discuss each orientation and review associated empirical evidence.

A. Fritz's Therapeutic Community

The earliest sociology of disaster researchers observed the emergence of altruistic behavior and increased social solidarity following disaster events. In 1920, Samuel Henry Prince noted that in the wake of the 1917 Halifax disaster in Nova Scotia, the affected community displayed "a very general consciousness which seemed to draw all together into a fellowship of suffering as victims of a common calamity" (1920: 63). In his account, Prince highlighted that social distinctions among disaster victims disappeared as all "shared each other's woes" (ibid.).

Forty-one years later, Fritz (1961) argued that a therapeutic community regularly arises following disaster and that this phenomenon explains social order following disasters. Highlighting popular misconceptions of disaster behavior, Fritz (1961) noted that disasters rarely create panic and chaos. Rather "convergence behavior" and cooperation can be considered an emergent disaster norm where individuals and groups combine their energies to meet collectively held needs (see also Fischer 2008; Quarantelli and Dynes 1976). In this regard, disasters may be conceived of as focusing events for those involved, creating high levels of altruism (Barton 1969) and effectively increasing levels of community cohesion.

In Fritz's terminology, disasters engender "situational therapeutic features" which unify the affected community. First, the disaster represents an external objective threat toward which collective action can be directed. Second, the remedial needs—search and rescue, restoration of basic services, etc.—of the event are often clear and uniformly understood as to create a general consensus of what actions should be taken. Third, a disaster may temporarily restructure the social order allowing for the discernment of innovative adjustments during the post-disaster emergency period. Specifically, people see "the possibility of wiping out old inequalities and injustices…[and] that these changes in the culture may be effected and continued lends a positive aspect to disasters not normally present in other types of crisis" (685). Finally, according to Fritz (1961), a disaster can act as an equalizing event whereby social distinctions may be temporarily eliminated within the impacted community, thus allowing for greater solidarity and cohesion.

A number of Fritz's propositions have been challenged or revised, such as the idea that disaster events are equalizing forces that level pre-existing status distinctions that mark society. For example, using qualitative and quantitative data on disaster impacts (property loss, injuries, and deaths) coupled with survey measures of social support following Hurricane Hugo, Kaniasty and Norris (1995) found that while helping behavior and social support increased following the storm, race and education moderated the emergence of altruistic behavior in the study communities. Specifically, African Americans and the less educated were less likely to report receiving help from other community members following the hurricane.

Bolin and Bolton (1986) reached similar conclusions with a comparative analysis of four disaster types—tornadoes, floods, earthquakes, and hurricanes. They found that the economically disadvantaged and minorities routinely faced the greatest difficulty in obtaining shelter and housing assistance during the disaster recovery process from these events. Likewise, in their review of the literature on poverty and disasters, Fothergill and Peek (2004), contend that disasters and the economic social structure are not independent and that disasters routinely reproduce social inequality as the poor are more likely to lack access to both public and private recovery assets. In their review of the literature on race-ethnicity and disaster, Fothergill, Maestas, and DeRouen-Darlington (1999) assert that throughout the stages of disaster, from preparation and warning to impacts and recovery, various racial and ethnic minority groups experience and respond to disasters in different ways. Importantly, socio-structural conditions of economic inequality associated with race and ethnic minority status increases vulnerability to disasters. Finally, in their review of literature on gender and natural disasters, Enarson, Fothergill, and Peek (2007) note that gender intersects with both race and/or ethnicity and class to further disadvantage women in disaster situations. As a whole, research documenting patterns of social support following disasters shows that community cohesion and networks of support are common, but can be stratified by race, gender, education, religion, and age.

Even though the therapeutic community hypothesis has been challenged by stratification and social vulnerability scholars, it continues to inform contemporary research regarding disaster and social order. An excellent example is Miller's (2007) analysis of an East Texas community's response to the effects of Hurricanes Katrina and Rita. In her qualitative analysis, Miller used a social capital framework to analyze the normative mechanisms of helping behavior of residents' aid to the survivors of the hurricanes. What made this research unique was that the altruistic community emerged in an area that did not experience direct physical damage from the hurricanes, and utilized existing social networks to meet the needs of displaced disaster survivors. While Miller (ibid.) did not investigate the effect of the therapeutic community on crime in Huntsville, the study underscores an important point for this research: Namely, disasters elicit helping behavior, and they do so by utilizing existing social support networks, even in areas not directly impacted by the events. The implication of this finding for this research is that even in areas that may be proximal to disaster events, the potential for the emergence of a therapeutic community exists.

Research investigating the effects of the therapeutic community on crime has notably focused on the act of looting. Looting is generally conceived as widespread opportunistic theft in the wake of a disaster event or social disruption (Quarantelli 2007; Quarantelli and Dynes 1970). Case studies of looting in the aftermath of a disaster have found that investigating looting is problematic because, first, many people may think their goods were taken, but they were really just lost during the event (Fischer 1998); and second, looting data is often colored by the confusion of looting with “appropriate” acquiring of essential survival supplies. For example, in the month following Hurricane Katrina, Barsky (2006), and Barsky, Trainor, and Torres (2006) toured sections of Louisiana and Mississippi to collect qualitative data regarding perceptions of looting. They found that while residents of the area concurred that looting did occur, there was no clear distinction between reports of looting and reports of appropriating behavior (the former was viewed by survivors as illegitimate and illegal; the latter was viewed as legitimate). This confusion may account for the discrepancy between researchers who assert that looting following natural disaster is common (Harper and Frailing 2010), and others who assert that looting following catastrophic events is relatively rare (Drabek 1986; Dynes and Quarantelli 1968; Fritz and Mathewson 1957; Gray and Wilson 1984;

Quarantelli 1994; Tierney, Lindell, and Perry 2001; Wenger, Dykes, Sebok, and Neff 1975).

Aside from looting, investigations of patterns of property and violent crime following disaster events generally support the therapeutic community hypothesis in that both violent and property crime either remain unaffected or decrease after disaster (Lemieux 1999; Quarantelli 1994; Quarantelli and Dynes 1970; Zahran et al. 2009). For example, in a recent publication, Leitner and colleagues used a spatial and temporal analysis to investigate the impact of Hurricane Katrina on reported crimes in Louisiana parishes (Leitner, Barnett, Kent, and Barnett 2011). Using Louisiana Uniform Crime Report data from January 2000 to June 2006, the authors analyzed monthly crime reports to determine how patterns of crime altered relative to pre-Katrina trends. They found that while two Louisiana parishes experienced an increase in reported crimes, the majority of parishes experienced either no change or a decrease in violent and non-violent crime rates relative to pre-Katrina trends (ibid. 258-259).

Similar findings were reported by Zahran and colleagues who investigated changes in crime patters in Florida for the years 1990-2005 (Zahran et al. 2009). Using natural hazard data from the Spatial Hazards Events and Losses Database for the United States (SHELDUS) and crime data from Florida Department of Law Enforcement's Uniform Crime Reports, Zahran et al. concluded that disasters had a modest effect in reducing the incidence of violent and property crime. However, their findings also indicated that the effect of the therapeutic community did "not extend to the most private and intimate spheres of social life" as an increase in domestic violence was associated with disasters and their impacts (ibid. 45). One possible limitation of the aforementioned studies which both found decreases in reported violent and property crime following disaster includes the effect of the disaster on citizen reporting of crimes as well as changes in the reporting practices of law enforcement during the period immediately following a disaster. As Barsky (2006) observed when researching looting during the immediate post-hurricane period, reporting of criminal activity declines as law enforcement personnel prioritized search, rescue, and crime control activities over record keeping.

In sum, Fritz's (1961) therapeutic community hypothesis argues that post-disaster behavior is oriented toward communal restoration, pro-social and altruistic behavior, adaptive action, and the promotion of safety. Negative effects of disasters such as property loss and suffering are experienced publically rather than privately and thus foster a sense of solidarity among members of the affected community. Such public experiences of suffering increases empathy and induces cooperation among groups who may have not previously acknowledged or observed the suffering of others. The implication of the emergence of a therapeutic community in the wake of natural disaster for this research is that increased social cohesion decreases the likelihood of criminal acts.

B. Social Disorganization Theory

The concept of social disorganization was first proposed by Thomas and Znaniecki (1918). They observed that systematically organized social institutions may become disorganized or experience a "decrease in influence of existing social rules of behavior upon individual members of the group" when the existing social organization is challenged and cannot meet the emerging needs of a changing social system (ibid. 68). Developing this idea further, Park, Burgess, and McKinzie (1925) highlighted how increasing racial heterogeneity associated with urbanization and migration in American cities during the early 20th century created conditions where traditional institutions of social control—the school, the family, and the courts—could no longer function to maintain social order. Further, the social disorganization observed by Park, Burgess, and McKinzie (1925) had a geographic character. Their "concentric zone theory" recognized that urban development reflected social processes of a perpetual displacement of residents. The constant growth of business centers at the heart of the city increased the pressure to migrate such that poverty and the most recently arrived immigrants concentrated in the city's center. The effect of this process of displacement was weakened familial and communal ties. Such weakened ties, according to this model were at the heart of social disorganization and resulted in higher crime rates in cities.

Shaw and McKay (1942) empirically tested the claims of these earlier social disorganization theorists and concluded that a neighborhood's social organization was central to understanding juvenile delinquency. Specifically, they demonstrated that racial and ethnic heterogeneity, economic status, and levels of residential (in)stability strained conventional institutions of social control. Further, Shaw and McKay (ibid.) recognized that while migration and diminished social control led to social disorganization and crime, neighborhoods characterized by social disorganization produced cultural values that transmitted delinquency. In short, neighborhood social disorganization effectively socialized "criminal traditions" through a vicious cycle (ibid. 173).

Building on Shaw and McKay's (1942) predictions, Sampson and Groves (1989) provide a more complex model of social disorganization based on their empirical tests of the hypothesis that economic status, ethnic heterogeneity, residential mobility, family disruption, and urbanization bring about social disorganization and subsequently an increase in crime rates at the community level (774). In their analysis, they note that social disorganization is mediated by the collective efficacy of a community in realizing the goal of maintaining social control. The structural dimensions of community efficacy, accordingly, refer to the prevalence and interdependence of formal and informal social networks in a community (ibid. 777). In sum, social disorganization, characterized by low socioeconomic status, ethnic and racial heterogeneity, residential mobility, family disruption, and urbanization is mediated by levels of social integration through informal and formal social networks that act to control crime and delinquency. Using rates of household and property victimization and violent crime victimization as measures of crime, they found that urbanization, socioeconomic status, heterogeneity, family disruption, and residential stability have a strong direct effect on formal and informal associational networks and accordingly, a strong direct and indirect effect on levels of victimization in a community.

Veysey and Messner (1999) utilized advanced statistical techniques to verify Sampson and Grove's conclusions regarding the mediating effects of indicators of social disorganization. They found that multiple mechanisms of disruption including levels of urbanization, social heterogeneity, family and friendship network disruption, and low socioeconomic status contribute significantly to increased levels of crime in an area. Browning, Feinberg, and Dietz (2004) report similar findings, but note that collective efficacy and social networks do not represent the same dimension of social (dis)organization. Specifically, they found that social networks, measured as interaction with neighbors, may actually facilitate criminal acts, thereby undermining the community's efficacy in controlling potential offenders. That is, social networks do have an effect on reducing crime in a community, but that effect depends on the level of community trust and social cohesion.[7]

As a whole, research investigating the effects of social disorganization on crime have tested whether indicators of social disorganization (racial heterogeneity, income-based estimates of socioeconomic status, and indicators of residential instability) have a verifiable influence on crime (Pratt and Cullen 2005). Meta-analytical research indicates that measuress of social disorganization, "are among the strongest and most stable predictors" of crime (ibid. 373). In the next section, I provide an overview of research that utilizes theories of social disorganization in the context of disaster.

C. Social Disorganization and Disaster

In contrast to the therapeutic community hypothesis, researchers using a social disorganization orientation when studying disasters view disaster events as an additional disorganizing factor. In this regard, disasters have the potential to create or aggravate existing social disorganization by disrupting the social cohesion the collective efficacy of a community and therefore may render the community unable to self-monitor and sanction anti-social behavior (Berkowitz 1993; Curtis et al. 2000; Davila, Marquart, and

[7] In this research social cohesion and community efficacy were measured using a "social capital index," which was constructed using survey data identifying networks and trust relationships among community members.

Mullings 2005; Siman 1984). Siegel, Bourque, and Shoaf (1999) highlight how disruption of a disaster event can have the effect of increasing crime:

> *…frustration and hostility can be directed toward the self or others. Although not always recognized, this hypothesized sequence of events assumes that the community affected by the disaster becomes socially disorganized. Thus, norms are relaxed that generally restrict the expression of socially unacceptable behavior, such as criminal violence. Individuals and groups may believe that such behaviors will either not be sanctioned, or will be forgiven or explained away as possibly inappropriate, yet 'understandable' in light of the perpetrators' experiences during or after the disaster* (266).

The disruption caused by a natural disaster can have life-changing effects. For example, a common situation for disaster survivors includes temporary evacuation or, increasingly, permanent displacement (see Weber and Peek 2012). Congruent with the predictions of social disorganization and the effect of residential instability, research shows that in such situations drug and alcohol use become more prevalent, increases in psychological and interpersonal stress is common, and a loss of social support networks is likely (Adams and Adams 1984; National Survey on Drug Use and Health 2008; Norris, Friedman, Watson, Bryne, Diaz, and Kaniasty 2002; Peek and Fothergill 2008). For example, Curtis, Miller, and Berry (2000) utilized child abuse reports and confirmations coupled with FEMA presidential declarations and interviews with Child Protective Service workers to investigate if there were higher incidence of child abuse associated with the 1989 natural disasters of Hurricane Hugo and the Loma Prieta Earthquake. The authors hypothesized that increased stress from the disaster events precipitated an increase in child abuse. In analyzing data from 11 months pre- and post-disaster, they found statistically significant evidence of an increase in child abuse and, informed by interview data, concluded that disasters have a negative impact on family and friend support networks that in turn led to increased incidences of child abuse.

Not all research, however, confirms the effects of the disaster-related stress and social disorganization. Siegel Bourque, and Shoaf (1999) utilized three successive cross-sectional surveys to investigate sampled community members affected by the 1994 Northridge earthquake to assess levels of post-disaster victimization and traumatic stress (Siegel et al. 1999). They compared their findings with National Crime Victimization survey data for the area to address the questions of whether social disorganization[8] and subsequent criminal victimization increased as a result of the earthquake. Controlling for common covariates for crime, they found no confirming evidence that crime increased in areas most directly impacted by the earthquake.

Empirical research investigating the coupling of disaster-created social disorganization with low socioeconomic conditions also provides mixed support for social disorganization theory. Using pre- and post-Katrina burglary rates, Harper and Frailing (2007) assert that the socioeconomic conditions, and especially high rates of inequality, in New Orleans prior to Hurricane Katrina explain an "astronomical" rise in burglary following the storm (see also Frailing and Harper 2010: 97). However, the research of Leitner and colleagues, which used more sophisticated statistical longitudinal analyses of pre- and post-Katrina crime rates, contradicted these findings (Leitner et al. 2011). Yet, there is some evidence to suggest that post-Katrina crime patterns in New Orleans reflected a displacement of crime to other cities. Varano, Schafer, Cancino, Decker, and Green (2010) investigated displacement of Hurricane Katrina survivors and

[8] Social disorganization was not directly measured in this research but indicated by a series of questions regarding how individual's social networks were disrupted and whether they had "life changes" in their employment or residence.

crime patterns in three cities—Houston, Phoenix, and San Antonio—that experienced an influx of Katrina evacuees. This research highlighted a number of disaster effects that can be clearly coupled with social disorganization theory—migration, residential instability, poverty, urbanization, and lack of social networks and community efficacy. For example, the authors note that the city of Houston alone accepted over 240,000 disaster survivors in the week following Hurricane Katrina. Such an influx clearly taxed Houston's educational, health, and social welfare systems. Further, the authors note that many of these evacuees where economically disadvantaged, either prior to the storm or as a result of it, and had been separated from their support networks. Using an interrupted time-series method to analyze UCR weekly crime reports in the three focal cities, the authors find modest support for the displacement of crime into Houston and Phoenix, but no statistically significant increases in San Antonio.

In summary, social disorganization theory predicts an increase in crime as a result of the disorganizing effect of natural disasters. Natural disasters threaten not only life and well being, they have the potential to traumatize individuals, families, and communities. Those who experience natural disasters encounter a suite of financial, residential, emotional, and community-wide stressors that threaten the efficacy of a community to respond to and suppress deviant acts.

D. Routine Activity Theory

Routine activity theory was proposed by Cohen and Felson (1979) and Felson and Cohen (1980) to suggest that changes in crime rate patterns post-World War II were the result of changes in the socio-structural organization of "routine" or everyday activities.

In essence, they argue that the structure of everyday social activity and its relationship to direct-contact predatory violations[9] reflects the convergence of three necessary elements in both space and time: (1) the availability of suitable targets such as property or individuals, (2) the absence of capable guardians such as police or community members and, (3) the presence of motivated offenders (Cohen and Felson 1979: 589). The probability that crime will occur is increased when these three conditions converge. Further, the absence of any one of these conditions is sufficient to prevent the exercise of direct-contact predatory violations.

Routine activity theory is grounded in human ecology theory,[10] which posits that legitimate symbolic and communalistic human activity is organized in both time and space (Hawley 1950). Simply stated, the organization of criminal activity reflects a socio-structural interdependence with the rhythm, tempo, and timing of legitimate activity (Felson and Cohen 1980). This interdependence is conceived of as "predatory" whereby criminal offenders acquire a symbolic and physical gain with their illegal acts to the detriment of their victims. Importantly, the technological organization of society—e.g. transportation and communication technology—and the legitimate use of this technology facilitates this interdependence. While legitimate community activity is enabled, structured, and patterned by the use of technology, offenders increase their criminal efficiency with its use (ibid. 590-591).

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[9] Direct-contact predatory violations are "illegal acts in which someone definitely and intentionally takes or damages the person or property of another person" (Cohen and Felson 1979: 589).
[10] Lilly, Cullen and Ball (2007) refer to this orientation as "environmental criminology."

i. The Offender

As a macro-level theory, the original approach to routine activity did not offer individualistic explanations of criminal acts—criminal inclination was simply assumed, and the supply of motivated offenders was taken as a given. Subsequent revisions to the theory accounted more carefully for the offender's motivations (Clark and Felson 1993) and considered the effect of social control of offenders (Felson and Gottfredson 1984).

To account for the motivation of the offender, the notion of the criminal as a rational actor can be invoked and a rational choice explanation of criminal motivation is now considered compatible with routine activity theory (Clark and Felson 1993; Lilly, Cullen, and Ball 2007). Rational choice theory uses a utilitarian framework to explain human behavior in cost-benefit terms. In the context of the crime, offenders are conceived of as goal-oriented, rational actors, who calculate their behavior and its costs based on a set of preferences or utilities. In line with this reasoning, Felson (2002) argues that crime is less likely to occur when a crime is more difficult to commit—the difficulty of the crime is directly related to the both the availability of the potential targets and the level of guardianship. When suitable targets are unavailable, they must be sought out, thereby costing a potential offender time and energy. Likewise, the existence of capable guardians increases the likelihood of apprehension or discovery in the commission of an act. Discovery or the increased risk of discovery increases the cost if the potential offender wishes to avoid detection.

To address issues of social control, Felson (1995) utilized Hirschi's (1969) control theory (see also Felson and Gottfredson 1984), and noted that an offender's social bonds may have the effect of reducing an individual's willingness to commit a crime. The addition of this theoretical element means that the offender, his or her rationale, and the control of his or her behavior are conditioned by "capable guardians" not originally theorized by Cohen and Felson (1979).

ii. Guardianship

The notion of guardianship, as originally proposed by Cohen and Felson (1979) and Felson and Cohen (1980), focused on those individuals who have the capability to prevent criminal acts. These included both formal and informal guardians such as police and community members. Without developing the concept further, Cohen and Felson (1979) simply noted that guardianship by ordinary citizens during their legitimate routine activity "links social roles and relationships to the occurrence and absence of illegal acts" (590). The connection of social roles and relationships inherent in illegal acts and the absence thereof is central to Eck's (2003) further development of the notion of guardianship.

Eck's (2003) expansion of this element of routine activity theory includes a concept of guardians as "controllers" or those who discourage crime through their particular relationship to the potential offender, the target, or the site of the potential crime. Three types of controllers exist in Eck's framework—the guardian, the intimate handler, and the manager. The first type of controller, the guardian, acts as a custodian of his or her own property. This guardian is conceived of in much of the same way as Cohen and Felson's (1979) guardian. There is a direct relationship between the potential target and the guardian. That is, the guardian reduces the likelihood of crime by being present to potentially thwart the criminal act.

The second controller is called a handler. A handler's relationship to the potential offender is direct as handlers have social ties to the offender and include people such as family members, significant others, or acquaintances. The social bonds shared between potential offenders and handlers act to control the potential offender whenever the handler is present. Thus, while not directly acting as a guardian of suitable targets, the handler's presence precludes the commission of crime.

The third type of controller is the manager. His or her relationship to the crime is through their control of the location or place where a crime might occur. Managers maintain the functioning of particular places through their roles as employees. Given this, managers may be people such as teachers, store clerks, or even doormen. As with both handlers and guardians, managers may not act during their routine activity as formal crime controllers, but rather control crime through their presence in regard to their relationship with the potential offender, the target, and the physical location associated with the potential crime.

In sum, the handler supervises the likely offender, the guardian supervises the likely target, and the manager supervises the physical place. Presence of any of these three is thought to diminish the likelihood that a crime will occur.

iii. The Suitable Target

Cohen and Felson (1979) argued that suitable targets included both property and persons. While their discussion of persons as "suitable targets" is minimal, they note that victims of rape, robbery, assault, and personal contact larceny is generally a function of the victim's proximity to motivated offenders and lack of guardianship, rather than a target's suitability. In contrast, Cohen and Felson's (ibid.) discussion of property as suitable targets highlights "expensive," and "durable" items, such as automobiles and electronic appliances, as having the highest probability of theft (595). Highlighting expensive and durable items as suitable targets reflected their substantive focus of explaining post World War II increases in crime as reflecting changes in routine activity and increases in relative affluence. With this framework, property crime is not a function of economic deprivation as a theory of social disorganization might assert, but rather a function of relative affluence and suitable targets associated with personal wealth. This claim that prosperity could have the effect of increasing crime rates has been criticized as ignoring the role of poverty and inequality in explaining crime (Lilly et al. 2007).

In response to this criticism Felson (2002) observed that in areas where poverty is concentrated, there is an increase in suitable targets because of the proximity to commercial and industrial centers—areas which have a disproportionately high number of suitable targets relative to residential suburban areas. Areas of concentrated poverty thus effectively make targets more suitable as there are more opportunities to offend. With this defense, Felson still fails to adequately address how political economy structures illegal opportunity (Lilly et al. 2007).

iv. Space

The notion of physical "space" is central to understanding routine activity and crime as environmentally conditioned. While patterned or routine behaviors create conditions whereby suitable targets and motivated offenders converge, they must do so in a particular space. This orientation thus highlights the physical environment as mediating crime. Importantly, the characteristics of space are not disconnected from the considerations of the potential offender, guardians, or suitable targets. In this case, the notion of space in routine activity theory emphasizes the crime event in lieu of theories of criminal actors themselves (Eck and Weisburd 2003).

Early sociological research into crime highlighted geographic space as indicative of crime and its concentration (Guerry 1833; Shaw and McKay 1942). These early macro-level approaches emphasized characteristics of the urban environment as facilitating certain types of crime. Micro-level analyses of the specific places were crime occurs note the effect of urban design and architecture as facilitating criminal opportunity and suggest that place be considered a central component of theories of crime and prevention (Eck and Weisburd 2003).

Rational choice theory and crime pattern theory inform the contemporary development of routine activity theory and its consideration of place in theories of crime (Brantingham and Brantingham 1975). Crime pattern theory proposes that crime and criminal opportunity reflects the structure of routine activity, awareness of one's space and the urban structure and how space intersects with social structure to create a "crime template" (Brantingham and Brantingham 1975). A crime template is a series of regularized activity that structures a decision to commit a crime. Space influences the crime template by creating "activity spaces" or places where a potential offender intersects both the potential target and when that intersection is congruent with the offender's regularized activity.

Crime pattern theory thus combines elements of both routine activity theory and rational choice theory to explain the distribution of crimes in space. In this regard, the rational offender, while engaging in regular or routine activity will recognize spaces with suitable targets that lack capable guardians. The patterns of their own activity within these spaces structure the choices of the potential offender and influence his or her decision of whether to commit a crime and for which target. In sum, crime pattern theory situates space with reference to potential targets by focusing on how space is used by potential offenders for both legitimate and illegitimate activity and how a potential offender's choices are structured by that activity.

On the whole, meta-analytic research investigating the effects of variables relevant to routine activity theory on crime (measures of formal guardianship and unemployment—a proxy for motivated offenders) has found only modest support for this theoretical orientation and its predictors of criminal activity (Pratt and Cullen 2005: 413-414). In the next section, I turn to a discussion of research that demonstrates how routine activity theory may be used to frame an analysis of crime following disasters.

E. Routine Activity Theory and Disaster

Importantly for this research, routine activity theory is centrally concerned with *the nature of opportunity* for criminal acts. Research that uses routine activity theory to investigate disaster and crime commonly states that a disaster event has the potential to create changes in the structure of a community's routine activity such that an increase in the likelihood suitable targets, motivated offenders, and lack of guardianship converge in time and space (Cromwell et al. 1995; Trainer and Bolin 1976).

Empirical investigations of routine activity and crime following disasters provide mixed support for this orientation. Cromwell et al. (1995) employed routine activity theory to frame their qualitative investigation of crime in Dade County, Florida following Hurricane Andrew. Through semi-structured interviews with community members, police officers and officials, and individuals arrested for hurricane-related offenses, Cromwell et al. investigated how the newly established routine of "digging out" from the disaster influenced the supply of motivated offenders, suitable targets, and absence of guardians in the aftermath of the storm. They found that immediately after the storm, motivated offenders reflected a particular subset of criminals. These included "the most hard-core criminals" and juveniles. Police noted that juveniles committed the majority of reported crimes in the immediate hours following the storm and that these crimes were "primarily looting stores and businesses" (ibid. 61). This finding was explained in the context of participation in the "new routine" of search, rescue, and clean up—as young offenders were often excluded from these activities. However, once the immediate post-impact phase of the of the storm had passed, police reported a relative influx of motivated out-of-town criminal "entrepreneurs" seeking to take advantage of the opportunity created by the storm. Notably, the character of the crimes associated with this group of offenders did not fit the definition of "direct-contact predatory violations" but reflected activities such as price-gouging. A third type of offender with "moderate to high criminal motivation" also emerged in the several weeks following the storm. These included construction workers and contractors whose rebuilding activities were often coupled with fraud or civil disruption. Many of these workers were reported to engage in criminal activity associated with lifestyle activities of "getting drunk, getting into fights, and creating problems" (ibid. 62).

Cromwell’s et al. (1995) investigation also found that following the hurricane, physical security of homes and businesses was notably lacking. This increase in suitable targets was the result of the devastation created by the storm and the unavailability of a communication infrastructure. An additional increase in suitable targets included “a large number of cash-carrying home-owners” (62). The increase in this population was the result of insurance claims activity and the emergence of a cash-only economy that reflected the unavailability of electrical power and temporary closure of local banks.

In terms of guardianship, Cromwell et al. (1995) noted that while damage to road and communication infrastructure decreased the availability and efficacy of formal police guardianship, “both police and citizen respondents agreed that neighborhood social solidarity increased…and that informal social controls formed almost immediately” (63). What emerged was a series of citizen-led neighborhood patrols, where citizens guarded not only their own property, but that of their neighbors as well. A notable characteristic of these emergent community-patrolling activities was the use of firearms as both a symbolic and direct deterrent to crime. Coupled with an armed patrol, community members regularly created painted signs indicating that looters would be shot. As one respondent noted “those signs were symbolic of guardianship and territoriality. They gave looters a message ‘this is my property and I’ll defend it’”(ibid. 65). Cromwell et al. did not investigate whether or not disaster increased crime. Instead they found that motivated offenders, suitable targets, and guardianship can all be affected by disaster in different ways.

Curtis and Mills (2011) demonstrated how motivated offenders, suitable guardians, and lack of guardianship can converge in a post-disaster environment. Using a

GIS analysis augmented with video documentation the Holy Cross Neighborhood following Hurricane Katrina, they investigated how building occupancy and the conditions of the residential infrastructure patterned the geographic distribution of crime. They found that crime was inversely related to the degree of resettlement and rebuilding activity in the neighborhood. Curtis and Mills (2011) concluded that crime occurrence in the Holy Cross neighborhood reflected both lack of guardianship and the opportunity to commit criminal acts.

LeBeau (2001) used routine activity theory to investigate the effects of Hurricane Hugo on calls for police service. He found that calls for police services increased substantially after the storm. Further, there was a statistically significant increase in the reports of burglary and “man with a gun” complaints to the police. LeBeau concluded that the hurricane changed routine activity in such a way that it increased informal guardianship in the city.

In summary, routine activity theory predicts that if a disaster event is capable of increasing the likelihood that three conditions—suitable targets, motivated offenders, and lack of guardianship—converge in time and space, crime in an affected community is also likely to increase. However, disasters motivate community members to act as informal guardians, or if guardianship increases in a disaster’s wake, routine activity theory predicts a decrease in crime following a disaster.

III. Summary of the Theoretical Approaches to Disaster and Crime

The three theoretical orientations most often employed to explain the effect of disaster on crime are the therapeutic community hypothesis, social disorganization theory and routine activity theory. As noted above, each of these community-level theories offer differing predictions as to how a disaster will affect a community and crime patterns in disaster areas and areas proximal to disaster zones. Fritz's (1961) therapeutic community hypothesis predicts that when a disaster strikes, community members engage in altruistic behavior and norms of reciprocity increase. With these conditions, it is hypothesized that crime rates will *decrease* in the aftermath of disaster. Research reviewed above notes that the therapeutic community may in fact extend beyond the zone of disaster impact (Miller 2007). However, the emergence of a therapeutic community may be hindered by pre-exiting social inequality associated with race, class, gender, religion, and age (Enarson et al. 2007; Fothergill et al. 1999; Fothergill and Peek 2004; Kaniasty and Norris 1995).

The second orientation draws on theories of social disorganization (Park et al. 1925; Shaw and McKay 1942; Thomas and Znaniecki 1918) and predicts an *increase* in criminal activity following natural disasters. Social disorganization theory proposes that communities characterized by residential instability, low socioeconomic status, racial and ethnic heterogeneity, and poor collective efficacy do not possess adequate resources to control crime (Sampson and Groves 1989; Sampson, Morenoff, and Earls 1999; Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997; Shaw and McKay 1942). Researchers using social disorganization theory when studying disasters view disaster events as an additional disorganizing factor. In this regard, disasters have the potential to create or aggravate existing social disorganization by disrupting the collective efficacy of a community and may lead to the inability of the community to self-monitor and sanction anti-social behavior (Berkowitz 1993; Curtis et al. 2000; Davila et al. 2005; Siman 1984).

The third orientation utilizes the routine activity theory of crime (Cohen and Felson 1979; Felson and Cohen 1980) and predicts that *increases* or *decreases* in criminal activity following disasters may occur and are conditioned by the level of guardianship, availability of suitable targets, and supply of motivated offenders in an affected community. For the purpose of this research, it is notable that different disaster types may affect changes in guardianship, availability of suitable targets and supply of motivated offenders in different ways. As Cromwell et al. (1995) demonstrated, this is also true during various stages of disaster recovery and reconstruction.

A keen reader of the above review may note that while these theoretical orientations offer differing predictions regarding the relationship between disaster and crime, they share a number of important elements when describing the source of social control of crime. For example the therapeutic community hypothesis and social disorganization theory share a concern with community efficacy and social cohesion as they act as social controls on crime. Likewise, the "handler" revision to routine activity theory is also grounded in a social capital crime control framework. A second shared element among the theoretical traditions includes the notion that social support networks are stratified by class (therapeutic community hypothesis), and that collective efficacy is partially the result of socioeconomic status (social disorganization theory). This shared concern with how social class may have an effect on the social organization of the community response to disaster suggests an important relationship that should not be neglected in the analysis.

IV. Conceptual Variables and Hypotheses

Based on this review, a number of key variables are suggested in order to test the hypotheses suggested by each of the three theoretical orientations and associated empirical research. To prefigure the next chapter on the methodological design, the present section briefly reviews the competing hypotheses associated with each theory and identifies which variables will be employed to test these hypotheses in the context of disaster magnitude and crime.

Hypothesis 1: The therapeutic community thesis suggests that disaster alone operates to stimulate the formation and organization of an altruistic or therapeutic community, which in turn reduces the likelihood that crime will occur. Therefore, a disaster's magnitude should be *negatively* related to crime rates.

Hypothesis 2: According to the social disorganization theory, disaster magnitude alone should be *positively* related to an increase in crime rates in an area.

Hypothesis 3: According to social disorganization theory, in areas possessing the empirical characteristics associated with social disorganization—high poverty, high economic inequality, high racial and ethnic heterogeneity, and low levels of community efficacy—a disaster's magnitude will be *positively* related to an increase in crime rate.

Hypothesis 4: According to routine activity theory, the presence of formal and informal guardianship, the availability of suitable targets, and the presence of motivated offenders suggests that disasters may limit or enable criminal activity, and that this effect depends on the disaster's effect on these conditions. Therefore, a disaster's magnitude will have a variable effect on crime rates as these conditions vary according to a disaster's type.

V. Concluding Remarks

This review reveals that the three dominant approaches to theorizing crime and disaster offer contradictory predictions. Empirical research supporting each theoretical framework is also inconsistent. These contradictory findings may be the result of unreliable data, unrepresentative and small sample comparisons, limited geographic representation, and non-equivalent case comparisons examining disasters of different types and magnitudes. It is these limitations which this research seeks to remedy. With the above theories and predictions in mind, Chapter 3 offers a detailed description of the research design. The present research is aimed at addressing the limitations of earlier attempts to investigate the question of whether natural disasters of different types and magnitudes differentially affect crime outcomes?

CHAPTER 3: CONCEPTUAL AND METHODOLOGICAL DESIGN

I. Introduction

This chapter offers a detailed explanation of the research design, describes the process of obtaining and managing the data relevant to this dissertation, and coding its content to reflect relevant theoretical constructs. I follow this with a discussion of the unit of analysis, describe the independent and dependent variables (including their sources and operationalization), and offer some descriptive accounts of the disaster data's content.

II. Research Design

This research entailed three phases of data management and statistical modeling. *Phase one* involved data collection and management of the relevant variables discussed below. Eight different organizations or database repositories were accessed to obtain the data required for this dissertation. Because of the different data recording procedures used by these organizations, data were recoded and combined into data sets appropriate for subsequent statistical techniques (Mitchell 2010; Murray 2010; Singer and Willett 2003; Theobald 2007). *Phase two* employed basic statistical techniques to investigate simple relationships among variables. Exploratory and descriptive analyses using univariate and bivariate statistics and spatial displays of the data were used to inform more complex multivariate modeling pursued in phase three (Berry and Feldman 1985;

Lewis-Beck 1980; Theobald 2007). In *phase three*, a combination of hierarchical linear modeling (HLM) and geographically weighted regression (GWR) was used to test explicit hypotheses (Charlton and Fotheringham 2009; Pearce 1999; Rabe-Hesketh and Skrondal 2008; Singer and Willett 2003). The data were managed using Microsoft Excel and STATA, spatial modeling was accomplished using GeoDA and ArcGIS, and higher-order statistical analysis was conducted using STATA.

III. The Unit of Analysis

The unit of analysis for this study is the county. Counties are identified by the variable *FIPS*, or the "Federal Information Processing Standards" identifier. The continental United States is comprised of 3,141 counties that vary in dimensions relevant to this research. Variable geographic diversity of latitude, longitude, altitude, aridity, coastal proximity, and land area are related to natural disaster types and their impacts (Guha-Sapir, Hargitt, and Hoyois 2004; Mileti 1999a). Likewise the intersection of environmental conditions with regional characteristics such as population, relative disaster risk, and county-level crime rates highlight the need to consider counties—whose values on these indicators vary—as an important analytical unit. Moreover, the choice of the county as the unit of analysis was logistically warranted. First, the county as a spatial unit provides the highest resolution for longitudinal data analysis. Second, data for all the hypothesized predictors are only available at the county scale or higher. Although some of the data for the predictors are available at the more refined scale of census tracts, the data for these units could not be reconciled with the dependent variables of annual crime rates. Third, the variable *time* could easily be integrated into the periodicity of data collection and reporting schedule. Unless stated otherwise, all variables and their operators are represented at the county level.

The identification and geographic indicator variable, *FIPS*, was obtained from the TIGER/line shape files from the U.S. Census Bureau. Two shape files were used in the analysis: a shape file for the years 1995-2001, and a shape file for the years 2002-2008. The shape files represent county borders for the study period. *FIPS* was essential to the data management process of the research as the combination of all data sources discussed below required a common indicator for which to merge the data. Shape files were managed in ArcGIS version 10.1.[10]

Several *FIPS* indicator changes occur in the TIGER/line shape file for the study period. The first included the creation of Broomfield County, Colorado in 2002. The creation of Broomfield County in 2002 necessitated the use of the two different TIGER/line shape files. Second, the county of Dade, Florida changed its name to Miami-Dade and *FIPS* designation in 1997. This county's geographic borders did not change. To account for this change, the pre-1997 *FIPS* code was recoded to reflect the new *FIPS* indicator. Also in 1997, Yellowstone National Park, Montana was dissolved as a county equivalent. Data from this county was excluded from the analysis. These above changes to the TIGER/line shape files were also repeated for the data sets below. Finally, a number of cities in Virginia are identified as counties according to the Census Bureau. These cities were dissolved into their surrounding counties according to the Bureau of Economic Analysis codification regime.[11]

[10] Map projections for all shape file data sets are North America, Albers Equal Area, Conic, unless stated otherwise.
[11] The Bureau of Economic Analysis collapses these cities based on contiguity or inclusion in the county of interest. A full listing of these combined counties is available upon request.

IV. DEPENDENT AND INDEPENDENT VARIABLES

This section provides a description of all variables used in the research, their operational definition, a clarification of the data sources for these variables, and descriptive characteristics of the data's content. Broadly, variables included in the analysis include *crime measures*, *time*, *geographic space*, *natural disaster variables*, *socio-demographic variables*, and *social order variables*.

A. Measures of Crime

Crime outcomes, the dependent measure, were measured as the annual rates of crime reported to police in a county. The crime rate was calculated using equation 3.1:

$$\left(\frac{\text{Number of Crimes Reported}}{\text{Population}}\right) \times 100,000 = \text{Crime Rate per } 100{,}000. \qquad \text{[Equation 3.1]}$$

Sub-categories of crime types used in the analyses included *index*, *property,* and *violent* crimes. *Index crimes* are measured as the sum total of property and violent crimes. *Property crimes* are measured as the numbers of *burglaries*, *larcenies*, *motor vehicle thefts*, and *arsons* in a county. *Violent crimes* are measured as the numbers of criminal *homicide*, *forcible rapes*, *robberies*, and *aggravated assaults*. Twelve rates for all specific crime types were calculated using equation 3.1. For modeling purposes, all crime rates were log-transformed for normality. Definitions for these sub-types of crime are as follows (James 2008: 54-55):

- Criminal Homicide: "a) Murder and non-negligent manslaughter: The willful (non-negligent) killing of one human being by another. Deaths caused by negligence, attempts to kill, assaults to kill, suicides, and accidental death are excluded. Justifiable homicides are classified separately and the definition is limited to: 1) the killing of a felon by a law enforcement officer in the line of duty; or 2) the killing of a felon, during the commission of a felony, by a private citizen. b) Manslaughter by negligence: The killing of another person through gross negligence. Deaths of persons due to their own negligence, accidental deaths not resulting from gross negligence, and traffic fatalities are not included in this category 'Manslaughter by negligence.'"

- Forcible Rape: "The carnal knowledge of a female forcibly and against her will. Rapes by force and attempts or assaults to rape, regardless of the age of the victim, are included Statutory offenses (no force used—victim under age of consent) are excluded."[12]
- Robbery: "The taking or attempting to take anything of value from the care, custody, or control of a person, or persons by force or threat of force or violence and/or by putting the victim in fear."
- Aggravated Assault: An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded."
- Burglary (breaking and entering): "The unlawful entry of a structure to commit a felony or theft. Attempted forcible entry is included."

[12] In 2012 the FBI altered the definition of rape to "The penetration, no matter how slight, of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim." (Federal Bureau of Investigation 2012).

- Larceny-theft (except motor vehicle theft): “The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples are thefts of bicycles, motor vehicle parts and accessories, shoplifting, pocket-picking, or the stealing of any property or article that is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, confidence games, forgery, check fraud, etc. are excluded.”
- Motor vehicle theft: “The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on land surface not on rails. Motorboats, construction equipment, airplanes, and farming equipment are specifically excluded from this category.”
- Arson: “Any willful or malicious burning or attempt to burn, with or without intent to defraud, a dwelling house, public building, motor vehicle or aircraft, personal property of another, etc.”

All crime data were obtained from the National Archive of Criminal Justice Data (NACJD), U.S. Uniform Crime Report (UCR) database, county-level detailed arrest and offense data (U.S. Department of Justice 1995-2008). The data were downloaded through the Inter-university Consortium for Political and Social Research (ICPSR) database portal. The UCR data represent the most comprehensive source of data on county-level crime outcomes. Annual county population estimates, used to calculate crime rates, were obtained from U.S. Census data whose source is discussed below.

The UCR data are, in the best scenario, reported numbers of crimes, of a particular type, in the county of interest and for the year observed. However, because of incomplete reporting on the part of the individual law enforcement jurisdictions, a series of imputation procedures are used by the UCR staff. The imputation process is available in the data set documentation for each study year (U.S. Department of Justice 1995-2008).[13]

A discussion of several other data management procedures relevant to the UCR data used in this research is required. First, there were a number of *FIPS* id numbers in the UCR data that did not match the TIGER/line shape file *FIPS* codes. Investigation revealed certain states and/or jurisdictions did not report county-level data and that state estimates were included in the UCR data. These states included Connecticut, Vermont, and New Jersey. Per the data set documentation, the UCR staff allocated the number of crimes per county according to population estimates for counties in these states, during the study years (U.S. Department of Justice 1995-2008). Thus, use of these counties, and their data required recoding the *FIPS* identifiers to reflect the county equivalent. A second issue with the UCR data included crimes reported by the New Jersey and New York Port Authorities. These cases were removed because no geographic indicator (*FIPS*) could be assigned to each year's estimates. As such, the estimates for New Jersey and New York for each year, 1996-2008, are conservative. Third, beginning in 2008, U.S. Tribal agencies began reporting to the UCR. Again, these data were left out of the analysis because they could not be matched on the unit of analysis. Finally, a total of 4,383 observations in the UCR data were missing data. These observations were excluded from the analysis.

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[13] In general, but not regular for each data year used in this research, data are imputed for the states of Illinois, Kansas, Montana, Kentucky, New Hampshire, Vermont, Delaware, Wisconsin, Maine. Only data for counties in Illinois are consistently missing for multiple years between 1995 and 2008.

B. Time

The discrete measure of *time*, in years, is fundamental to HLM procedures. Its inclusion in the model is to explicitly control for serial (temporal) autocorrelation among county-level observations. The data used in the analysis represented 14 years, beginning in 1995 and ending in 2008.[14] The measure of *time* was "centered" at zero to make interpretation of results manageable (Singer and Willett 2003: 29).

C. Geographic Space

Geographic space was used to explicitly control for spatial autocorrelation in the HLM maximum likelihood estimation modeling procedures (Legendre 1993; Moran 1948; Ord and Getis 2010; Theobald 2007; Tobler 1970). Geographic space is measured by generating the variable spatial *lag term* using the geographic analysis computer program GeoDa. The variable quantifies the spatial proximity of counties to one another and is a statistical control for spatial dependence. Proximity in generating the spatial weights matrix was defined as "first order contiguity" using a "queen" neighborhood.[15]

D. Natural Disaster Variables

Four natural disaster variables were used in this research. First, *FEMA declaration*, is a binary variable used to identify counties that experienced a

[14] Choice of study period reflects the availability and content of the data at the beginning of the research endeavor. For example, as of 2/8/2012, the UCR data for 2009 was available but the variables and their operators had changed and could not be compared to earlier UCR data sets; the UCR data for 2010 had not been released.

[15] For this research, spatial analysis requires a definition of the county's "neighborhood" or which geographic area is specified as a potential influence on the dependent measure. That is, are neighbors correlated with one another on the dependent measure? The queen neighborhood defines the neighborhood in terms of 8 axial directions relative to the county of interest.

presidentially-declared disaster and qualified for federal disaster funding during a given year. *FEMA declarations* used in this research are of two types. These include “Major Disaster Declarations” and “Fire Management Assistance Declarations”.[16] The data source for *FEMA declarations* was the Federal Emergency Management Agency’s inventory of FEMA disaster declarations (FEMA 2011b).

The second disaster variable used in the analysis was the Disaster Effect Magnitude Index (DEMI). The DEMI index was developed specifically for this research and is a relative composite score representing the overall impact of hazard events in a county in a given year. It was calculated using total annual property damage, crop damage, injuries, and fatalities that were the result of the natural hazard events.[17] Calculating DEMI requires the use of four sub-indices, one for each category of economic and human impacts. Each sub-index is a proportion of the maximum annual loss total (property damage, crop damage, injuries, and fatalities) for all counties during the study period. The calculation for DEMI is shown in Equation 3.2 and 3.3:

$$\text{DEMI} = \left(\frac{\Upsilon}{\Upsilon_{\max}}\right) \times 100, \qquad \text{[Equation 3.2]}$$

and

$$\Upsilon = \frac{d_{1_i}}{d_{1_{\max}}} + \frac{d_{2_i}}{d_{2_{\max}}} + \frac{h_{1_i}}{h_{1_{\max}}} + \frac{h_{2_i}}{h_{2_{\max}}}, \qquad \text{[Equation 3.3]}$$

[16] The FEMA declaration process involves a request application made by the governor of the impacted state and includes impact assessments and a commitment of state funds toward the recovery process. FEMA staff review the request and make recommendations to the President, based on the specifics of the event and whether the disaster exceeds the community and the state’s ability to recover (FEMA 2011a).

[17] These loss totals do not fully capture the full effects of disasters in terms of the disruption of routine activity, loss of social networks, loss of employment and production activity, etc. These hazard indicators represent the most reliable and comprehensive data available to indicate the relative size of a disaster. A further discussion of a disaster’s magnitude and the limits to this variable is provided in Chapter 6.

where *i* is the individual county in a given year, d_1 is property damage, d_2 is crop damage. h_1 and h_2 are human injuries and deaths, respectively. The subscript "max" indicates the maximum observed losses for each loss category in Equation 3.3, and the observed maximum value of Υ for the study period in Equation 3.2. As is apparent in equation 3.2, DEMI is scaled from 0 to 100 where 0 indicates no losses in a given year, and 100 indicates the largest relative impact from hazard events during the study period. Finally, for modeling purposes, DEMI was log-transformed for normality. The resulting variable used in the analysis is identified as *lnDEMI.* The primary source of data to estimate the losses used to calculate DEMI was the Spatial Hazard Events and Losses Database for the United States (SHELDUS) version 8.0.[18] These data were also utilized to create the remaining two disaster variables.

The third natural disaster variable used in the analysis was *hazard type*. Raw data records by *hazard type* included 17 different types of natural hazards for the study period.[19] These hazard types were recoded into 12 alternative groupings following the convention of Borden and Cutter (2008). The resulting *hazard types* are displayed as the "Generalized Category" in Table 3.1 below. The generalized category reflects groupings of hazards that are similar in physical origin or physical effects. For example, both earthquakes and tsunamis result from seismic activity. In the section below, I offer a detailed description of the disaster and hazard data and the operationalization process to prepare this critically important measure for analysis. For HLM modeling purposes, the

[18] The main source for SHELDUS raw data is the National Climate Data Center (NCDC), although a total of 18 data sources are used to develop the database. For example, to derive impact estimates for earthquakes, SHELDUS uses the National Geophysical Data Center, Earthquake Research Institute, University of Tokyo, Japan. See SHELDUS (2011) Metadata for a listing of these data sources.
[19] SHELDUS records 18 disaster types. For the study period and area there were no volcanic eruptions, reducing the number of hazard types to 17.

hazard types are binary variables indicating presence or absence of that hazard type in the county during a given year.

Table 3.1: Generalized SHELDUS Hazard Types

SHELDUS "Raw" Category	Generalized Category
Coastal	Coastal (e.g. storm surge, rip currents, coastal erosion)
Flooding	Flooding (e.g. flash, riverene)
Earthquake	Geophysical
Tsunami/Seiche	
Drought	Heat/Drought
Heat	
Hurricane/Tropical Storm	Hurricane/Tropical Storm
Lightning	Lightning
Avalanche	Mass Movement
Landslide	
Fog	Severe Weather
Hail	
Severe Storm/Thunderstorm	
Tornado	Tornado
Wildfire	Wildfire
Wind	Wind
Winter Weather	Winter Weather

The fourth and final disaster variable included in the analysis was the number of hazard events indicated by SHELDUS that impacted a county in a given year. This variable was included as a necessary control to assess the effect of the DEMI, independent of the number of events that caused measurable property and crop damage, injuries or fatalities. To contextualize this variable, consider two different counties that have an equivalent DEMI score. In county A, 25 events caused the sum total of all damage and human losses. In county B, one event accounts for all losses indicated by the DEMI score. Thus in county A, disaster is chronic, while in county B it is acute. The disruption to the social system in county B should be characteristically different from that in county A. For modeling purposes, the variable, number of hazard events, was log-transformed for normality. The resulting variable used in the analysis is identified as *lnEvents*.

As was indicated in Chapter 2, the hypothesized effect of disaster on crime depends on the theory used to describe the relationship between the variables. A discussion of these competing hypotheses in the context of the empirical indicators is thus provided at the end of this chapter.

E. Socio-demographic Variables

Socio-demographic variables included in the modeling procedure act as theoretically relevant statistical controls and were used to test hypotheses derived from each of the theories. *Population size* was measured as the total number of people residing in a county and was used to calculate county-level crime rates. The variable percent of the population who are male age 15-24 (*pctMale15-24*) is included in the analysis as a proxy for motivated offenders, as it is well known that criminal acts are committed disproportionately by male members of this age group (Hirschi and Gottfredson 1983). That is, *pctMale15-24* will be positively related to crime rates.

Several socio-demographic indicators of social disorganization were also utilized in the analysis. The first is the local Theil Index of income *inequality* (Theil 1967; Theil 1996). The local Theil Index was derived from income[20] and census population data at both the national and county scale. Its calculation is shown in Equation 3.4:

[20] Personal income is defined as "income received by all persons from all sources…the sum of net earnings by place of residence, rental income of persons, personal dividend income, personal interest income, and personal current transfer receipts." (Bureau of Economic Analysis 2011)

$$T_l = \left(\frac{p_i}{P}\right) * \left(\frac{y_i}{\mu}\right) * \ln\left(\frac{y_i}{\mu}\right), \qquad \text{[Equation 3.4]}$$

where i indexes the counties, p_i is the population of county i, P is the total national population, y_i is the per capita income for county i, and μ is the per capita income of the total national population. The local Theil Index is reverse-scaled, such that higher values indicate a lower level of income inequality. Two other measures of social disorganization used in this research were *racial heterogeneity* and *ethnic heterogeneity*. A Herfindahl Index (Kwoka 1985) indicator of heterogeneity was calculated for each of these measures. For *racial heterogeneity*, the Herfindahl index is calculated as the sum of squared proportions of racial categories in a county during a given year. For this research, the measure included the four racial categories of Black, White, Native American/Pacific Islander, and Asian.[21] Thus, its mathematical limits are 0.25 and 1, where 1 indicates exclusive racial composition and 0.25 would indicate equal representation of all four racially identified groups. The Herfindahl's functional representation is given by Equation 3.5:

$$\sum_{j=1}^{g} p_j^2 = H , \qquad \text{[Equation 3.5]}$$

where p is the proportion of racial category j in the total population in county g. Similarly, *ethnic heterogeneity* was calculated as the sum of the squared proportion of the population who identify as belonging to the ethnic groups, Hispanic and non-Hispanic, in a county during a given year.[22] The index for *ethnic heterogeneity* has the mathematical

[21] The data source for racial groups, Survey Epidemiology and End Results (SEER), collapses the racial categories of Native American and Pacific Islander.
[22] The data source for ethnicity, the U.S. Census, only uses these two ethnicity identifiers. Clearly other ethnic groups reside in the U.S., but data regarding additional ethnic groups was unavailable for the study period.

limits of 0.5 and 1, where 1 indicates exclusive ethnic composition, and 0.5 indicates equal representation of the two ethnic groups. According to social disorganization theory, the empirical measures of inequality*, racial heterogeneity*, and *ethnic heterogeneity* will all be negatively[23] associated with crime rates.

Annual county- and national-level population and ethnic composition estimates were obtained from the U.S. Census Bureau (United States Census Bureau 1995-2008). Variables derived from these estimates include, *index crime rate, property crime rate, violent crime rate, burglary rate*, *larceny rate*, *motor vehicle theft rate*, *arson rate criminal homicide rate*, *forcible rape rate*, *robbery rate*, and *aggravated assault rate, population size*, *pctMale15-24*, the local *inequality*, and *ethnic heterogeneity*. Economic data, county and national per capita gross domestic product (GDP), used in the calculation of the local *Theil Index,* was obtained from the Bureau of Economic Analysis, local area income and employment files (U.S. Bureau of Economic Analysis 2010).

Intercensal estimates from the Census Bureau's "Population Estimates Program" are created using data on births, deaths, and migration, relative to the most recent decennial census. Thus, for the study period, the census years of 1990, 2000, and 2010 were used to create a time series of both county population and its ethnic, age, and gender composition. A complete technical bulletin regarding the methodology for creating these estimates is available from the U.S. Census (United States Census Bureau 2009). Finally, estimates of racial composition used to calculate *racial heterogeneity* were obtained from the National Cancer Institute, Surveillance Epidemiology and End Results (SEER) database (National Cancer Institute 2011). SEER data for race was used because the U.S.

[23] Note that each of these variables is reverse scaled such that larger values of Theil indicates lower levels of inequality, and higher values of both racial and ethnic heterogeneity indicate homophily.

census changed their racial category codification for the 2000 census. Data from SEER represents a reconciliation of these changes to make pre- and post-2000 comparisons between racial groups possible.

F. Social Order Variables

Two social order variables were included in the analysis: police guardianship and non-profit organization count. Police guardianship represents a proxy for the level of guardianship in a community and was measured as the number of full- and part-time sworn officers in a county. Police guardianship data were obtained from the Law Enforcement Management and Administrative Statistics (LEMAS) Sample Survey of Law Enforcement Agencies (U.S. Department of Justice 2011). The data were downloaded through the Inter-university Consortium for Political and Social Research (ICPSR) database portal. LEMAS data were only available for the years 1997, 1999, 2000, 2003, and 2007.

Non-profit organization count is used as a proxy for community efficacy and existing social networks (c.f. Zahran et al. 2009) and was measured as the number of tax-exempt non-profit organizations with $25K in gross receipts that are required to file Form 990 with the Internal Revenue Service (IRS). Data for non-profits were obtained from the National Center for Charitable Statistics (NCCS 2011). The raw data supplied a unique identifier for each non-profit organization that filed a Form 990 with the IRS in a given year. Each identifier was coupled with a *FIPS* code. A simple count of the number of unique identifiers in a county was taken to create the variable. For modeling purposes, both non-profit organization count and police guardianship were log-transformed for normality. The resulting variables used in the analysis can be identified by the indicators *lnNProfit* and *lnPolice*, respectively.

Based on routine activity theory, *lnPolice* should be associated with a decrease in crime rates, given guardianship is believed to preclude the commission of criminal acts. The variable *lnNProfit* is relevant to both the therapeutic community hypothesis and social disorganization theory. As the therapeutic community hypothesis suggests, mobilization of helping behavior utilizes existing social networks in a community. In this regard, *lnNProfit* should be negatively associated with crime rates. Relevant to social disorganization, as a proxy for community efficacy, *lnNProfit* should be negatively related to crime outcomes.[24]

V. Disaster Variables and Their Management

A. SHELDUS Data

The SHELDUS data used in this research required extensive management for operationalization, data structure, and data quality. In this section, I provide an overview of these procedures as well as descriptive analysis of the contents of the SHELDUS data. The raw SHELDUS data included every hazard event recorded for each county in the U.S. Because this research only included counties in the continental U.S., the first step in the data management process was to remove all hazard events that occurred in the states

[24] Using the number of non-profits as a proxy for community efficacy may be problematic given the emergence of non-profit relief organizations following a disaster event. That is, non-profit count may reflect networks formed as a result of the disaster, not those formed prior to the event. A more extensive discussion of this limitation is provided in Chapter 6.

of Hawai'i and Alaska. The second step in the management process included the removal of a number of cases that were miscoded in the SHELDUS database.[25]

The structure of the raw SHELDUS data was changed significantly for various analyses in this research. For the raw data, for each year, variables listed include the following:

- hazard id,
- hazard start date,
- hazard end date,
- hazard type,
- name of the county for the record,
- state for each record,
- FIPS code,
- number of recorded injuries,
- number of recorded fatalities,
- property damage measured as dollar amounts and adjusted for inflation (2000), and,
- crop damage measured as dollar amounts and adjusted for inflation (2000).

"Hazard id" is a unique identifier for each county-event. For example, in 1999, Hurricane Floyd caused injuries, deaths and property damage in two Delaware counties.

[25] These included cases whose start and end dates were coded in years other than that of the specified dataset. For example, in the 1995 data, 13 cases of a "winter weather" event were coded as beginning and ending on "1/1/96." The 13 cases that were listed in 1995 were also listed in 1996. After careful inspection of each year's data, I found that there was a systematic repetition of cases for each year. To correct his error, each year's data was inspected for repeated cases and each case removed from the data set. All removed cases for the above two data removal procedures were saved in an alternate database and are available upon request.

Thus, SHELDUS has a unique hazard id for New Castle and Sussex counties in Delaware. The “hazard start date” and the “hazard end date” taken together represent the beginning and end of the listed hazard event for the county listed. Again, using Hurricane Floyd as an example, while the storm affected much of the eastern seaboard spanning from Florida to Maine, the dates for each county-event correspond to the beginning and end dates for the hazard for each county and not the entire life-cycle of the storm. The variables for the identification of each county include the name, state and FIPS code for each county.

An important step in the research process included the operationalization of SHELDUS hazard types that would later be classified as distinct *hazard events*. SHELDUS’ classes of hazard types are not mutually exclusive as damage may be recorded as two or more hazard types. There are a total of 45 unique hazard combinations in the SHELDUS database for the study period. Table 3.2 provides a breakdown of these types and their relative frequency in the database.

Table 3.2: SHELDUS Raw Classification Tabulation 1995-2008

Type	Count	Percent	Type	Count	Percent
Avalanche	356	0.18	Hail - Lightning - Wind	2	0.00
Coastal	892	0.45	Hail - Severe Storm/Thunder Storm	55	0.03
Coastal - Flooding	214	0.11	Hail - Severe Storm/Thunder Storm - Tor	3	0.00
Coastal - Flooding - Wind	8	0.00	Hail - Severe Storm/Thunder Storm - Wind	481	0.24
Coastal - Hurricane/Tropical Storm	4	0.00	Hail - Tornado	4	0.00
Coastal - Severe Storm/Thunder Storm -	34	0.02	Hail - Wind	14	0.01
Coastal - Wind	54	0.03	Heat	3,636	1.82
Drought	3,850	1.93	Hurricane/Tropical Storm	2,561	1.28
Drought - Heat	78	0.04	Landslide	343	0.17
Earthquake	12	0.01	Lightning	9,191	4.60
Flooding	26,204	13.11	Lightning - Severe Storm/Thunder Storm	3	0.00
Flooding - Hail	1	0.00	Lightning - Severe Storm/Thunder Storm-wind	19	0.01
Flooding - Hail - Severe Storm/Thunder	10	0.01	Severe Storm/Thunder Storm	898	0.45
Flooding - Severe Storm/Thunder Storm	39	0.02	Severe Storm/Thunder Storm - Tornado -	1	0.00
Flooding - Severe Storm/Thunder Storm - Wind	67	0.03	Severe Storm/Thunder Storm - Wind	73,728	36.90
Flooding - Wind	1	0.00	Severe Storm/Thunder Storm - Winter Weather	9	0.00
Flooding - Wind - Winter Weather	26	0.01	Tornado	9,900	4.95
Flooding - Winter Weather	1	0.00	Tornado - Wind	12	0.01
Fog	308	0.15	Tsunami/Seiche	12	0.01
Fog - Winter Weather	1	0.00	Wildfire	962	0.48
Hail	17,823	8.92	Wind	23,380	11.70
Hail - Lightning	2	0.00	Wind - Winter Weather	266	0.13
			Winter Weather	24,366	12.19

The classification of these hazards is not determined by SHEDUS staff. Instead, SHELDUS staff relies on their main data source, National Center for Climatic Data (NCDC), to classify the hazards (Personal Communication, C. Emrich). It is clear from Table 2 that NCDC uses certain categories more frequently than others. For example, “Severe Storm / Thunderstorm-Wind” is the most commonly used category for classifying severe storms, with other “severe storm” designations comprising a very small portion of all coded events. In total, about one percent of the cases in the study years fall into “non-favored” categories. While having events classified in mutually exclusive categories presents a methodological challenge, the multiple designation of hazard types reflects the reality of hazards as complex events that cross political boundaries.

To code the data into one and only one category, the first category of the “non-favored” category combinations was used. I made this decision after carefully reviewing the NCDC raw data. There was no clear logic in the NCDC data as to which category should be used as the primary hazard designation. This process resulted in the creation of 17 categories or hazard types. Following Borden and Cutter (2008), the final categorization process combined these 17 categories into 12 distinct groupings to make comparisons among different disaster types consistent with prior research. Note that these categories are not without their own operationalization problems. For example, a tsunami (geophysical event) may cause “coastal” flooding. Droughts and heat, while related are not equivalent in their effects. Wildfires may be the result of lightning, etc.[26] Below, I discuss each SHELDUS loss variable and its empirical representation in the study period before moving on to discuss operationalization of the hazard data into “Disasters.”

[26] A full discussion of these limitations is provided in Chapter 6.

The first SHELDUS hazard variables for the study were a simple aggregate of all loss data for a given year, and county, for each variable—property damage, crop damage, injuries, and fatalities. In this case, no effort was made to distinguish the type of hazard that caused damage. Totals for these variables included multiple hazard types. These variables were used for the descriptive analysis presented in this chapter, and the geographic analysis presented in Chapter 4.

The second SHELDUS hazard variables created for the study included aggregated losses for a given year, and county, by disaster type, and for each variable—property damage, crop damage, injuries, and fatalities. These variables were used to distinguish the differential effects of disaster type on the dependent variables of interest (e.g. property crime rate, violent crime rate, etc.).

In Table 3.3 below, I provide a simple overview of the generalized categories SHELDUS hazard data. Of note, severe weather is the most common hazard event in these data, accounting for nearly 47 percent of all county-events. Following this, flooding accounts for over 13 percent of hazard events; winter weather accounts for over 12 percent of the hazard events; wind accounts for nearly 12 percent; tornadoes and lightning each account for less that 5 percent of hazard events; heat and drought account for almost 4 percent of county-events; hurricanes and tropical storms account for slightly more than 1 percent of county-events; finally, wildfires, mass movements, and geophysical events such as earthquakes each account for less than one-half percent of all county-events in the SHELDUS data set, for the years 1995-2008.

Table 3.3: Generalized Hazard Categories and Representation in SHELDUS 1995-2008

Type	Count	Percent
Severe Weather	93,329	46.70
Flooding (e.g. flash, riverene)	26,349	13.19
Winter Weather	24,366	12.19
Wind	23,646	11.83
Tornado	9,912	4.96
Lightning	9,213	4.61
Heat/Drought	7,564	3.79
Hurricane/ Tropical Storm	2,561	1.28
Coastal (e.g. storm surge, rip currents, coastal erosion)	1,206	0.60
Wildfire	962	0.48
Mass Movement	699	0.35
Geophysical	24	0.01
Total	199,831	100.00

In Figure 3.1, I offer a visual representation of the hazard types, by percent, in SHELDUS.

Figure 3.1: Percent Occurance of Hazard County-Events in SHELDUS, 1995-2008

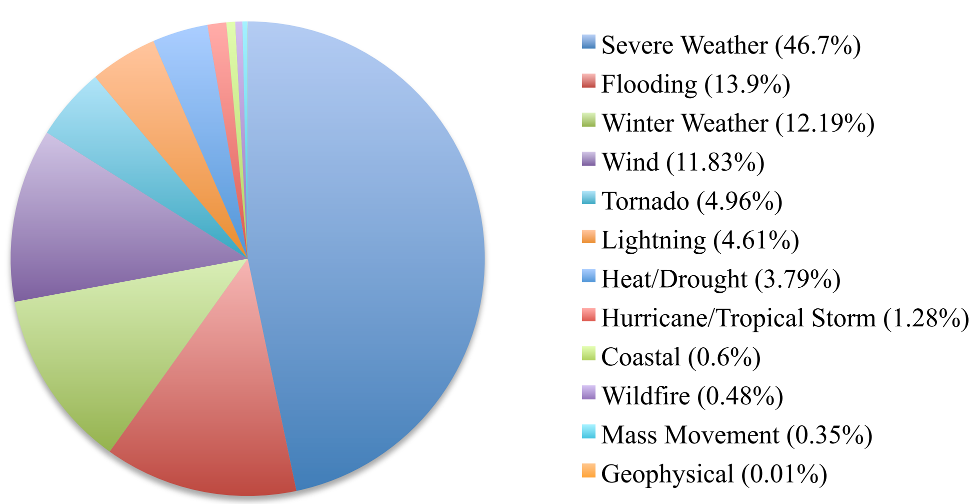


Table 3.4 offers an overview of the total losses in property damage, crop damage, injuries, and deaths according to the SHELDUS data and for each hazard type. To visually compare these estimates, Figures 3.2 through 3.5 are provided.

Table 3.4: Descriptive Statistics for Hazard Types, SHELDUS, 1995-2008

	Total	Mean	Standard Deviation	Range		Total	Mean	Standard Deviation	Range
Coastal					**Mass Movement**				
Injuries	576	0.478	2.56	0-55	Injuries	134	0.192	0.708	0-10
Fatalities	460	0.381	0.63	0-6	Fatalities	186	0.266	0.794	0-14
Property Damage	3.94e+10	3.27e+07	3.64e+08	0-4.61e+09	Property Damage	1.12e+09	1,606,055	2.91e+07	0-7.56e+08
Crop Damage	5,460.54	4.527	157.240	0-5460.54	Crop Damage	1.71e+07	24,482.85	322,950	0-4,278,378
Flooding					**Severe Weather**				
Injuries	8,196	0.311	9.732	0-800	Injuries	6,590	0.071	1.135	0-109
Fatalities	1,065	0.040	0.313	0-16	Fatalities	490	0.005	0.094	0-9
Property Damage	3.53e+10	1.34e+06	4.36e+07	0-5.99e+09	Property Damage	1.97e+10	211,534.7	5,529,402	0-5.99e+08
Crop Damage	5.49e+09	208,401.7	3,742,870	0-2.5e+08	Crop Damage	3.70e+09	39,639.98	1,078,517	0-2.10e+08
Geophysical					**Tornado**				
Injuries	17	0.708	2.053	0-8	Injuries	13,338	1.346	8.980	0-293
Fatalities	6	0.250	0.717	0-3	Fatalities	877	0.088	0.825	0-32
Property Damage	2.26e+09	9.43e+07	2.19e+08	0-6.43e+08	Property Damage	1.22e+10	1,234,762	1.09e+07	0-4.67e+08
Crop Damage	0	0	0	0	Crop Damage	1.97e+08	19,836.74	638,783.7	0-6.18e+07
Heat/Drought					**Wildfire**				
Injuries	7,557	0.999	6.784	0-437	Injuries	1,287	1.338	5.008	0-90
Fatalities	2,960	0.391	6.816	0-568	Fatalities	77	0.080	0.656	0-14
Property Damage	1.37e+09	181,150.6	1,063,936	0-1.18e+07	Property Damage	6.74e+09	7,009,602	6.53e+07	0-4.67e+08
Crop Damage	1.37e+10	1,810,734	4,758,211	0-1.00e+08	Crop Damage	3.73+08	387,680.7	4,466,901	0-6.18e+07
Hurricane/TS					**Wind**				
Injuries	1,000	0.390	6.910	0-156	Injuries	2,187	0.092	0.788	0-33
Fatalities	155	0.060	0.330	0-10	Fatalities	411	0.017	0.175	0-10
Property Damage	8.44e+10	3.29e+07	1.45e+08	0-2.21e+09	Property Damage	4.83e+09	204,100.6	5,706,825	0-3.95e+08
Crop Damage	5.76e+09	2,248,570	8,846,619	0-1.24e+08	Crop Damage	6.25e+08	26,452.16	575,692.5	0-5.32e+07
Lightning					**Winter Weather**				
Injuries	3,684	0.400	1.375	0-51	Injuries	3,872	0.159	1.370	0-100
Fatalities	626	0.068	0.274	0-4	Fatalities	831	0.034	0.234	0-14
Property Damage	5.86e+08	63,552.94	319,869.3	0-1.25e+07	Property Damage	5.80e+09	238,194.3	1,441,805	0-4.00e+07
Crop Damage	6,639,626	720.680	38,874.14	0-3,151,892	Crop Damage	3.52e+09	144,453.2	3,320,168	0-1.87e+08

It is worth noting several apparent trends in these data (Figure 3.2). According to SHELDUS data, hurricanes and tropical storms caused the most property damage for the study period. These estimates contradict previous estimates that show flooding to be the most costly natural hazard in the United States (Mileti 1999a). Such a discrepancy may be the result of different data sources or differences in the coding strategies employed by SHELDUS and Mileti (1999). Careful inspection of the data showed that several notable hurricane and tropical storm events during the study period, including Hurricane Katrina, were especially costly.

Figure 3.2: Property Damage Estimates from SHELDUS, 1995-2008, in Billions

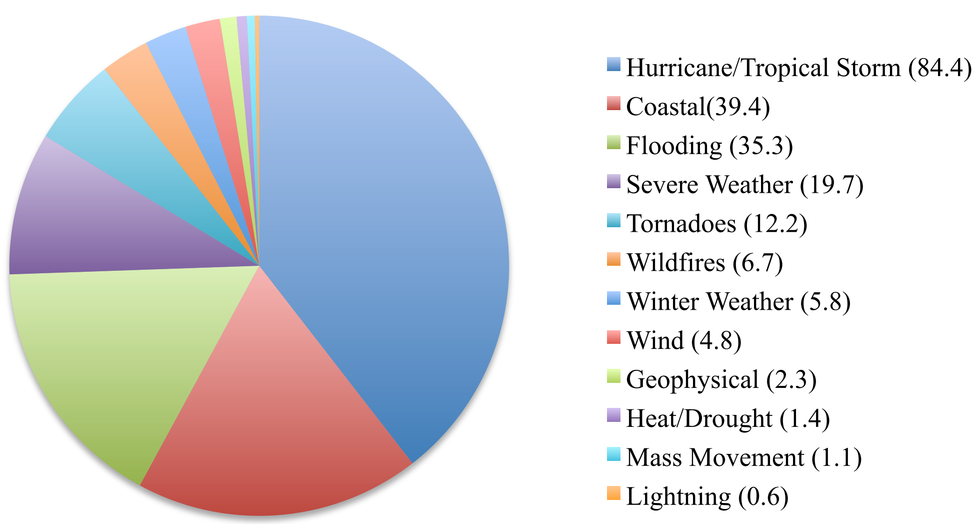


Figure 3.3 reproduces total crop damage estimates by hazard type according to SHELDUS data. Even though heat and drought account for only 4% of all hazard events, they cause the majority of dollar losses in this category.

Figure 3.3: Crop Damage Estimates from SHELDUS, 1995-2008, in Billions

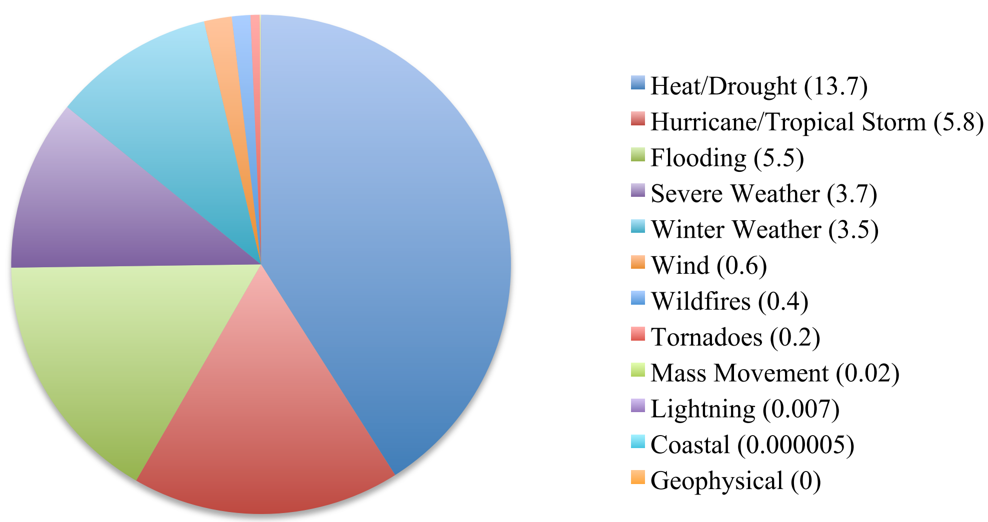
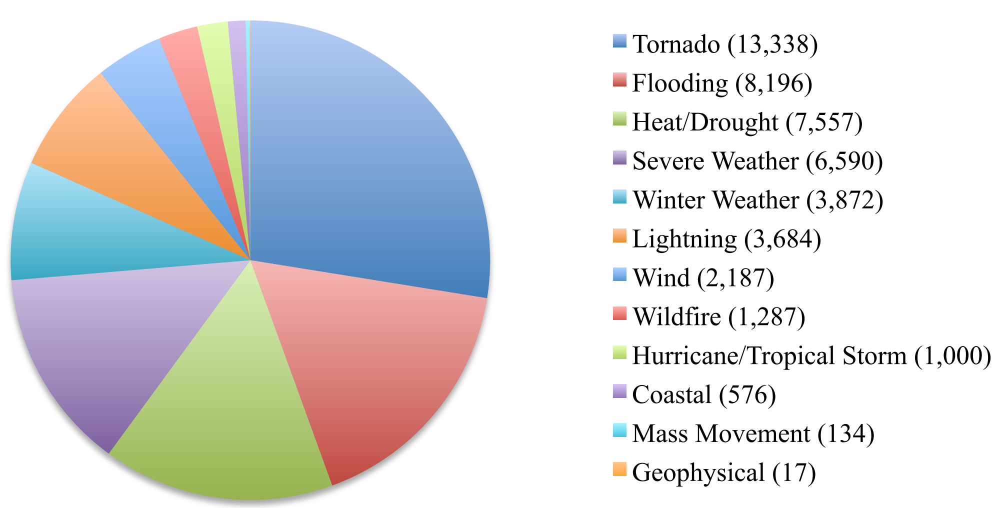


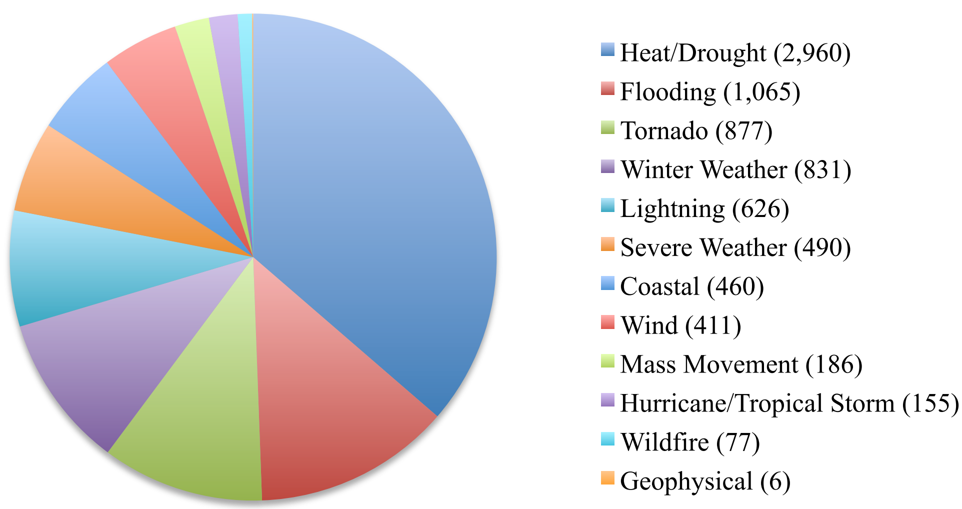
Figure 3.4 displays the total number of injuries, by hazard type for the years under study. Tornadoes comprise the most injurious of hazards for the years under study. This observation confirms earlier tabulations of hazard data (Mileti 1999a).

Figure 3.4: Injury Estimates from SHELDUS, 1995-2008



Finally, Figure 3.5 displays fatality estimates, by hazard type, for the study period. The data are congruent with other research claims that find heat to be the most deadly natural hazards (Klineberg 2002). However, it is notable that the fatality estimates for the study period and category of "hurricane and tropical storm" are unrealistically low, suggesting SHELDUS data underestimates fatalities according to their data processing procedures.

Figure 3.5: Fatality Estimates from SHELDUS, 1995-2008



B. FEMA Declarations

The FEMA data set represents an inventory of all presidential disaster and emergency declarations for the study period (FEMA 2011b). FEMA declarations or "Presidential Declarations" deserve special discussion. The Robert T. Stafford Disaster Relief and Emergency Assistance Act, commonly known as "Stafford Act" legislates the federal government's response to catastrophic events. According to the Stafford Act, two types of declarations may be made by the President of the U.S. Emergency Declarations are typically made for smaller events where the federal government's role in emergency management is limited. In contrast, major Disaster Declarations are made when "recovery appears to be beyond the combined resources of both the state and local government" (FEMA 2011a: 1). Events for which the Stafford Act qualifies as major disasters include: "Natural catastrophes (including any hurricane, tornado, storm, high water, wind driven water, tidal wave, tsunami, earthquake, volcanic eruption, landslide, mudslide, snowstorm, or drought), or regardless of cause, any fire, flood or explosion" (Moss and Shelhamer 2007: 7). The original raw data included the following variables:

- the disaster identification number,
- whether or not particular relief programs were mobilized as a result of the declaration,
- the names of counties affected by the disaster declaration,
- the declaration date,
- disaster type,
    - emergency declaration or,
    - disaster declaration,
- the incident type (e.g. hurricane, earthquake, tornado, etc.),
- the incident start and end dates, and
- disaster "close out" date

For the purpose of this research, only records that specified presidential disaster declarations or fire suppression emergencies were used. Emergency declarations were not treated as identifiers for "major disasters" as these declarations are typically anticipatory of a disaster event. For example, emergency declarations are used to mobilize resources for evacuation in the days preceding a hurricane. Following this, the incident start and end dates and the county and state names were retained in order to identify which counties and during what years presidential disasters were declared according to FEMA records.

The FEMA data set required some cleaning prior to its use. First, all FEMA declarations in the states of Hawai'i and Alaska were removed. Additionally all declarations for French Micronesia, American Samoa, the Virgin Islands, Guam, and Puerto Rico were removed. Some FEMA declarations for the study period were removed because they could not be qualified as "natural." Examples of these cases include a hydroelectric dam failure, and the September 11, 2001 terrorist attacks.

For the study period, there were a total of 14,155 county-events identified as emergency declarations or fire suppression emergencies. In general, the counties where declarations occurred only received one declaration for a given year. However, a total 2,393 counties received more than one FEMA declaration in a given year. For example, in 2007, Seminole County, Oklahoma was named in six presidential declarations or fire suppression emergencies. As mentioned above, for modeling purposes, the variable *FEMA declaration* is a binary variable indicating if one or more declarations was made for a county in a particular year.

VII. A Population of Data Points

The data used in this research can be considered population of data points.[27] That the data points represent a population of counties for the study period means traditional interpretations of statistical "estimates" were inappropriate. Specifically, *p*-values, and standard errors, while informative, could not be interpreted as traditional statistical measures of probability and sampling variability based on sampling theory. As such, unless otherwise stated, traditional statistical estimates used in this analysis are to be conceived of as population parameters that inform hypothesis testing through a non-inferential process.

VIII. Modeling Crime Longitudinally: Hierarchical Linear Modeling

The primary modeling procedure used in this research was hierarchical linear modeling or HLM.[28] Among other uses, HLM allows researchers to investigate change over time while using longitudinal or multiple waves of data (Singer and Willett 2003). Relevant to this research, HLM also controls for serial autocorrelation when analyzing longitudinal data. For this dissertation, the data was "time structured" in annual waves. That is, each county measure was recorded annually. Technically, HLM is used to predict within-county and between-county variation in crime rates as a function of disaster occurrence and magnitude.

Assumptions of HLM are similar to those of multiple regression: it is assumed that (1) observations are independent of one another; (2) the functional form of the

[27] The exception to this is the LEMAS data set where values obtained for county-level counts of police officers reflected the results of a stratified random sample of police agencies in the United States. Separate models are provided for analysis when LEMAS data are used.
[28] HLM is synonymous with term multi-level modeling. Other terminology for the same procedure includes individual growth models, random coefficient models, and mixed models.

relationship between predictors and the outcome is linear, unless otherwise specified; (3) residuals or errors are normally distributed with a mean of zero and a standard deviation of one; and (4) all variables have homoscedasticity or homogeneity of variance (Singer and Willett 2003).

For these data the assumption that observations are independent is violated in two ways. First, counties are observed at multiple times in the study period, thus a crime rate in one year is related to that county's crime rate the next. Second, and relevant to my discussion of geographically weighted regression below, counties that are near one another can not be considered independent (Tobler 1970). HLM procedures used in this research did not require the first independence assumption to be met because dependence is explicitly modeled in the growth trajectories of each county's outcome of interest. A solution to the violation of the second assumption is discussed below in the context of geographically weighted regression. Additional assumptions for HLM include measurement reliability and validity or "outcome equitability" of both predictors and the dependent variable over the study period and at each time data was collected (Singer and Willett 2003).

A. Data Structure and HLM

For this research, HLM models utilized a "person-period" data set whereby each county is represented on each measurement occasion. There are two "Levels" for each model used in this research. The Level-1 component represented the predicted change all counties experienced in crime rates for the entire study period. The Level-l components of the modeling procedure may be considered the "overall effect." The Level-2 component represented in this research specifies the inter-county difference in change and depends on the county's values on Level-2 time-varying predictors.

IX. Modeling Crime Spatially: Geographically Weighted Regression

A special problem faced by researchers using data that is tied to geographic space is that of spatial autocorrelation (Tobler 1970). Spatial autocorrelation violates the independence assumption of the regression and regression-like techniques of HLM. In general, data points that are more proximal are more alike than those that are more distal. To account for this violated assumption, geographically weighted regression assigns a "spatial lag" term or spatial controls to data points that account for statistical dependence between these points (Anselin 1988). In this research, the geographic spatial lag control was treated as a separate variable for each modeled crime rate and was specified as first order contiguity with a "queen" neighborhood. Geographic lags were generated using the open-source spatial statistical software *GeoDa.*

X. Modeling Crime Outcomes by Disaster Magnitude and Type

The analysis process used to investigate whether disaster magnitudes and types differentially affect crime rates proceeds as follows. First, Chapter 4 provides descriptive statistics regarding annual number of events, property damage, injuries, and fatalities, property damage, both in aggregate and by disaster type. Second, I provide an analysis of the geographic distribution of crime rates for the study period. Third, both disaster and crime outcomes are investigated in the context of time, addressing the question of whether disasters (and their impacts) and crime rates are increasing or decreasing over time?

Chapter 5 begins with a brief restatement of the competing hypotheses followed by a descriptive overview of the variables used in the analysis and the correlations among them. HLM/GWR is then used to test explicit hypotheses regarding the relationship between disaster magnitude and crime rates (index, property, and violent crime). Following this, I use HLM/GWR to evaluate the effect of police guardianship on crime rates. I conclude the analysis with HLM/GWR tests addressing whether different disaster types differentially impact crime rates.

XI. Research Hypotheses

For each disaster type/crime type analysis, each competing hypothesis from the three guiding theoretical perspectives will be interrogated. First Fritz's (1961) *therapeutic community hypothesis* argues that post-disaster behavior is oriented toward communal restoration, pro-social and altruistic behavior, adaptive action, and the promotion of safety. Negative effects of disasters such as property loss and suffering are experienced publically rather than privately and thus foster a sense of solidarity among members of the affected community. Such public experiences of suffering increases empathy and thus induce cooperation among groups who may have not previously acknowledged or observed the suffering of others. This theory proposes that disasters create conditions whereby crime rates should decrease. Given this, two hypotheses for the research are available. H1: An *increase* in the magnitude of a disaster (*lnDEMI*) will be associated with a *decrease* in crime rates; and H2: The variable *FEMA declaration* will be associated with a *decrease* in crime rates.

Social disorganization theory predicts that communities characterized by residential instability, low socioeconomic status, and poor collective efficacy, do not possess adequate resources to control crime. Disaster events are conceived of as disorganizing factors and have the potential to create or aggravate existing social disorganization by disrupting the social cohesion and the collective efficacy of a community and may lead to the inability of the community to self-monitor and sanction anti-social behavior. Thus, two hypotheses are suggested. H3: an increase in disaster magnitude will be associated with an *increase* in crime rates; and H4: the variable *FEMA declaration* will be associated with an *increase* in crime rates.

Routine activity theory predicts that a temporal and spatial convergence of motivated offenders, lack of guardianship, and availability of suitable targets increases the likelihood that a crime will be committed. Should a disaster increase the likelihood that these three conditions exist, two hypotheses are suggested. H5: An *increase* in the magnitude of a disaster will be associated with an *increase* in crime rates. H6: The variable *FEMA declaration* will be associated with an *increase* in crime rates. Alternatively, should a disaster decrease the likelihood that these three conditions exist two opposite hypotheses are suggested. H7: An *increase* in the magnitude of a disaster will be associated with an *decrease* in crime rates. H8: The variable *FEMA declaration* will be associated with an *decrease* in crime rates.

A further consideration of the variables and their hypothesized effect on crime rates is necessary. Because the basic HLM modeling procedure will assess the impact of disaster impact variables independent of control variables, it will be necessary to determine if particular predictors interact with a disaster's magnitude to differentially affect crime rates. That is, the social organization that facilitates or inhibits crime may likely interact with a disaster in unique ways. Thus, for each measure related to the therapeutic community hypothesis, routine activity theory and social disorganization theory, interaction effects will be modeled to address the following questions:

- Does the effect of a disaster's magnitude on crime rates depend on the number of motivated offenders in a county, as measured by the variable *ageMale15-24*?
- Does the effect of a disaster's magnitude on crime rates depend on the level of guardianship in a county, as measured by the variable *lnPolice*?
- Does the effect of a disaster's magnitude on crime rates depend on the measured level of *inequality*?
- Does the effect of a disaster's magnitude on crime rates depend on the level of social disorganization, as measured by the variable *racial heterogeneity*?
- Does the effect of a disaster's magnitude on crime rates depend on the level of social disorganization, as measured by the variable *ethnic heterogeneity*?
- Does the effect of a disaster's magnitude on crime rates depend on the level of social efficacy or existing social networks, as measured by the variable *lnNProfits*?

Like the global hypotheses regarding the overall effect of disaster on crime, hypothesized relationships among interacting variables differ, depending on the theory being considered. Overall, the therapeutic community hypothesis predicts a decrease in crime rates as the magnitude of a disaster increases. In terms of interaction among variables, evidence for the therapeutic community hypothesis would show a *decrease* in the effect of *inequality*, *racial heterogeneity*, and *ethnic heterogeneity* on crime rates, as the magnitude of the disaster *increases*. Further, should the therapeutic community utilize existing social networks to facilitate increased social cohesion, an *increase* in social efficacy (*lnNProfits*) would be associated with an increase in disaster magnitude.

Alternatively, social disorganization theory predicts that higher levels of social disorganization are associated with increases in crime. Should a disaster exacerbate existing social disorganization, interaction effects will exist between disaster magnitude and the measures *inequality*, *racial heterogeneity*, *ethnic heterogeneity*, and *lnNProfits.* That is, *inequality*, *racial heterogeneity* and *ethnic heterogeneity* will all have an *increased* effect as disaster magnitudes *increase*. Lastly, the effect community efficacy, as measured by *lnNProfits*, will be *decreased* as disaster magnitude increases.

Finally, routine activity theory predicts that increases in motivated offenders and decreases in guardianship increase the likelihood crime will occur. Should a disaster increase the likelihood that routine crime occurs, the overall effect of the disaster will be an increase in crime rates. If a disaster's magnitude interacts with these variables, the effect of *ageMale15-24* (a proxy for motivated offenders) on crime rate will increase as a disaster's magnitude increases. As well, should the disaster reduce formal guardianship, the effect of *lnPolice* will *decrease* as the disaster's magnitude *increases*.

XII. CONCLUDING REMARKS/SUMMARY

In this chapter, I have provided an overview of research design—the variables used in the analysis, their sources and operations, the modeling procedures employed in this research, and the hypotheses to be tested. In Chapter 4 and Chapter 5 I summarize the results of the descriptive, geographic, and temporal analyses of disaster and crime, and the results of the hypothesis tests relevant to each theoretical orientation. Chapter 4 is largely descriptive and offers a contextual overview of the study area. It also includes a geographic and temporal analysis of disasters and crime. In Chapter 5, higher order statistical techniques are employed to explicitly test the competing hypotheses.

CHAPTER FOUR: THE SETTING OF THE STUDY–GEOGRAPHY, TIME, DISASTERS, AND CRIME IN THE UNITED STATES

I. Introduction

This chapter provides a descriptive contextualization of the study's data regarding disasters and crime and their geographic and temporal distribution in the continental United States. I begin with a general overview of disaster and geography in the United States, reporting the total number of events, property damage, crop damage, injuries and fatalities for the study period. Then, utilizing GIS analysis and univariate and bivariate statistics, I provide a description of the study area relative to all disaster types and their impacts, including a descriptive account of the relationship between time and crime, Following this, I offer a description of crime and its geographic distribution and the relationship between crime and time.

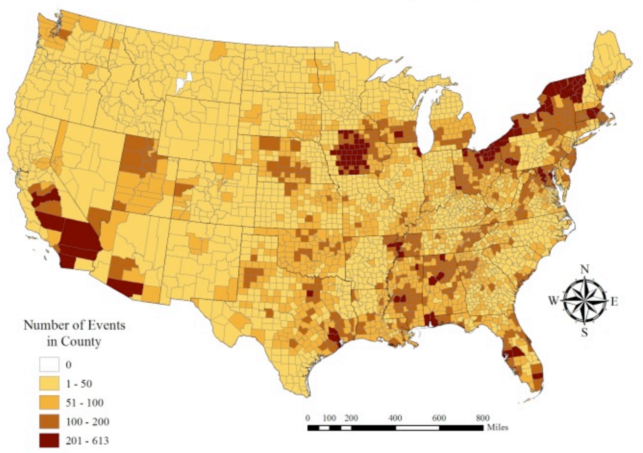
II. Disaster Variables and their Geographic Distribution

A. Disaster Counts

Figure 4.1 below displays the overall geographic distribution of disaster counts in the United States for the study period. In all, there were 199,956 county-events[30] recorded

[30] "County-events" refers to the recorded number of events impacting each county. For example, should a single storm cause property damage in 20 counties, this equates to 20 county-events.

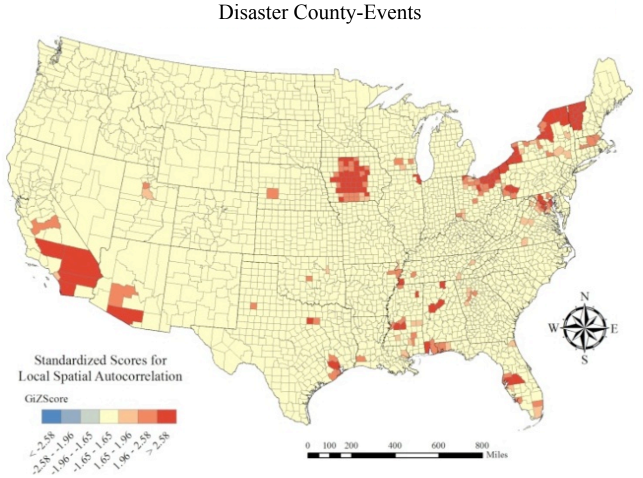
Figure 4.1: Total Number of Natural Disaster County-Events, 1995-2008



in 3,081 counties between 1995 and 2008.[31] The mean number of disaster events per county was 64.39 (*sd*=57.06) with a median of 49. Very few counties experienced only 1 event (7) and only two counties experienced no disaster events during the study period—Sweet Grass County and Golden Valley County, both in Montana. The county that experienced the most disaster events was Polk County, Iowa, which saw 613 disaster events between 1995 and 2008.

As is apparent in Figure 4.1, there are number of areas where disaster events are geographically concentrated in localized areas in the Northeast, the Midwest, the Deep South, the Southwest and California. Figure 4.2 displays the result of the Hot-Spot analysis (Getis-Ord Gi) which quantifies the degree of local spatial autocorrelation among counties on this measure (Ord

Figure 4.2: Hot-Spot Analysis (Getis-Ord Gi) for the Number of Disaster County-Events



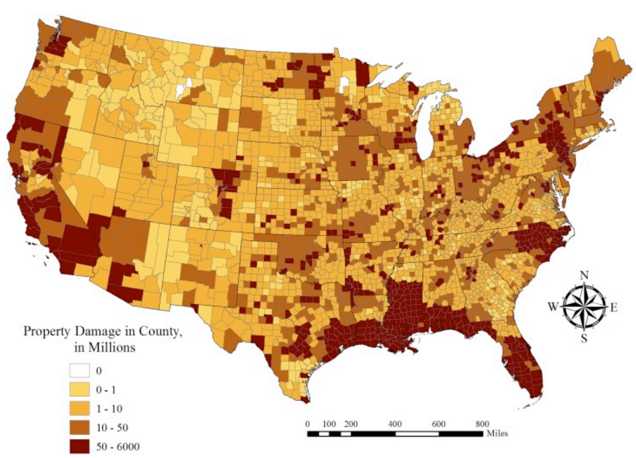
[31] As mentioned in Chapter 3, counties in both Hawai'i and Alaska were excluded from the analysis and a number of counties in Virginia were collapsed into a single county which results in a reduced number of counties analyzed for the study period.

and Getis 2010).[32] This analysis confirms that a high frequency of natural disasters cluster in the localized areas of the Southwest, the Midwest, the Northeast, and scattered regions in the Southeast U.S. Moran's *I* measure of global spatial autocorrelation (Moran 1948), is 0.444 ($p<0.001$) for the total number of natural disaster county-events in the study period . Together, these findings indicate that certain regions experience a statistically significant disproportionate number of natural disasters.

B. Property Damage

Figure 4.3 provides a visual display of the total property damage from all disaster types between 1995 and 2008.[33] There were a total of approximately 213 billion dollars in property damage from all disaster types during the study period. The mean property damage in a county was 69.3 million (*sd*=3.51 billion) with a median property loss of approximately 8.2 million dollars indicating that property loss totals are highly skewed. For the measure of property damage, Moran's *I* is 0.268 ($p<0.001$), confirming a moderate level of spatial

Figure 4.3: Total Property Damage from All Disaster Types, 1995-2008



[32] Hot-Spot analysis is the name given to this analysis of local spatial autocorrelation by ArcGIS. The analysis was performed for each of the disaster impact measures--fatalities, injuries, property damage and crop damage. To save space, the results are not displayed. Their visual displays confirm the result of the reported Moran's *I* analysis and are available upon request.

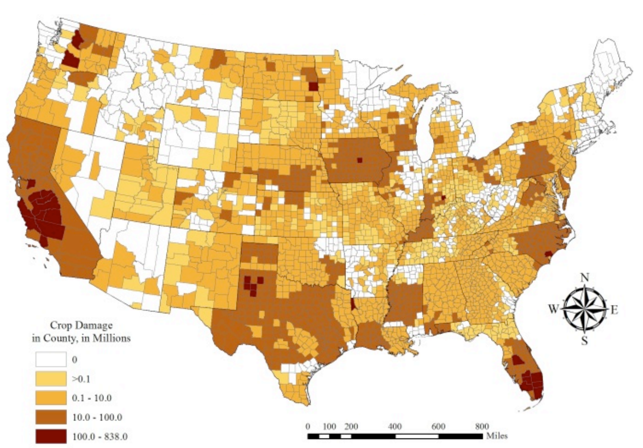
[33] Note that legend entries for each figure reflect intervals that were determined according to which cartographic display generated the most contrast among counties. Thus, all legends are unique to the variable of interest.

autocorrelation on this measure. As indicated by the median, half of the counties had total property losses of less than 8.2 million dollars. Thirty counties had property losses exceeding 1 billion dollars during the study period. The majority of these counties are in the Gulf Coast region, in the states of Mississippi (3) Louisiana (6), and Florida (16), and the remaining 5 counties scattered throughout the country. The county with the greatest total property damage was Linn County, Iowa with a total of approximately 6 billion dollars in property damage. This county experienced a catastrophic flood in 2008, which accounts for the majority of these losses.

C. Crop Damage

Figure 4.4 displays the geographic distribution of total crop damage from all disaster types during the study period. The total crop damage for the country, between 1995 and 2008, was approximately 33 billion dollars, with a mean crop damage of approximately 1.1 million (*sd*=3.3 million), and the median crop damage was 1.2 million. There were 29 counties that lost 100 million dollars or more in crop damage from all disaster types. Of these, five counties are in Texas, seven counties are in Florida, eleven counties are in California, while the remaining six counties

Figure 4.4: Total Crop Damage from All Disaster Types, 1995-2008

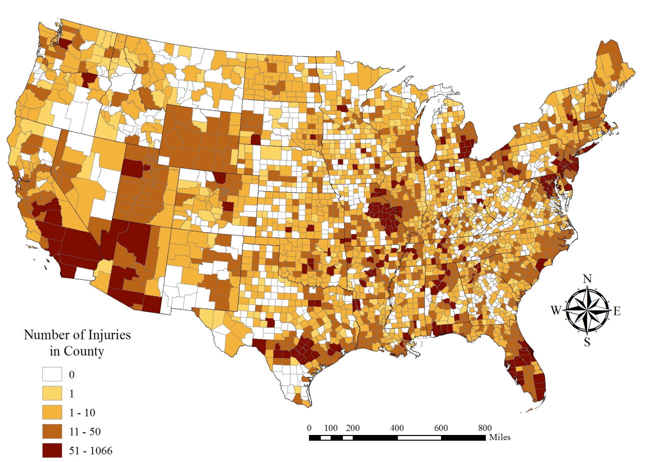


were scattered throughout the United States. Miami-Dade County, Florida experienced the greatest crop damage with approximately 31.4 billion dollars in losses. For the measure of crop damage, Moran's *I* is 0.192 (p<0.001), indicating moderate, but statistically significant spatial autocorrelation.

D. Injuries

Figure 4.5 provides the geographic distribution of injuries[34] from all disaster types. In total, there were 48,489 injuries reported in SHELDUS for the study period. The mean number of injuries in a county between 1995 and 2008 was 15.75 (*sd*=2.92), with a median of 3.73. Moran's *I* for total injuries is 0.203 (p<0.001), indicating moderate geographic clustering in the data. Of thirty counties experiencing the most injuries during the study period, 13 of the counties are in the state of Texas with Bexar County, Texas having the highest number of total injuries (1,066) between 1995 and 2008.

Figure 4.5: Total Number of Injuries from All Disaster Types, 1995-2008

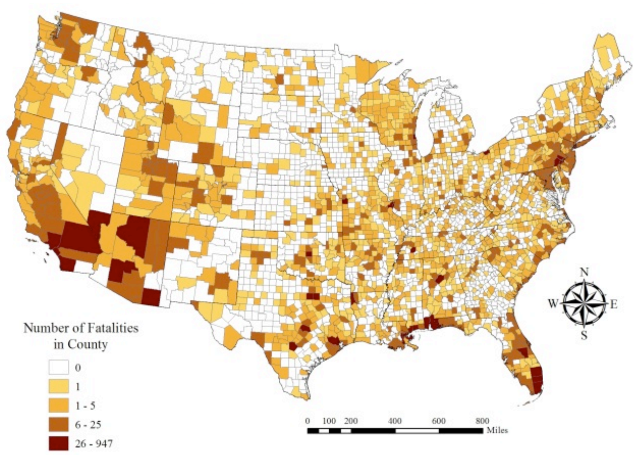


[34] Because the SHELDUS data divides injuries and fatalities across multiple counties, whole number intervals in the fatality and injury values used in each figure reflect the upper and lower real limits of the interval.

E. Fatalities

Figure 4.6 displays the total number of fatalities from natural disasters. There were a total of 9,001 fatalities recorded in SHELDUS between 1995 and 2008. Over half of the counties experienced no fatalities and a few counties experienced only a few number of events with very high numbers of fatalities. These include Cook County, Illinois that had 947 fatalities, and Orleans Parish, Louisiana, that had 522 fatalities. Like the number of events, the map for total fatalities also appears to have some geographic clustering. Moran's *I* for total fatalities is 0.031 ($p>0.001$), indicating a much smaller degree of global spatial autocorrelation, in comparison to the total number of natural disaster events. That is, the number of fatalities from natural disaster is much more geographically dispersed.

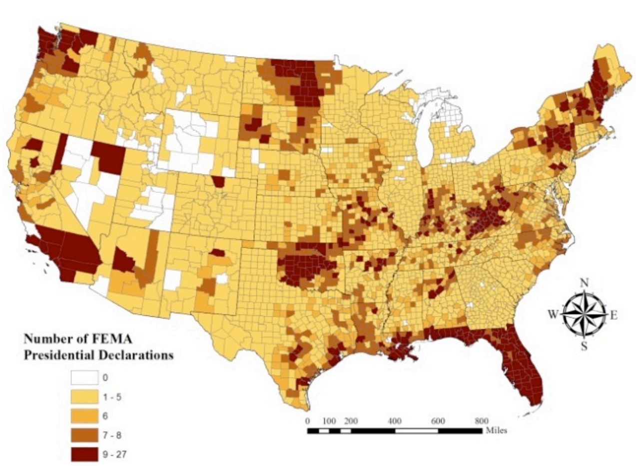
Figure 4.6: Total Number of Fatalities from All Disaster Types, 1995-2008



F. FEMA Declarations

Figure 4.7 displays the total number of FEMA declarations for the study

Figure 4.7: Total Number of County-Level FEMA Declarations, 1995-2008



period. There were a total of 14,155 FEMA declarations in counties between 1995 and 2008. Of these 13,511 were Presidential disaster declarations, while the remaining 644 were fire suppression emergencies. In general, counties that receive FEMA declarations have only one declaration per year. However, there are a total of 2,393 counties that received more than one presidential declaration in a particular year. Moran's *I* for FEMA declarations indicates a very high degree of global spatial autocorrelation, $I=0.719$ ($p<0.001$) for this measure. A visual examination of Figure 4.7 illustrates this clustering in eight regions: Florida and the Gulf Coast, Oklahoma, Central Appalachia, the Northeast, the North Central U.S., Southern California, and the Pacific Northwest.

G. Relationships among Disaster Impacts

A comparison of Figures 4.1–4.7 suggests that there is some relationship among the measures of fatalities, injuries, property damage, crop damage, and FEMA declarations. That is, one might expect that where one of these indicators is high, other indicators might also be high. Pearson correlation among these measures provides some support for this observation (Table 4.1).

Table 4.1: Correlation Among Totals for Disaster Measures

	Events	Fatalities	Injuries	Property Damage	Crop Damage
Fatalities	0.145***	---	---	---	---
Injuries	0.213***	0.166***	---	---	---
Property Damage	0.146***	0.066***	0.123***	---	---
Crop Damage	0.209***	0.054**	0.086***	0.205***	---
FEMA Declarations	0.215***	0.060***	0.164***	0.242***	0.157***

***$p<0.001$; **$p<0.01$

Table 4.1 demonstrates that while these measures are in fact correlated, the coefficients indicate that high values for one measure does not necessarily translate into high values on others. Fatalities in particular have the weakest relationship to other measures of disaster. Further, the highest correlation among all indicators is between FEMA declarations and property damage (*r* =0.242), while FEMA declarations are very weakly correlated with fatalities (*r* =0.060). The correlations between crop damage and injuries (*r* =0.054) and fatalities (*r* =0.086) are also small, relative to others, perhaps reflecting that human exposure to events that cause crop damage is low given crop production is generally a rural activity.

As a whole, an analyis of the overall distribution and relationship among disaster indicators demonstrates that while some areas experience a large number of disasters in the United States, almost no areas are spared from the effects of these events. In the next section, the indicators of event counts, property damage, crop damage, injuries and fatalities are explored in the context of the geography of disaster. That is, where are the different types of disasters located and what regions might be considered disaster-type specific regions?

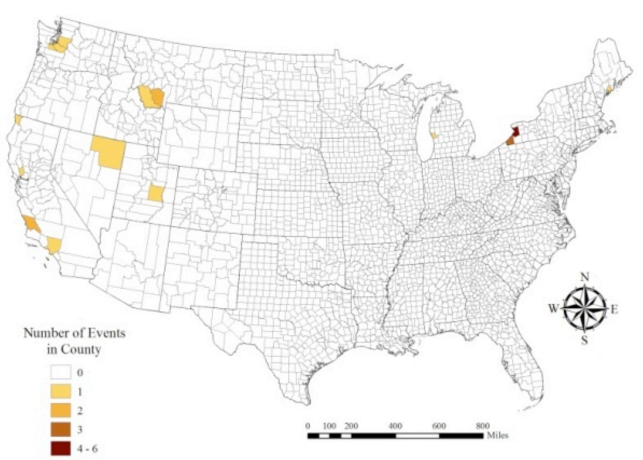
III. Disaster Types and Geography

This section provides a geographic analysis of the twelve disaster types analyzed in this dissertation. I begin with a brief discussion of geophysical events, the least common of the disaster types according to SHELDUS, and conclude with a discussion of severe weather, the most common disaster type.[35] For each disaster type, I provide a general overview of the relevant data from SHELDUS and briefly consider specific disaster events or locations that stand out as experiencing very high levels of human and economic losses. In some cases, geographic displays for impacts are not provided because there is either very limited impact or there are no events for the measure of interest.

A. Geophysical

Geophysical events (earthquakes and tsunami/sieche) were relatively rare during the study period. Between 1995 and 2008, there were a total of 24 geophysical county-events in the United States. Figure 4.8, illustrates the geographic distribution of events of this type. A total of 17 injuries, 6 fatalities, and more that 2.2 billion dollars in property damage are accounted for by geophysical events during the study period. Note that 11 of these events were coded as earthquakes while the remaining 13 events where categorized in SHELDUS as tsunami/seiche. Of those geophysical events that occurred on the great lakes, all were seiche water events. (On the Great Lakes these are referred to as “slosh”). The largest geophysical event, in terms of property damage was

Figure 4.8: Total Number of Geophysical County-Events, 1995-2008



[35] Severe weather events account for approximately 46.7% of all events recorded in SHELDUS.

the 2001 Nisqually Earthquake which affected Pierce, Thurston, and King Counties, all in Washington. This event caused nearly 2 billion dollars in damage and had 1 fatality. No injuries were recorded in SHELDUS for this event.

B. Mass Movements

Mass movements include both landslides and avalanches. Figure 4.9 provides the geographic distribution of these events. Note that the variegated Western United States experienced the majority of mass movement disasters. In total, there were 699 mass movement county-events, between 1995 and 2008, accounting for 134 injuries, 186 fatalities, over 1.1 billion dollars in property damage and approximately 17.1 million dollars in crop damage. The distribution of property damage from these events is provided in Figure 4.10. According to the SHELDUS data, the most costly events, in terms of property

Figure 4.9: Total Number of Mass Movement County-Events, 1995-2008

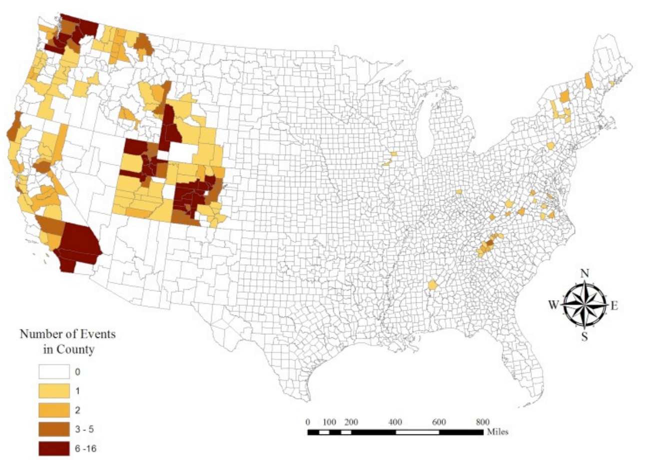
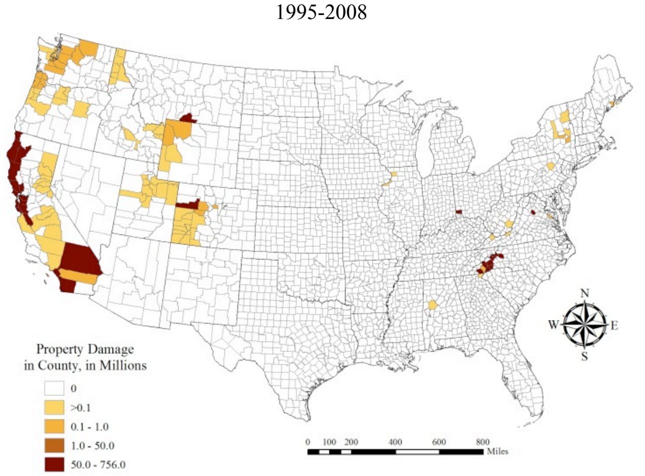


Figure 4.10: Total Property Damage from Mass Movement Events, 1995-2008



damage, occurred as the result of a series of storms along the California Pacific Coast in 2006, which led to a number of landslides in the region. These landslides also accounted for the only crop damage from mass movement events (not pictured), and occurred in Humboldt, Del Norte, Napa, and Sonoma Counties in California. As a whole, California also accounts for the majority of injuries (Figure 4.11) and fatalities (Figure 4.12) from mass movements. However, injuries and fatalities from mass movements are more geographically dispersed than are property and crop damages. As Figures 4.11 and 4.12 demonstrate, there are also a number of mass movement events that caused injuries and fatalities in the intermountain west.

Figure 4.11: Total Number of Injuries from Mass Movement Events, 1995-2008

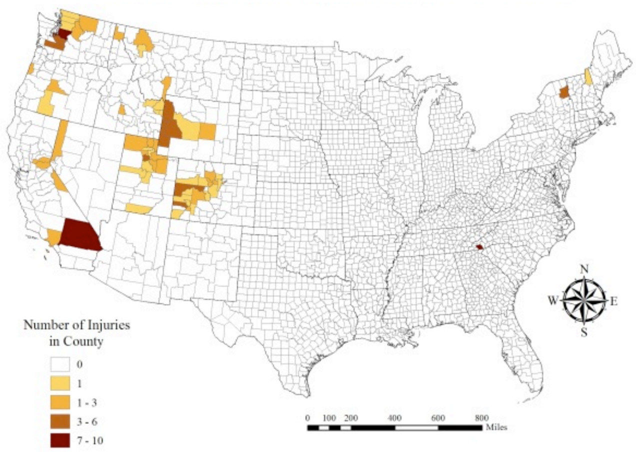
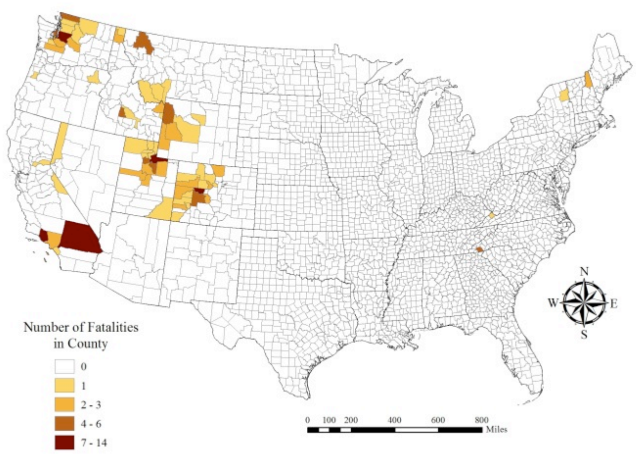


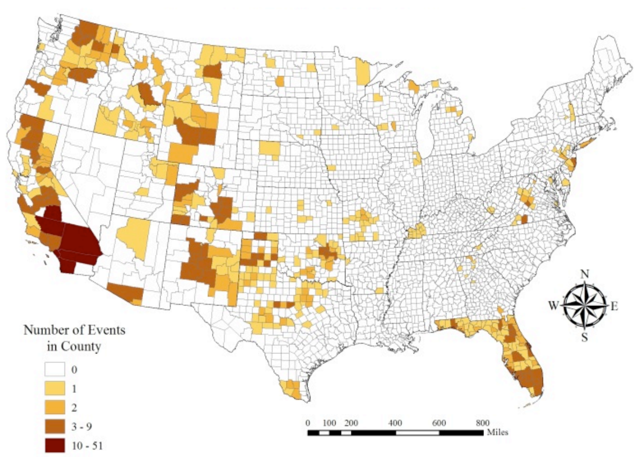
Figure 4.12: Total Number of Fatalities from Mass Movement Events, 1995-2008



C. Wildfires

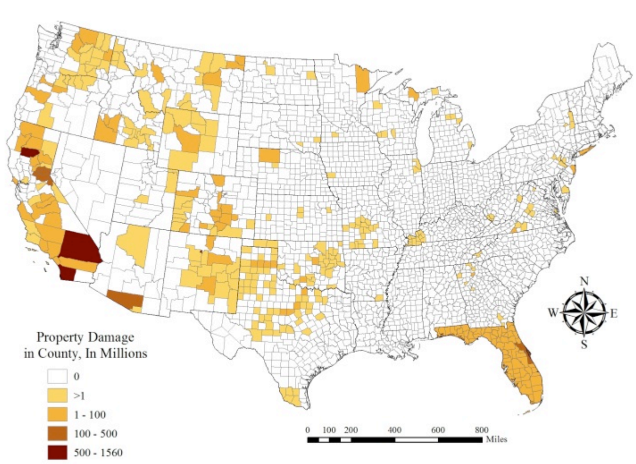
Figure 4.13 illustrates that wildfire events in the United States are most common in the West, although, Florida and areas of the central U.S., experienced a number of wildfires between 1995 and 2008. There were a total of 962 wildfire county-events for the study period, accounting for 1,287 injuries, 77 fatalities, over 6.7 billion dollars in property damage, and more than 370 million dollars in crop damage. Upon a visual inspection of Figure 4.13, it is notable that Florida's wildfire events are distinct in the region. Inspection of the raw data indicated that almost no events were recorded in SHELDUS directly north of the Florida border.

Figure 4.13: Total Number of Wildfire County-Events, 1995-2008



Property damage from wildfires (Figure 4.14) is most notable in San Bernardino and San Diego Counties, California. These two counties account for over one-third of all property losses, 2.5 billion dollars, from wildfires during the study

Figure 4.14: Total Property Damage from Wildfire Events, 1995-2008



period. Also worth noting is Los Alamos County, New Mexico, which experienced property damage in excess of 1.5 billion dollars during the study period. Inspection of the raw SHELDUS data indicates these losses were the result of one event, the Cerro Grande Fire of 2000. Figure 4.15 illustrates the geographic distribution of crop damage from wildfires. As indicated on this map, counties in Texas, California, and Washington saw the greatest crop damage from wildfires. Four counties in Texas, four counties in California, and one county in Washington account for about 96%, (over 357 million dollars), of crop losses from wildfires. Figures 4.16 and 4.17 illustrate the geographic distribution of injuries and fatalities from wildfires, respectively. Wildfires have the largest injury to death ratio of all the disaster types used in this research at 16.7:1. San Diego County, California experienced the most injuries from disasters of this type with 457 injuries recorded for the study period. San Diego County, California also experienced the most fatalities from

Figure 4.15: Total Crop Damage from Wildfire Events, 1995-2008

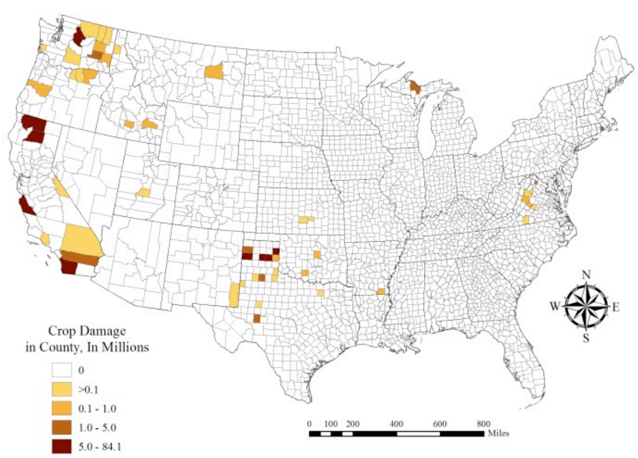


Figure 4.16: Total Number of Injuries from Wildfire Events, 1995-2008

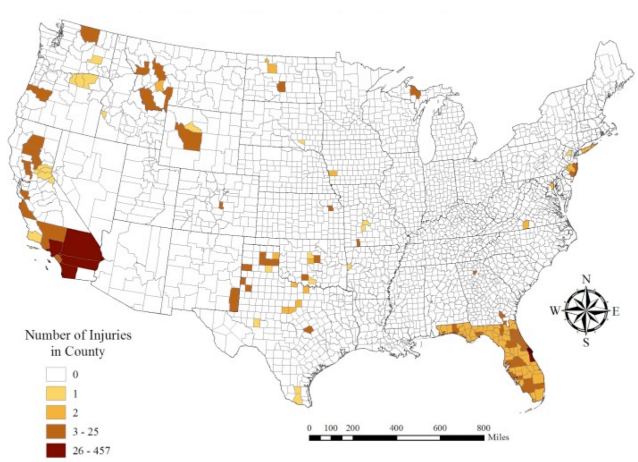
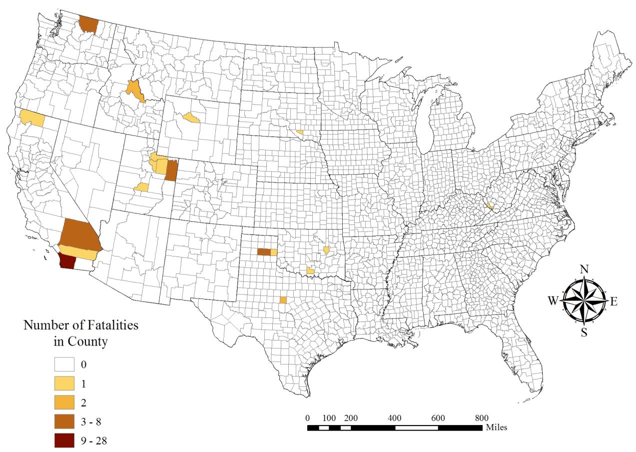


Figure 4.17: Total Number of Fatalities from Wildfire Events, 1995-2008



wildfires with 28. Inspection of the raw SHELDUS data indicated that the 2003 Cedar Fire and a series of wildfires in 2007 accounted for San Diego County's human losses during the study period. And while, according to the SHELDUS data, Florida experienced no fatalities from wildfires, it clearly had a large number of injuries from disasters of this type.

D. Coastal Events

Coastal disaster events include damage, injuries, and fatalities caused by coastal surf, storm surges, coastal erosion, and rip currents. There were a total of 1,206 coastal events recorded in SHELDUS for the study period. Figure 4.18 illustrates that coastal events occur in marine areas along the western and eastern seaboards, along Gulf Coast, and the Great Lakes.

Figure 4.18: Total Number of Coastal County-Events, 1995-2008

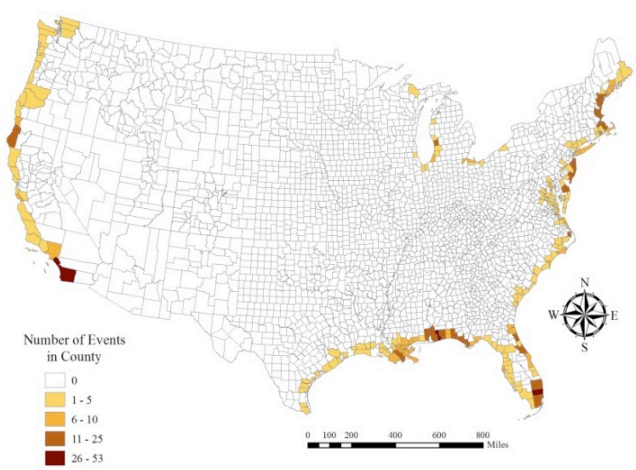
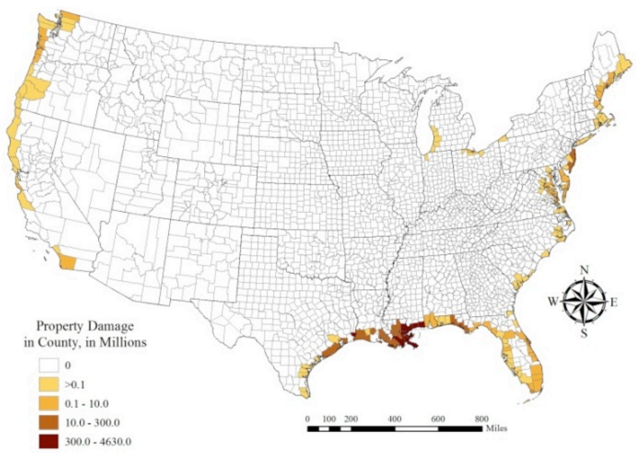


Figure 4.19 displays the geographic distribution of property damage from coastal events. Of the top 25 counties experiencing property damage from coastal events, Louisiana has 19 counties represented. Six of these counties have property damage totaling more than 4.6 billion each. Counties in Mississippi and Texas comprise the remaining 25 counties in the top 25. There is only one county, Caddo Parish, Louisiana, with crop damage from coastal events, totaling $5,460 (not pictured).

Figure 4.19: Total Property Damage from Coastal Events, 1995-2008



The geographic distribution of injuries from coastal events is provided in Figure 4.20. In all, there were a total of 460 injuries from coastal events. Of the ten counties with the most injuries, San Diego County, California has the most with 117, and Florida represents five of the top ten counties for injuries from coastal events with a total of 165 injuries during the study period in these counties. Figure 4.21 displays the total

Figure 4.20: Total Number of Injuries from Coastal Events, 1995-2008

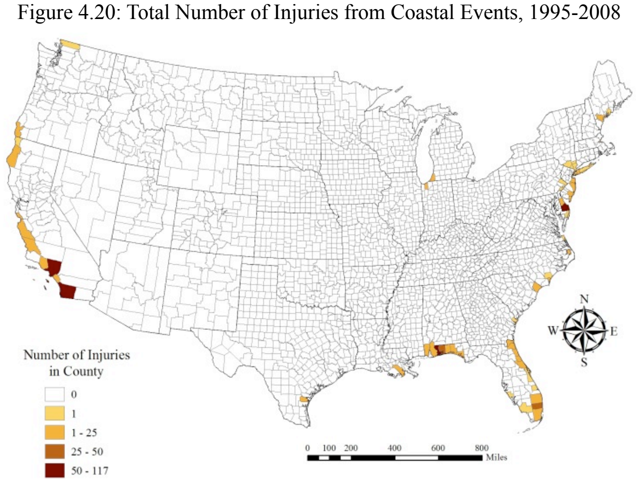
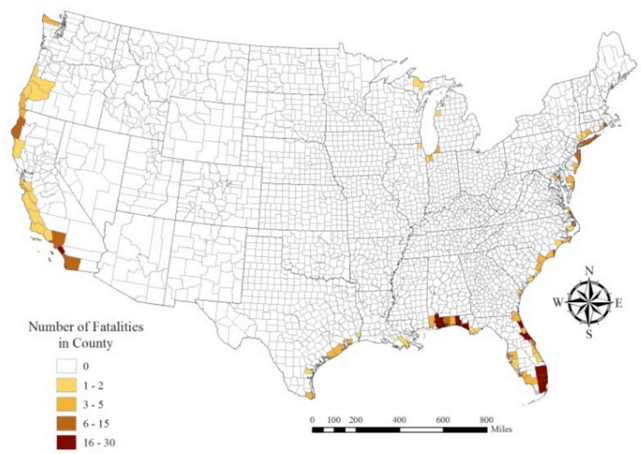


Figure 4.21: Total Number of Fatalities from Coastal Events, 1995-2008

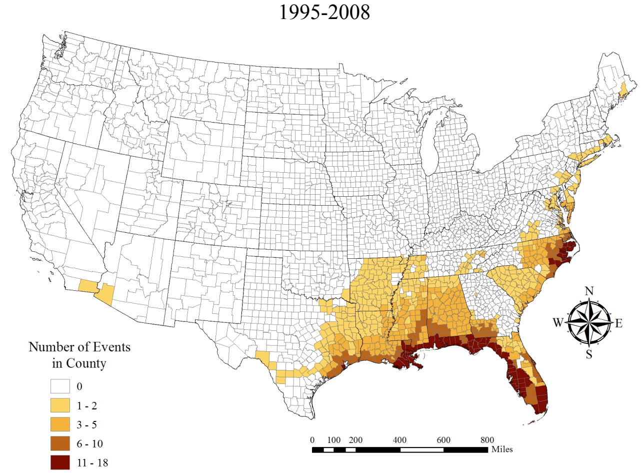


number of fatalities from coastal events. In total, there were 460 fatalities from coastal events. Of the top ten most deadly counties for coastal disasters, seven counties are in Florida. These counties alone had a total of 158 fatalities from coastal disasters.

E. Hurricanes and Tropical Storms

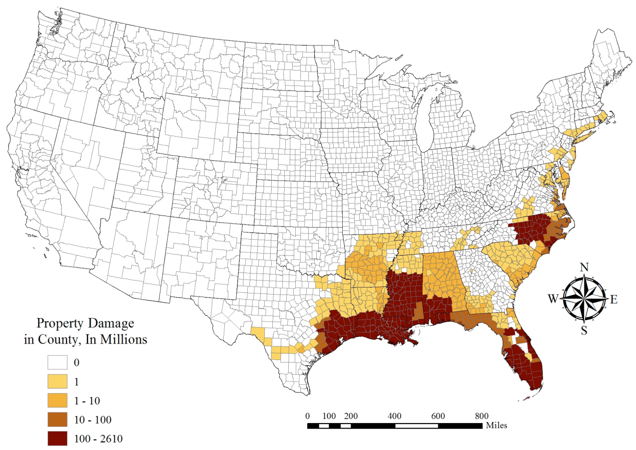
The number of hurricane and tropical storm county-events recorded in SHELDUS between 1995 and 2008 was 2,561. As is visible in Figure 4.22, the Gulf Coast

Figure 4.22: Total Number of Hurricane and Tropical Storm County-Events, 1995-2008



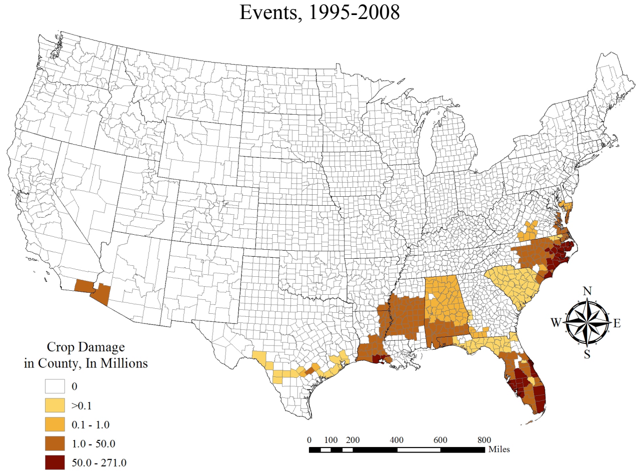
experienced the highest number of disaster events of this type. In all, 60 counties experienced eleven or more hurricane or tropical storm events during the study period. The geographic distribution of property losses from hurricanes and tropical storms is displayed in Figure 4.23. The top 20 counties with recorded property losses in this category are in Florida in the years 1995, 2004 and 2005.

Figure 4.23: Total Property Damage from Hurricane and Tropical Storm Events, 1995-2008



Property losses during these years are directly related to Tropical Storm Allison, Hurricane Ivan, and Hurricanes Katrina and Rita. Notably missing from these top property damage counties in this category are counties along the Gulf Coast that were impacted by Hurricane Katrina. Inspection of the raw data shows that Katrina property losses for Mississippi and Louisiana were coded as "coastal" events by SHELDUS staff.[36] Total property losses from hurricanes and tropical storms exceeded 84.4 billion dollars for the study period. In contrast, crop damage from hurricanes and tropical storms (Figure 4.24) was much lower, but still exceeded 5.7 billion dollars. High crop loss regions include North Carolina and Florida, perhaps representing the tobacco and citrus industries in these states. Figures 4.25 and 4.26 represent injuries and fatalities, respectively, from

Figure 4.24: Total Crop Damage from Hurricane and Tropical Storm Events, 1995-2008



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[36] Losses in Georgia from disasters of this type were not listed in the SHELDUS database. There is no indication that these losses were coded in an alternate category.

hurricanes and tropical storms. A comparison of these two figures illustrates that the geographic distribution of fatalities and injuries are not geographically congruent. As is visible in Figure 4.25, fatalities are concentrated along the Gulf Coast and in the Mississippi Delta region. Fatalities in the Mississippi river delta region from Hurricane Katrina comprise the high number of fatalities during the study period. SHELDUS provides a conservative estimate of fatalities in this disaster category with a total of 1006 fatalities and 1000 injuries from hurricanes.[37]

Figure 4.25: Total Number of Injuries from Hurricane and Tropical Storm Events, 1995-2008

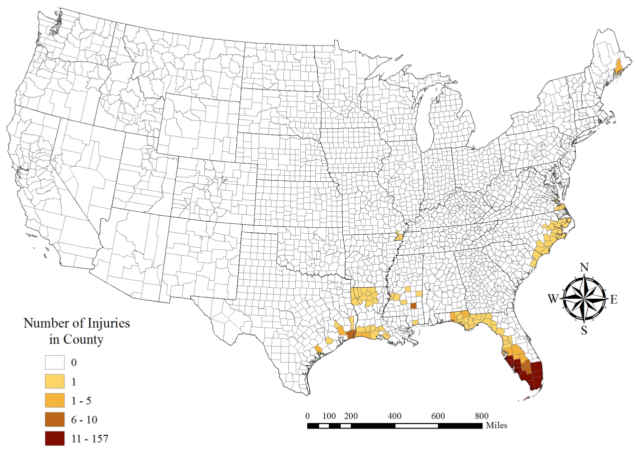
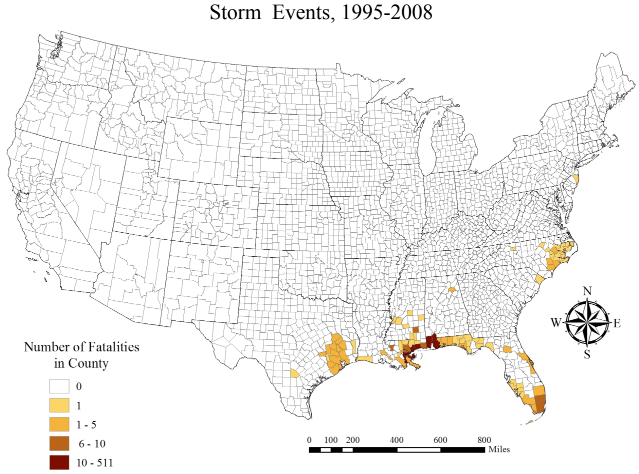


Figure 4.26: Total Number of Fatalities from Hurricane and Tropical Storm Events, 1995-2008



[37] Note that because of the complex nature of these types of events, human and economic losses from particular events may also be recorded as flooding and coastal losses.

F. Heat/Drought

There were a total of 7,564 heat/drought county-events between 1995 and 2008 recorded in SHELDUS (Figure 4.27). Of these, 3,636 were heat events; the remaining 3,928 were drought events. This is the only disaster category where crop damages exceed property damage. There was a total of over 1.37 billion dollars in property damage from heat/drought events during the study period. As is visible in Figure 4.28, the highest levels of property damage from heat/drought are concentrated in Oklahoma, Texas and Iowa. In contrast to property damage, crop damage totals from heat/drought exceeded 13.7 billion dollars. Visible in Figure 4.29, these losses were concentrated in Texas, Florida, California, Nebraska, Kansas, Louisiana, and Iowa. Injuries from heat/drought are very high, relative to other disaster types with 7,577 injuries recorded in SHELDUS

Figure 4.27: Total Number of Heat and Drought County-Events, 1995-2008

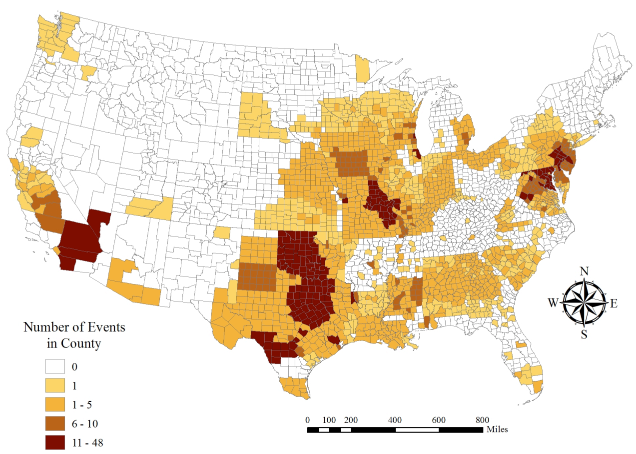


Figure 4.28: Total Property Damage from Heat and Drought Events, 1995-2008

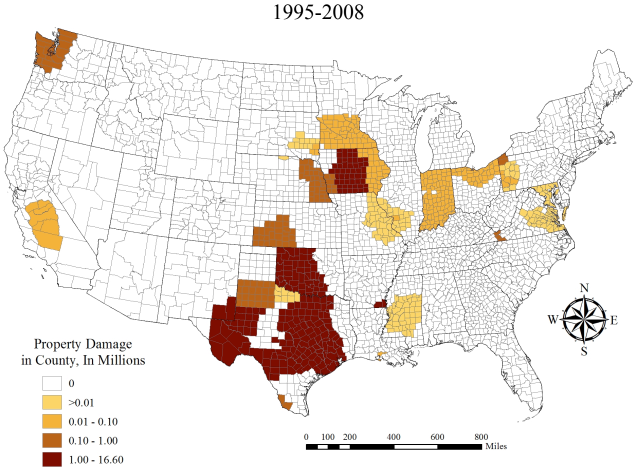


Figure 4.29: Total Crop Damage from Heat and Drought Events, 1995-2008

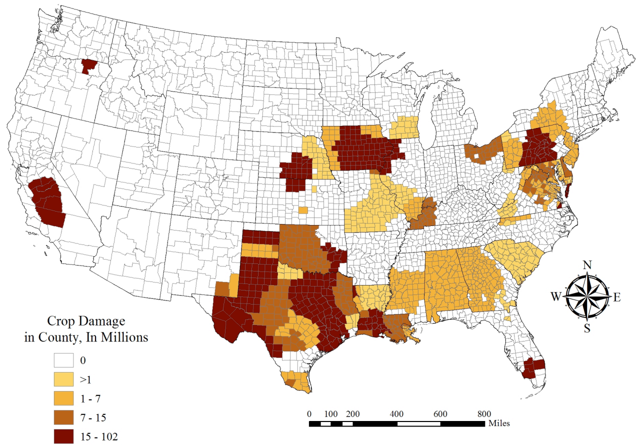


Figure 4.30: Total Number of Injuries from Heat and Drought Events, 1995-2008

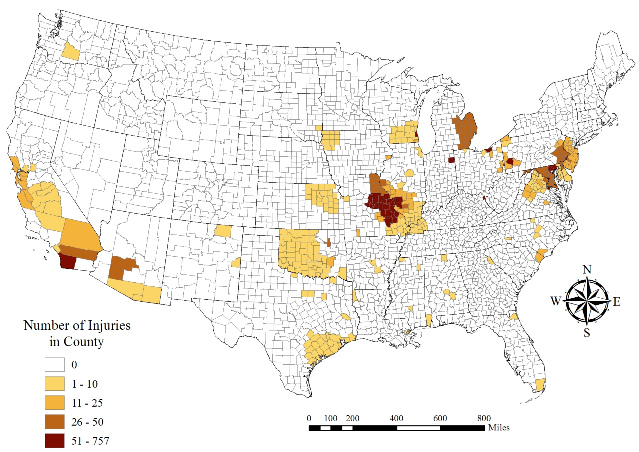
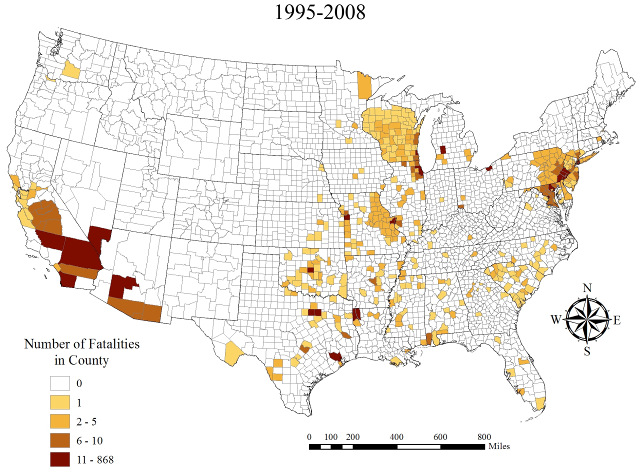


Figure 4.31: Total Number of Fatalities from Heat and Drought Events, 1995-2008



during the study period. Displayed in Figure 4.30, injuries from heat/drought are concentrated in Missouri and Illinois in the St. Louis area. According to SHELDUS data, heat and drought events are the most deadly of all the disaster types with 2,960 fatalities. Visible in Figure 4.31, fatalities are concentrated in the Chicago area and the Southwest. The largest number of fatalities to occur in any county from heat/ drought was 948, in Cook County Illinois. The majority of these occurred during the heat wave of 1995.

Figure 4.32: Total Number of Lightning County-Events, 1995-2008

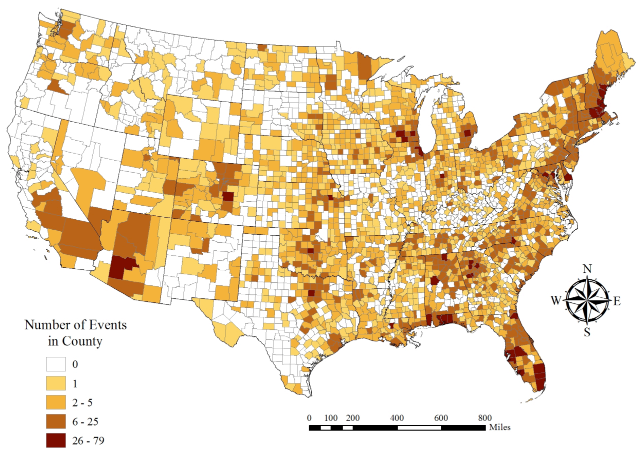


Figure 4.33: Total Property Damage from Lightning Events, 1995-2008

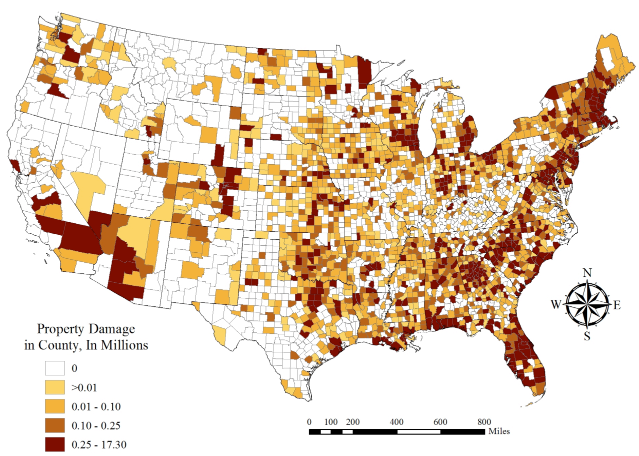
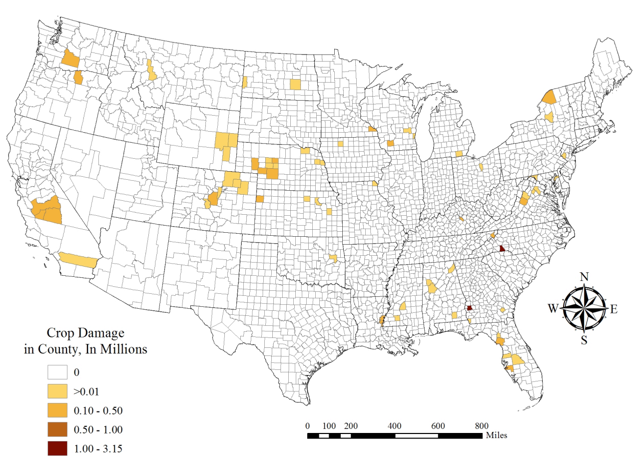


Figure 4.34: Total Crop Damage from Lightning Events, 1995-2008



G. Lightning

There were a total of 9,213 lightning disaster events between 1995 and 2008. As is visible in Figure 4.32, lightning events are the least geographically clustered of any disaster type. However, there are a few regions that experience more lightning events than others. For example, five counties in Florida and Maricopa County, Arizona have the highest number of lightning events with over 70 events each during the study period. Of all disaster types, lightning causes the least amount of property damage (Figure 4.33) and crop damage (Figure 4.34). In total, about 586 million dollars in property damage can be attributed to lightning events, while crop damages from lightning totaled approximately 6.6 million dollars during the study period.

Figure 4.35: Total Number Injuries from Lightning Events, 1995-2008

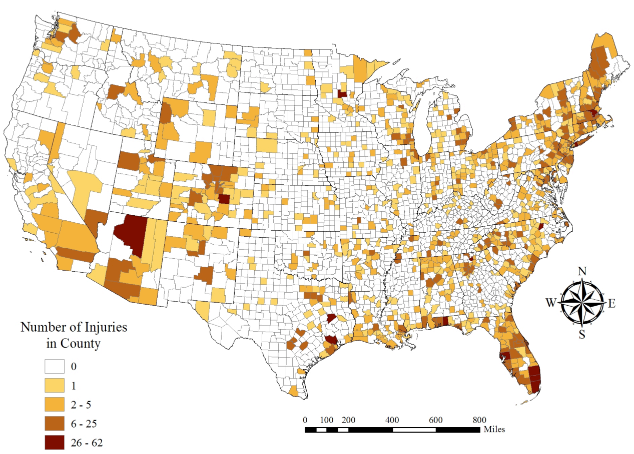


Figure 4.36: Total Number Fatalities from Lightning Events, 1995-2008

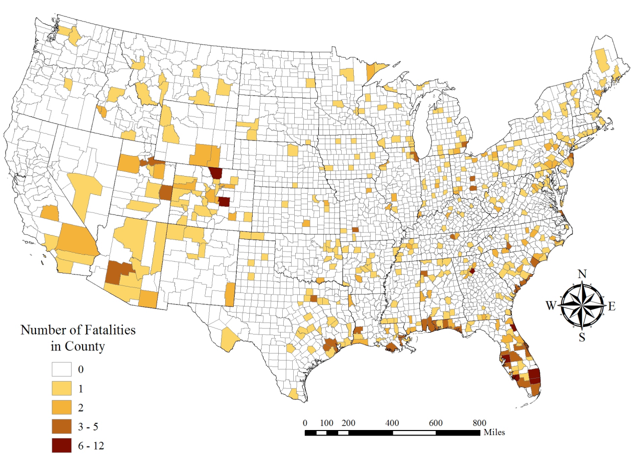
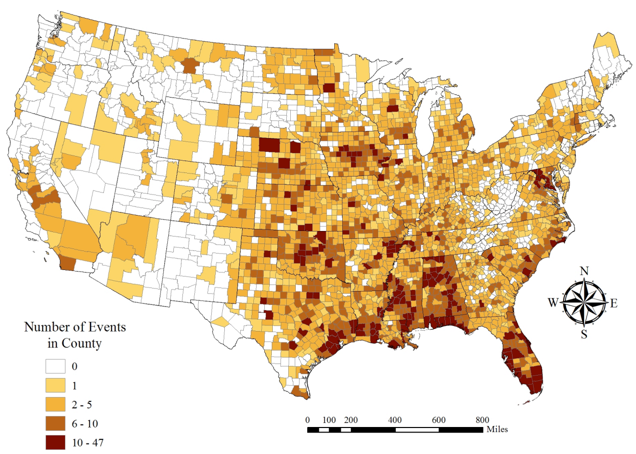


Figure 4.35 displays the overall distribution of injuries from lightning, and Figure 4.36 displays the overall distribution of fatalities from lightning events. In total, there were 3,685 injuries and 626 fatalities from lightning events during the study period. Broward County, Florida experienced the most injuries and fatalities from lightning, with 12 fatalities and 63 injuries between 1995 and 2008.

H. Tornadoes

Between 1995 and 2008, there were a total of 9,912 county-events classified by SHELDUS as tornadoes. The geographic distribution of theses events is displayed in Figure 4.37. The number of tornado events concentrate in the plains region, the Deep

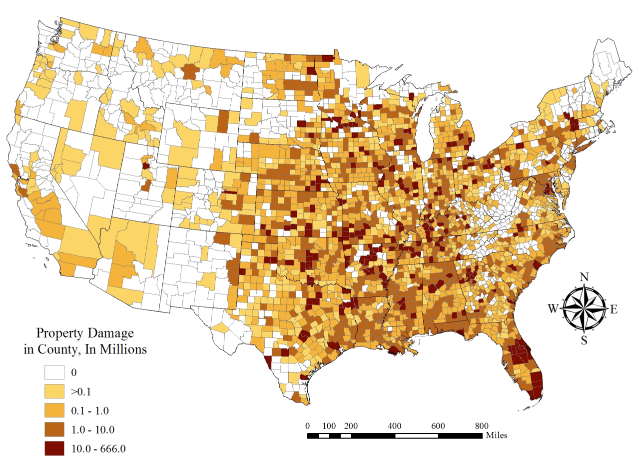
Figure 4.37: Total Number of Tornado County-Events, 1995-2008



South, and Florida. Of the 25 counties with the most tornado events, 11 are in Florida, while Texas, Oklahoma, and Alabama have four counties represented in the top 25. Each of these counties had 20 tornado events or more during the study period.

Property Damage from tornado events is displayed in Figure 4.38. According to SHELDUS, tornadoes were responsible for approximately 12.2 billion dollars in property

Figure 4.38: Total Property Damage from Tornado Events, 1995-2008



damage during the study period. Two counties in Oklahoma, Cleveland County and Oklahoma County had the largest property damage from tornado events with over 640 million dollars in property damage each.

Figure 4.39: Total Crop Damage from Tornado Events, 1995-2008

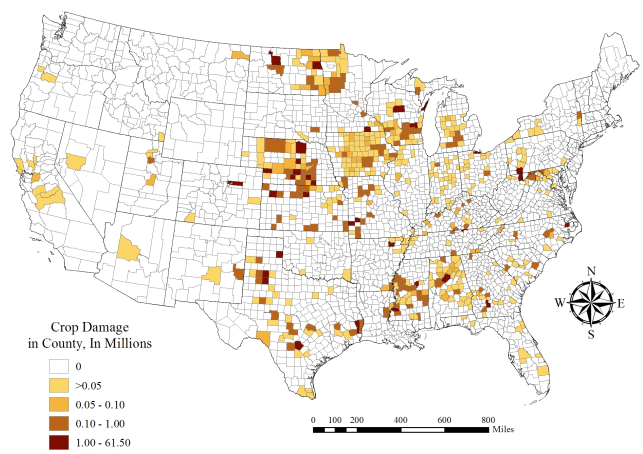


Figure 4.40: Total Number of Injuries from Tornado Events, 1995-2008

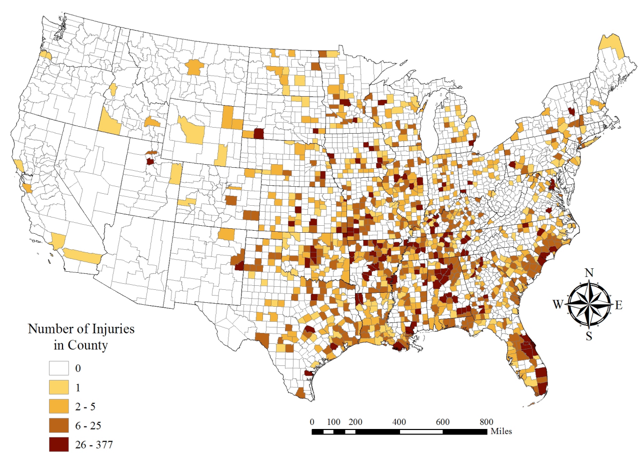
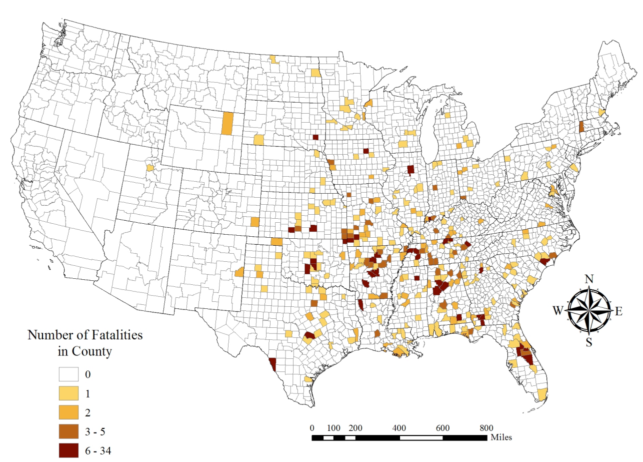


Figure 4.41: Total Number of Fatalities from Tornado Events, 1995-2008



Crop damage from tornado events (Figure 4.39) is much less widespread than either events or property damage. According to SHELDUS, crop damage from tornadoes exceeded 196 million.

Injuries from tornado events are displayed in Figure 4.40. Tornadoes are the most injurious of all the disaster types studied in this research. A total of 13,338 injuries are recorded in SHELDUS for the study period. Fatalities from tornadoes are displayed in Figure 4.41. A visual comparison of Figures 4.40 and 4.41 illustrates the relative dearth of fatalities relative to tornado injuries. The injury to fatality ratio for tornadoes is

15.2 to 1, the second largest of all disaster types, behind wildfires. A final note regarding entries for tornado events in SHELDUS is indicative of this disaster type. There are multiple events coded as “tornado outbreaks” in the raw data, highlighting the reality that storms that produce tornadoes rarely produce singular events.

I. Wind

There were a total of 23,646 county-events categorized as wind disasters in SHELDUS between 1995 and 2008. Figure 4.42 displays the geographic distribution of these events. As Figure 4.42 illustrates, high numbers of wind events clearly cluster in particular areas. These include the Puget Sound area in Washington, the Central Valley of California and central Iowa, along the Great Lakes shoreline, and the northeastern U.S. Figure 4.43 displays the geographic distribution of property damage from wind events. According to

Figure 4.42: Total Number of Wind County-Events, 1995-2008

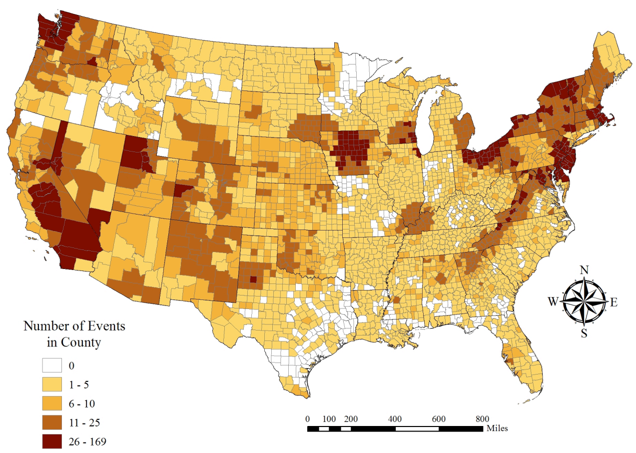
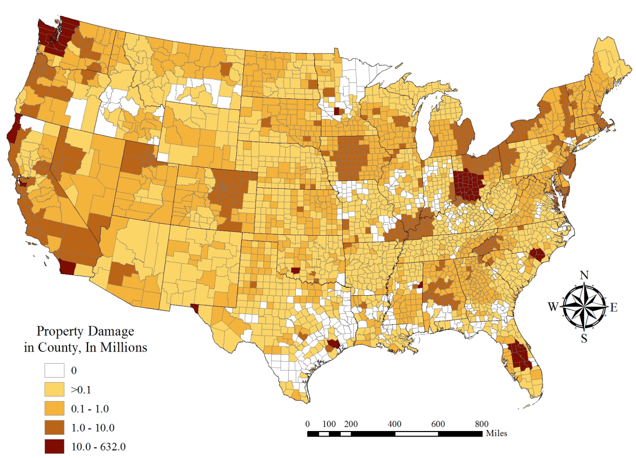


Figure 4.43: Total Property Damage from Wind Events, 1995-2008



SHELDUS, there was approximately 4.83 billion dollars in property damage from wind events during the study period. Visible in Figure 4.43, areas where property damage exceeds 10 million dollars include clusters of counties in Ohio, Florida, Washington, and North Carolina. Included in these clusters are 7 counties in Florida that experienced the greatest property damage of all losses in the category, accounting for approximately 2.3 billion dollars in losses. Crop damage from wind events is presented in Figure 4.44. In total, approximately 626 million dollars in crop damage can be attributed to events of this type.

Figure 4.44: Total Crop Damage from Wind Events, 1995-2008

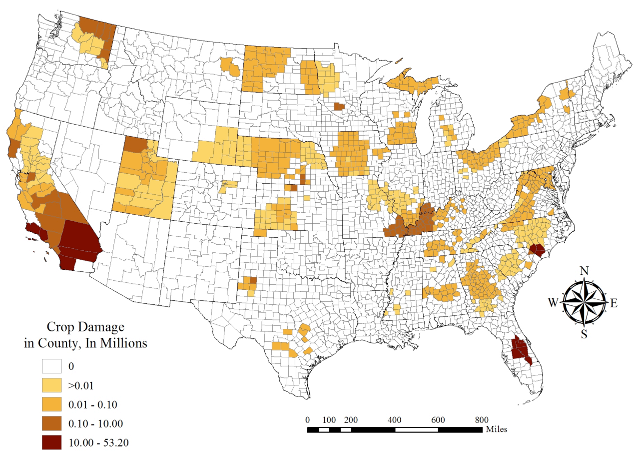
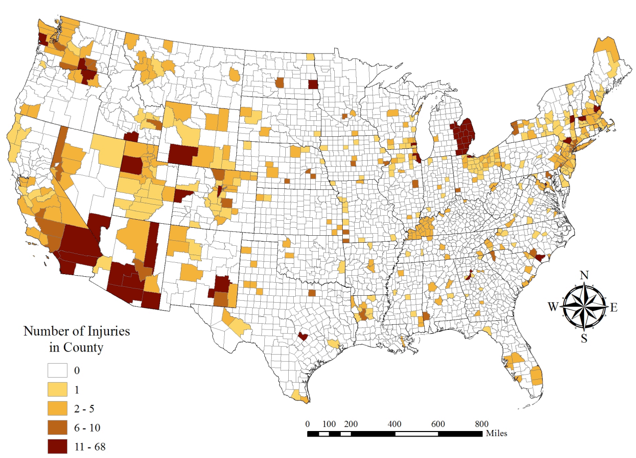
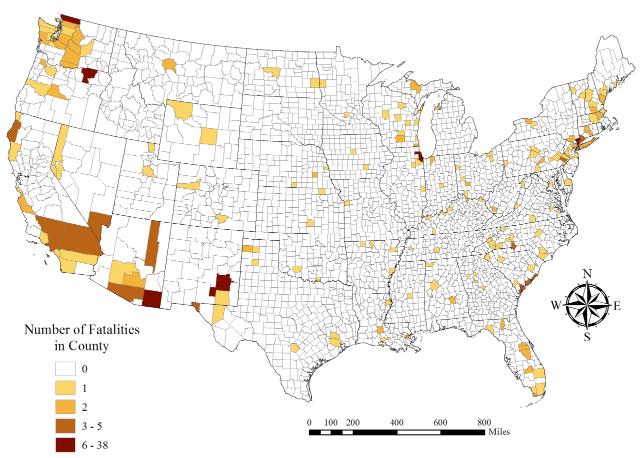


Figure 4.45: Total Number Injuries from Wind Events, 1995-2008



The geographic distribution of injuries and fatalities from wind are presented in Figure 4.45 and Figure 4.46, respectively. A total of 2,187 injuries and 411 fatalities are attributed to wind events. As is apparent in Figure 4.45, the western U.S. experienced a disproportionate number of wind-related injuries relative to the rest of

Figure 4.46: Total Number Fatalities from Wind Events, 1995-2008

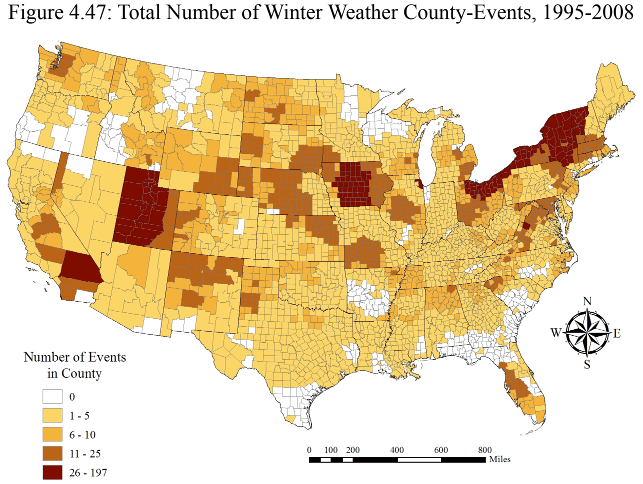


the country. Inspection of the raw data confirms that counties in California, Arizona, and Washington comprise the majority of the 25 counties with the greatest number of injuries from wind events. Home of the "Windy City" of Chicago, Cook County, Illinois experienced the most fatalities from wind events, with 38.

J. Winter Weather

Winter weather is the third most common disaster event listed in SHELDUS, with a total of 24,366 events categorized as winter weather. Figure 4.47 displays the geographic distribution of these events. The clustering of high number of winter weather events occurs in the Northeast, Utah, and Iowa. Of the 20 counties that experienced the largest number of winter weather events, 11 are in New

Figure 4.47: Total Number of Winter Weather County-Events, 1995-2008



York, eight are in Vermont, and one is in Pennsylvania. Each of these 20 counties experienced over 110 winter weather events during the study period. The geographic distribution of property damage from winter weather is provided in Figure 4.48.

Figure 4.48: Total Property Damage from Winter Weather Events, 1995-2008

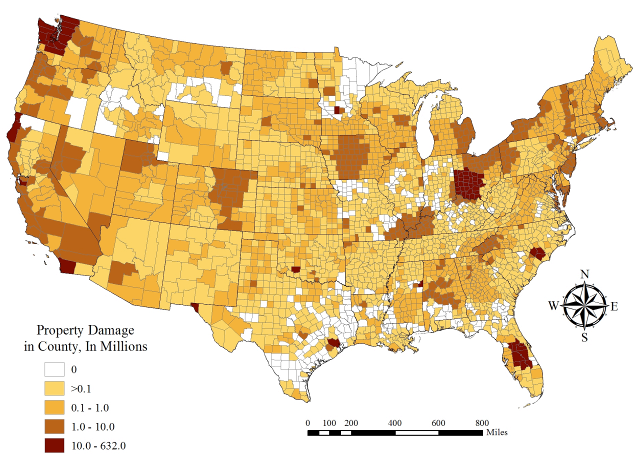
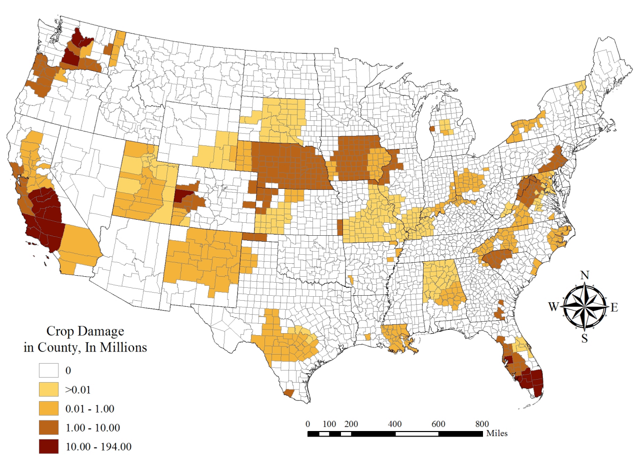
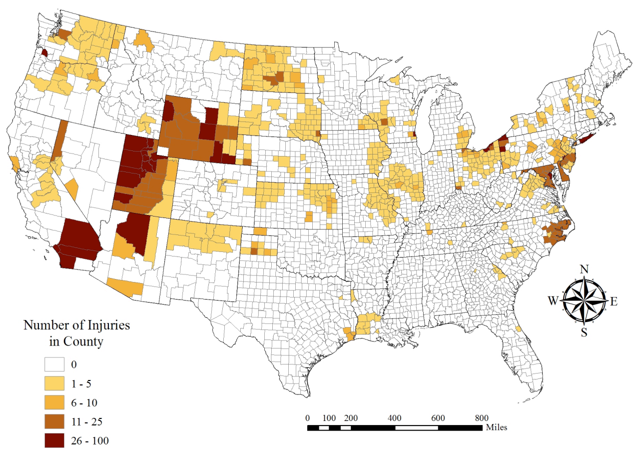


Figure 4.49: Total Crop Damage from Winter Weather Events, 1995-2008



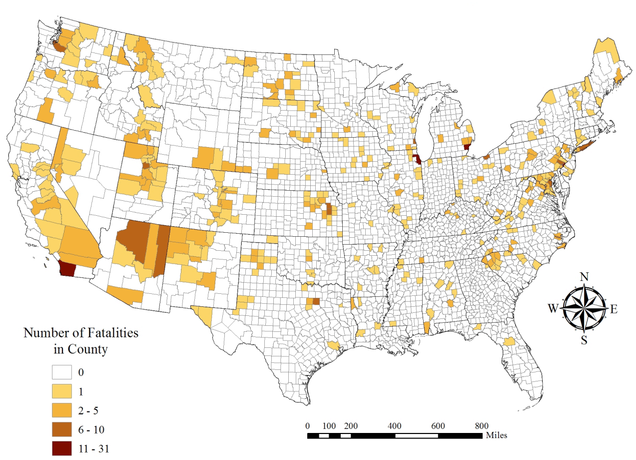
According to SHELDUS, over 5.8 billion dollars in property damage can be attributed to winter weather. Again, counties in the Northeast experienced the greatest property losses from events of this type. Figure 4.49 displays the geographic distribution of crop losses from Winter Weather. According to SHELDUS, crop losses from winter weather exceeded 3.5 billion. Notably, the largest of these losses are clustered along the eastern slope of the Cascades in Washington, in the Central Valley in California, and on the tip of the Florida peninsula. Figure 4.50 provides the geographic distribution of injuries from winter weather. In total, there were 3,872 injuries associated with winter weather. Southern

Figure 4.50: Total Number Injuries from Winter Weather Events, 1995-2008



California and the Intermountain West states of Wyoming, Utah, and Arizona stand out as especially injurious in terms of winter weather events. Curiously, there are relatively few winter weather injuries recorded in Colorado in comparison to these other states. Inspection of the raw data confirms that counties in Utah and California claim several hundred injuries during the study period, while the remaining injury totals in other counties are small in comparison.

Figure 4.51: Total Number Fatalities from Winter Weather Events, 1995-2008

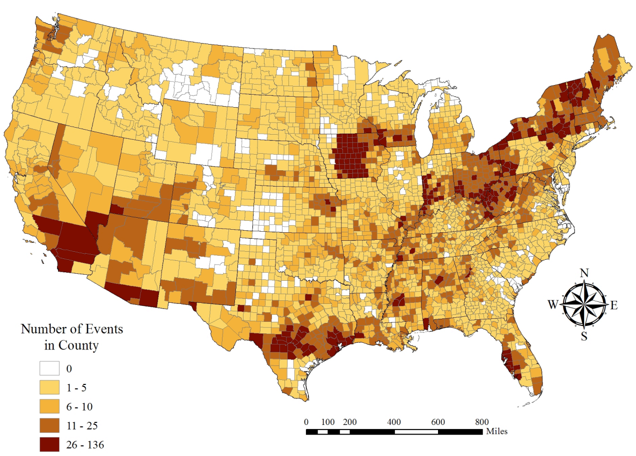


The geographic distribution of fatalities from winter weather is displayed in Figure 4.51. In total, there were 831 fatalities from winter weather reported in SHELDUS. The greatest number of fatalities in a county were in Crawford County Illinois and San Diego County, California with 31 and 28 fatalities from winter weather, respectively.

K. Flooding

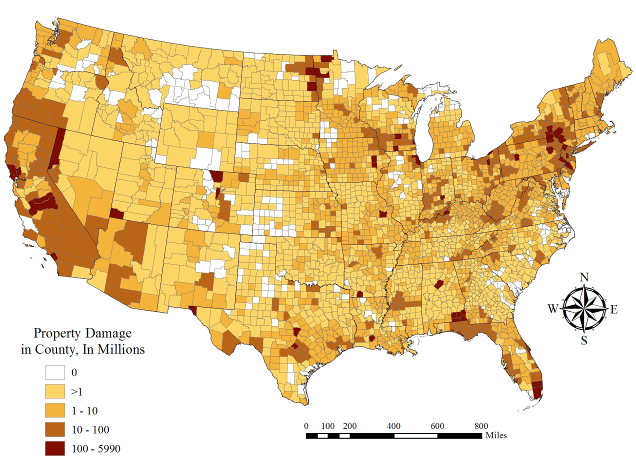
The second most common disaster event indexed by SHELDUS was flooding. There were a total of 26,349 county-events categorized as flooding disasters in SHELDUS between 1995 and 2008. Figure 4.52 displays the geographic distribution of these events. Visible in the center of the country, Iowa's number of events indicate extensive experience with this type of disaster event. Several counties in this area experienced over 130 flood county-events during the study period.

Figure 4.52: Total Number of Flooding County-Events, 1995-2008



Property damage from flood events is displayed in Figure 4.53. In total, SHELDUS indicated there was approximately 35.3 billion dollars in property damage from flood events. While the clustering in Iowa is not as apparent in this figure as it is in Figure 4.52, the largest property damage from flood events was in Linn County, Iowa. Property damage in this county was approximately 6 billion dollars.

Figure 4.53: Total Property Damage from Flooding Events, 1995-2008



This damage is attributed to the flooding of the city of Cedar Rapids in 2008. The geographic distribution of crop damage attributed to flood events is displayed in Figure 4.54. Crop damage from flood events exceeded 5.4 billion dollars. Geographic centers of these high crop losses include the Central Valley of California, South-Central Wisconsin, and Southern Florida.

Figure 4.54: Total Crop Damage from Flooding Events, 1995-2008

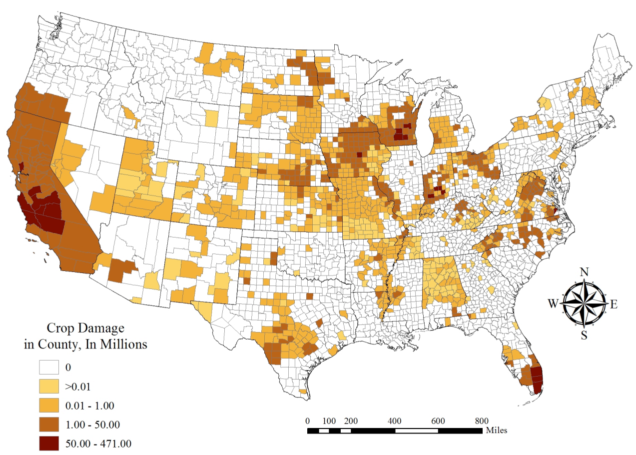


Figure 4.55 provides the geographic distribution of injuries from flood events. According to SHELDUS, there were 8,196 injuries attributable to flood events between 1995 and 2008. In Figure 4.55, the high number of injuries visible in south-central Texas are notable. The majority of the injuries pictured here were the result of a single flood event, lasting two days in October 1998. Fatalities from this event are also apparent in Figure 4.56. In total 1,065 fatalities from floods are recorded in SHELDUS. The 1998 Texas flood is clearly represented in the counties that experienced

Figure 4.55: Total Number Injuries from Flooding Events, 1995-2008

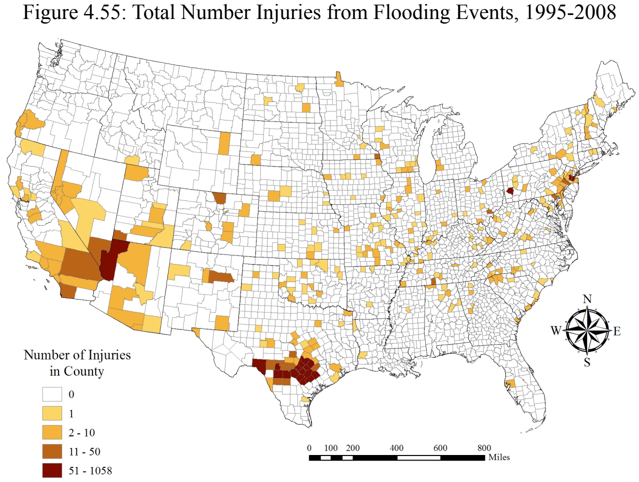
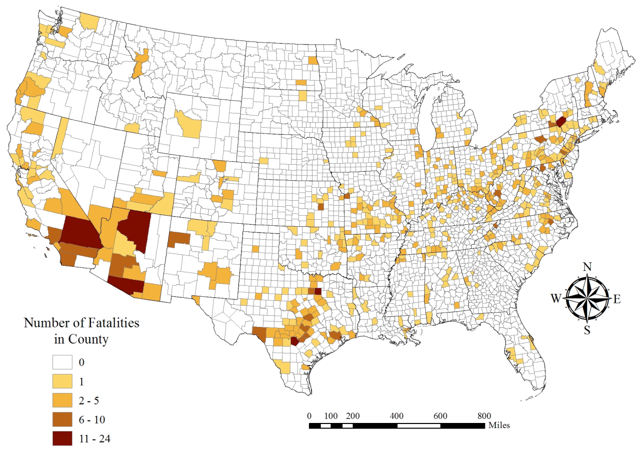


Figure 4.56: Total Number Fatalities from Flooding Events, 1995-2008

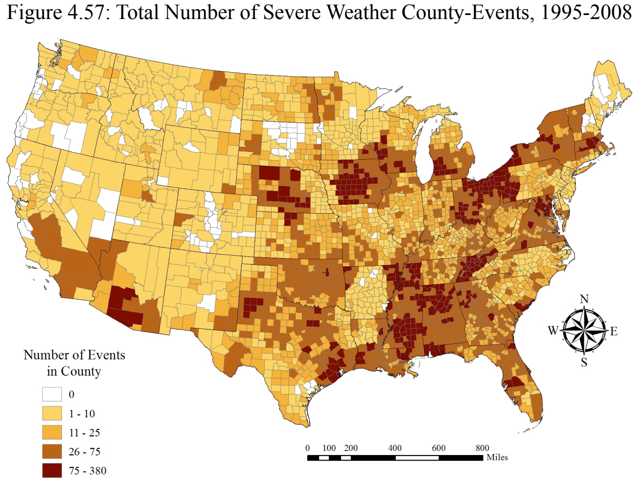


the largest number of fatalities from flood events, with five Texas counties in this area having 8 or more fatalities from floods during the study period.

L. Severe Weather

The most common disaster event in SHELDUS is severe weather and comprises a total of 93,329 county-events between 1995 and 2008. The distribution of the total number of severe weather events is provided in Figure 4.57. With the exception of the southwestern U.S., the west experiences few severe weather events relative to the central part and eastern half of the country. The relative frequency of severe weather events does not translate into large property damage (Figure 4.58) and crop damage (Figure 4.59) from these events. Even so, there was a total of over

Figure 4.57: Total Number of Severe Weather County-Events, 1995-2008



19.7 billion dollars in property damage and over 3.7 billion dollars in crop damages attributed to disaster events of this type. The total number of injuries from severe weather events is provided in Figure 4.60. There were a total of 6,590 injuries attributed to severe weather in SHELDUS. Inspection of the raw SHELDUS data indicates that a series of storms over several years account for the clustering of injuries from severe weather in central and southern California. With the exception of this clustering, there are no other clear severe weather clustering of injuries. Figure 4.61 provides the geographic distribution of

Figure 4.58: Total Property Damage from Severe Weather Events, 1995-2008

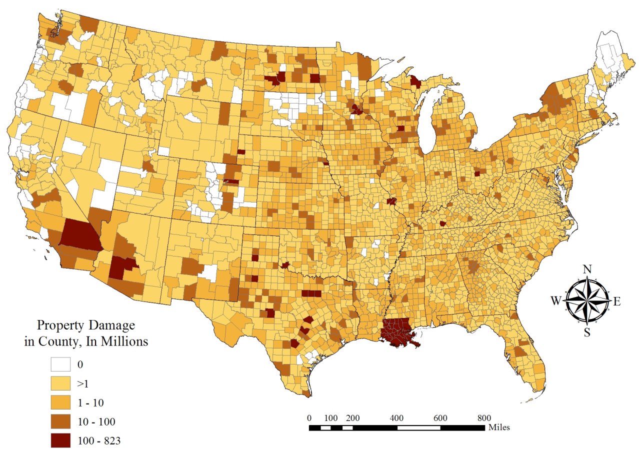


Figure 4.59: Total Crop Damage from Severe Weather Events, 1995-2008

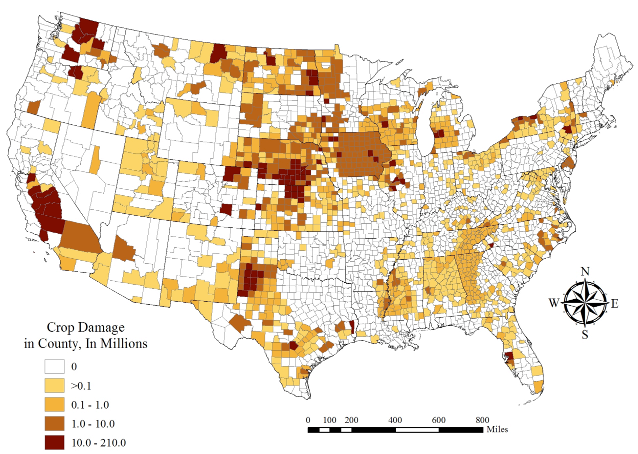
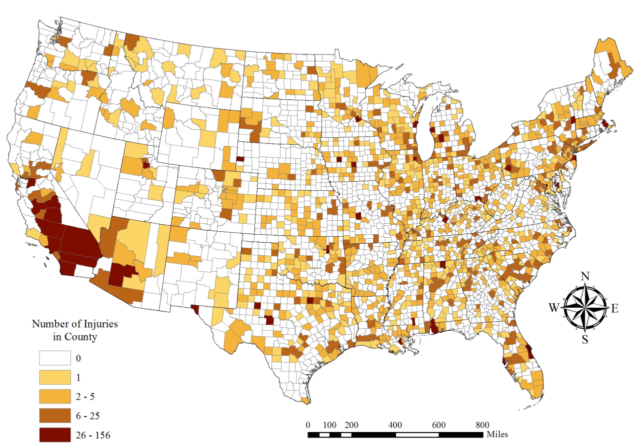
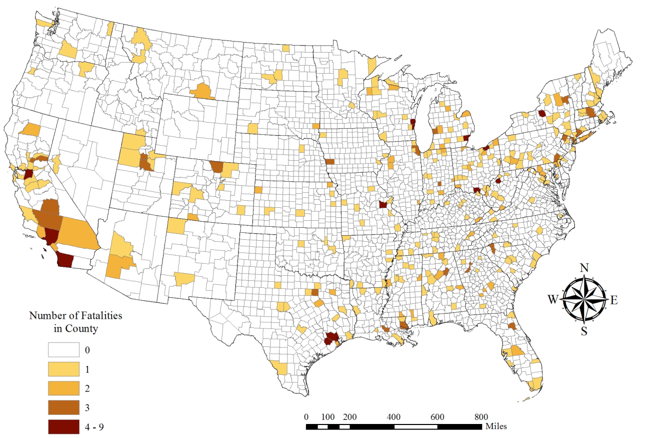


Figure 4.60: Total Number Injuries from Severe Weather Events, 1995-2008



fatalities from severe weather events. According to SHELDUS, there were 490 fatalities attributed to severe weather between 1995 and 2008. The ratio of injuries to fatalities for severe weather (13.45:1) is similar to that of tornadoes. This likely reflects the similar meteorological origins of these two disaster types.

Figure 4.61: Total Number Fatalities from Severe Weather Events, 1995-2008



IV. Comparison of Disaster Types on Impact Metrics

A review of the previous section suggests that the geographic distribution of disaster types are not independent. That is, there are clear relationships between the meteorological or physical properties of events whereby some event types cannot be considered distinguishable from one another. Hurricanes exemplify this relationship. The complexity of a hurricane event may, in effect, create damage caused by wind, lightning, coastal and riparian flooding, hail, tornadoes, and lightning, and could saturate the ground acting as a catalyst for landslides. In sum, the above review of the disaster impacts and indicates a need to assess the geographic overlay among disasters.

A second justification of investigating the relationship among the disaster types on the categories of losses is relevant to construction of the composite measure DEMI. The variable DEMI, used as an indicator of a disaster's magnitude combines economic and human losses in such a way that each category of losses are given equal weight. Thus, the relationship between the disaster types and their impacts as measured by property damage, crop damage, injuries, and fatalities should be clarified to determine which combination of disaster types are most likely to cause a particular type of damage. In Tables 4.2–4.5, correlation matrices are provided to uncover which disasters are alike in their effect on these measures.

Table 4.2: Correlation Among 12 Disaster Types on Property Damage Estimates

	Geophysical	Mass Movements	Wildfire	Coastal	Hurricane/ T.S.	Heat/ Drought	Lightning	Tornadoes	Wind	Winter Weather	Flooding
Mass Movements	0.000	--									
Wildfire	-0.002	0.004	--								
Coastal	-0.002	-0.001	-0.003	--							
Hurricane/ T.S.	-0.006	-0.005	0.013	0.256***	--						
Heat Drought	0.003	-0.006	0.011	-0.013	-0.026	--					
Lightning	0.004	-0.006	0.016	-0.001	-0.203***	-0.006	--				
Tornadoes	-0.006	-0.004	0.000	-0.004	0.070***	0.033	0.144***	--			
Wind	0.023	0.008	0.021	-0.005	0.021	-0.004	0.041*	0.039	--		
Winter Weather	0.069***	-0.008	-0.012	-0.021	-0.054**	-0.011	0.047**	0.049	0.001	--	
Flooding	0.001	0.000	0.010	0.001	0.020	-0.011	0.013	0.044	-0.001	0.026	--
Severe Weather	0.022	-0.002	0.029	0.113***	0.080***	0.060***	0.115***	0.031	0.012	0.001	0.019

***p<0.001; **p<0.01; *p<0.05

Table 4.2 provides the results of Pearson correlations among property damage estimates. First, winter weather and geophysical events have a small but statistically significant correlation. This relationship reflects the corresponding location of geophysical events and winter weather, but clearly not their causes. As was noted above, the most damaging geophysical event was the Nisqually Earthquake, which struck the Seattle area in 2001. While the Seattle area's climate consists of rain, winter weather events in the Puget Sound region create substantial property damage (see Figure 4.48).

Additionally, the Great Lakes region, where winter weather is likely, also experiences slosh wave events, accounting for damage in the geophysical category.

The relationship between hurricanes/tropical storms and other disaster events is more informative. Areas that experience high property damage from hurricanes and tropical storms also experience higher property damage from coastal events, tornadoes, and severe weather. Likewise, there are small but statistically significant positive relationships between lightning and tornadoes, wind, winter weather and severe weather. Finally, severe weather is correlated with environmental extremes of coastal events, hurricanes and tropical storms, and lightning.

Table 4.3 provides correlations among disaster types on the measure of crop damage. In contrast to property damage above, there are fewer statistically significant correlations among event types on crop damage. Hurricanes are associated with wind and flooding on this measure. Additionally, severe weather, flooding, and winter weather are all positively related to one another on this measure. Finally, both heat/drought and severe weather have a small but statistically significant relationship on this measure.

Table 4.3: Correlation Among 12 Disaster Types on Crop Damage Estimates

	Geophysical	Mass Movements	Wildfire	Coastal	Hurricane/ T.S.	Heat/ Drought	Lightning	Tornadoes	Wind	Winter Weather	Flooding
Mass Movements	--	--									
Wildfire	--	0.000	--								
Coastal	--	0.000	0.000	--							
Hurricane/ T.S.	--	-0.001	-0.001	0.000	--						
Heat Drought	--	-0.001	-0.001	-0.001	-0.007	--					
Lightning	--	0.000	0.000	0.000	0.001	-0.001	--				
Tornadoes	--	0.000	0.000	0.000	0.003	-0.001	0.000	--			
Wind	--	0.000	0.000	0.000	0.058***	-0.002	0.000	0.000	--		
Winter Weather	--	0.000	0.000	0.000	-0.002	-0.009	0.001	0.001	-0.001	--	
Flooding	--	0.023	-0.001	0.000	0.118***	-0.003	0.000	0.003	0.015	0.065***	--
Severe Weather	--	-0.001	-0.001	0.000	-0.003	0.037***	0.000	0.002	0.003	0.159***	0.035***

***p<0.001; **p<0.01; *p<0.05

Table 4.4 and Table 4.5 provide correlations among disaster types for injury and fatality estimates, respectively. Both tables suggest multiple interrelationships among disaster types on the measures. Wind, winter weather, flooding, and severe weather stand out has having the largest number of statistically significant relationships with other disaster types. Clearly these disaster types and their impacts are indicative of complex events. As these tables also suggest, areas routinely impacted by one disaster type are likely to be impacted by other disaster types.

Table 4.4: Correlation Among 12 Disaster Types on Total Injuries Estimates

	Geophysical	Mass Movements	Wildfire	Coastal	Hurricane/ T.S.	Heat/ Drought	Lightning	Tornadoes	Wind	Winter Weather	Flooding
Mass Movements	0.098***	--									
Wildfire	0.072***	0.121***	--								
Coastal	0.236***	0.035	0.616***	--							
Hurricane/ T.S.	-0.002	-0.005	0.011	0.014	--						
Heat Drought	0.004	-0.007	0.069***	0.045*	-0.006	--					
Lightning	0.008	0.061	0.044*	0.152***	0.118***	0.036*	--				
Tornadoes	-0.006	-0.008	-0.001	0.000	-0.001	-0.001	0.099***	--			
Wind	0.026	0.234***	0.191***	0.191***	0.005	0.085***	0.165***	0.000	--		
Winter Weather	0.035	0.196***	0.228***	0.228	-0.010	0.129***	0.081***	-0.001	0.272***	--	
Flooding	0.084***	0.116***	0.091	0.091	0.000	0.045**	0.156***	0.013	0.279***	0.160***	--
Severe Weather	0.078***	0.126***	0.148	0.148	0.000	0.130***	0.159***	0.079***	0.294***	0.123***	0.231***

***p<0.001; **p<0.01; *p<0.05

Table 4.5: Correlation Among 12 Disaster Types on Total Fatalities Estimates

	Geophysical	Mass Movements	Wildfire	Coastal	Hurricane/ T.S.	Heat/ Drought	Lightning	Tornadoes	Wind	Winter Weather	Flooding
Mass Movements	0.039*	--									
Wildfire	-0.001	0.140***	--								
Coastal	0.012	0.010	0.164	--							
Hurricane/ T.S.	-0.001	-0.004	-0.002	0.022	--						
Heat Drought	-0.001	0.001	0.013	0.004	0.001	--					
Lightning	0.013	0.092***	0.037*	0.429***	0.111	0.120***	--				
Tornadoes	-0.005	-0.019	-0.007	-0.001	0.007	0.002	0.051**	--			
Wind	0.003	0.100***	0.039*	0.053**	0.036*	0.753***	0.151***	0.003	--		
Winter Weather	0.021	0.085***	0.395***	0.092***	-0.006	0.615***	0.156***	-0.006	0.443***	--	
Flooding	-0.004	-0.005	0.139***	0.023	0.052**	0.120***	0.138***	0.014	0.160***	0.203***	--
Severe Weather	0.009	0.009	0.171***	0.085***	-0.004	0.121***	0.180***	0.009	0.131***	0.252***	0.156***

***p<0.001; **p<0.01; *p<0.05

V. TIME AND DISASTER

Central to the relationship between disasters and time is the question of whether disasters are increasing and what the overall changes in their effects are. That is, are the number of events, fatalities, injuries, property and crop damages increasing or decreasing across the study period?

Figure 4.62: Observed Number of County-Events and Linear Trend, by Year, for all Disaster Types

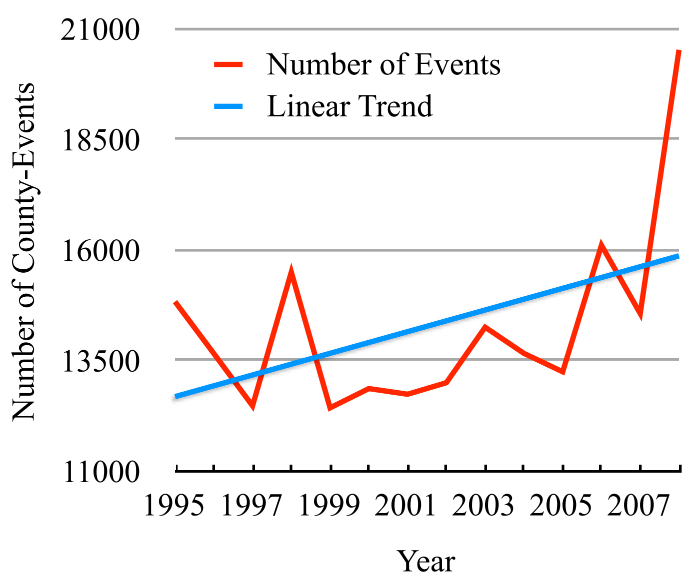


Figure 4.62 displays the observed number of events, per year, recorded in SHELDUS. There is large inter-year variation for the measure of number of events. To ascertain whether the number of events have increased or decreased over

the study period, the number of events was regressed on year. The result of this analysis is the linear trend line in Figure 4.62.The slope of this line indicates that on average, during the study period, the number of disaster events has increased by approximately 222 per year.

The observed property damage from all disasters and the associated linear trend line is displayed in Figure 4.63. On average, property damages have increased by about 1.3 billion per year, during the study period. However, this trend colors the fact that average increases reflect the influence of the observed property damages in 2005. The exclusion of 2005 in the calculation of the linear trend in property damage reveals a more modest average year to year increase in property damage from disaster events.

Figure 4.63: Observed Property Damage and Linear Trend by, Year, for all Disaster Types

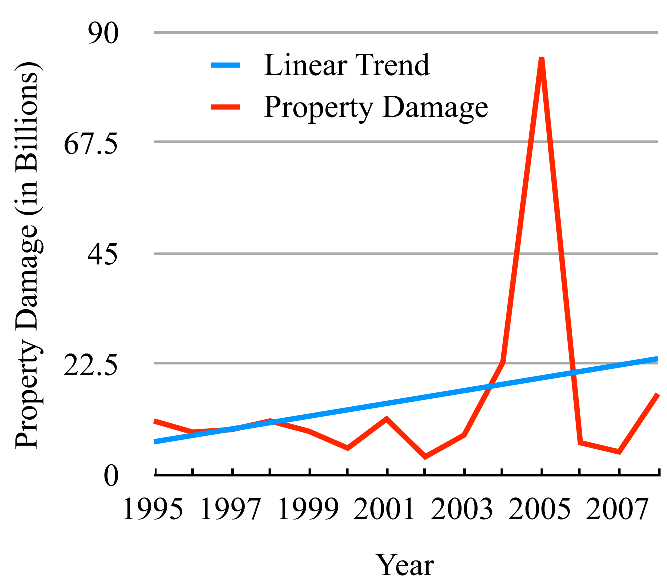


Figure 4.64 displays the observed yearly crop damage and linear trend resulting from disasters. It is notable that year-to-year crop damage is highly variable. In general, there is a decline in crop damage over the study period. The slope for the regression line indicates that, on average, crop damage has declined by approximately 136 million dollars per year, during the study period.

Figure 4.64: Observed Crop Damage and Linear Trend, by Year, for all Disaster Types

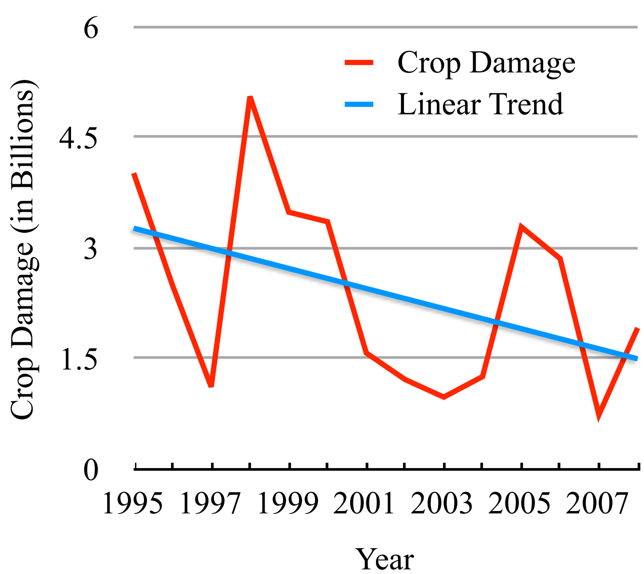
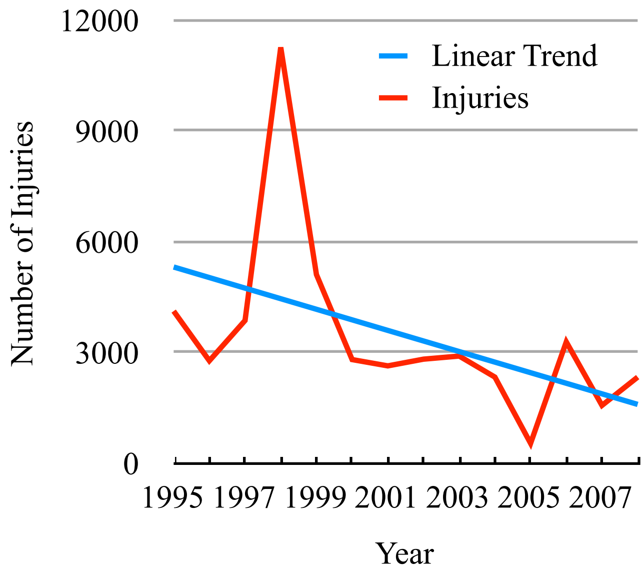


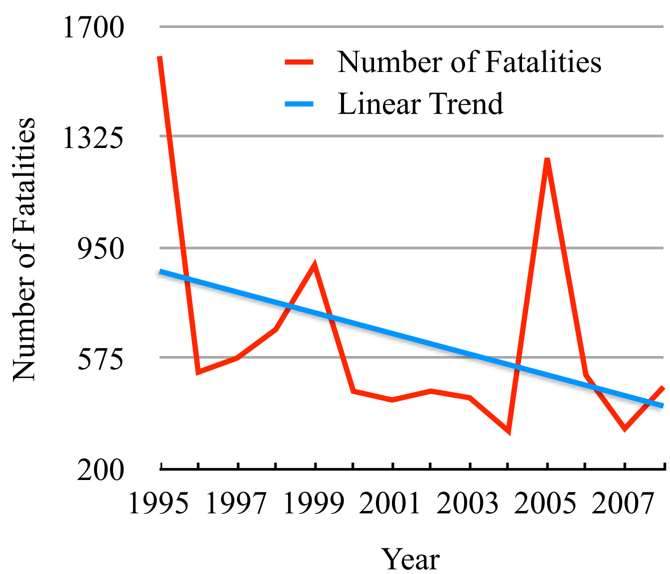
Figure 4.65 displays the observed number of injuries and linear trend, by year, for the study period. As with crop damage, on average, the number of injuries from disaster events has also declined. The average year-to-year decline in injuries is approximately 286. As with property damage there does appear to be clear leveraging of the linear trend line. The injuries in 1998 are quite high relative to other years. Thus, the average decline reflects the extreme injury totals in 1998.

Figure 4.65: Observed Number of Injuries and Linear Trend, by Year, for all Disaster Types



Finally, Figure 4.66 displays the observed number of fatalities from disaster and the associated linear trend for the time period. While there is high year-to-year variation in fatalities from disasters, on average, during the study period the number of fatalities from natural disasters has declined. The slope of this regression line was -35.11 indicating that, on average, there is an annual decrease in fatalities of about 35 per year. Collectively, the data indicates that while property damage and the number of events are increasing during the study period, other measured disaster indicators are declining.

Figure 4.66: Observed Number of Fatalities and Linear Trend, by Year, for all Disaster Types



VI. GEOGRAPHY AND CRIME

This section presents an overview of crime rates and their geographic distribution. I begin with univariate and bivariate descriptive statistics for crime outcomes. Then, I provide a geographic display of average county-level crime rates for the study period and the results of the Hot-Spot analysis, cluster, and outlier analyses. Each of these was required to determine if spatial autocorrelation among crime measures exists, and if so where? The geographic analysis is then repeated for both property and violent crime rates.

A. Descriptive Statistics for Crime Outcomes

Table 4.6 displays the total number of crimes recorded in the UCR data for the study period. There were a total of over 156.5 million index crimes reported by police agencies to the FBI between 1995 and 2008. Of these, approximately 87.61% were property crimes while the remaining crimes were categorized as violent crimes (12.39%). As indicated in the table, the most common of the sub-types of crime was larceny, accounting for 58.13% of all index crimes. The least common crime was criminal homicide with 230,645 homicides accounting for roughly 0.15 percent of all index crimes.

Table 4.6: Total Number of Reported Crimes, 1995-2008

Crime Type	Number	Percent of Index Crimes
Index Crimes	158,575,378	100.00
Property Crimes	138,925,689	87.61
Violent Crimes	19,649,689	12.39
Arson	1,069,445	0.67
Burglary	29,248,919	18.44
Larceny	92,178,647	58.13
Motor Vehicle Theft	16,428,678	10.36
Aggravated Assault	12,160,255	7.67
Criminal Homicide	230,645	0.15
Forcible Rape	1,180,002	0.74
Robbery	6,078,787	3.83

Table 4.7 displays zero-order correlations among all crime rates used in this research. The coefficients demonstrate a high degree of positive correlation among each of the different crime types. Without exception, all correlations are statistically significant. Correlations among the sub-types of crime–arson, burglary larceny, motor vehicle theft, aggravated assault, criminal homicide, forcible rape, and robbery–are highly variable. The three types of theft, larceny, burglary, and motor vehicle theft highly correlated with one another with each bivariate relationship having a coefficient

exceeding 0.600. Criminal homicide, in general, has the weakest relationships with all other crime measures, relative to other bivariate relationships. The weakest correlation in this matrix is between the forcible rape rate and the criminal homicide rate (r =0.295).

Table 4.7: Correlation Among UCR Crime Rates

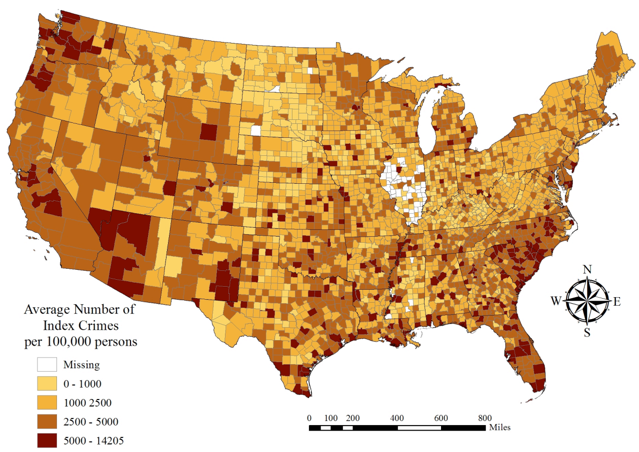
	Index Rate	Property Rate	Violent Rate	Arson Rate	Burglary Rate	Larceny Rate	MV Theft Rate	Aggravated Assault Rate	Criminal Homicide Rate	Forcible Rape Rate
Property Rate	0.978***	--								
Violent Rate	0.721***	0.637***	--							
Arson Rate	0.510***	0.493***	0.413***	--						
Burglary Rate	0.838***	0.842***	0.616***	0.427***	--					
Larceny Rate	0.912***	0.931***	0.581***	0.445***	0.699***	--				
MV Theft Rate	0.756***	0.746***	0.586***	0.448***	0.639***	0.671***	--			
Aggravated Assault Rate	0.675***	0.594***	0.954***	0.381***	0.580***	0.543***	0.543***	--		
Criminal Homicide Rate	0.410***	0.378***	0.436***	0.276***	0.360***	0.316***	0.370***	0.373***	--	
Forcible Rape Rate	0.558***	0.528***	0.565***	0.414***	0.462***	0.500***	0.476***	0.453***	0.292***	--
Robbery Rate	0.644***	0.602***	0.626***	0.411***	0.526***	0.545***	0.575***	0.536***	0.477***	0.481***

***p<.001, **p<.01, *p<.05, ~p<.10

B. Geography and Index Crime

The geographic distribution of the average index crime rate for the study period is presented in Figure 4.67.[38] The average county level index crime rate for the study period was 2,713.36 crimes per 100,000 persons. In general, counties with high average crime rates are scattered throughout the south and in population centers in the Pacific Northwest, central California, and Arizona. The county with the highest index crime rate is St. Louis County Missouri with an average index crime rate of 14,204.30 crimes per 100,000 persons between 1995 and 2008. Many of the of the counties with the highest index crime rates have very small populations. For example, DeBaca County, New Mexico has a population fluctuating between 200 and 226 between 1995 and 2008. Its average index crime rate for the study period was 11,555.76. Likewise, Loving County, Texas has a population that fluctuated between 45 and 54 and has an average index crime rate of 10,239.79 between 1995 and 2008. This county had a population of 54 and had 21 index crimes reported in 2007. This gave Loving County, Texas the highest recorded index crime rate for the study period with 38,888.88 index

Figure 4.67: Average County-Level Index Crime Rate, 1995-2008



[38] Notably there are a number of counties missing data from the state of Illinois and areas in Mississippi, North Dakota and South Dakota. These missing values are the result of UCR coding procedures and represent a limitation in the analysis. Pearson correlation for missing counties with DEMI is r=0.030, and with the number of events is r=0.090.

crimes per 100,000 persons. Counties with very low index crime rates are scattered throughout the midwest. Generally these counties have index crime rates of less than 200 crimes per 100,000.

The Hot-Spot analysis (Figure 4.68) highlights areas of high spatial autocorrelation, or correlation among direct neighboring counties on this measure. In general there are a few concentrated areas of high autocorrelation. However, there are areas where such influences exist and suggest the need to use HLM modeling procedures, which control for spatial autocorrelation. Results of the cluster and outlier analysis, Anselin's local Moran's *I* (Figure 4.69), indicates a number of geographic crime "centers." In this analysis, areas where high crime rate counties cluster with extended neighbors are indicated in black. Clustering of low index crime rates are indicated in blue. Together, the Hot-Spot analysis and the cluster and outlier analysis indicate the appropriateness of

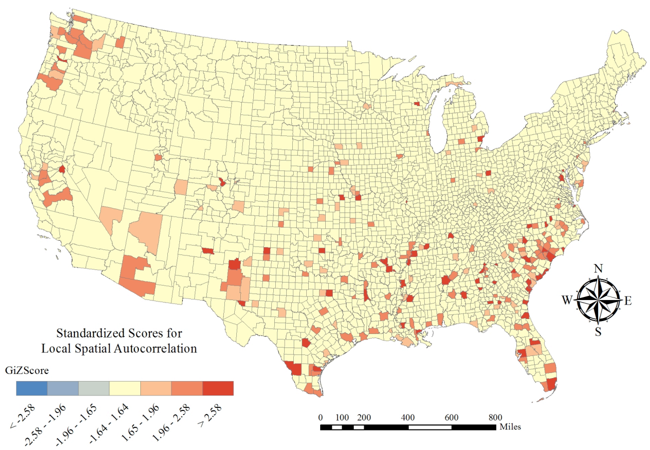


Figure 4.68: Hot-Spot Analysis (Getis-Ord Gi) for Average County-Level Index Crime Rate

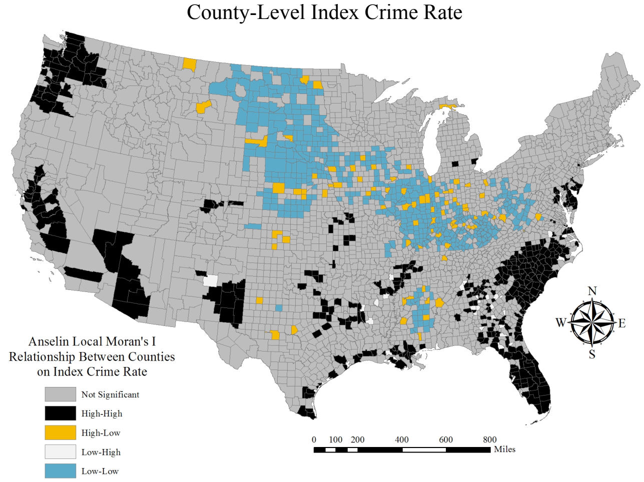


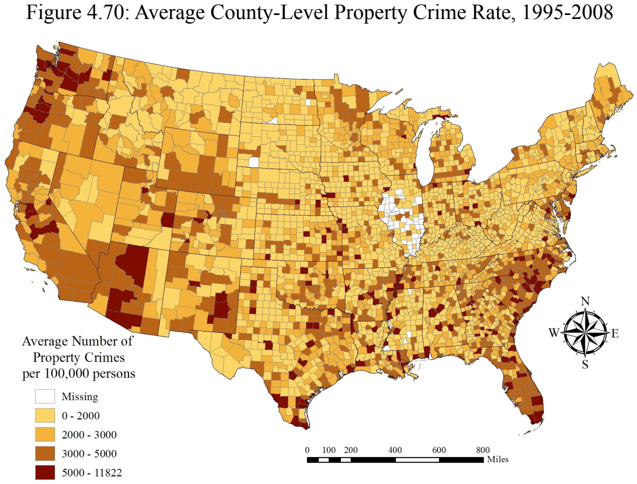
Figure 4.69: Results for Cluster and Outlier Analysis for Average County-Level Index Crime Rate

including spatial lag control variables to control for spatial dependence in the HLM procedures. A comparison of Figure 4.69 with various disaster maps, presented in the previous sections suggest that coastal areas along the East and Gulf coasts, impacted by a variety of disaster types also have clusters of high crime rate counties. Similar clustering of high crime counties are visible in California's Central valley and in the Southwest U.S. Finally, there are also areas of low crime spatial clustering throughout the Midwest and in areas in the Deep South.

C. Geography and Property Crime

Figure 4.70 provides a geographic display of average county-level property crime rates for the study period. The average county-level property crime rate for the study period was 2,430.69. The county with the highest average property crime rate was St. Louis, Missouri with 11,821.81 property crimes per 100,000 persons. As with index crime rates, counties with high average property crime rates often have very small populations. Counties with very low average property crime rates are scattered throughout the Midwest. Of the the 35 counties with the lowest recored average property crime rate, all had rates less that 200 property crimes per 100,000

Figure 4.70: Average County-Level Property Crime Rate, 1995-2008



persons. Average property crime rates for the study period indicate a general scattering of high crime rate counties throughout the south, in the population centers of the Pacific Northwest, Central California, and Arizona.

The Hot-Spot analysis of average property crime rates (Figure 4.71) indicates some areas of clustered spatial autocorrelation and generally reflects similar spatial dependence as that of index crime rates (Figure 4.68). These exist in the Pacific Northwest, Central California, along the southeastern seaboard, and throughout the southeast. Results of the Anselin's local Moran's *I* cluster and outlier analysis indicates a number of geographic property crime "centers" (Figure 4.72). In this analysis, areas where high crime rate counties cluster are indicated in black and areas where low crime rate counties cluster are indicated in blue.

Figure 4.71: Hot-Spot Analysis (Getis-Ord Gi) for Average County-Level Property Crime Rate

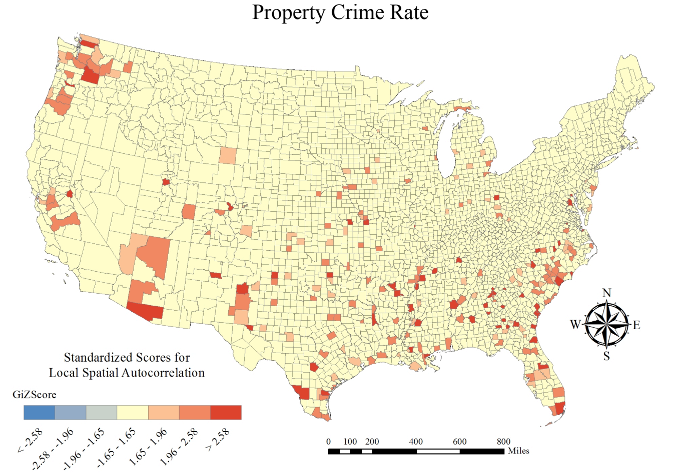
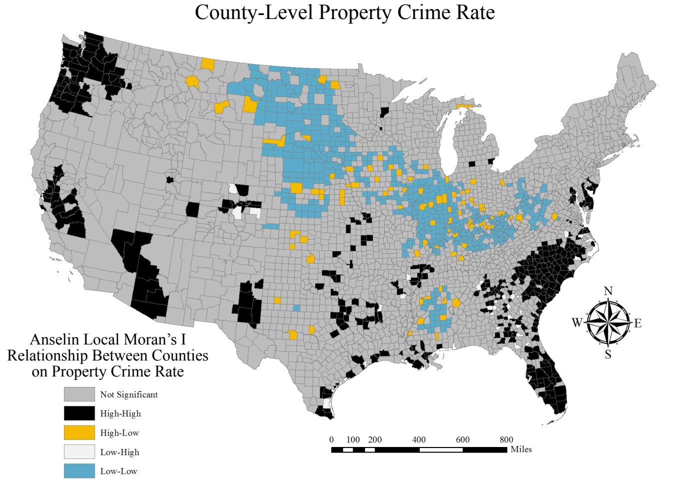


Figure 4.72: Results for Cluster and Outlier Analysis for Average County-Level Property Crime Rate

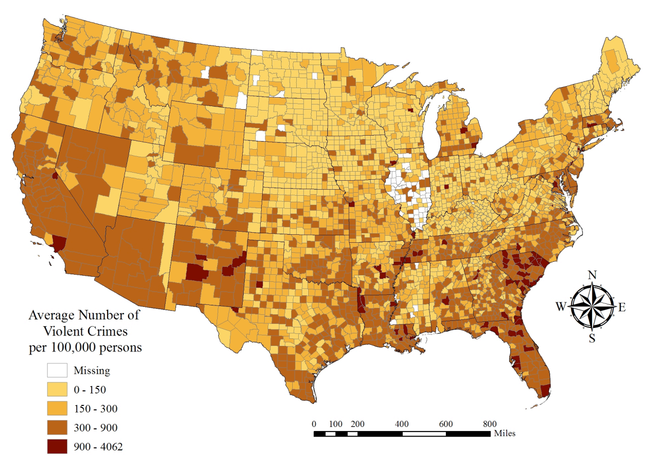


Like the geographic analysis of index crime rates, these results suggest the necessary inclusion of spatial lag variable in the HLM modeling procedures to control for spatial dependence.

D. Geography and Violent Crime

The geographic distribution of average county-level violent crime rates is presented in Figure 4.73. The highest rates are those in maroon and can be observed in Los Angeles County, California, scattered counties throughout the south, in New Mexico, Louisiana, North Carolina, and Florida. DeBaca County, New Mexico had the highest average violent crime rate during the study period, with 4,061.67 violent crimes per 100,000 persons. And St. Louis County, Missouri had the second highest average violent crime rate with 2,382.49 violent crimes per 100,000 persons. Counties with very low violent crime rates are scattered throughout the Midwest. Of the counties with the lowest violent crime rates, 35 have rates less than 30.

Figure 4.73: Average County-Level Violent Crime Rate, 1995-2008



Results of the Hot-Spot analysis for the average violent crime rate are presented in Figure 4.74. The analysis confirms that some degree of spatial autocorrelation exists for those areas where violent crime rates are high. Figure 4.75 displays the results of

Figure 4.74: Hot-Spot Analysis (Getis-Ord Gi) for Average County-Level Violent Crime Rate

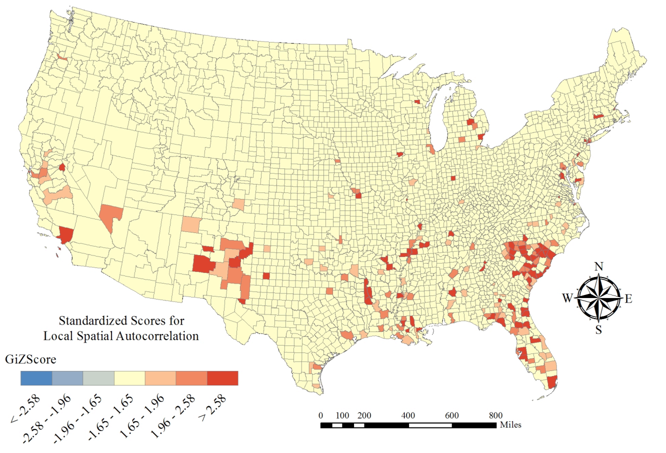
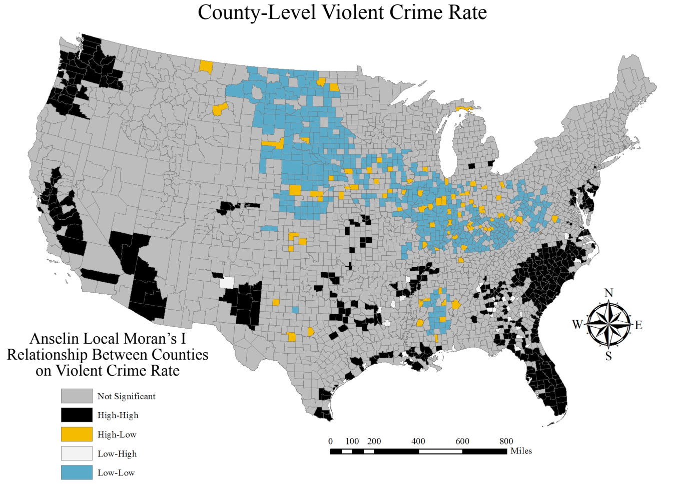


Figure 4.75: Results for Cluster and Outlier Analysis for Average County-Level Violent Crime Rate



Anselin's local Moran's *I* cluster and outlier analysis and indicates a number of geographic violent crime "centers". These results, closely mirror the results of the cluster and outlier analysis of property crime.[39] Like the geographic analysis of index and property crime rates, these results also suggest the necessary inclusion of spatial lag variable in the HLM modeling procedures to control for spatial dependence.

VII. Time and Crime

In this section, I address the question of the whether crime rates are increasing or declining over the study period. It is well known that crime rates have been on the overall decline since the early 1990s (U.S. Department of Justice 2008). The UCR data on index crimes, property crime and violent crime confirm this. Figure 4.76 illustrates the

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[39] The correlation between violent and property crime is 0.660 ($p<0.001$), indicating that areas with high property crime rates, in general, also have high violent crime rates.

observed decline in overall index crime rates between 1995 and 2008. On average, index crime rates for the country have declined by about 44 crimes per 100,000 persons, per year, during the study period.

Figure 4.76: Average Index Crime Rate and Linear Trend, by Year

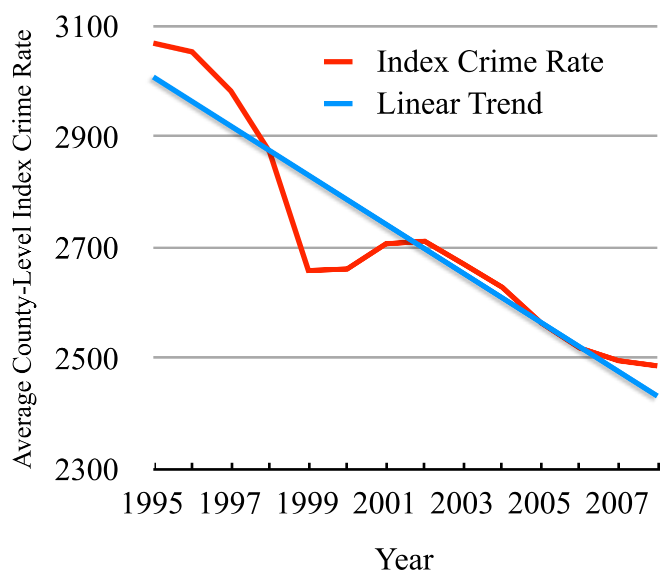
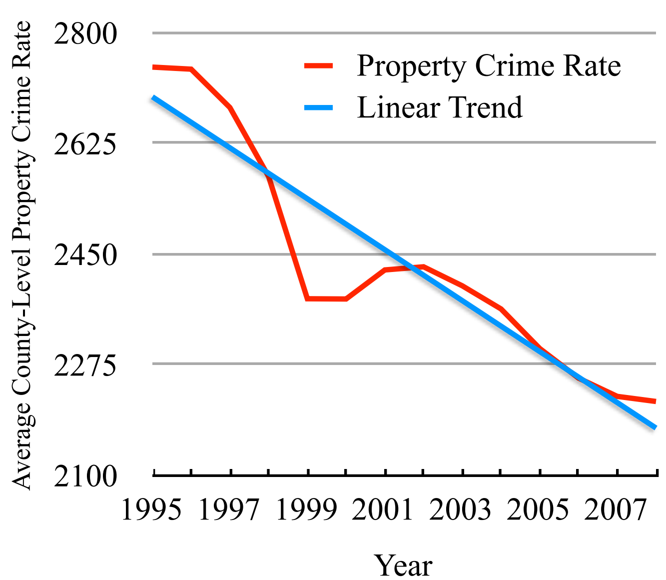


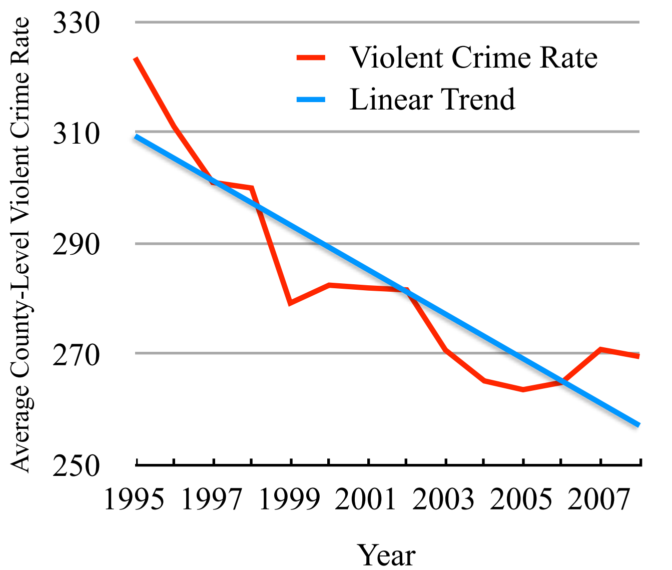
Figure 4.77, displays the observed annual property crime rates and the associated linear trend for the study period. The observed decline in property crime rates mirrors the pattern of the trend in index crimes, and the yearly rate of change for property crime is approximately -40, indicating on average, the property crime rate declines by 40 crimes per 100,000 persons per year.

Figure 4.77: Average Property Crime Rate and Linear Trend, by Year



Finally, Figure 4.78 provides the observed average violent crime rate plotted with the linear trend. As with property crime, violent crime is also on the decline during the study period. The average rate of change in the property crime rate is approximately -4. On the whole, these trends, while not surprising, illustrate the need to control for year-to year variations in crime rates when modeling the crime data longitudinally.

Figure 4.78: Average Violent Crime Rate and Linear Trend, by Year



VI. Concluding Remarks/Summary

In this chapter, I have provided an overview of the geographic and temporal distribution of the two variables that are of central interest in this research–crime and disasters. This contextualization of these variable was a necessary precursor to Chapter 5 where explicit hypotheses regarding the relationship between disaster and crime will be tested. In the next chapter, I briefly review the competing hypotheses of the research, provide a descriptive summary of the variables used in the analyses to test these hypotheses, and report the main findings of the research.

CHAPTER FIVE: SPATIAL AND TEMPORAL MODELING OF DISASTER AND CRIME

I. Introduction

This chapter reports the results of the statistical analyses to assess if disasters of different magnitudes and types have a differential effect on crime rates across space and over time. I begin with a brief restatement of the competing hypotheses to orient the reader to the purpose of the modeling procedures, followed by an overview of the descriptive data for the variables used in the analysis, including zero-order correlations among the measures. Following this, HLM models (Singer and Willett 2003) are then used to evaluate the empirical relationship between disasters and index crime rates. In subsequent models evaluating the relationship between disasters and property and violent crime rates, I offer an abbreviated description of the complete modeling process. For both property crime and violent crime, HLM analyses are repeated to determine which sub-types of crime (criminal homicide, forcible rape, aggravated assault, robbery, arson, larceny, burglary, and motor vehicle theft) display a relationship with disaster magnitude. I proceed with the modeling of crime rates utilizing the police guardianship variable, a variable not included in the previous analyses.[40] Following this, I introduce the disaster

[40] As mentioned in Chapter 3, the variable for police guardianship does not include data for each year, as is the case with all other variables. Thus, models utilizing this variable were conducted separately to determine if guardianship has an effect on crime rates.

type variable into the full HLM models to examine if disasters of different types differentially affect crime outcomes. I conclude with a discussion of the overall findings.

II. General Hypotheses

There are three competing hypotheses in this research. Hypothesis one is based on the notion of the therapeutic community (Barton 1963; Fritz 1961) and proposes that when a community experiences a disaster, crime rates will fall. If there is support for this hypothesis, the coefficient for disaster magnitude (*lnDEMI*) in the Level-one portion of the model should be negative. Simply put, an increase in the size of *lnDEMI* should correspond to a *decrease* in the overall crime rate when controlling for other correlates of crime.

Social disorganization theory (Park et al. 1925; Sampson and Groves 1989; Shaw and McKay 1942) suggests a second set of hypotheses. In this regard, disasters have the potential to create social disorganization thereby increasing the likelihood crime will occur. If there is support for this hypothesis, the coefficient for *lnDEMI* in the Level-one portion of the model should be positive, indicating an *increase* in the crime rate corresponds with an increase in disaster magnitude. An additional element of this theory suggests that disasters may exacerbate existing social disorganization. Therefore, indicators of social disorganization (inequality, racial heterogeneity, and ethnic heterogeneity) will interact with disaster magnitude to condition the effect on crime rates.

Routine activity theory (Cohen and Felson 1979; Felson and Cohen 1980) suggests a third set of hypotheses. First, disasters increase the likelihood that suitable targets, motivated offenders and lack of capable guardianship converge in time and space.

If there is support for this hypothesis the coefficient for *lnDEMI* in the Level-one portion of the model should be positive indicating an *increase* in the crime rate corresponds with an increase in disaster magnitude. However, because different disaster types may have a variable effect on the three conditions, a second hypothesis is warranted. The second hypothesis states that independent of disaster magnitude, different disaster types will have a variable effect on crime rates.

III. DESCRIPTIVE STATISTICS

Table 5.1 provides the descriptive statistics for the variables used in the analysis below. Note that all crime rates, the DEMI index, disaster frequency, the number of non-profits, and the number of full-time police are presented in Table 5.1 as real values, while these variables were log transformed for normality (Mosteller and Tukey 1977) when utilized in the HLM models presented in this chapter.

Table 5.1: Descriptive Statistics for HLM Analysis Variables

	Mean	Standard Deviation	Median	Minimum	Maximum
Index Crime Rate	2,713.361	1,733.317	2,406.979	2.495	38,888.890
Property Crime Rate	2,430.685	1,542.203	2,169.684	0.000	37,037.040
Violent Crime Rate	282.677	271.320	207.369	0.000	8,089.261
Arson Rate	17.485	24.887	11.858	0.000	1,851.852
Burglary Rate	590.448	394.608	513.042	0.000	9,259.260
Larceny Rate	1,652.364	1,103.285	1,479.422	0.000	30,000
MV Theft Rate	170.388	182.625	123.724	0.000	3,582.577
Aggravated Assault Rate	211.370	213.360	151.224	0.000	8,089.261
Criminal Homicide Rate	3.718	6.979	0.986	0.000	241.546
Forcible Rape Rate	24.245	23.690	19.918	0.000	729.671
Robbery Rate	43.345	76.876	16.736	0.000	1,624.376
DEMI Index	0.287	1.812	0.003	0.000	99.999
Number of Events	4.807	5.767	3.000	0.000	150
Theil (inequality)	-2.41e-11	8.43e-11	-5.02e-12	-2.57e-09	-2.80e-14
Percent Age 15-24	13.565	3.307	12.942	2.703	45.337
Racial Heterogeneity	0.831	0.162	0.899	0.325	1.000
Ethnic Heterogeneity	0.904	0.124	0.959	0.500	1.000
Count Non-Profits	85.879	299.056	16.000	0.000	9,639
Number of Full-Time Police	385.780	1,973.425	28.000	0.000	78,718

The tables below provide zero-order correlations among all variables used in the HLM analysis.[41] These tables were not used to test specific hypotheses, but are provided for the reader as a general reference detailing the bivariate relationships among independent and dependent variables. All correlation coefficients were statistically significant.[42] In general, bivariate relationships among the variables reflect observed patterns of disaster and crime illustrated in the Chapter 4 and theoretically-informed relationships among control variables. For example, in Table 5.2 the coefficient between *lnDEMI* and *time* is negative, indicating that during the study period disaster magnitude declines. This is consistent with the observation that three of the four components of the DEMI index, crop damage, injuries, and fatalities have, on average, declined during the study period.[43] Likewise the correlation between *time* and the number of events is positive, reflecting the relative increase in disaster events over time, during the study period.

The bivariate relationship among control variables is consistent with theoretical expectations. In Table 5.2, indicators of social (dis)organization, *racial heterogeneity*, *ethnic heterogeneity*, the Theil index of *inequality*, and the number of non-profits (*lnNProfit*) all operate in tandem. That is, inequality and measures of heterogeneity are positively related, while inequality is negatively related to the measure of community efficacy, measured as the number of non-profits in a county.

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[41] In contrast to Table 5.1, all correlation coefficients were calculated using the exact variable used in the analyses. That is, all crime rates, the DEMI index, the number of events, non-profit count, and the number of police were all log-transformed for normality.

[42] Note that N=38,753 for tables 5.2 through 5.3, with the exception of correlation coefficients using the number of police. In this case, N=7,125 because LEMAS data represents a sample of police organizations for the years 1997, 1999, 2000, 2003, and 2007.

[43] Although property damage increased during the study period, equal weight is given to each of the four impact measures in the calculation of DEMI. The result is an overall decline in magnitude over time.

Table 5.3 provides correlations among dependent and independent variables. It is notable that all crime rates are positively correlated with *lnDEMI* and the number of events (*lnEvents*). Likewise, with the exception of police guardianship (*lnPolice*) and *lnNProfit*, theoretically relevant controls behave in their predicted direction. That is, both *lnPolice* and *lnNProfit* are positively correlated with crime rates when both theories of social disorganization and routine activity suggest community efficacy and police guardianship should reduce crime.[44]

[44] The relationship between guardianship and non-profit count with crime rate is likely the function of population. That is, the number of police and non-profit organizations increase as population increases. Population was originally included in the modeling process but was excluded from the analysis because a) population is included in the calculation of crime rates, and b) controlling for population had little effect on HLM parameter estimates.

Table 5.2: Correlation Among Independent Variables Used to Model Crime Outcomes

	Time	*lnDEMI*	*lnEvents*	*Inequality*	*pctMale15-24*	*Racial Heterogeneity*	*Ethnic Heterogeneity*	*lnNProfit*
lnDEMI	-0.102***	--						
lnEvents	0.018***	0.294***	--					
inequality	0.020***	-0.193***	-0.142***	--				
pctMale15-24	0.021**	0.015**	0.044***	-0.001***	--			
Racial Heterogeneity	-0.028*	-0.083***	-0.079***	0.203***	-0.190***	--		
Ethnic Heterogeneity	-0.098***	-0.127***	0.050***	0.216***	-0.137***	0.016**	--	
lnNProfit	-0.134***	0.131***	0.178***	-0.445***	0.124***	-0.136***	-0.076***	--
lnPolice	-0.434***	0.247***	0.222***	-0.492***	0.***	-0.338***	-0.218***	0.706***

***p<.001, **p<.01, *p<.05, ~p<.10

Table 5.3: Correlation Among Dependent and Independent Variables Used to Model Crime Outcomes

	Time	*lnDEMI*	*lnEvents*	*Inequality*	*pctMale15-24*	*Racial Heterogeneity*	*Ethnic Heterogeneity*	*lnNProfit*	*lnPolice*
Index Rate	-0.071***	0.100***	0.099***	-0.185***	0.158***	-0.309***	-0.179***	0.386***	0.374***
Property Rate	-0.070***	0.093***	0.101***	-0.170***	0.151***	-0.267***	-0.157***	0.381***	0.358***
Violent Rate	-0.015**	0.083***	0.079***	-0.182***	0.148***	-0.422***	-0.200***	0.288***	0.333***
Arson Rate	-0.037***	0.070***	0.102***	-0.156***	0.099***	-0.126***	-0.113***	0.351***	0.346***
Burglary Rate	-0.066***	0.077***	0.080***	-0.102***	0.101***	-0.286***	-0.286***	0.240***	0.321***
Larceny Rate	-0.053***	0.082***	0.111***	-0.152***	0.156***	-0.210***	-0.122***	0.389***	0.420***
MV Theft Rate	-0.041***	0.091***	0.106***	-0.247***	0.102***	-0.281***	-0.129***	0.409***	0.470***
Aggravated Assault Rate	-0.018***	0.074***	0.063***	-0.141***	0.131***	-0.383***	-0.197***	0.235***	0.329***
Criminal Homicide Rate	-0.060*	0.091***	0.101***	-0.182***	0.075***	-0.405***	-0.092***	0.243***	0.389***
Forcible Rape Rate	0.011***	0.046***	0.196***	-0.115***	0.170***	-0.208***	-0.096***	0.350***	0.320***
Robbery Rate	-0.011***	0.127***	0.196***	-0.313***	0.178***	-0.548***	-0.157***	0.483***	0.587***

***p<.001, **p<.01, *p<.05, ~p<.10

IV. Index Crime and Disaster

In this section, I provide a detailed overview of the modeling process for county-level index crime rates. In each sub-section, I describe the process and interpret the coefficients in terms of their effect on the overall index crime rate and the rate of change in the index crime rate. I conclude the analysis of index crime rates and disaster with a discussion of the implications for the hypotheses forwarded by each theoretical orientation. Tables 5.4 and 5.5 detail the results of fitting a taxonomy of models for change to annual county-level index crime rates. These tables should be used in conjunction as Table 5.4 provides the overall parameter estimates and Table 5.5 provides the variance components for each of the models shown in Table 5.4. A total of four models are presented in Tables 5.4 and 5.5, as each model is required to evaluate the effects of adding additional predictors to the analysis. All modeling processes were informed by the methods promoted by Singer and Willett (2003), unless stated otherwise.

A. Model A: The Unconditional Mean Model

Model A, the unconditional mean model provides a starting point for analysis, giving the maximum likelihood estimation for the overall partitioned variation in indexed crime rates. The coefficient for the intercept in this model is the grand mean of the natural log of index crimes reported per 100,000 persons. The observed value of 7.600 on this metric may be converted to the observed crime rate of 1998.20.[45] Alternatively, this is the county-level, average index crime rate reported for the years of 1995 until the end 2008.

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[45] Note that this value is lower than the observed mean of 2,713.361 in Table 5.1. This reflects the effect of the log-transformation of index crime rates whereby extreme values for the crime rate do not increase the mean, as they do using the raw average.

Table 5.4: Results of Fitting a Taxonomy of Models for Change to County-Level UCR Index Crime Rate; [1995, 2008], N=3,019, Obs.=38,753. Standard errors in parentheses.

	Predictors	**Model A:** Unconditional Means	**Model B:** Unconditional Growth	**Model C:** Disaster Magnitude, Gross Effects	**Model D**: Theoretical Controls
Level-1					
	Intercept	7.600*** (0.014)	7.674*** (0.016)	7.682*** (0.018)	8.807*** (0.156)
Disaster Variables	*lnDEMI*	--	--	0.045*** (0.012)	0.039** (0.012)
	lnEvents	--	--	-0.011~ (0.006)	-0.015** (0.006)
	FEMA Declaration	--	--	-0.004 (0.009)	0.003 (0.009)
Routine Activity Variables	*pctMale15-24*	--	--	--	0.002 (0.006)
	lnPolice	--	--	--	--
Social Order Variables	*Inequality*	--	--	--	-2.88e+08~ (1.72e+08)
	Racial Heterogeneity	--	--	--	-1.170*** (0.082)
	Ethnic Heterogeneity	--	--	--	-1.016*** (0.111)
	lnNProfit	--	--	--	0.098*** (0.008)
Spatial Lag	*Lag Term*	--	--	--	0.073*** (0.005)
Level-2					
Rate of Change	Intercept (*Time*)	--	-0.011*** (0.001)	-0.014*** (0.001)	-0.044** (0.013)
Disaster Variables	*lnDEMI*	--	--	-0.007*** (0.002)	-0.007*** (0.002)
	lnEvents	--	--	0.003*** (0.001)	0.004*** (0.001)
	FEMA Declaration	--	--	0.000 (0.001)	-0.000 (0.001)
Routine Activity Variables	*pctMale15-24*	--	--	--	0.002** (0.001)
	lnPolice	--	--	--	--
Social Order Variables	*Inequality*	--	--	--	-4.06e+07** (1.46e+07)
	Racial Heterogeneity	--	--	--	-0.005 (0.007)
	Ethnic Heterogeneity	--	--	--	0.023** (0.009)
	lnNProfit	--	--	--	-0.008*** (0.001)
Spatial Lag	*Lag Term*	--	--	--	0.002* (0.001)

***p<.001, **p<.01, *p<.05, ~p<.10

Table 5.5: Variance Components for a Taxonomy of Models for Change to County-Level UCR Index Crime Rate

Variance Components			**Model A**	**Model B**	**Model C**	**Model D**
Level-1	Within-County	σ_ε^2	0.172*** (0.001)	0.129*** (0.001)	0.128*** (0.001)	0.128*** (0.001)
Level-2	In Initial Status	σ_0^2	0.685*** (0.019)	0.685*** (0.019)	0.683*** (0.019)	0.474*** (0.015)
	In ROC	σ_1^2	--	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
	Covariance	σ_{01}^2	--	-0.017*** (0.001)	-0.017*** (0.001)	-0.014*** (0.001)
Pseudo R^2 and Goodness-of-fit	Log Likelihood		-26546.14	-23699.53	-23721.85	-23148.58
	$R^2_{Y\hat{Y}}$		--	0.005	0.009	0.240
	R^2_ε		--	0.250	0.256	0.256
	R^2_0		--	--	0.003	0.308
	R^2_1		--	--	0.006	0.176
	Deviance		53092.28	47399.06	47443.70	46297.16
	AIC		53098.29	47411.07	47467.70	46345.16
	BIC		53123.98	47462.46	47570.48	46550.72
	Wald χ^2		--	115.07***	151.86***	1545.58***

***p<.001, **p<.01, *p<.05, ~p<.10

Several estimates are of particular interest in Table 5.5. The first variance estimate for Model A, within-county variance, σ_ε^2, is the pooled variance of each county's crime rate about its mean variance components. The second variance estimate, the between-county variance, σ_0^2, is the pooled variance of county-specific means about the grand mean. These variance components are utilized to estimate the amount of residual variation in index crime rates that exist at the 2 levels. These values indicate statistically sufficient Level-1 and Level-2 variation to warrant the inclusion of additional variables in the model and provide a starting point for evaluating subsequent models in terms of the variance accounted for, when adding additional predictors. Also in Table 5.5, the deviance statistic compares the log-likelihood statistics for two models; Model A versus a "saturated" model which is a hypothetical *ad hoc* model that fits the data perfectly (i.e. all variance is accounted for). Deviance is considered a likelihood ratio test of the difference in deviance statistics between the hypothetical and the observed model. By itself, this statistic in Model A provides little information except that it indicates the need for additional variables if we are expecting to further explain the variation in index crime rates. As with the variance components, one can simply consider this deviance statistic in Model A as a starting point from which we might evaluate subsequent models. Similarly, both AIC and BIC log-likelihood statistics provide estimates of the goodness-of-fit more conservatively than deviance (Singer and Willett 2003: 116-122). The reason for their inclusion concerns the ability to make comparisons across models. Deviance requires: a) that the same data is used in each model being compared; b) and that comparisons between models must involve nested models (e.g. crime rates nested in time). In contrast, both AIC and BIC only require that the former requirement be met in order to compare goodness-of-fit values. For this reason, later comparisons will utilize AIC and BIC statistics to make model comparisons. In Model A, all parameter estimates and variance components are statistically significant at the $p<0.001$ level.

B. Model B: Unconditional Growth Model

Model B, the unconditional growth model is also presented to clarify the baseline for which subsequent growth models are evaluated. The Level-1 coefficient for the intercept, represents the natural log of the average 1995 index crime rate of 7.674. This equates to approximately 2,151.67 index crimes per 100,000 persons. The Level-2 coefficient for the intercept (*Time*) represents the average annual rate of change in the natural log of the crime rate at the county level. As was noted previously, the observed average index crime rate has been falling between 1995 and 2008. This is congruent with the sign (-) associated with the coefficient for *time*. Because the variable for index crime rates represents the natural log, one may add $-0.011(time)$, where *time* is measured as the number of years since 1995, to the Level-1 intercept coefficient, and obtain a predicted value for crime rates in a given year. For example, in 1996 the predicted value for the natural log of crime rates was $7.674 - 0.011(1) = 7.663$. Converting this to an interpretable crime rate requires Euler's constant, *e*, and raising *e* to the power of the predicted value. Mathematically, the transformation is $e^{(\text{level-1 intercept + time})}$. Thus, for 1996, the predicted value for the average county-level crime is $e^{(7.674-0.011)}$, or 2,128.13 crimes per 100,000 persons. It is important to note that while the average annual rate of change of -0.011 is constant in terms of logged crime rates, the predicted value for the rate of change in calculated crime rates is technically considered an exponential decay, and is not linear.

In Table 5.5, The Pseudo$-R^2$ statistics are provided to assess the amount of variance explained when additional predictors are added to the model. $R^2_{Y\hat{Y}}$ is calculated by taking the square of the correlation between the predicted outcome and the observed. In Model B, $r = 0.071$, and yields a $R^2_{Y\hat{Y}}$ of 0.005 indicating that about 0.5% of the total variability in the number of index crimes reported is explained by time alone. R^2_{ε} is obtained using the variance components and is calculated using the Equation 5.1:

[Equation 5.1]

$$R^2_{\varepsilon} = \frac{\hat{\sigma}^2_{\varepsilon}(\text{unconditional means model}) - \sigma^2_{\varepsilon}(\text{unconditional growth model})}{\hat{\sigma}^2_{\varepsilon}(\text{unconditional means model})} = \frac{\hat{\sigma}^2_{\varepsilon} - \sigma^2_{\varepsilon}}{\hat{\sigma}^2_{\varepsilon}},$$

and indicates the proportion of within-county variation explained by the variable *time*. In this model, a $R_{\varepsilon}^2 = 0.250$ indicates that about 25% of the within-county variation in the natural log of indexed crime rates is explained by linear time. To further increase the magnitude of R_{ε}^2 additional time-varying predictors must be added to the model.

C. Model C: Disaster Magnitude Model, Gross Effects

In Model C in, the natural disaster variables *lnDEMI*, *lnEvents,* and *FEMA Declaration* are introduced. In this model, the Level-1 and Level-2 intercept coefficients represent the average 1995 crime rate and average annual rate of change, respectively, while controlling for disaster magnitude and the number of disaster events. In comparison to Model B, there is a small change in both the initial status, intercept = 7.682, and rate of change, *Time* = -0.014 for crime outcomes. Utilizing the coefficient for the Level-1 intercept, to calculate the indexed crime rate, the model predicts an average indexed crime rate for all counties in 1995 at about 2,168.95 crimes per 100,000 while holding the disaster variables constant at zero. The coefficient for *lnDEMI*, 0.045, indicates an overall increase in the index crime rate as the disaster magnitude increases, when controlling for the number of events. The coefficient for the number of events, *lnEvents*= 0.011. indicates that independent of disaster magnitude, the number of events is associated with a decrease in the index crime rate. There is no statistically significant change in the overall index crime rate associated with *FEMA declarations*.

The Level-2 disaster predictors in the model can be interpreted in regards to their effect on the average rate of change in index crime rates between 1995 and 2008. Overall, the coefficient for *time*, -0.014, like Model B, indicates a decline in index crime rates over time. The Level-2 disaster predictor *lnDEMI* indicates an increase in the rate of change. That is, disaster magnitude increases the rate at which the crime rate falls. In contrast, the coefficient for the number of events, *lnEvents* = -0.011, indicates that the crime rate declines as the number of events increases. As with the Level-1 predictor for *FEMA declaration*, there is no statistically significant effect of *FEMA declaration* on the rate of change in crime rates.

The variance components in Model C indicate a small increase in variance accounted for in the explanatory model with the addition of the disaster variables. The Pseudo-$R^2_{Y\hat{Y}}$ of 0.009 indicates the model explains only about 0.9% of the variation in index crime rates. Likewise the small changes in the R^2_{ε} statistic indicates a small increase in the explanatory power of the model when adding the disaster variables. Two additional Pseudo-R^2 statistics are available for Model C. R^2_0 provides an estimate of the within-county variance explained by Level-2, time-varying, predictors. R^2_1 provides an estimate of the between-county variance explained by Level-2 time-varying predictors. For Model C, the value for these estimates are very small at 0.003 and 0.006 respectively. In comparison to Model B, Deviance, AIC, and BIC values all increase with the addition of the disaster variables. The increase indicates that very little explanatory power is gained from the inclusion of disaster variables alone.

D. Model D: Theoretical Controls Model

Model D is presented as the full model utilizing all relevant controls.[46] Beginning with the overall effects, the disaster variable *lnDEMI* indicates a statistically significant overall increase in crime associated with disaster size, given the coefficient of 0.039, independent of the control variables. The coefficient for the number of events (*lnEvents*) is -0.015 and indicates that as the number of events increases, crime rates decrease. As with the previous model, there is still no effect of *FEMA declarations* on overall index crime rates. With the exception of the variable for *lnNProfits*, the theoretical control variables behave in a predictable manner in terms of their overall effect on index crime rates. *Inequality*'s statistically significant coefficient (-2.88e+08) indicates that on average, higher levels of *inequality* increase the index crime rate. The coefficient for motivated offenders, *pctMale15-24* is not statistically significant.[47] In contrast *racial heterogeneity* (-1.170), and ethnic heterogeneity (-1.016),[48] are statistically significant and indicate an increase in overall index crime rates associated with increased heterogeneity. The coefficient for *lnNProfits* (0.098), indicates an increase in the index crime rate is associated with an increase in number of non-profit organizations in a county. Finally, the coefficient for the *Lag Term* control variable of 0.073 indicates a statistically significant effect of spatial autocorrelation among crime rates, and effectively justifies the inclusion of this control term to control for spatial dependence (Charlton and Fotheringham 2009; Pearce 1999).

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[46] Again, the variable for police guardianship, *lnPolice*, is removed from this model due to missing data. Models utilizing *lnPolice* are provided later in this chapter.
[47] *pctMale15-24* interacts with the variables *inequality, racial heterogeneity, and ethnic heterogeneity.* Because the focus of the investigation is disaster magnitude, the more parsimonious model, without interaction, is used.
[48] Note that, inequality, racial, and ethnic heterogeneity are scaled such that higher levels of inequality and heterogeneity are indicated by lower values on these indices.

The Level-2 coefficients of Model D indicate the effect of these variables on the rate of change in index crime rates. The Level-2 intercept, indicated by the coefficient for *time*, is -0.043, and again shows an overall decrease in the index crime rate during the study period. The disaster magnitude coefficient *lnDEMI* is -0.007, and indicates that an increase in *lnDEMI* has the effect of increasing the rate of change in index crime rates.[49] This somewhat counterintuitive finding that *lnDEMI* increases the overall crime rate while *lnDEMI* increases the rate of decline in crime rates may be explained by conceiving of the disaster as upsetting the general trend of decline in crime rates. A disaster may increase the crime rate, at one point in the study period, but a return to the "normal" crime levels will reflect an increased overall rate of change. The coefficient for number of events (*lnEvents*) is positive (0.004), indicating that an increase in the number of events decreases the rate at which crime rates fall. There is no effect of *FEMA declaration* on the rate of change in index crime rates. According to Model D, *inequality* has a statistically significant effect of slowing the rate of decline in crime. The coefficient *pctMale15-24* is 0.002, and indicates a small but statistically significant effect of slowing the rate of decline in crime. There is no statistically significant effect of *racial heterogeneity* on the rate of change in index crime rates. There is a statistically significant effect of *Ethnic heterogeneity* decreasing the rate of change, indicated by its positive coefficient of 0.023. Finally, the *Lag Term* (0.002) indicates a statistically significant effect of spatial dependence on the rate of change, and justifies its inclusion in the model to statistically control for spatial autocorrelation.

[49] Because the rate of change is negative, indicating a decline in the crime rate over time, other Level-2 predictors with a negative coefficient *increase* the rate at which crime falls.

Analysis of the variance components in Model D indicate a substantial improvement in variance explained in comparison to previous models. Within-county, initial status, and rate of change variance components are all reduced. The pseudo R^2 statistic, $R^2_{Y\hat{Y}} = 0.240$, indicates that the model predicts about 24.7% of overall variation in variation in crime rates for the study period. The pseudo$-R^2$ statistic, $R^2_{\varepsilon} = 0.256$, indicates that about 25.6% of the within-county variation in the index crime rate is explained by linear time and changes time-varying predictors. A R^2_0 of 0.312 indicates that about 31.2% of overall between-county variance in the rate of change is explained by the model. And, the pseudo$-R^2$ statistic $R^2_1 = 0.176$ indicates that about 17.6% of the overall variance in the within-county rate of change in the index crime rate is explained by the model. Finally, Deviance, AIC, and BIC all indicate an improvement over previous models, given their reduced value over previous models.

E. Hypothesis Testing and Index Crime Rate

The core research question addressed by the above analysis is whether natural disasters of different magnitudes differentially affect the aggregate crime rate for all crimes analyzed in this research. Using Models C and D in tandem, *the empirical evidence suggests that, on the whole, counties impacted by natural disasters of larger magnitudes experience higher index crime rates.* Even after controlling for theoretically-relevant correlates of crime, a disaster's magnitude is positively related to the overall index crime rate. While the overall index crime rate appears to increase in counties impacted by natural disasters, the question must be address as to how each theory's hypotheses compare to the findings in Table 5.4 and Table 5.5.

The first question involves the relationship between a disaster's magnitude and whether there is evidence to suggest that a therapeutic community inhibits crime. Based on Model D, there is no support for the therapeutic community hypothesis that disasters decrease crime. In contrast, Model D does provide support for both routine activity theory and social disorganization theory in the context of disaster, both of which predict that disasters will increase crime.

In the case of routine activity theory, disasters may generate conditions whereby motivated offenders, suitable targets, and lack of capable guardians converge in time and space and would thus increase crime. Without utilizing measures of police guardianship in Model D, conclusions regarding the effects of disasters and routine crime are limited. However, the effect of the variable *pctMale15-24* (used as a proxy for motivated offenders) indicates, at the very least, disasters may lead to situations where crime is more likely, independent of the effects of the presence or absence of motivated offenders. Finally, using social disorganization theory, disasters are hypothesized to either create social disorganization, or exacerbate existing levels of disorganization and increase crime. In the context of a social disorganization hypothesis, Model D indicates strong support for the hypothesis that disasters have a disorganizing effect in that a disaster's magnitude is associated with an increase in crime rates.

Model D does not fully address all elements of each of the three theoretical orientations. As Fritz (1961) proposed when discussing the therapeutic community, disasters create conditions whereby "old inequalities and injustices may be wiped out" and that disasters can act as an equalizing force whereby social distinctions may be temporarily eliminated within the impacted community. Further, as Miller (2007) found, post-disaster therapeutic responses may catalyze existing networks of support. Both Fritz and Miller's propositions may be tested utilizing statistical interactions among disaster variables and controls. Specifically, do disasters mitigate or facilitate the effects of social conditions that are associated with crime?

In Table 5.6 below, coefficients for Level-1 predictors are presented to test hypotheses relevant to conceiving the disaster as intersecting pre-existing social arrangements.[50] In each model, interaction terms are included to address the question of whether a disaster's effects are conditioned by the effects of other crime correlates.

Table 5.6: HLM Models for Interaction Effects Between Disaster Magnitude and Theoretical Controls for Index Crime Rate

Level-1 Predictors	**Model D**: No Interaction	**Model E**: *pctMale15-24*	**Model F**: Inequality	**Model G**: Racial Heterogeneity	**Model H**: Ethnic Heterogeneity	**Model I**: Non-Profit
lnDEMI	0.038** (0.012)	0.056 (0.050)	0.041** (0.012)	-0.006 (0.056)	-0.050 (0.058)	0.041 (0.024)
lnEvents	-0.015* (0.006)	-0.015* (0.006)	-0.015* (0.006)	-0.016* (0.007)	-0.016* (0.006)	-0.015 (0.006)
pctAge15-24	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.007)	0.002 (0.005)
Inequality	-2.88e+08~ (1.72e+08)	-2.87e+08~ (1.72e+08)	-3.15e+08* (1.83e+08)	-2.96e+08* (1.72e+08)	-2.99e+08* (1.72e+08)	-2.90e+08 (1.73e+08)
Racial Heterogeneity	-1.170*** (0.008)	-1.171*** (0.082)	-1.170*** (0.082)	-1.174*** (0.083)	-1.170*** (0.082)	-1.170 (0.082)
Ethnic Heterogeneity	-1.016*** (0.008)	-1.017*** (0.111)	-1.015*** (0.111)	-1.016*** (0.111)	-1.041*** (0.112)	-1.017 (0.111)
lnNProfit	0.098*** (0.098)	0.098*** (0.008)	0.098*** (0.008)	0.098*** (0.008)	0.098*** (0.008)	0.098 (0.008)
Interaction effects with *lnDEMI*						
pctMale15-24	--	-0.002 (0.007)	--	--	--	--
Inequality	--	--	2.58e+07 (5.91e+07)	--	--	--
Racial Heterogeneity	--	--	--	0.058 (0.069)	--	--
Ethnic Heterogeneity	--	--	--	--	0.108 (0.068)	--
lnNProfit	--	--	--	--	--	-0.001 (0.006)
$R^2_{Y\hat{Y}}$	0.240	0.239	0.239	0.239	0.239	0.239

***p<.001, **p<.01, *p<.05, ~p<.10

[50] Note that full models and variance components are not presented in this table in order to economize space. Relevant Level-2 predictors and spatial lags were included in the production of each model. The predictor "FEMA declaration" was dropped from these analyses, as it provided no explanatory value. Results for the full models are available in the appendix in Tables A.1–A.5.

Model E examines the effects of the interaction of percent of the population who are male, age 15-25 (*pctMale15-25*) with disaster. This model is relevant to routine activity theory's prediction that the existence of motivated offenders following a disaster may increase crime. There is no statistically significant evidence to suggest that the effect of disaster on index crime rate is conditioned by the existence of potential offenders in a county.

Model F is presented to interrogate Fritz's (1961) proposition that disasters mitigate the effects of inequality. Based on this interaction model, there is no statistical evidence that the effects of a disaster's magnitude on crime are conditioned by preexisting economic inequality in a county.

Models G through Model I are relevant to both social disorganization theory and the therapeutic community hypothesis. Model G is presented to evaluate if the effects of a disaster's magnitude on index crime rate are conditioned by racial heterogeneity. Based on this analysis, there is insufficient statistical evidence to suggest that disasters mitigate the effect of racial heterogeneity on the index crime rate. Model H is presented to determine if a disaster's magnitude is conditioned by the ethnic heterogeneity in a county. Again, there is no statistically significant evidence to suggest that disasters eliminate social distinctions based on ethnicity, as Fritz's (1961) proposition claims.

Finally, assuming that the variable for social efficacy, measured as the number of non-profits, may be thought of as networks of support, Model I test's Miller's (2007) claim that disasters mobilize existing networks to produce a therapeutic community. While this mobilization may occur, there is no statistically significant evidence to conclude that such mobilization has an effect of reducing the index crime rate.

The proceeding analysis has addressed the overall effect of disaster on index crime rates. As was noted in the literature review, previous research has shown that some types of crime are affected by the social situation created by a disaster, while other types of crime remain unaffected (Curtis et al. 2000; Leitner et al. 2011; Zahran et al. 2009). These findings suggest the need to evaluate if different types of crime and if disasters have a differential effect on the sub-types of crime included in the index crime rate. In the next sections, I disaggregate violent and property crime rates from index crimes to determine if there is a differential effect of disaster magnitude on property and violent crime. Assuming the reader is now familiar with the process of hierarchical linear modeling, I offer an abbreviated account of the modeling process presented above, to avoid repetition.

V. Property Crime and Disaster

A. Taxonomy of Models for Property Crime Rate

In this section, I present the results of the analysis investigating the relationship between property crime rates and disaster magnitude. Table 5.7 and Table 5.8 provide the results of fitting a taxonomy of models for change to county-level property crime rates. Model A presents the unconditional means model. The coefficient of 7.476 indicates that the average annual county-level crime rate between 1995 and 2008 is about 1,765.17 property crimes per 100,000 persons. Model B takes into account longitudinal changes in the overall property crime rate. The Level-1 and Level-2 intercept coefficients in this model can be interpreted as average annual property crime rate in 1995 and the average annual rate of change in property crime rate for the study period, respectively. According to the data, the property crime rate declines during the study period, indicated by the coefficient for *time* of -0.012.[51]

Model C introduces the disaster variables into the analysis. Controlling for the number of events, the magnitude of a disaster increases the overall property crime rate as indicated by the positive coefficient of *lnDEMI* = 0.043. Similarly to the analysis of index crime rates, there is no effect of *FEMA declaration* on the property crime rate during the study period. The effect of disaster magnitude on the rate of change for property crime rate is negative, indicating that a disaster's magnitude increases the rate at which the property crime rate falls.[52] Finally, in Model D is a full model that includes theoretically-relevant control variables. In comparing Model C to Model D, the effect of *lnDEMI* on property crime rates is reduced when statistical controls are added. However, the coefficient for *lnDEMI*, 0.038, remains statistically significant and indicates an overall increase in the property crime rate associated with an increase in disaster magnitude. Examination of the pseudo$-R^2$ statistics for the property crime rate models (Table 5.8) indicates that about 22.4% of overall variation in crime rates can be accounted for by Model D $\left(R^2_{Y\hat{Y}} = 0.224\right)$. $R^2_{\varepsilon} = 0.244$, indicates that about 24.4% of the within-county variation in the property crime rate is explained by linear time and changes time-varying predictors. An R^2_0 of 0.301 indicates that about 30.1% of the overall between-county variance in the rate of change is explained by the model. And finally, the pseudo-R^2 statistic, $R^2_1 = 0.157$, indicates that about 15.7% of the overall

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[51] Because the rate of change is negative, indicating a decline in the crime rate over time, other Level-2 predictors with a negative coefficient *increase* the rate at which crime falls.
[52] The coefficient for *time* is negative, indicating crime rates are decreasing over time. A negative sign in for Level-2 indicators thus increases the decline in crime rates over time.

variance in the within-county rate of change in index crime rate is explained by the variables in Model D.

Table 5.7: Results of Fitting a Taxonomy of Models for Change to County-Level UCR Property Crime Rate; [1995, 2008], N=3,019, Obs.=38,753. Standard errors in parentheses.

	Predictors	**Model A:** Unconditional Mean	**Model B:** Unconditional Growth	**Model C:** Disaster Magnitude, Gross Effects	**Model D**: Theoretical Controls
Level-1					
	Intercept	7.476*** (0.015)	7.559*** (0.016)	7.562*** (0.019)	8.423*** (0.168)
Disaster variables	*lnDEMI*	--	--	0.043** (0.014)	0.038** (0.014)
	lnEvents	--	--	-0.007 (0.007)	-0.014~ (0.007)
	FEMA Declaration	--	--	0.000 (0.010)	0.001 (0.010)
Routine Activity Variables	*pctMale15-24*	--	--	--	0.007*** (0.007)
	lnPolice	--	--	--	--
Social order variables	*Inequality*	--	--	--	-1.35e+08 (1.84e+08)
	Racial Heterogeneity	--	--	--	-1.033*** (0.087)
	Ethnic Heterogeneity	--	--	--	-0.982*** (0.118)
	lnNProfit Count	--	--	--	0.116*** (0.009)
Spatial Lag	*Lag Term*	--	--	--	0.079*** (0.006)
Level-2					
Rate of Change	Intercept (*Time*)	--	-0.012*** (0.001)	-0.015*** (0.002)	-0.043*** (0.015)
Disaster Variables	*lnDEMI*	--	--	-0.007*** (0.002)	-0.007** (0.002)
	lnEvents	--	--	0.003** (0.001)	0.004*** (0.001)
	FEMA declaration	--	--	-0.000 (0.001)	-0.000 (0.001)
Routine Activity Variables	*pctMale15-24*	--	--	--	0.002** (0.001)
	lnPolice	--	--	--	--
Social Order Variables	*Inequality*	--	--	--	-5.52e+07** (1.62e+07)
	Racial Heterogeneity	--	--	--	-0.008 (0.007)
	Ethnic Heterogeneity	--	--	--	0.025** (0.010)
	lnNProfit	--	--	--	-0.009*** (0.001)
Spatial Lag	*Lag Term*	--	--	--	0.002* (0.001)

***p<.001, **p<.01, *p<.05, ~p<.10

Table 5.8: Variance Components for a Taxonomy of Models for Change to County-Level UCR Property Crime Rate

Variance Components			Model A	Model B	Model C	Model D
Level-1	Within-County	σ_{ε}^2	0.221*** (0.001)	0.168*** (0.001)	0.168*** (0.001)	0.168*** (0.001)
Level-2	In initial status	σ_0^2	0.626*** (0.017)	0.750*** (0.022)	0.748*** (0.022)	0.527*** (0.018)
	In ROC	σ_1^2	--	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
	Covariance	σ_{01}^2	--	-0.019*** (0.001)	-0.019*** (0.001)	-0.016*** (0.001)
Pseudo R^2 and Goodness-of-fit	Log Likelihood		-31122.45	-28583.88	-28608.76	-28096.33
	$R_{Y\hat{Y}}^2$		--	0.070	0.092	0.217
	R_{ε}^2		--	0.240	0.240	0.240
	R_0^2		--	--	0.003	0.158
	R_1^2		--	--	0.000	0.158
	Deviance		62244.90	57167.76	57217.52	56192.66
	AIC		62250.90	57179.76	57241.51	56240.66
	BIC		62276.59	57231.15	57344.29	56446.22
	Wald χ^2		--	12.32***	141.97***	1382.30***

***p<.001, **p<.01, *p<.05, ~p<.10

B. Hypothesis Testing and Property Crime Rate

The core research question addressed by the above HLM analysis of property crime rates is whether disasters of different magnitudes differentially affect property crime rates. *Model D suggests that, when controlling for theoretically-relevant correlates of crime, disaster magnitude is associated with an increase the property crime rate in a county.* As with the above discussion of index crime rate, there are theoretical questions relevant to the interaction of disaster magnitude and the control variables. In general, the effect of disaster magnitude is incongruent with the predictions of the therapeutic community hypothesis in that an increase in disaster magnitude is associated with an decrease in disaster magnitude. The results of the HLM modeling of property crime rates are consistent with the hypotheses of both routine activity theory and social disorganization theory in that disaster magnitude is associated with an increase in property crime.

In Table 5.9 below, a series of models are presented which test if the effect of disaster magnitude on property crime rates is conditioned by the levels of theoretically-relevant control variables. Model E examines the effects of the interaction of percent of the population age 15-25 with disaster. This model is relevant to routine activity theory's prediction that the existence of motivated offenders following a disaster may increase crime. There is no statistically significant evidence to suggest that the effect of disaster on property crime rate is conditioned by the existence of potential offenders in a county. Model F is presented to interrogate Fritz's (1961) proposition that disasters mitigate the effects of inequality. Based on this interaction model, there is no statistical evidence that the effects of disaster magnitude on property crime are conditioned by preexisting economic inequality in a county. Models G through I are relevant to both social disorganization theory and the therapeutic community hypothesis. Model G is presented to evaluate if the effects of a disaster's magnitude on property crime rate is conditioned by racial heterogeneity. Based on this analysis, there is insufficient statistical evidence to suggest that disasters mitigate the effect of racial heterogeneity on the property crime rate.

Table 5.9: HLM Models for Interaction Effects Disaster Magnitude and Theoretical Controls on Property Crime Rate[53]

Level-1 Predictors	**Model D**: No Interaction	**Model E**: *pctMale15-24*	**Model F**: Inequality	**Model G**: Racial Heterogeneity	**Model H**: Ethnic Heterogeneity	**Model I**: Non-Profit
Intercept	8.423*** (0.168)	8.423*** (0.168)	8.423*** (0.168)	8.424*** (0.168)	8.459*** (0.168)	8.427*** (0.156)
lnDEMI	0.038** (0.014)	0.032 (0.057)	0.038** (0.014)	0.009 (0.064)	-0.100** (0.066)	0.020** (0.028)
lnEvents	-0.014~ (0.007)	-0.013~ (0.007)	-0.014~ (0.007)	-0.014~ (0.007)	-0.015 (0.007)	-0.013~ (0.007)
pctMale15-24	0.007 (0.007)	0.007 (0.007)	0.007*** (0.006)	0.008*** (0.006)	0.008*** (0.006)	0.007*** (0.004)
Inequality	-1.35e+08 (1.84e+08)	-1.38e+08 (1.84e+08)	-1.48e+08 (1.97e+08)	-1.41e+08 (1.84e+08)	-1.53e+08 (1.84e+08)	-1.21e+08 (1.85e+08)
Racial Heterogeneity	-1.033*** (0.087)	-1.033*** (0.087)	-1.033*** (0.087)	-1.034*** (0.088)	-1.032*** (0.087)	-1.032*** (0.087)
Ethnic Heterogeneity	-0.982*** (0.118)	-0.982*** (0.118)	-0.981*** (0.118)	-0.983*** (0.118)	-1.019*** (0.119)	-0.984*** (0.118)
lnNProfit	0.116*** (0.009)	0.116*** (0.009)	0.116*** (0.009)	0.116*** (0.009)	0.116*** (0.009)	0.116*** (0.009)
Interaction effects with *lnDEMI*						
pctMale15-24	--	-0.001 (0.008)	--	--	--	--
Inequality	--	--	1.19e+07 (6.74e+07)	--	--	--
Racial Heterogeneity	--	--	--	0.036 (0.079)	--	--
Ethnic Heterogeneity	--	--	--	--	0.163* (0.077)	--
lnNProfit	--	--	--	--	--	0.004 (0.007)
$R^2_{Y\hat{Y}}$	0.217	0.217	0.215	0.215	0.215	0.215

***p<.001, **p<.01, *p<.05, ~p<.10

Model H is presented to determine if a disaster's magnitude is conditioned by the ethnic heterogeneity in a county. In this case there *is* statistically significant evidence to suggest that disaster magnitude in some way interacts to differentially affect property crime rates.

Finally, Model I test's Miller's (2007) claim that disasters lead to a mobilization of existing social networks among affected populations to produce a therapeutic community effect. While this mobilization may occur, there is no statistically significant

[53] Full models and their variance components are available in Tables A.6–A.10 in the appendix.

evidence to conclude that such mobilization has an effect of reducing the property crime rate.

C. Disaster and Property Crime Sub-Types

One final analysis of property crime is warranted. Because property crime is comprised of four types of crime—burglaries, larceny, motor vehicle theft, and arson—recorded by the UCR, the rate of each of these crime types can also be modeled and discussed in the context of the theoretical orientations. In Table 5.10 below, five models are compared to determine if disasters have a differential effect on the different types of property crime. Model D from the analyses presented in Table 5.7 is provided for reference. In the models in Table 5.10 coefficients reflect the full HLM modeling procedure used in the above analyses, but *FEMA declaration* was removed from these models because of its consistent lack of predictive power. Coefficients for Level-2 predictors are not provided to conserve space.[54]

[54] Full models and their variance components are available in Tables A.11–A.14 in the appendix.

Table 5.10: Level-1 Portion of HLM Models for Subsets of Property Crime and Their Rates

Level-1 Predictors	**Model D**: Property Crime	**Model J**: Arson	**Model K**: Burglaries	**Model L**: Larceny	**Model M**: Motor Vehicle Theft
Intercept	8.423*** (0.168)	1.589*** (0.263)	7.681*** (0.188)	7.469*** (0.211)	5.423 (0.216)
lnDEMI	0.038** (0.014)	0.031 (0.032)	0.050** (0.019)	0.039* (0.018)	0.043~ (0.025)
lnEvents	-0.014~ (0.007)	-0.036* (0.016)	-0.033** (0.010)	-0.005 (0.009)	-0.033** (0.012)
pctMale15-24	0.007 (0.007)	0.021~ (0.012)	-0.018* (0.008)	0.025*** (0.009)	0.003 (0.008)
Inequality	-1.35e+08 (1.84e+08)	2.08e+08 (2.75e+08)	3.06e+09 (2.01e+08)	2.23e+08 (2.30e+08)	-6.40e+08** (2.28e+08)
Racial Heterogeneity	-1.033*** (0.087)	-0.549*** (0.128)	-1.471*** (0.095)	-0.968*** (0.109)	-1.457*** (0.107)
Ethnic Heterogeneity	-0.982*** (0.118)	-0.936*** (0.175)	-1.035*** (0.129)	-0.906*** (0.148)	-0.885*** (0.147)
lnNProfit	0.116*** (0.009)	0.304*** (0.015)	0.084*** (0.010)	0.179*** (0.011)	0.263*** (0.012)
Spatial Lag	0.079*** (0.006)	0.126*** (0.012)	0.085*** (0.007)	0.086*** (0.008)	0.074*** (0.009)
$R^2_{Y\hat{Y}}$	0.217	0.163	0.172	0.198	0.250

***p<.001, **p<.01, *p<.05, ~p<.10

Table 5.10 results provide a differentiation among the property crime types as they are affected by disaster. As is evident in Model J, there is insufficient evidence to suggest that arson rates are related to disaster magnitude. In contrast, there is statistically sufficient evidence to suggest that burglaries (Model K), larcenies (Model L) and motor vehicle thefts (Model M) all increase in relation to disaster magnitude (*lnDEMI*). Of these the burglary rate increase is largest indicated by the coefficient of 0.051. Note that interaction effects among theoretical control variables and disaster magnitude were investigated for the sub-types of property crime but were not presented in Table 5.10 because no interactions among these variables were apparent in the data.

VI. Violent Crime and Disaster

A. Taxonomy of Models for Violent Crime Rates

This section reports the results of the HLM modeling procedures to test whether disasters have an effect on violent crime rates. Table 5.11 provides the results of fitting a taxonomy of models for change to county-level UCR violent crime rates and Table 5.12 provides the variance components for these models. Model A provides the unconditional means model and the coefficient for the intercept of 5.071 indicates that the average annual county-level crime rate between 1995 and 2008 is about 159.33 violent crimes per 100,000 persons. Model B takes into account longitudinal changes in the overall violent crime rate. The Level-1 and Level-2 intercept coefficients in this model can be interpreted as average annual violent crime rate in 1995 and the average annual rate of change in violent crime rate for the study period, respectively.

Table 5.11: Results of Fitting a Taxonomy of Models for Change to County-Level UCR Violent Crime Rate; [1995, 2008], N=3,019, Obs.=38,753. Standard errors in parentheses.

	Predictors	**Model A:** Unconditional means	**Model B:** Unconditional Growth	**Model C:** Disaster Magnitude, Gross Effects	**Model D**: Theoretical Controls
Level-1					
Initial status,	Intercept	5.071*** (0.020)	5.077*** (0.023)	5.102*** (0.028)	8.233*** (0.229)
Disaster variables	*lnDEMI*	--	--	0.068** (0.023)	0.044* (0.023)
	lnEvents	--	--	-0.024* (0.012)	-0.034** (0.012)
	FEMA Declaration	--	--	-0.009 (0.018)	-0.011 (0.018)
Routine Activity Variables	*pctMale15-24*	--	--	--	0.001 (0.010)
	lnPolice	--	--	--	--
	Inequality	--	--	--	2.12e+08 (2.41+08)
Social order variables	*Racial Heterogeneity*	--	--	--	-3.021*** (0.116)
	Ethnic Heterogeneity	--	--	--	-1.805*** (0.156)
	lnNProfit	--	--	--	0.153*** (0.012)
Spatial Lag	*Lag Term*	--	--	--	0.147*** (0.011)
Level-2					
Rate of Change	Intercept *(Time)*	--	-0.002 (0.002)	-0.007** (0.002)	-0.104*** (0.021)
Disaster Variables	*lnDEMI*	--	--	-0.007* (0.003)	-0.007* (0.003)
	lnEvents	--	--	0.005** (0.001)	0.006*** (0.001)
	FEMA Declaration	--	--	0.001 (0.002)	0.001 (0.002)
Routine Activity Variables	*pctMale15-24*	--	--	--	0.003*** (0.001)
	lnPolice	--	--	--	--
Social order variables	*Inequality*	--	--	--	-7.48e+07*** (2.18e+07)
	Racial Heterogeneity	--	--	--	0.047*** (0.011)
	Ethnic Heterogeneity	--	--	--	0.038*** (0.013)
	lnNProfit	--	--	--	-0.012*** (0.001)
Spatial Lag	*Lag Term*	--	--	--	0.004** (0.001)

***p<.001, **p<.01, *p<.05, ~p<.10

According to the data, the violent crime rate declines during the study period, indicated by the coefficient of -0.002 for *time*. However, without controls, this observed decline is not statistically significant, suggesting large variation in the overall trend of violent crime rates over time. That is, the data indicate that violent crime rates, on average are falling, but many counties experience an increase in violent crime rates during the study period, thereby making this estimate statistically insignificant.

Model C introduces the disaster variables into the analysis. Controlling for the number of events, the magnitude of a disaster increases the overall violent crime rate as indicated by the positive coefficient, *lnDEMI* = 0.068. The coefficient for the number of events (*lnEvents* = -0.024) is negative, indicating that as the number of events in a county is associated with a decrease in crime rates. Similar to the models for index and property crime rates, there is no effect of FEMA declarations on the violent crime rate during the study period. In the Level-2 portion of the Model C, the effect of disaster magnitude on the rate of change for violent crime rate is negative, *lnDEMI* = -0.007 indicating that a disaster's magnitude increases the rate at which the violent crime rate falls.[55] In contrast, the number of events is inversely related to the rate of change (*lnEvents* = 0.006), indicating that an increase in the number of events is associated with a decrease in the rate of change in crime rates.

Finally Model D presents the results of the full model, utilizing all theoretically-relevant control variables. In comparing Model C to Model D, the effect of disaster magnitude on violent crime rates is reduced with the addition of statistical controls. However, the coefficient for disaster magnitude, *lnDEMI* =0.044, remains statistically

[55] Because the rate of change is negative, indicated by the coefficient for *time* (-0.104), other Level-2 predictors with a negative coefficient *increase* the rate at which crime falls.

significant at the p<0.10 level and indicates an overall increase in the violent crime rate associated with an increase in the magnitude of disasters. The coefficient for the control variable *lnEvents* (-0.034), indicates that as the number of events increases the crime rate decreases. Table 5.12 displays the variance components for the taxonomy of models for change in violent crime rates. The control variables *pctMale15-24* and *inequality* have no statistically significant effect on violent crimes rates. In contrast, the statistically significant indicators *racial heterogeneity* (-3.021), *ethnic heterogeneity* (1.805), and *lnNProfit* (0.153), are each positively related to violent crime rates.[56] The coefficient for the number of non-profits, *lnNProfit*=-0.012, indicates that the number of non-profits increases the rate at which violent crime rates fall.

Examination of the pseudo $-R^2$ statistics for the violent crime rate models indicates that about 31.5% of overall variation in violent crime rates can be accounted for by Model D, ($R^2_{Y\hat{Y}} = 0.315$). The pseudo $-R^2$ statistic, $R^2_{\varepsilon} = 0.137$ indicates that about 13.7% of the within-county variation in the violent crime rates is explained by linear time and changes time-varying predictors. A R^2_0 of 0.458 indicates that about 45.8% of the overall between-county variance in the rate of change is explained by the model. And finally, the pseudo R^2 statistic $R^2_1 = 0.236$ indicates that 23.6% of the overall variance in the within-county rate of change in violent crime rate is explained by the variables in Model D.

[56] Both *ethnic heterogeneity* and *racial heterogeneity* are reverse scaled such that smaller values on these indicators indicate larger values of these variables indicate lower levels of heterogeneity.

Table 5.12: Variance Components for a Taxonomy of Models for Change to County-Level UCR Violent Crime Rate

Variance Components			Model A	Model B	Model C	Model D
Level-1	Within-County	σ_{ε}^2	0.569*** (0.004)	0.491*** (0.004)	0.491*** (0.004)	0.491*** (0.000)
Level-2	In initial status	σ_0^2	1.174*** (0.032)	1.475*** (0.043)	1.473*** (0.043)	0.804*** (0.026)
	In ROC	σ_1^2	--	0.005*** (0.000)	0.005*** (0.000)	0.005*** (0.000)
	Covariance	σ_{01}^2	--	-0.038*** (0.002)	-0.038*** (0.002)	-0.029*** (0.002)
Pseudo R^2 and Goodness-of-fit	Log Likelihood		-48994.53	-47970.14	-47996.21	-47110.92
	$R_{Y\hat{Y}}^2$		--	0.015	0.075	0.315
	R_{ε}^2		--	0.137	0.137	0.137
	R_0^2		--	--	0.001	0.458
	R_1^2		--	--	0.000	0.236
	Deviance		97989.06	95940.28	95992.42	94285.16
	AIC		97995.06	95952.28	96016.41	94333.16
	BIC		98020.76	96003.67	96119.19	94538.72
	Wald χ^2		--	0.57	19.97***	2412.33***

***p<.001, **p<.01, *p<.05, ~p<.10

B. Hypothesis testing and Violent Crime Rates

In general, the models presented in Table 5.11 and Table 5.12 address the question of whether disaster magnitude is associated with a change in violent crime rates. While the therapeutic community hypothesis predicts a decrease in crime rates resulting from disaster, routine activity theory predicts an increase in crime rates should a disaster increase the likelihood that motivated offenders, suitable targets, and lack of guardianship converge in time and space. Likewise utilizing a theory of social disorganization, disaster magnitude should be positively associated with an increase in crime, if the disaster creates social disorganization, or exacerbates existing levels of social disorganization.

As with both index and property crime rates, there is some question as to how the theoretically relevant correlates of crime interact with a disaster's magnitude to condition the violent crime rate. Should the therapeutic community hypothesis be true, the effects of variables associated with social disorganization (inequality, racial and ethnic heterogeneity) should be mitigated by the disasters effect and overall magnitude. Likewise, utilizing Miller's (2007) observation, existing non-profits, used as indicator of social efficacy, may act to facilitate helping behavior, and have the potential to reduce crime outcomes. Testing the effect of routine activity theory with these models is limited by the use of only one variable relevant to the theory, *pctMale15-24*. Should support for a routine activity theory of crime a disaster exist, there would be an increase in violent crime associated with an increase in percent of population who are male, age 15-24. A positive interaction with *pctMale15-24* and disaster magnitude would also indicate support for routine activity theory, if the effect of *pctMale15-24* was larger at higher levels of disaster magnitude. Finally, interrogating theories of social disorganization and disaster, *inequality*, *heterogeneity* and *ethnic heterogeneity* will all be positively associated with an increase in violent crime, while a disaster's magnitude may intensify the effects of these variables, should a disaster exacerbate existing levels of social disorganization.

In regards to the overall effect of disaster magnitude, Model D in Table 5.11 provides no support for the therapeutic community hypothesis. That is, there is statistically significant evidence to suggest that violent crimes increase as the result of a disaster. Predictions relevant to routine activity theory are not supported by the analysis presented in Model D, as there is no statistically significant effect of the variable *pctMale15-24.* Social disorganization theory is supported by the analysis in Model D, indicated by the coefficients for economic *inequality*, *racial heterogeneity*, and *ethnic* *heterogeneity*. That is, each of these variables is associated with a statistically significant increase in violent crime rates. The variable for social efficacy, *lnNProft*, does not behave in the predicted direction, given that both therapeutic community hypothesis and theories of social disorganization would predict that an increase in social efficacy and/or networks of support decrease the violent crime rate. According to Model D, the opposite is true.

To test if theoretically relevant control variables interact with a disaster's magnitude to condition crime outcomes, I investigated interaction effects between a disaster's magnitude with theoretical control variables were investigated. The results of this investigation are presented in Table 5.13 below.[57] Three main questions are addressed by these models. First does a therapeutic community arise in a disaster in such a way that it mitigates the effects of social disorganization? If this were the case, the effects of *inequality*, *racial heterogeneity*, and *ethnic heterogeneity* would be reduced as a disaster size increases. The second question involves the theory of social disorganization and asks: Does a disaster exacerbate existing conditions of social disorganization? Should a disaster have this effect, the effects of *inequality*, *racial heterogeneity* and *ethnic heterogeneity* would be greater at higher levels of disaster magnitude. Third, does the effect of *pctMale15-24*, used as a proxy for motivated offenders, increase as a function of disaster magnitude? Should routine activity's prediction regarding the convergence of motivated offenders following disaster be supported by the interaction of disaster and the existence of offenders, an increase in crime would be associated with the intersection of *pctMale15-24* and disaster magnitude. Based on the results in presented in Table 5.13, there is no evidence to suggest that any of

[57] Full models and their variance components are available in Tables A.15–A.19 in the appendix.

the theoretical control variables interact with disaster magnitude to condition violent crime outcomes.

Table 5.13: HLM Models for Interaction Effects Between Disaster Magnitude and Theoretical Controls on Violent Crime Rate

Level-1 Predictors	**Model D**: No Interaction	**Model E**: *pctMale15-24*	**Model F**: Inequality	**Model G**: Racial Heterogeneity	**Model H**: Ethnic Heterogeneity	**Model I**: Non-Profit
Intercept	8.233*** (0.229)	8.234*** (0.230)	8.234*** (0.230)	8.232*** (0.230)	8.225*** (0.231)	8.230*** (0.230)
lnDEMI	0.044* (0.023)	0.037 (0.096)	0.038 (0.024)	0.048 (0.107)	0.067 (0.111)	0.058 (0.047)
lnEvents	-0.034** (0.012)	-0.034** (0.012)	-0.034** (0.012)	-0.034** (0.012)	-0.034** (0.012)	-0.035** (0.012)
pctMale15-24	-0.011 (0.018)	-0.001 (0.010)	0.001 (0.010)	0.001*** (0.010)	0.001*** (0.005)	0.001*** (0.005)
Inequality	2.12e+08 (2.41+08)	2.09e+08 (2.41+08)	2.75e+07 (2.69+08)	2.11e+08 (2.42+08)	2.13e+08 (2.42+08)	1.94e+08 (2.42+08)
Racial Heterogeneity	-3.021*** (0.116)	-3.021*** (0.116)	-3.022*** (0.116)	-3.020*** (0.118)	-3.021*** (0.116)	-3.021*** (0.116)
Ethnic Heterogeneity	-1.805*** (0.156)	-1.807*** (0.156)	-1.809*** (0.156)	-1.807*** (0.155)	-1.799*** (0.155)	-1.806*** (0.156)
lnNProfit	0.153*** (0.012)	0.153*** (0.012)	0.154*** (0.012)	0.153*** (0.012)	0.153*** (0.009)	0.154*** (0.012)
Interaction effects with lnDEMI						
pctMale15-24	--	-0.000 (0.007)	--	--	--	--
Inequality	--	--	-6.07e+07 (1.12e+08)	--	--	--
Racial Heterogeneity	--	--	--	-0.008 (0.133)	--	--
Ethnic Heterogeneity	--	--	--	--	-0.030 (0.130)	--
lnNProfit	--	--	--	--	--	-0.004 (0.012)
$R^2_{Y\hat{Y}}$	0.315	0.311	0.311	0.311	0.311	0.311

***p<.001, **p<.01, *p<.05, ~p<.10

C. Disaster and Violent Crime Sub-Types

In the preceding analysis disaster magnitude was shown to have an effect on the overall violent crime rate. An additional question that can be addressed, given the nature of the UCR data, is relevant to the sub-types of violent crimes—aggravated assault, forcible rape, criminal homicide, and robbery—potentially influenced by disaster. That is, is there a differential effect of disaster magnitude for the sub-types of violent crime? To answer this question, a rate for each crime type was calculated and modeled according to the HLM modeling procedure used to model overall violent crime rates. Results for these analyses are available in Table 5.14. Again, because guardianship is addressed later it is excluded from this analysis. Also, FEMA declarations failed to provide any predictive effect for modeling of any crime rates, thus it is also removed from the analysis. Finally, to conserve space, the spatial lag and Level-2 predictors used in the analysis are not presented in the Table 5.14.[58] I include Model D, the model for violent crime rates, for purposes of comparison.

Table 5.14: Level-1 Portion of HLM Models for Sub-Types of Violent Crime and Their Rates

Level-1 Predictors	**Model D**: Violent Crime	**Model J**: Aggravated Assault	**Model K**: Forcible Rape	**Model L**: Homicide	**Model M**: Robbery
Intercept	8.233*** (0.229)	8.078*** (0.250)	1.160*** (0.260)	2.915*** (0.165)	6.838*** (0.240)
lnDEMI	0.044* (0.023)	0.028 (0.025)	0.044 (0.030)	0.060* (0.026)	0.061* (0.027)
lnEvents	-0.034** (0.012)	-0.028* (0.013)	-0.091*** (0.015)	-0.056*** (0.012)	-0.041** (0.013)
pctMale15-24	-0.011 (0.018)	-0.012 (0.006)	0.068*** (0.011)	-0.011 (0.007)	0.020~ (0.010)
Inequality	2.12e+08 (2.41+08)	6.57e+08* (2.63e+08)	1.53e+09*** (2.63e+08)	1.16e+08 (1.62e+08)	-1.43e+09*** (2.48e+08)
Racial Heterogeneity	-3.021*** (0.116)	-2.974*** (0.126)	-1.188*** (0.126)	-2.420*** (0.079)	-5.160*** (0.121)
Ethnic Heterogeneity	-1.805*** (0.156)	-1.995*** (0.169)	-0.424** (0.169)	-0.435*** (0.105)	-1.433*** (0.162)
Non-Profits	0.153*** (0.012)	0.150*** (0.013)	0.338*** (0.014)	0.122*** (0.009)	0.291*** (0.012)
Spatial Lag	0.147*** (0.011)	0.157*** (0.012)	0.136*** (0.013)	0.072*** (0.009)	0.085*** (0.011)
$R^2_{Y\hat{Y}}$	0.315	0.268	0.213	0.221	0.469

***p<.001, **p<.01, *p<.05, ~p<.10

Results of the crime type analyses presented in Table 5.14 indicate that while the overall violent crime rate is associated with an increase in disaster magnitude, that increase is not uniform across violent crime types. In fact, there is no statistically

[58] Full models and their variance components are available in Tables A.20–A.23 in the appendix.

significant increase in rates for either aggravated assault or forcible rape. In contrast, both criminal homicide and robbery rates are positively associated with an increase in disaster magnitude. There is also a statically significant decrease in violent crime associated with the number of events (*lnEvents*) for each of the sub-types of violent crime. Note that interaction effects with control variables and disaster magnitude were investigated, but are not presented in Table 5.14, as no interaction effects were apparent in the data.

VII. Modeling Crime Rates Using Police Guardianship

Because data for police guardianship, indicated by the variable *lnPolice* was not collected for each year of the study duration, as all other variables were, it was necessary to model crime outcomes as a function of police guardianship separately. Note that these analyses contain data from a national stratified random sample of police organizations for the years 1997, 1999, 2000, 2003, and 2007. While all theoretically-relevant controls are utilized in the analysis, police guardianship is most relevant to routine activity theory as the theory posits that an increase in guardianship decreases crime.

Table 5.15 presents the results of fitting HLM models to crime rate outcomes for each crime type, index, property, and violent crime.[59] With 2,923 counties and a total of $n = 7{,}125$ observations utilized in the analysis, two models are presented for each crime type. The first model provides the results of predicting crime outcomes as a function of disaster variables *lnDEMI* and *lnEvents* only. The second model includes all control variables including police guardianship.

[59] Full models with variance components are available in Tables A.24–A.29 in the appendix.

Table 5.15: HLM Models for Index, Property, and Crime Rates Utilizing Police Guardianship, n=2,2923, Obs. =7,125

Level-1 Predictors	**Model A**: Index Crime and Disaster	**Model B**: Index Crime with Controls	**Model C**: Property Crime and Disaster	**Model D**: Property Crime with Controls	**Model E**: Violent Crime and Disaster	**Model F**: Violent Crime with Controls
Intercept	7.678*** (0.035)	8.723*** (0.272)	7.554*** (0.038)	8.192*** (0.301)	5.142*** (0.057)	7.512*** (0.438)
lnDEMI	-0.002 (0.038)	0.004 (0.039)	-0.006 (0.042)	0.001 (0.043)	-0.066 (0.066)	-0.071 (0.068)
lnEvents	-0.013 (0.019)	-0.02 (0.019)	-0.005 (0.021)	-0.01 (0.021)	-0.020 (0.032)	-0.025 (0.033)
pctMale15-24	--	0.023* (0.011)	--	0.031* (0.012)	--	0.005 (0.018)
lnPolice	--	0.035* (0.015)	--	0.036* (0.016)	--	0.056* (0.024)
Inequality	--	1.41e+09*** (2.34e+08)	--	1.53e+09*** (2.56e+08)	--	1.15e+09** (3.61e+08)
Racial Heterogeneity	--	-1.357*** (0.132)	--	-1.198*** (0.145)	--	-2.846*** (0.215)
Ethnic Heterogeneity	--	-1.162*** (0.177)	--	-1.020*** (0.193)	--	-1.522*** (0.277)
lnNProfits	--	0.214*** (0.019)	--	0.234*** (0.021)	--	0.179*** (0.031)
Lag Term	--	0.038** (0.013)	--	0.043** (0.014)	--	0.145*** (0.025)
Level-2 Predictors						
intercept (*time*)	-0.011*** (0.003)	-0.137 (0.025)	-0.011*** (0.004)	-0.132*** (0.028)	-0.008 (0.006)	-0.174*** (0.042)
lnDEMI	0.002 (0.006)	-0.001 (0.006)	0.003 (0.006)	-0.001 (0.007)	0.012 (0.010)	0.007 (0.011)
lnEvents	0.003 (0.002)	-0.000 (0.002)	0.002 (0.002)	-0.001 (0.002)	0.005 (0.003)	0.001 (0.004)
pctMale15-24	--	-0.001 (0.001)	--	-0.001 (0.001)	--	0.002 (0.002)
lnPolice	--	-0.000 (0.001)	--	-0.001 (0.001)	--	-0.003 (0.002)
Inequalty	--	1.09e+07 (2.21e+07)	--	1.33e+07 (2.45e+07)	--	3.31e+07 (3.79e+07)
Racial Heterogeneity	--	0.023~ (0.012)	--	0.024~ (0.013)	--	0.055** (0.021)
Ethnic Heterogeneity	--	0.044** (0.015)	--	0.040* (0.017)	--	0.036 (0.026)
lnNProfit	--	0.001 (0.002)	--	0.001 (0.002)	--	0.004 (0.003)
Lag Term	--	0.009*** (0.001)	--	0.009*** (0.002)	--	0.013*** (0.003)
$R^2_{Y\hat{Y}}$	0.027	0.368	0.029	0.338	0.006	0.374

***p<.001, **p<.01, *p<.05, ~p<.10

Models A and B provide the results for the analysis of index crime rate. In both models there is no statistically significant effect of the disaster variables on index crime rates. In Model B, the police guardianship variable is associated with a statistically significant increase in the index crime rate, as indicated by the coefficient for *lnPolice* of

0.036. Similar results exist for the analyses of both property crime rates and violent crime rates. In each case, there is no statistically significant effect of disaster magnitude on the crime rate of interest, and police guardianship is associated with an increase in crime rates in a county. In the Level-2 portion of the models in Table 5.15, almost all variables are insignificant, with the exception of *racial heterogeneity* and *ethnic heterogeneity*. Each of these variables are associated with a decrease in the rate of change in each crime rate. That is, increased heterogeneity retards the downward trend in crime rates.

In general, the results presented in Table 5.15 offer no conclusive support for the notion that disasters have an effect on crime rates. This perhaps reflects the dearth of data points available in this analysis, relative to the preceding analysis using the population of data points where N = 3,019 with 38,753 observations. Further, the fact that police guardianship is associated with an increase in crime rates is incongruent with predictions of routine activity theory. However, such conclusions can be made tentatively since the guardianship variable of the number of police may simply correspond with the crime rate variable representing "reported" crimes. That is, if there are more police in a county, there are likely a larger number of reported crimes or that there are more police counties with higher crime rates.

VIII. Crime and Disaster Types

The next question to address in the analysis of crime and disaster is whether disasters of different types have a differential effect on crime outcomes, independent of disaster magnitude. Table 5.16 presents the results of six models investigating this question. There are two models for each crime rate type, index, property, and violent crime.[60] Model A represents the model for disaster magnitude and types, without theoretically-relevant controls. It is notable that disaster magnitude is associated with an increase in the crime rate independent of disaster type. Only three disaster types have a statistically significant positive effect on index crime rates independent of disaster magnitude. These were *coastal events*, and *heat/drought*, and *floods*. With controls added (Model B), only *heat/drought*, and *floods* have a statistically significant effect on index crime rates. Curiously, according to the data each of these three types of disaster events have high levels of impacts relative to other disaster types (see Chapter 4). And because the magnitude of the disaster is controlled for in these models, these findings suggest that the disruption of the community impacted by these disaster types extends beyond the simple measured impacts of injuries, fatalities, crop damage and property damage.

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[60] Control variables used in the analyses were included in the modeling procedures, but excluded from table 5.16 due to space limitations. Thus for Models B, D, and F, modeling procedures utilized the control variables of *pctMale15-24, inequality, Racial Heterogeneity, Ethnic Heterogeneity, lnNProfit,* and the *Lag Term.* The variable *FEMA Declaration* was excluded from this analysis because of lack of predictive value. *lnPolice* was also excluded from these analyses. Complete models presented in Table 5.16 are available in Tables A.29–A.35 the appendix.

Table 5.16: HLM Models for Index, Property and Violent Crime Utilizing Disaster Types

	Index Crime Rate		Property Crime Rate		Violent Crime Rate	
Level-1 Variables	**Model A**: Disasters Only	**Model B**: With Controls	**Model C**: Disasters Only	**Model D**: With Controls	**Model E**: Disasters Only	**Model F**: With Controls
Intercept	7.687*** (0.018)	8.821*** (0.156)	7.567*** (0.019)	8.434*** (0.168)	5.098*** (0.028)	8.227*** (0.230)
lnDEMI	0.034** (0.013)	0.030** (0.013)	0.033* (0.015)	0.029* (0.015)	0.048~ (0.025)	0.028 (0.025)
lnEvents	-0.013 (0.011)	-0.021~ (0.011)	-0.009 (0.013)	-0.020 (0.013)	-0.025 (0.021)	-0.047* (0.021)
Geophysical	-0.224 (0.261)	-0.261 (0.261)	-0.202 (0.299)	-0.252 (0.299)	-0.328 (0.508)	-0.386 (0.508)
Mass Movements	-0.029 (0.033)	-0.034 (0.033)	-0.026 (0.038)	-0.031 (0.038)	-0.041 (0.064)	-0.055 (0.064)
Wildfires	0.026 (0.036)	-0.001 (0.036)	0.038 (0.041)	0.007 (0.041)	0.033 (0.070)	0.000 (0.070)
Coastal Events	0.074~ (0.038)	0.038 (0.038)	0.081~ (0.044)	0.039 (0.044)	0.093 (0.073)	0.016 (0.073)
Hurricanes/TS	0.032 (0.022)	0.021 (0.022)	0.028 (0.025)	0.015 (0.025)	0.091* (0.042)	0.048 (0.043)
Heat and Drought	0.027* (0.013)	0.029* (0.013)	0.024~ (0.015)	0.029~ (0.015)	0.026 (0.025)	0.037 (0.025)
Lightning	0.005 (0.012)	-0.003 (0.012)	0.004 (0.014)	-0.006 (0.014)	0.026 (0.023)	0.006 (0.023)
Tornadoes	-0.011 (0.012)	-0.005 (0.012)	-0.012 (0.013)	-0.006 (0.013)	0.003 (0.023)	0.013 (0.023)
Wind	-0.005 (0.011)	-0.011 (0.011)	-0.002 (0.013)	-0.010 (0.013)	-0.046* (0.021)	-0.046* (0.021)
Winter Weather	0.004 (0.011)	0.016 (0.011)	0.001 (0.012)	0.016 (0.012)	-0.036~ (0.021)	-0.002 (0.021)
Floods	0.024* (0.011)	0.023* (0.011)	0.024* (0.012)	0.023~ (0.012)	0.022 (0.020)	0.028 (0.020)
Severe Weather	-0.019 (0.012)	-0.010 (0.012)	-0.017 (0.014)	-0.006 (0.014)	0.019 (0.024)	0.031 (0.024)
Level-2 Variables						
Intercept (*time*)	-0.015*** (0.001)	-0.047*** (0.013)	-0.015*** (0.002)	-0.045** (0.015)	-0.006** (0.002)	-0.105*** (0.021)
lnDEMI	-0.006** (0.002)	-0.006** (0.002)	-0.006** (0.002)	-0.006** (0.002)	-0.005 (0.003)	-0.005 (0.003)
lnEvents	0.004** (0.001)	0.005** (0.001)	0.004* (0.002)	0.005** (0.001)	0.004 (0.003)	0.007** (0.003)
Geophysical	0.023 (0.028)	0.026 (0.028)	0.021 (0.032)	0.026 (0.032)	0.034 (0.054)	0.039 (0.054)
Mass Movements	0.003 (0.004)	0.004 (0.004)	0.002 (0.005)	0.004 (0.005)	0.004 (0.008)	0.007 (0.008)
Wildfires	-0.003 (0.004)	0.001 (0.004)	-0.006 (0.005)	-0.002 (0.005)	0.000 (0.008)	0.004 (0.008)
Coastal Events	-0.007~ (0.004)	-0.003 (0.004)	-0.008~ (0.005)	-0.004 (0.005)	-0.007 (0.008)	0.001 (0.008)
Hurricanes/TS	-0.000 (0.003)	-0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	-0.006 (0.005)	-0.004 (0.005)
Heat and Drought	-0.006** (0.002)	-0.006** (0.002)	-0.006** (0.002)	-0.006** (0.002)	-0.004 (0.004)	-0.006~ (0.004)
Lightning	0.000 (0.002)	0.001 (0.002)	0.000 (0.002)	0.001 (0.002)	-0.002 (0.003)	-0.000 (0.003)
Tornadoes	0.000 (0.001)	-0.001 (0.001)	0.000 (0.002)	-0.001 (0.002)	0.000 (0.003)	-0.001 (0.003)
Wind	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.002)	-0.000 (0.002)	0.004 (0.003)	0.005~ (0.003)
Winter Weather	-0.002 (0.001)	-0.003 (0.001)	-0.001 (0.002)	-0.003* (0.002)	0.002 (0.003)	-0.001 (0.003)
Floods	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.002)	-0.002 (0.002)	-0.001 (0.003)	-0.001 (0.003)
Severe Weather	0.002 (0.002)	0.000 (0.002)	0.001 (0.002)	-0.001 (0.002)	0.000 (0.003)	-0.002 (0.003)
$R^2_{Y\hat{Y}}$	0.012	0.242	0.011	0.219	0.026	0.312

***p<.001, **p<.01, *p<.05, ~p<.10

In Model C and Model D property crime rates are modeled with respect to disaster type. Independent of disaster magnitude, and without controls, *coastal events*, *heat/drought,* and *floods* can be differentiated from other disaster types in terms of the effect on property crime rates. For each of these types of events, their occurrence is associated with an increase in the property crime rate. Once control variables are taken into account, only *heat/drought* and *floods* have a statistically significant positive effect on property crime rates. Finally, in Models E and F, violent crime rates are modeled with respect to disaster types. Findings from these analyses point to a different set of disaster events associated with violent crime. *Hurricanes/tropical storms* and *winter weather* have a positive and statistically significant effect on violent crime rates without theoretically-relevant control variables. In contrast, *wind* events are associated with a statistically significant decrease in violent crime rates. Only the relationship between *wind* and violent crime remains after adding controls.

IX. Concluding Remarks/Summary

In this chapter, I presented the findings that address the question of whether disasters of different types and magnitudes differentially affect crime outcomes. In terms of the hypotheses forwarded by each theoretical orientation used in this research, in general, the analyses provide the strongest support for both routine activity theory and social disorganization theory. Additionally, there is limited support for the therapeutic community hypothesis. In the next chapter, these findings are discussed in much greater detail, as are the limitations of the study and future research directions.

CHAPTER SIX: DISCUSSION AND CONCLUSIONS

I. INTRODUCTION

This dissertation has sought to answer the question of whether disasters of different magnitudes and types differentially affect crime outcomes. Three competing theoretical orientations informed this investigation: the therapeutic community hypothesis, social disorganization theory, and routine activity theory. Results indicated support for two of these orientations as disasters were found to be consistently associated with an increase in post-disaster crime rates. This chapter provides a discussion of these findings and a summary of the limitations of the research. It also identifies future directions for research involving disaster and crime. I conclude with an overview of the contributions of this dissertation to research on disaster and crime, and a brief discussion of how these findings may inform policy regarding crime control following disaster.

II. SUMMARY OF FINDINGS

A. Disaster Magnitude and Crime

In order to answer the research questions, I had to first contextualize the nature and extent of disaster and crime in the United States for the study period. This process involved first, tabulating the disaster measures used in this dissertation. The most common disaster event was severe weather. Severe weather caused an estimated 6,590 injuries, 490 fatalities, over 19.7 billion dollars in property damage, and over 3.7 billion dollars in property damage in the continental U.S. between 1995 and 2008. Hurricanes and tropical storms were the most costly disaster type. Over 84.4 billion dollars in property damage can be attributed to hurricanes and tropical storms. The largest dollar losses in crop damage between 1995 and 2008 were the result of heat/drought disaster events with losses over 13.7 billion dollars. Heat/drought events were also the most deadly disaster type during the study period. An estimated 2,960 people lost their lives to these disaster events. The largest number of injuries from disaster events between 1995 and 2008 were the result of tornadoes. The number of injuries attributed to tornadoes was estimated to be 13,338.

In addition to tabulating disasters and their impacts, both disasters and crime measures were analyzed in both time and space. This process, presented in Chapter 4, answered the question: where and when do disasters and crime occur? Results indicated a relatively high degree of spatial dependence, among counties, for the measures of crime and disaster. That is, the findings justified the use of geographically weighted regression to investigate if disasters beget crime. Further, the analyses presented in Chapter 4 confirmed that crime rates declined during the study period and that disaster impacts were, in general, increasing. Together, the geographic and temporal analysis of crime and disaster laid the groundwork for model specification using the hierarchical linear modeling (HLM).

The results of the HLM analyses presented in Chapter 5 indicate that for the years 1995 to 2008, a disaster's magnitude is positively related to crime rates. There was no evidence in any of the models to suggest that a disaster's magnitude was associated with a decrease in crime rates. This relationship was consistent for the measures of index, property, and violent crime rate, both with and without statistical controls. Analyses of the relationship between disaster magnitude and sub-types of crime—aggravated assault, criminal homicide, forcible rape, robbery, arson, burglary, larceny and motor vehicle theft—indicated that disaster magnitude was positively associated with increases in rates of criminal homicide, robbery, burglary, larceny, and motor vehicle theft. Findings were null for the analysis of disaster and arson, forcible rape, and aggravated assault. None of the sub-types of crime decreased as a function of increased disaster magnitude. One exception to these aforementioned results was the analysis of the effect of police guardianship on crime rates. In this case, the modeling utilized a reduced sample of data and the findings were null—the results indicated neither an increase nor decrease in crime was associated with disaster magnitude.

A total of 41 HLM models interrogated the question of how a disaster's magnitude influences 11 different types and categories of crime rates. With some minor exceptions, the results were relatively consistent. Across locations in the U.S. and hazard types, consistent with the predictions of social disorganization theory and routine activity theory, *disasters are associated with an increase in crime*. This finding should be interpreted with caution however. In all models where a statistically significant increase in crime was associated with disaster magnitude, the effect size was very small. In many of these cases, the empirical relationship only indicates an increase in the crime rate of a fraction of a percent. That is, while the relationship is robust, the meaningfulness of the increase in crime rates is open to interpretation.

B. Explaining the Relationship between Disaster and Crime

According to the definition of disaster provided in Chapter 1, disasters create conditions whereby normal community functioning is transformed or stressed by the creation of social disruption. The findings in this dissertation are congruent with this orientation and suggest that disasters may disrupt the conditions that normally act to control or suppress criminal acts. Used in the context of disaster, social disorganization theory (Sampson and Groves 1989; Shaw and McKay 1942) and routine activity theory (Cohen and Felson 1979; Felson and Cohen 1980) propose different disruptive effects that may engender crime. Social disorganization theory suggests that disasters create conditions that disrupt social cohesion and institutions of social control in a community. That is, disasters have the potential to create economic and residential instability and disrupt the social system in such a way that traditional institutions of social control—the school, the family, churches, and so forth—no longer function to maintain social order. Routine activity theory suggests that disasters restructure human ecology in such a way that motivated offenders, suitable targets, and lack of capable guardianship converge in space and time. Disasters thus reorganize the routine relationship among these elements, increasing the likelihood that crime will occur. This research however did not directly measure if disasters created social disorganization or restructured human ecology associated with routine activities that may lead to crime. Instead, variables associated with these theoretical approaches were utilized as statistical controls. The results of this research thus indicate that independent of these social disorganization and routine activity variables, disasters have the effect of increasing the crime rate in an impacted community.

C. The Number of Disaster Events

Independent of disaster magnitude this research found that the control variable, number of events, consistently predicted a decrease in crime rates. That is, as the number of events in a county increased, crime rates decreased. This seemingly contradictory finding can be explained in the context of the operationalization of the SHELDUS data. Because DEMI represented aggregate annual impacts of injuries, fatalities, property damage, and crop damage, it was necessary to control for the possibility that single high impact event might be conflated with multiple smaller events causing equal annual impacts. Thus, the number of events served as a control for the structure of the reported impact measures. The finding that the number of events is associated with a decrease in crime rates is therefore consistent with the claim that a single large event would be more disruptive than multiple small events, having equivalent annual impacts. A comment on an alternative explanation is needed. It is possible that areas that experience many disasters are socially habituated from their disruptive effects. Communities that regularly experience disruptive storms, hurricanes, or other disasters have developed mitigation and adjustment mechanisms to nullify, or minimize the disruption of these events. Should these strategies and prior experience with disaster sensitize the community to possible disruption, there may be informal mechanisms of social control which serve to suppress crime.

D. FEMA Declarations

In every model, the variable *FEMA declaration* had no statistically significant effect. This null effect was so prevalent that the variable was dropped from a number of analyses, as it had no predictive value. The fact that this variable showed no relationship to crime outcomes is curious. FEMA declarations are made when disasters create conditions whereby "the combined local, county, and state resources are insufficient and that the situation is beyond their recovery capabilities" (FEMA 2011: 1). That is, disasters are declared when the impacted community cannot adequately adapt to the conditions created by the event. Previous research suggests that the FEMA declaration process is highly politicized (Downton and Pielke 2001) and that the geographic distribution of FEMA declarations do not correspond to the geography of major hazard events (Schmidtlein, Finch, and Cutter 2008). These factors may account for the null findings regarding the use of FEMA declarations as an indicator of a disaster event. That is, FEMA declarations not only indicate social disruption, but also reflect other sociopolitical processes.

E. Disaster Types

The analyses to address whether disaster types[61] have a differential effect on crime rates, independent of disaster magnitude, indicated that floods and heat/drought are positively related to both index crime rates and property crime rates. There was no statistically significant effect of these disaster types on violent crime rates. In contrast,

[61] Disaster types included severe weather, flooding, winter weather, wind, tornadoes, lightning, heat/drought, hurricane/tropical storms, coastal events, wildfires, mass movements, and geophysical events.

the disaster type "wind" was associated with a decrease in violent crime rates. It is unclear why these disaster types are unique in their effect on crime rates. However, other findings in this research suggest some possibilities.

Floods were the second most common disaster type used in the analysis, with 26,349 county events recorded in SHELDUS between 1995-2008. In terms of property damage, floods represented the third most costly disaster type (35.3 billion), for the study period.[62] Heat/drought accounted for highest total number of fatalities (2,960) and the largest crop losses (13.7 billion) during the study period. These two disaster types are thus clearly disruptive in terms of measured impacts.

Previous research specific to the effects of flooding on crime is sparse.[63] Erikson (1976) investigated the effects of the Buffalo Creek Flood[64] and noted that there were widespread reports of looting, increases in alcohol and drug use, juvenile delinquency, and theft during the recovery period (205). It is difficult to say exactly why floods might be considered different than other disaster types in their effect on crime without further research.

Prior research into the effect of heat on crime rates indicates a consistent positive relationship between heat and assault, rape, domestic violence, and burglary and inconsistent findings regarding the relationship between heat and homicide, robbery, and larceny (for a review of these findings, see Cohn 1990). Explanations for increases in crime associated with heat generally engage theories of aggression (Bell and Baron 1976)

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[62] Mileti (1999) notes that floods were the most costly natural hazard in the United States between 1975 and 1994.
[63] An exception to this is the literature regarding crime and the flooding of New Orleans during Hurricane Katrina. Flooding from Hurricane Katrina was classified in this research as storm surge "coastal" event.
[64] The source of this flood was technological, given it was the result of a dam failure. This is notable, because technological disasters often elicit different responses from community members when compared to those perceived to be "acts of god" (c.f. Freudenburg 1997).

and routine activity theory (Rotton and Cohn 2000). These approaches explain crime in the context of situational and physiological stress and increased opportunities for crime associated with changes in routine activity during periods of high heat.

There is very little research investigating the relationship between wind and crime. Cohn (1990) notes that the two studies are available that considered the influence of wind on criminal behavior produced contradictory results. Cohn concludes that it is possible that wind may affect routine activities by making crime more difficult to commit, thereby decreasing crime, but that wind may intensify emotional and physical distress.

F. Routine Activity and Social Disorganization Variables

In terms of other control variables, across all models, measures of racial heterogeneity, ethnic heterogeneity, and inequality were all positively related to an increase in crime rates. These findings are consistent with social disorganization theory and its related predictions regarding the economic and racial/ethnic compositions of a socially disorganized community. The variable used as a proxy for motivated offenders, percent of the population who are male age 15-24, was positively related to crime rates in only some instances. These include models for rates of forcible rape, burglaries, larcenies, and the analysis using sample data, for limited years, to investigate the effect of police guardianship on crime rates. With the exception of the models for burglaries, when statistically significant, *pctMale15-24* was positively associated with crime rates. Notably, the variable *pctMale15-24* interacted with a number of variables in the model.[65]

[65] These findings were not presented in the dissertation, but are available upon request. Interaction effects with *pctMale15-24* did not substantially alter the results relevant to the disaster variables.

Two variables used in this research did not operate in their predicted directions. The number of non-profits in a county, used as a proxy for community efficacy, and police guardianship were both positively related to crime rates. These findings were inconsistent with the predictions of social disorganization theory and routine activity theory. Social disorganization theory predicts that increased community efficacy should be associated with a decrease in crime. And, routine activity theory predicts that a decrease in capable guardianship coupled with suitable targets and motivated offenders would increase the likelihood of crime.

Research documenting the role of community efficacy in reducing crime is well established (e.g. Sampson and Groves 1989). The findings in this research thus suggest that the variable of non-profit count may not be adequately capturing what social disorganization theorists conceive of as community efficacy—defined as social cohesion among members in the community, coupled with a willingness to contribute to the common good (Sampson, Raudenbush, and Earls 1997). However, many non-profits listed in the raw data (over 300,000 total) clearly represent organizations that foster such cohesion and helping behavior. These include churches and religious organizations, homeless shelters, schools, volunteer fire departments, and other organizations whose explicit purpose is to reduce crime (e.g. domestic violence advocacy groups and community watch organizations). However, there were many organizations listed in these data that may not be indicative of community efficacy. These include medical research associations, gun clubs, or political action groups such as the Heritage Foundation.

The variable for police guardianship also behaved opposite of the predicted direction. This finding begs the following questions of a) whether increasing police in an area increases or decreases crime rate, b) if high crime areas employ more police, and c) if the number of police in an area increases the reporting and recording of crime. Recent research investigating the first question indicate that increased police levels reduce crime rates at the county level (Kovandzic and Sloan 2002). However, these findings may not be generalizable to the national scale used in this research. Research investigating whether areas with high crime rates employ an increased number of police has found that an increase in police is inversely related to homicide, assault, robbery and burglary (Worrall and Kovandzic 2010). And research investigating whether increases in the number of police increase the reporting of crime finds evidence suggests that police presence does increase the likelihood that a crime is reported (Levitt 1998). These inconsistent findings cloud the results of the present research in that police are associated with an increase in crime.

III. Limitations of the Research

A. Measuring Disaster

The data on disasters and their impact represent the most fundamental limitation to the findings of this research. The question of what a disaster entails is widely debated (Perry and Quarantelli 2005; Quarantelli 1998). More so, the impacts of a disaster clearly extend beyond the DEMI measure used in this research. Property damage, crop damage, injuries and fatalities are certainly not the only measures of a disaster's impact. Among other issues, these measures cannot account for disruption of family routines, individual and community stress, and organizational inadequacies to respond to the disruption. Further, the disaster magnitude measure used in this research does not address the theoretical concerns of either routine activity theory or social disorganization. That is, a more appropriate disaster measure might include an indicator of how routines are affected by disasters and their variable types (e.g. drought versus a hurricane) or how disasters create conditions specific to social disorganization (e.g. displacement, poverty and inequality, etc.).

An additional limitation regarding the use of DEMI as an impact measure concerns the location and character of the community impacted by an event. That is, larger cities may have large disaster events, relative to damages and loss of human life, while much smaller losses in a small community may in fact be more disruptive to the functioning of that community. For example, 10 fatalities in a small rural town will likely have a much larger disorganizing effect than 10 fatalities in a city of 5 million. The DEMI measure does not take this relative impact into account.

Further, different types of damage may differentially affect locations relative to their industrial or agricultural economic base. For example, crop damages may indicate more disruption of a rural community when compared to urban centers. And property damage in a residential neighborhood may be more disorganizing than similarly high values of property damage in industrial areas.

An additional limitation of the disaster variables used in this research included the operationalization of the disaster types. The raw SHELDUS data categorizes disaster types which cannot be justified as independent events. This is most evident when examining the SHELDUS entries related to Hurricane Katrina. Katrina's damage estimates and human losses were categorized in multiple disaster categories, (i.e. coastal storm surge, flooding, and hurricane/tropical storm). A better measure of disaster type might delineate specific events as arising from a single cause (the storm itself) and forgo dividing the impacts among different hazard types. This is a difficult proposition given the raw SHELDUS data used in this research contained over 200,000 entries.

B. Measuring Crime

The crime variables utilized in this research have a number of limitations as well. First, the UCR data represent only reported crime and not all victimization events. It is well established that most crimes in the United States go unreported and that crime rates calculated using UCR data may misrepresent changes in crime over time (Eck and Riccio 2002; Mosher, Miethe, and Hart 2011). The implication of this limitation for this research is that there is no way to determine whether crime actually increases in a disaster's wake or if reporting of crime increases.

A second limitation is that the UCR data used in this research only included Part I offenses, which comprise only a small number of all the crimes committed in the U.S. Thus, many crimes such as petty theft, drug crimes, fraud, and some forms of domestic violence are not included in the analysis. These are crimes that ostensibly may be affected by disaster, as argued by Zahran et al. (2009) and Walsh (2010).

A third limitation concerns the reporting practices of law enforcement. Patterns of reporting by law enforcement may reflect political pressures to limit the amount of crime that is reported in the disaster aftermath (Seidman and Couzens 1974). Additionally, reporting agencies may not follow the FBI's reporting specifications for crimes reported to the UCR, and these data may be excluded from the final UCR report (James 2008).

A fourth limitation of the UCR data is that of missing data. Local law enforcement agencies are not required to submit UCR offense data. While over 90% of agencies do report UCR data, small jurisdictions (i.e. populations less than 2,500) and college law enforcement agencies are the least likely to report (Maltz 2006). Finally, if a law enforcement agency fails to report UCR data, the FBI uses data from the National Incident-Based Reporting System (NIBERS) to impute missing values (James 2008). Problematical in this process is that imputation procedures are different depending on a) the number of months in a year that were reported, and b) the size of the population in the area for which the data are missing (James 2008). Thus imputation processes may not capture changes in crime relative to a disaster's effect.

C. Socio-demographic Variables

The socio-demographic variables of percent male age 15-25, racial heterogeneity and ethnic heterogeneity were created using data from Surveillance Epidemiology and End Results (SEER) and the U.S. Census. With the exception of the year 2000 (a census year) the variables represent estimates of the age, gender, racial, and ethnic composition of the counties. Census estimates are based on predicted migratory patterns, births and deaths (U.S. Census Bureau 2009). Thus changes in the socio-demographic composition may not reflect intra-year changes brought about disaster events. The exception to this is the SEER data for racial and ethnic heterogeneity, which do account for yearly demographic shifts associated with Hurricane Katrina (National Cancer Institute 2011).

D. Police Guardianship

The variable for police guardianship, the number of full-time sworn offices in a county has severe limitations. First, these data represent sample data from the Law Enforcement and Administrative Statistics (LEMAS) survey for the years 1997, 1999, 2000, 2003, and 2007 (U.S. Department of Justice 2011). The periodicity of the data collection meant that analysis of the relationship between disaster and crime, when using this control variable, only included disaster events from these years. This relates to the second limitation of these data. Years for which there were large disaster events (e.g. the 1998 Texas flood, Flooding in Linn County Iowa in 2008, Hurricanes Katrina and Rita in 2005, and many others) were excluded from the analysis when this variable was employed. Third, the LEMAS data reflect the results of a stratified random sample of *police organizations*, and not of counties, the unit of analysis used in this research. Thus, estimates of the number of police *in a county* may not represent the actual number of sworn law enforcement personnel in a county.

E. Non-Profit Data

Data on the number of non-profits in a county obtained from the National Center of Charitable Statistics (NCCS 2011) represents a full census of public charities and private foundations who are required to file an IRS form 501(c)(3) who have gross receipts of at least $25,000 in a given year. Three limitations are relevant to the use of these data in this dissertation.

First, non-profit organizations that receive less than $25,000 annually are excluded from this census. That is, there are non-profits operating in any given county whose activity are unaccounted for by NCCS. It is unknown what effect this exclusion would have on the findings in this research. Second, charities often receive extensions on their IRS filing. These extensions result in an tabulation of the number of non-profits in a county for the most recent years (specifically 2007 and 2008). Finally, as was mentioned above, the variable of the count of non-profits in a county was utilized as a proxy for community efficacy. There are many organizations listed in these data that may not have the goal of increasing community cohesion and helping behavior.

F. Other Limitations

Other limitations in this research are relevant to a) the unit of analysis, b) theoretical and empirical assumptions, and c) possible statistical model misspecification. First, the unit of analysis for this research was the county and the decision for its use reflected the availability of the data to derive variables of interest, and the scale at which data was collected for these indicators. Disasters, however, do not operate according to the geography of political boundaries that counties represent. Some disasters, such as tornadoes and landslides, may be highly localized and only impact a small portion of a given county, whereas, other disasters, such as hurricanes, devastate wide swaths of the American landscape. While the SHELDUS data attempts to account for the distribution of a disaster's impacts, their solution of dividing damages and human losses among neighboring counties is less than optimal. That is, damages or human losses from an event may be concentrated in a particular county, but SHELDUS allocates these losses across all impacted areas. Improvements to this accounting procedure would entail tabulating losses at the county scale to reflect more realistic localized impacts. There is however no data available for which such a tabulation could be made.

Second, a limitation of this research is relevant to theoretical and empirical assumptions made when constructing the variables of interest. The variables used to test the hypotheses relevant to routine activity theory could be improved and new variables added. Specifically, no variable was used in the analysis to account for the availability of "suitable targets," a key component of routine activity theory. The variable for motivated offenders is also problematic in that, no accounting for the offender's motivation is provided. The offender is simply assumed to be a rational actor. In terms of the variable used to represent capable guardians, the number of police in a county does not capture the true nature of what Cohen and Felson (1979) proposed as guardianship. Guardianship can also be, and often is, informal (e.g. through churches, schools, family, etc.)

The variables used to test hypotheses related to social disorganization theory generally captured the nature of social disorganization. The exception to this was the use of the number of non-profits used as a measure of community efficacy, as was previously discussed.

The variable of the number of non-profits was also utilized to capture the potential organizational capacity to facilitate the emergence of a therapeutic community. Again, theoretical predictions regarding the therapeutic community and community efficacy included the prediction that the number of non-profits would be associated with a decrease in crime. This was not the case. It is clear that the number of non-profits in a county is measuring something of interest since the actual number is associated with an increase in crime.

A third limitation of the research includes the specification of model parameters. The HLM models used in this research provided two levels for which variables were operating. That is all variables were nested in time. An alternative specification using three levels might yield more informative results. For example, the independent variables used in the analysis might be nested in disaster type, which is nested in time. This specification is logical given the geographic clustering of certain types of disasters. Investigation of crime and disaster using this logic is clearly a next step for future research.

IV. Contributions of the Research

This research is unique in that there has never been a national county-level geographic and longitudinal analysis of the relationship between disaster and crime. Previous research has investigated the question of disaster and crime using case studies (Cromwell et al. 1995), event-specific research (Leitner, Barnett, Kent, and Barnett 2011), or has measured disaster and crime outcomes at much smaller scales (Harper and Frailing 2010; Zahran et al. 2009). Further, the majority of disaster events are not researched. That is, much of the research on crime and disaster often utilize one or two major events. In this research, all recorded hazard events between for the continental U.S. for 14 years were included in the analysis.

A second important contribution of this research includes the development of the Disaster Effect Magnitude Index or DEMI. Previous research has often relied on simple measures of FEMA declarations, the number of events (e.g. Zahran et al. 2009), or proximity to the disaster event (Siegel, Bourque, and Shoaf 1999).

Conclusions drawn from these projects are limited. Because the DEMI index combines four different impact measures, it has higher construct and content validity relative to univariate measures of disaster. Even still, as mentioned above, the DEMI index requires additional work if it is to further increase its content validity. That is the DEMI index may still underestimate the true impact/loss on a community.

A third contribution of this research is the comparative analysis of disaster types and their effect on crime outcomes. The findings that indicated floods, heat/drought and wind are differential in their effect on crime rates suggests the need for more research investigating the uniqueness of disaster types in conditioning crime outcomes. Additionally, the notion that disasters are similar in their effect on crime must be questioned, given these results. This point is especially relevant to disaster research which utilizes the generic moniker "disaster" to encapsulate all variants of disruptive events.[66]

Fourth, many investigations of disaster and crime focus on just a few types of crimes such as property crimes, violent crimes, or domestic violence (e.g. Harper and Frailing 2010; Zahran et al. 2009). This research investigated a total of 11 different crime rates and uncovered differential effects of disaster on each. Notably, some crime rates were unaffected by disasters (e.g. arson and aggravated assault), while others were clearly driving the changes in aggregate crime rates (e.g. burglary and larceny).

Fifth, the geographic analysis of disasters and crime also contributes to the larger discipline and crime by highlighting how these variables operate in space. That is, the some disaster types and high crime rates clearly cluster in particular regions in the U.S.

[66] I certainly implicate myself in this statement.

this insight suggests the need to further investigate the coupling of disaster and crime in these unique regions.

V. Future Research

The above overview of the findings and limitations of this research have implicated a number of possible avenues for future research into crime and disaster. The relationship between crime and disaster in this research was informed by three different theories. The results, in general, provided support for social disorganization theory and routine activity theory. Future research should consider changing the level of analysis and use the frameworks of both social disorganization and routine activity theory to investigate crime and disaster at the neighborhood or community level. Research might focus on how community, family, and formal law enforcement routines change to facilitate crime in highly disorganized areas. Comparative analyses among disaster types are also needed different types of disasters may change routines and create social disorganization in different ways.

The findings that floods and heat/drought have a differential effect on crime independent of the measure of impact also suggest the need for further study. Continued investigation into floods and crime might utilize a comparative analysis of floods with other disaster types and consider measured impacts other than property loss, crop loss, injuries and fatalities.

Future research investigating the relationship between heat/drought and crime should consider heat and drought separately. Additionally, drought is disruptive in ways unlike most of the disasters studied in this research. Research investigating drought and crime might consider rural composition and the political economy of water resources in areas experiencing drought. That is, what role does water management play in facilitating the onset of drought and subsequently crimes specific to drought impacted areas?

The variable used as a proxy for motivated offenders, percent of the population who are male, age 15-24, interacted with a number of the social disorganization variables (racial and ethnic heterogeneity and inequality). Further research should account for this interaction using structural equation modeling in order to uncover the functional relationship among routine activity variables and those indicating social disorganization.

The results using non-profits indicated that an increase in the number of non-profits is associated with an increase in crime rates. Future research using non-profits as a measure of community efficacy might utilize data specific to organizations whose stated mission involves creating social cohesion and promoting helping behavior. An additional research program might consider designating the variable for non-profits as a dependent variable and utilize disaster measures to predict non-profit formation in the wake of a disaster event. That is, how are non-profit organizations related to both social disorganization and disasters? Are places that have a glut of non-profits already socially disorganized? Or do disasters facilitate the emergence of a non-profit organizational complex?

Further research uncovering the relationship among police guardianship, levels of crime and disaster is clearly necessary. Such research might investigate the activity of police during disaster situations and the recovery period (c.f. Bonkiewicz and Bruback 2010), or how disasters effect changes in the reporting patterns of the community.

Another clear direction for future research includes a recalibration of the DEMI measure to account for impacts relative to the population and economic structure of places impacted by disasters. That is, a stronger indicator would account for a community's dominant industry (agriculture v. industry), or the proportion of a community's population that is physically harmed by a disaster.

While SHELDUS data represent the most comprehensive inventory of disaster events, the data limit what can be said about larger complex events. Future research investigating disaster types and their differential impacts might delineate disasters according to their temporal and spatial impact zones and explicitly recognize disaster are truly complex events with physical impacts from a variety of sources.

Finally, an additional direction for future research to uncover the relationship between disaster and crime is suggested by the use of control variables in the modeling procedures used in this research. Because the models sought to uncover the effect of disasters on crime independent of social disorganization and routine activity variables, future research should consider the possibility that disasters may create social disorganization *and* restructure human ecology to facilitate crime. That is, a logical research program to measure social disorganization and restructuring of human ecology following disasters should directly measure if disasters are unique in creating conditions whereby crime is more likely.

The benefits of considering disasters as disorganizing and restructuring events is evident when considering the anthropogenic origins of natural disasters. Specifically, what in society do disasters disrupt? First, disasters have the potential to disrupt the built environment, or technically, the human ecology of place (Hawley 1950). They do so by damaging or eliminating transportation and communication infrastructure (Mileti 1999). Roads, waterways, radio, telephone, and internet access may be destroyed or damaged to the point that they no longer function to facilitate routine human activity. Further, because these technologies facilitate interdependence among members of society, networks of mutual support and economic activity will be transformed through the reflexive adjustment of the impacted community to the physical damage created by a disaster. This adjustment may range from minor adjustments of one's routine, such as taking several days off work because a storm has damaged the power infrastructure, to major adjustments, such as the complete rebuilding of a community following a catastrophic event. In each case, routines change and the change in routines have the potential to impact crime. That is, new and old targets become available to motivated offenders as the geographic and temporal patterns of routine guardianship are transformed to create opportunity for crime to occur (c.f. Cromwell, Dunham, and Lanza-Kaduce 1995). The transformation of the routine activities following disaster is thus analogous to Cohen and Felson's (1979) observation that changes in daily routines post-World War II increased crime. However, in the case of disaster, new routines of "digging out" or rebuilding may be coupled with disaster-created social disorganization.

Second, the social disorganization created in the disaster-affected community can be substantial. Disasters may, and often do, generate economic instability through loss of property and/or employment, create residential instability through displacement, impact social networks, weaken communal or familial ties, and create conditions where existing social institutions are ill-equipped to address emergent needs (see Brunsma, Overfelt, and Picou 2010). The disruption in the community caused by disaster thus has the potential to increase crime because the community is unable to function to maintain social order. In short, the coupling of altered routines with social disorganization may create the perfect storm for the emergence of post-disaster crime.

VI. Conclusion

Disaster-related crime is increasingly a concern to social scientists. The academic debates regarding the relationship between these two phenomena highlight the need for continued research in this area. Additionally, the increasing vulnerability of the U.S. population to environmental hazards suggests that policy relevant to disaster-related crime is also needed. That is, training of members of law enforcement to understand which types of crime following a disaster event are more likely may increase their effectiveness in crime prevention. Harper and Frailing (2010) have offered a comprehensive inventory of policy recommendations in this regard. This research also indicates that much might be gained by considering regional variation in disaster types and their differential impacts when developing policies to address crime prevention in the context of disaster. That is, emergency preparedness plans for the public and law enforcement should be informed by the uniqueness of place in terms of vulnerability to disaster and their effects on crime.

In conclusion, the findings in this research implicate disaster in creating conditions whereby crime is more likely. That is, disasters of different magnitude and types clearly have a differential effect on crime rates. Given this, the suffering, loss of life, community, and livelihood may be the face of disaster, but a disaster’s underbelly is the further victimization of survivors.

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APPENDIX

This Appendix provides the full HLM models that are presented in abbreviated form in the main text.

Table A.1: Model E: Interaction of *lnDEMI* and *pctMale15-24* (Index Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0558706	.0497658	1.12	0.262	-.0416686	.1534097
lnEvents	-.0153211	.0062173	-2.46	0.014	-.0275068	-.0031354
pctMale15_24	.0022974	.0067076	0.34	0.732	-.0108492	.015444
theil	-2.87e+08	1.72e+08	-1.67	0.095	-6.23e+08	4.99e+07
herf_race	-1.170605	.0819113	-14.29	0.000	-1.331148	-1.010062
herf_ethnic	-1.016757	.1106097	-9.19	0.000	-1.233548	-.7999662
lnNP_count	.0979906	.008059	12.16	0.000	.0821953	.113786
inlag	.0732592	.0051465	14.23	0.000	.0631722	.0833461
time	-.0441708	.0134535	-3.28	0.001	-.0705392	-.0178024
pctMale15_~I	-.0022765	.006796	-0.33	0.738	-.0155965	.0110434
lnDEMIxtime	-.0131	.007276	-1.80	0.072	-.0273607	.0011607
lnEventsXt~e	.0034973	.0007572	4.62	0.000	.0020132	.0049813
pctMale15_~e	.0017755	.0006229	2.85	0.004	.0005547	.0029962
TheilXtime	-4.08e+07	1.46e+07	-2.80	0.005	-6.93e+07	-1.22e+07
HerfRaceXt~e	-.0047666	.0068142	-0.70	0.484	-.0181221	.0085889
herfEthXtime	.0232151	.0086998	2.67	0.008	.0061639	.0402664
lnNP_coXtime	-.0077713	.0006531	-11.90	0.000	-.0090513	-.0064912
InLagXtime	.001794	.000708	2.53	0.011	.0004064	.0031816
pctM15_24D~e	.0008229	.0009891	0.83	0.405	-.0011157	.0027615
_cons	8.805785	.1560543	56.43	0.000	8.499924	9.111646

Random effects Parameters

	Estimate	SE	95% Confidence Interval	
var(time)	.0026232	.0000913	.0024502	.0028085
var(_cons)	.4740733	.0148192	.4459001	.5040266
cov(time,_cons)	-.0143841	.0008741	-.0160972	-.012671
var(Residual)	.1280703	.0010068	.1261121	.130059

Table A.2: Model F: Interaction of *lnDEMI* and *inequality* (Index Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.04128	.0125106	3.30	0.001	.0167596	.0658003
lnEvents	-.0153855	.0062252	-2.47	0.013	-.0275867	-.0031843
pctMale15_24	.0021015	.0066196	0.32	0.751	-.0108727	.0150756
theil	-3.15e+08	1.83e+08	-1.72	0.085	-6.74e+08	4.37e+07
herf_race	-1.169717	.0819458	-14.27	0.000	-1.330328	-1.009106
herf_ethnic	-1.015083	.1106489	-9.17	0.000	-1.23195	-.7982148
lnNP_count	.0975015	.0081087	12.02	0.000	.0816087	.1133942
inlag	.0732352	.0051471	14.23	0.000	.063147	.0833234
theilXDEMI	2.58e+07	5.91e+07	0.44	0.663	-9.00e+07	1.42e+08
time	-.0443058	.0134414	-3.30	0.001	-.0706504	-.0179612
lnDEMIxtime	-.0073484	.0016722	-4.39	0.000	-.010626	-.0040709
lnEventsXt~e	.0035035	.0007581	4.62	0.000	.0020178	.0049893
pctMale15_~e	.001837	.0006111	3.01	0.003	.0006392	.0030348
TheilXtime	-3.76e+07	1.62e+07	-2.31	0.021	-6.94e+07	-5734652
HerfRaceXt~e	-.004922	.0068191	-0.72	0.470	-.0182872	.0084432
herfEthXtime	.0229801	.0087014	2.64	0.008	.0059256	.0400346
lnNP_coXtime	-.0077297	.000657	-11.77	0.000	-.0090174	-.006442
InLagXtime	.0017933	.000708	2.53	0.011	.0004056	.003181
theilDEMIx~e	-3062045	7909027	-0.39	0.699	-1.86e+07	1.24e+07
_cons	8.805862	.1559715	56.46	0.000	8.500164	9.111561

Random-effects Parameters

	Estimate	SE	95% Confidence Interval	
var(time)	.0026228	.0000913	.0024497	.002808
var(_cons)	.4742748	.0148299	.4460815	.5042501
cov(time,_cons)	-.0143867	.0008742	-.0161001	-.0126732
var(Residual)	.1280709	.0010069	.1261126	.1300597

Table A.3: Model G: Interaction of *lnDEMI* and *Racial Heterogeneity* (Index Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	-.0056297	.0558691	-0.10	0.920	-.115131	.1038717
lnEvents	-.0155601	.0062358	-2.50	0.013	-.0277821	-.003338
pctMale15_24	.0022724	.0066178	0.34	0.731	-.0106983	.015243
theil	-2.96e+08	1.72e+08	-1.72	0.085	-6.33e+08	4.11e+07
herf_race	-1.174584	.0825341	-14.23	0.000	-1.336348	-1.01282
herf_ethnic	-1.016084	.1106393	-9.18	0.000	-1.232933	-.799235
lnNP_count	.0979556	.0080602	12.15	0.000	.0821579	.1137532
inlag	.073166	.0051468	14.22	0.000	.0630784	.0832537
HR_DEMI	.0575136	.0691381	0.83	0.405	-.0779947	.1930219
time	-.0458535	.0134703	-3.40	0.001	-.0722548	-.0194522
lnDEMIxtime	.0034211	.0074071	0.46	0.644	-.0110966	.0179388
lnEventsXt~e	.0035578	.0007594	4.68	0.000	.0020693	.0050462
pctMale15_~e	.0018385	.000611	3.01	0.003	.000641	.003036
TheilXtime	-3.93e+07	1.46e+07	-2.69	0.007	-6.79e+07	-1.07e+07
HerfRaceXt~e	-.0031357	.006928	-0.45	0.651	-.0167143	.0104429
herfEthXtime	.0229642	.0086995	2.64	0.008	.0059134	.040015
lnNP_coXtime	-.007772	.0006532	-11.90	0.000	-.0090522	-.0064917
InLagXtime	.0018056	.000708	2.55	0.011	.0004179	.0031934
HR_DEMIxTime	-.0137016	.0092883	-1.48	0.140	-.0319064	.0045031
_cons	8.809446	.1560147	56.47	0.000	8.503663	9.115229

Random-effects Parameters

	Estimate	SE	95% Confidence Interval	
var(time)	.0026234	.0000914	.0024504	.0028087
var(_cons)	.4742244	.0148246	.4460408	.5041887
cov(time,_cons)	-.0143853	.0008742	-.0160987	-.0126719
var(Residual)	.1280591	.0010068	.126101	.1300476

Table A.4: Model H: Interaction of *lnDEMI* and *Ethnic Heterogeneity* (Index Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	-.0507846	.0580515	-0.87	0.382	-.1645636	.0629943
lnEvents	-.0159958	.0062344	-2.57	0.010	-.0282151	-.0037766
pctMale15_24	.0020975	.0066135	0.32	0.751	-.0108647	.0150596
theil	-2.99e+08	1.72e+08	-1.74	0.082	-6.36e+08	3.82e+07
herf_race	-1.169865	.0818941	-14.29	0.000	-1.330374	-1.009355
herf_ethnic	-1.041229	.1116561	-9.33	0.000	-1.260071	-.8223867
lnNP_count	.0977366	.0080573	12.13	0.000	.0819445	.1135287
inlag	.0731252	.0051464	14.21	0.000	.0630384	.083212
HE_DEMI	.1075335	.0676062	1.59	0.112	-.0249722	.2400392
time	-.0466849	.0135104	-3.46	0.001	-.0731647	-.020205
lnDEMIxtime	.0027292	.0084252	0.32	0.746	-.013784	.0192424
lnEventsXt~e	.0035631	.0007586	4.70	0.000	.0020762	.00505
pctMale15_~e	.0018305	.0006108	3.00	0.003	.0006333	.0030276
TheilXtime	-3.92e+07	1.46e+07	-2.69	0.007	-6.79e+07	-1.06e+07
HerfRaceXt~e	-.0049069	.0068126	-0.72	0.471	-.0182594	.0084455
herfEthXtime	.0255524	.0088519	2.89	0.004	.0082031	.0429018
lnNP_coXtime	-.0077525	.000653	-11.87	0.000	-.0090325	-.0064726
InLagXtime	.0018003	.0007079	2.54	0.011	.0004129	.0031877
HE_DEMIxTime	-.0117172	.0097807	-1.20	0.231	-.030887	.0074525
_cons	8.830805	.1565514	56.41	0.000	8.52397	9.13764

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0026208	.0000913	.0024479	.002806
var(_cons)	.4738222	.014814	.4456591	.5037652
cov(time,_cons)	-.0143562	.0008736	-.0160684	-.012644
var(Residual)	.1280732	.0010069	.1261148	.1300619

Table A.5: Model I: Interaction of *lnDEMI* and *lnNProfit* (Index Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0413831	.0243072	1.70	0.089	-.0062581	.0890242
lnEvents	-.015304	.0062301	-2.46	0.014	-.0275148	-.0030933
pctMale15_24	.0020359	.0066156	0.31	0.758	-.0109303	.0150022
theil	-2.90e+08	1.73e+08	-1.68	0.094	-6.29e+08	4.91e+07
herf_race	-1.170318	.0819181	-14.29	0.000	-1.330875	-1.009762
herf_ethnic	-1.016948	.1106186	-9.19	0.000	-1.233756	-.8001391
lnNP_count	.0979193	.0081065	12.08	0.000	.0820308	.1138077
inlag	.0732783	.0051468	14.24	0.000	.0631907	.0833659
NPxDEMI	-.000852	.0060177	-0.14	0.887	-.0126465	.0109425
time	-.044549	.0134385	-3.32	0.001	-.0708879	-.0182101
lnDEMIxtime	-.0083757	.0027784	-3.01	0.003	-.0138212	-.0029301
lnEventsXt~e	.0035014	.0007584	4.62	0.000	.0020149	.0049879
pctMale15_~e	.0018501	.0006111	3.03	0.002	.0006524	.0030477
TheilXtime	-3.98e+07	1.47e+07	-2.71	0.007	-6.87e+07	-1.10e+07
HerfRaceXt~e	-.0048138	.0068148	-0.71	0.480	-.0181706	.008543
herfEthXtime	.0232021	.0087002	2.67	0.008	.00615	.0402541
lnNP_coXtime	-.0078145	.0006603	-11.84	0.000	-.0091086	-.0065204
InLagXtime	.001795	.0007081	2.54	0.011	.0004072	.0031827
NPxDEMIxTime	.0004176	.0007034	0.59	0.553	-.0009611	.0017962
_cons	8.807745	.1559557	56.48	0.000	8.502078	9.113413

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0026239	.0000914	.0024508	.0028092
var(_cons)	.4741683	.0148237	.4459866	.5041308
cov(time,_cons)	-.0143846	.0008742	-.016098	-.0126711
var(Residual)	.1280659	.0010068	.1261077	.1300545

Table A.6: Model E: Interaction of *lnDEMI* and *pctMale15-24* (Property Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0413831	.0243072	1.70	0.089	-.0062581	.0890242
lnEvents	-.015304	.0062301	-2.46	0.014	-.0275148	-.0030933
pctMale15_24	.0020359	.0066156	0.31	0.758	-.0109303	.0150022
theil	-2.90e+08	1.73e+08	-1.68	0.094	-6.29e+08	4.91e+07
herf_race	-1.170318	.0819181	-14.29	0.000	-1.330875	-1.009762
herf_ethnic	-1.016948	.1106186	-9.19	0.000	-1.233756	-.8001391
lnNP_count	.0979193	.0081065	12.08	0.000	.0820308	.1138077
inlag	.0732783	.0051468	14.24	0.000	.0631907	.0833659
NPxDEMI	-.000852	.0060177	-0.14	0.887	-.0126465	.0109425
time	-.044549	.0134385	-3.32	0.001	-.0708879	-.0182101
lnDEMIxtime	-.0083757	.0027784	-3.01	0.003	-.0138212	-.0029301
lnEventsXt~e	.0035014	.0007584	4.62	0.000	.0020149	.0049879
pctMale15_~e	.0018501	.0006111	3.03	0.002	.0006524	.0030477
TheilXtime	-3.98e+07	1.47e+07	-2.71	0.007	-6.87e+07	-1.10e+07
HerfRaceXt~e	-.0048138	.0068148	-0.71	0.480	-.0181706	.008543
herfEthXtime	.0232021	.0087002	2.67	0.008	.00615	.0402541
lnNP_coXtime	-.0078145	.0006603	-11.84	0.000	-.0091086	-.0065204
InLagXtime	.001795	.0007081	2.54	0.011	.0004072	.0031827
NPxDEMIxTime	.0004176	.0007034	0.59	0.553	-.0009611	.0017962
_cons	8.807745	.1559557	56.48	0.000	8.502078	9.113413

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0026239	.0000914	.0024508	.0028092
var(_cons)	.4741683	.0148237	.4459866	.5041308
cov(time,_cons)	-.0143846	.0008742	-.016098	-.0126711
var(Residual)	.1280659	.0010068	.1261077	.1300545

Table A.7: Model F: Interaction of *lnDEMI* and *Inequality* (Property Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0381453	.0142965	2.67	0.008	.0101247	.0661659
lnEvents	-.0136566	.0070822	-1.93	0.054	-.0275375	.0002243
pctMale15_24	.0074722	.007219	1.04	0.301	-.0066767	.0216211
theil	-1.48e+08	1.97e+08	-0.75	0.453	-5.35e+08	2.39e+08
herf_race	-1.032538	.0873512	-11.82	0.000	-1.203743	-.8613327
herf_ethnic	-.9814382	.1183832	-8.29	0.000	-1.213465	-.7494115
lnNP_count	.1161173	.0088788	13.08	0.000	.0987152	.1335193
inlag	1.19e+07	6.74e+07	0.18	0.860	-1.20e+08	1.44e+08
NPxDEMI	.0786487	.0058136	13.53	0.000	.0672541	.0900432
time	-.0425452	.0148617	-2.86	0.004	-.0716735	-.0134169
lnDEMIxtime	-.0073629	.0019116	-3.85	0.000	-.0111095	-.0036163
lnEventsXt~e	.0035495	.0008626	4.11	0.000	.0018589	.0052402
pctMale15_~e	.0018777	.0006795	2.76	0.006	.000546	.0032094
TheilXtime	-5.38e+07	1.82e+07	-2.96	0.003	-8.93e+07	-1.82e+07
HerfRaceXt~e	-.0083209	.0075769	-1.10	0.272	-.0231714	.0065296
herfEthXtime	.0253958	.0096685	2.63	0.009	.006446	.0443456
lnNP_coXtime	-.0090394	.0007218	-12.52	0.000	-.0104541	-.0076246
InLagXtime	-1360753	9029476	-0.15	0.880	-1.91e+07	1.63e+07
NPxDEMIxTime	.001981	.0007997	2.48	0.013	.0004137	.0035484
_cons	8.422885	.1677291	50.22	0.000	8.094142	8.751628

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0031883	.0001141	.0029724	.00342
var(_cons)	.5275689	.0167584	.4957247	.5614587
cov(time,_cons)	-.0162146	.001034	-.0182412	-.0141879
var(Residual)	.1679934	.0013228	.1654207	.1706062

Table A.8: Model G: Interaction of *lnDEMI* and *Racial Heterogeneity* (Property Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0094115	.0638326	0.15	0.883	-.115698	.1345211
lnEvents	-.0137504	.0070949	-1.94	0.053	-.0276562	.0001553
pctMale15_24	.00764	.0072167	1.06	0.290	-.0065045	.0217845
theil	-1.41e+08	1.84e+08	-0.77	0.444	-5.02e+08	2.20e+08
herf_race	-1.034249	.0880793	-11.74	0.000	-1.206881	-.8616171
herf_ethnic	-.9825286	.1183751	-8.30	0.000	-1.21454	-.7505176
lnNP_count	.1163031	.0088214	13.18	0.000	.0990134	.1335928
inlag	.0356948	.0789956	0.45	0.651	-.1191336	.1905233
NPxDEMI	.0785631	.0058134	13.51	0.000	.0671691	.089957
time	-.0437858	.0148958	-2.94	0.003	-.0729811	-.0145905
lnDEMIxtime	.0016172	.0084664	0.19	0.849	-.0149766	.018211
lnEventsXt~e	.0035957	.0008642	4.16	0.000	.0019018	.0052895
pctMale15_~e	.0018767	.0006793	2.76	0.006	.0005454	.0032081
TheilXtime	-5.41e+07	1.62e+07	-3.33	0.001	-8.60e+07	-2.23e+07
HerfRaceXt~e	-.0069222	.0077048	-0.90	0.369	-.0220233	.008179
herfEthXtime	.0253654	.0096659	2.62	0.009	.0064205	.0443103
lnNP_coXtime	-.0090601	.0007173	-12.63	0.000	-.0104661	-.0076542
InLagXtime	-.011588	.010617	-1.09	0.275	-.0323969	.0092208
NPxDEMIxTime	.0019973	.0007997	2.50	0.013	.0004299	.0035647
_cons	8.424469	.1677947	50.21	0.000	8.095598	8.753341

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.003189	.0001141	.002973	.0034207
var(_cons)	.5275676	.0167543	.495731	.5614489
cov(time,_cons)	-.0162125	.001034	-.0182392	-.0141859
var(Residual)	.1679801	.0013227	.1654076	.1705925

Table A.9: Model H: Interaction of *lnDEMI* and *Ethnic Heterogeneity* (Property Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	-.0997782	.0663123	-1.50	0.132	-.229748	.0301915
lnEvents	-.0147326	.0070924	-2.08	0.038	-.0286334	-.0008317
pctMale15_24	.0075652	.0072114	1.05	0.294	-.0065689	.0216993
theil	-1.53e+08	1.84e+08	-0.83	0.405	-5.14e+08	2.07e+08
herf_race	-1.032008	.0872899	-11.82	0.000	-1.203093	-.860923
herf_ethnic	-1.019524	.119617	-8.52	0.000	-1.253969	-.7850794
lnNP_count	.1159954	.0088171	13.16	0.000	.0987141	.1332766
inlag	.1631854	.0772272	2.11	0.035	.011823	.3145479
NPxDEMI	.078431	.0058124	13.49	0.000	.0670388	.0898231
time	-.0460453	.01494	-3.08	0.002	-.0753272	-.0167634
lnDEMIxtime	.0085771	.0096287	0.89	0.373	-.0102948	.0274489
lnEventsXt~e	.0036582	.0008632	4.24	0.000	.0019663	.00535
pctMale15_~e	.0018609	.000679	2.74	0.006	.0005302	.0031916
TheilXtime	-5.28e+07	1.62e+07	-3.25	0.001	-8.47e+07	-2.10e+07
HerfRaceXt~e	-.0084368	.0075679	-1.11	0.265	-.0232696	.0063961
herfEthXtime	.0292697	.0098431	2.97	0.003	.0099776	.0485619
lnNP_coXtime	-.0090373	.0007171	-12.60	0.000	-.0104428	-.0076319
InLagXtime	-.0187982	.0111778	-1.68	0.093	-.0407062	.0031098
NPxDEMIxTime	.0019974	.0007994	2.50	0.012	.0004305	.0035642
_cons	8.459137	.1684391	50.22	0.000	8.129002	8.789271

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0031844	.000114	.0029686	.0034158
var(_cons)	.5270423	.0167399	.4952331	.5608946
cov(time,_cons)	-.0161652	.001033	-.0181899	-.0141404
var(Residual)	.1679889	.0013227	.1654163	.1706016

Table A.10: Model I: Interaction of *lnDEMI* and *lnNProfit* (Property Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0209555	.0277786	0.75	0.451	-.0334895	.0754004
lnEvents	-.0133097	.0070879	-1.88	0.060	-.0272016	.0005823
pctMale15_24	.0074228	.0072148	1.03	0.304	-.006718	.0215636
theil	-1.21e+08	1.85e+08	-0.65	0.513	-4.84e+08	2.42e+08
herf_race	-1.032482	.087329	-11.82	0.000	-1.203644	-.8613203
herf_ethnic	-.9839321	.1183607	-8.31	0.000	-1.215915	-.7519493
lnNP_count	.1155299	.0088769	13.01	0.000	.0981315	.1329284
inlag	.0042171	.0068753	0.61	0.540	-.0092583	.0176925
NPxDEMI	.078709	.0058133	13.54	0.000	.0673153	.0901028
time	-.0428807	.0148582	-2.89	0.004	-.0720022	-.0137593
lnDEMIxtime	-.0071061	.0031761	-2.24	0.025	-.0133313	-.000881
lnEventsXt~e	.003522	.000863	4.08	0.000	.0018305	.0052135
pctMale15_~e	.0018857	.0006794	2.78	0.006	.0005542	.0032172
TheilXtime	-5.59e+07	1.64e+07	-3.41	0.001	-8.80e+07	-2.38e+07
HerfRaceXt~e	-.0083187	.0075718	-1.10	0.272	-.0231591	.0065218
herfEthXtime	.0256549	.0096669	2.65	0.008	.0067081	.0446018
lnNP_coXtime	-.0090439	.0007258	-12.46	0.000	-.0104664	-.0076214
InLagXtime	.0000207	.000804	0.03	0.979	-.0015551	.0015965
NPxDEMIxTime	.0019812	.0007997	2.48	0.013	.0004138	.0035486
_cons	8.42721	.1677293	50.24	0.000	8.098467	8.755954

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0031898	.0001141	.0029738	.0034216
var(_cons)	.5276	.0167559	.4957602	.5614847
cov(time,_cons)	-.0162154	.0010342	-.0182423	-.0141884
var(Residual)	.1679784	.0013227	.1654059	.1705909

Table A.11: Model J: Full HLM Model for Arson

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0305395	.0319037	0.96	0.338	-.0319906	.0930696
lnEvents	-.036241	.015862	-2.28	0.022	-.0673299	-.005152
pctMale15_24	.0212588	.011793	1.80	0.071	-.001855	.0443726
theil	2.08e+08	2.75e+08	0.75	0.451	-3.32e+08	7.47e+08
herf_race	-.5488918	.1278775	-4.29	0.000	-.7995271	-.2982564
herf_ethnic	-.9355245	.1754393	-5.33	0.000	-1.279379	-.5916699
lnNP_count	.3044675	.0148942	20.44	0.000	.2752753	.3336596
inlag	.1261013	.0116256	10.85	0.000	.1033156	.148887
time	-.0065495	.0274547	-0.24	0.811	-.0603598	.0472607
lnDEMIxtime	-.0034706	.0042888	-0.81	0.418	-.0118765	.0049354
lnEventsXt~e	.0079273	.0019141	4.14	0.000	.0041758	.0116788
pctMale15_~e	.002662	.0012283	2.17	0.030	.0002546	.0050695
TheilXtime	-1.11e+08	2.84e+07	-3.90	0.000	-1.66e+08	-5.51e+07
HerfRaceXt~e	-.018919	.0133656	-1.42	0.157	-.045115	.0072771
herfEthXtime	.0161905	.017401	0.93	0.352	-.0179147	.0502958
lnNP_coXtime	-.0211948	.0012622	-16.79	0.000	-.0236686	-.018721
InLagXtime	.0029708	.0015962	1.86	0.063	-.0001577	.0060993
_cons	1.589495	.2629144	6.05	0.000	1.074192	2.104798

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0076588	.0003542	.0069951	.0083855
var(_cons)	.8954139	.0320441	.8347607	.9604741
cov(time,_cons)	-.0408744	.0027712	-.0463058	-.035443
var(Residual)	.9772456	.0076592	.9623486	.9923731

Table A.12: Model K: Full HLM Model for Burglaries

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0501136	.0186451	2.69	0.007	.0135698	.0866574
lnEvents	-.0326344	.0095024	-3.43	0.001	-.0512588	-.01401
pctMale15_24	-.0181134	.0082927	-2.18	0.029	-.0343667	-.0018601
theil	3.06e+08	2.01e+08	1.52	0.128	-8.85e+07	7.00e+08
herf_race	-1.47149	.0946288	-15.55	0.000	-1.656959	-1.286021
herf_ethnic	-1.035354	.1292948	-8.01	0.000	-1.288767	-.7819411
lnNP_count	.0839174	.0102192	8.21	0.000	.0638882	.1039466
plag_ln	.084359	.007351	11.48	0.000	.0699513	.0987668
time	-.0502929	.0178391	-2.82	0.005	-.0852568	-.015329
lnDEMIxtime	-.008961	.002506	-3.58	0.000	-.0138727	-.0040492
lnEventsXt~e	.0066622	.0011521	5.78	0.000	.0044041	.0089204
pctMale15_~e	.0029016	.0008058	3.60	0.000	.0013222	.004481
TheilXtime	-1.70e+07	1.90e+07	-0.89	0.371	-5.41e+07	2.02e+07
HerfRaceXt~e	-.0126355	.008875	-1.42	0.155	-.0300302	.0047592
herfEthXtime	.001575	.0114325	0.14	0.890	-.0208322	.0239823
lnNP_coXtime	-.0067576	.0008427	-8.02	0.000	-.0084093	-.0051059
plag_lnXtime	.0037289	.0010113	3.69	0.000	.0017468	.0057109
_cons	7.680953	.1878342	40.89	0.000	7.312805	8.049101

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.003883	.0001553	.0035903	.0041996
var(_cons)	.5664438	.0186521	.5310411	.6042066
cov(time,_cons)	-.0182333	.001316	-.0208126	-.015654
var(Residual)	.3254024	.0025616	.3204204	.3304619

Table A.13: Model L Full HLM Model for Larcenies

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0385127	.017569	2.19	0.028	.0040781	.0729473
lnEvents	-.00484	.0091575	-0.53	0.597	-.0227883	.0131084
pctMale15_24	.0251225	.0091749	2.74	0.006	.00714	.0431051
theil	2.23e+08	2.30e+08	0.97	0.334	-2.29e+08	6.74e+08
herf_race	-.9681478	.1090635	-8.88	0.000	-1.181908	-.7543873
herf_ethnic	-.9060964	.1477857	-6.13	0.000	-1.195751	-.6164417
lnNP_count	.1793647	.0112904	15.89	0.000	.1572359	.2014934
plag_ln	.0858811	.0075018	11.45	0.000	.0711778	.1005845
time	-.0429102	.0190228	-2.26	0.024	-.0801941	-.0056263
lnDEMIxtime	-.0076885	.0023597	-3.26	0.001	-.0123134	-.0030636
lnEventsXt~e	.0027157	.0011136	2.44	0.015	.0005331	.0048983
pctMale15_~e	.0019007	.000869	2.19	0.029	.0001975	.0036039
TheilXtime	-1.07e+08	2.06e+07	-5.20	0.000	-1.47e+08	-6.66e+07
HerfRaceXt~e	-.0022487	.0096315	-0.23	0.815	-.0211261	.0166288
herfEthXtime	.0353308	.0123488	2.86	0.004	.0111275	.059534
lnNP_coXtime	-.0139581	.0009197	-15.18	0.000	-.0157607	-.0121555
plag_lnXtime	.0021949	.0010256	2.14	0.032	.0001847	.0042051
_cons	7.469079	.2108709	35.42	0.000	7.05578	7.882379

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0051153	.000187	.0047615	.0054953
var(_cons)	.8094676	.0257538	.7605326	.8615512
cov(time,_cons)	-.0289363	.0016736	-.0322164	-.0256562
var(Residual)	.2827117	.0022274	.2783796	.2871113

Table A.14: Model M: Full HLM Model for Motor Vehicle Theft

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0429487	.0245167	1.75	0.080	-.0051031	.0910005
lnEvents	-.0332705	.0122152	-2.72	0.006	-.0572119	-.0093291
pctMale15_24	.0031209	.0096058	0.32	0.745	-.0157062	.021948
theil	-6.40e+08	2.28e+08	-2.81	0.005	-1.09e+09	-1.93e+08
herf_race	-1.457479	.1071331	-13.60	0.000	-1.667456	-1.247502
herf_ethnic	-.8853251	.1470447	-6.02	0.000	-1.173527	-.5971229
lnNP_count	.2630955	.0118598	22.18	0.000	.2398509	.2863402
plag_ln	.0738965	.0089948	8.22	0.000	.0562669	.091526
time	-.0427743	.0211004	-2.03	0.043	-.0841303	-.0014184
lnDEMIxtime	-.0089286	.0032969	-2.71	0.007	-.0153904	-.0024669
lnEventsXt~e	.0073491	.0014745	4.98	0.000	.0044591	.0102392
pctMale15_~e	.0023841	.0009436	2.53	0.012	.0005347	.0042336
TheilXtime	-1.09e+08	2.21e+07	-4.94	0.000	-1.52e+08	-6.57e+07
HerfRaceXt~e	-.0292111	.0103252	-2.83	0.005	-.0494481	-.0089742
herfEthXtime	.0267832	.0133669	2.00	0.045	.0005845	.052982
lnNP_coXtime	-.0169253	.00099	-17.10	0.000	-.0188657	-.0149849
plag_lnXtime	.0063821	.001239	5.15	0.000	.0039536	.0088106
_cons	5.423398	.216446	25.06	0.000	4.999171	5.847624

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0045698	.0002125	.0041716	.0050059
var(_cons)	.673153	.0234722	.6286851	.7207662
cov(time,_cons)	-.0188632	.0017162	-.022227	-.0154995
var(Residual)	.5761267	.0045306	.5673149	.5850753

Table A.15: Model E: HLM Interaction of *lnDEMI* and *pctMale15-24* (Violent Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0373286	.0957787	0.39	0.697	-.1503942	.2250513
lnEvents	-.0344674	.0116076	-2.97	0.003	-.057218	-.0117169
pctMale15_24	-.0008642	.0102305	-0.08	0.933	-.0209157	.0191872
theil	2.09e+08	2.41e+08	0.87	0.386	-2.64e+08	6.82e+08
herf_race	-3.021298	.1162753	-25.98	0.000	-3.249194	-2.793403
herf_ethnic	-1.80665	.1557317	-11.60	0.000	-2.111879	-1.501422
lnNP_count	.153116	.0123454	12.40	0.000	.1289195	.1773125
vlag_ln	.1472975	.010543	13.97	0.000	.1266335	.1679615
pctMale15_~I	.0006678	.0130805	0.05	0.959	-.0249695	.0263051
time	-.1034184	.021317	-4.85	0.000	-.1451989	-.0616379
lnDEMIxtime	-.0099709	.0140011	-0.71	0.476	-.0374127	.0174708
lnEventsXt~e	.0063939	.0013954	4.58	0.000	.0036589	.009129
pctMale15_~e	.0028639	.000969	2.96	0.003	.0009647	.0047631
TheilXtime	-7.47e+07	2.18e+07	-3.42	0.001	-1.17e+08	-3.19e+07
HerfRaceXt~e	.0468919	.0105987	4.42	0.000	.0261188	.067665
herfEthXtime	.0385097	.0134472	2.86	0.004	.0121537	.0648658
lnNP_coXtime	-.0117897	.0010178	-11.58	0.000	-.0137845	-.0097948
vlag_lnXtime	.0035705	.0013434	2.66	0.008	.0009374	.0062036
pctM15_24D~e	.0004699	.0019031	0.25	0.805	-.0032602	.0042
_cons	8.234328	.2300548	35.79	0.000	7.783429	8.685228

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.004858	.0002052	.004472	.0052774
var(_cons)	.8037637	.0265149	.7534399	.8574487
cov(time,_cons)	-.0294655	.001867	-.0331247	-.0258062
var(Residual)	.4918021	.0038686	.4842779	.4994432

Table A.16: Model F: HLM Interaction of *lnDEMI* and *Inequality* (Violent Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0378356	.0241042	1.57	0.116	-.0094077	.0850789
lnEvents	-.0340457	.011622	-2.93	0.003	-.0568244	-.0112669
pctMale15_24	-.0009133	.0100154	-0.09	0.927	-.0205432	.0187166
theil	2.75e+08	2.69e+08	1.02	0.306	-2.51e+08	8.02e+08
herf_race	-3.022422	.116286	-25.99	0.000	-3.250338	-2.794506
herf_ethnic	-1.80905	.1557455	-11.62	0.000	-2.114305	-1.503794
lnNP_count	.154298	.0124643	12.38	0.000	.1298684	.1787276
vlag_ln	.14746	.0105434	13.99	0.000	.1267954	.1681246
theilXDEMI	-6.07e+07	1.12e+08	-0.54	0.589	-2.81e+08	1.60e+08
time	-.1040228	.0212852	-4.89	0.000	-.145741	-.0623046
lnDEMIxtime	-.0057781	.003219	-1.79	0.073	-.0120872	.000531
lnEventsXt~e	.0063334	.0013973	4.53	0.000	.0035949	.009072
pctMale15_~e	.0029045	.0009412	3.09	0.002	.0010598	.0047492
TheilXtime	-8.47e+07	2.57e+07	-3.30	0.001	-1.35e+08	-3.43e+07
HerfRaceXt~e	.0472163	.0106087	4.45	0.000	.0264237	.0680089
herfEthXtime	.0387927	.0134528	2.88	0.004	.0124257	.0651598
lnNP_coXtime	-.0118827	.0010273	-11.57	0.000	-.0138962	-.0098692
vlag_lnXtime	.0035501	.0013435	2.64	0.008	.0009169	.0061834
theilDEMIx~e	1.17e+07	1.50e+07	0.78	0.434	-1.77e+07	4.12e+07
_cons	8.234642	.2297076	35.85	0.000	7.784423	8.684861

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0048567	.0002052	.0044707	.0052759
var(_cons)	.8032374	.0265158	.7529129	.8569255
cov(time,_cons)	-.0294505	.0018666	-.033109	-.025792
var(Residual)	.4918299	.0038691	.4843048	.499472

Table A.17: Model G: HLM Interaction of *lnDEMI* and *Racial Heterogeneity* (Violent Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0485454	.1074725	0.45	0.651	-.1620969	.2591877
lnEvents	-.0343305	.0116482	-2.95	0.003	-.0571605	-.0115004
pctMale15_24	-.0006603	.0100119	-0.07	0.947	-.0202832	.0189626
theil	2.11e+08	2.42e+08	0.87	0.384	-2.64e+08	6.85e+08
herf_race	-3.019581	.1178861	-25.61	0.000	-3.250633	-2.788528
herf_ethnic	-1.807082	.1557713	-11.60	0.000	-2.112388	-1.501776
lnNP_count	.1530834	.0123473	12.40	0.000	.1288832	.1772837
vlag_ln	.1473186	.0105441	13.97	0.000	.1266526	.1679846
HR_DEMI	-.0083463	.133025	-0.06	0.950	-.2690704	.2523779
time	-.1034018	.0213372	-4.85	0.000	-.1452218	-.0615817
lnDEMIxtime	-.0067648	.0142449	-0.47	0.635	-.0346843	.0211547
lnEventsXt~e	.0063811	.0014004	4.56	0.000	.0036364	.0091258
pctMale15_~e	.0028826	.0009408	3.06	0.002	.0010387	.0047264
TheilXtime	-7.48e+07	2.19e+07	-3.41	0.001	-1.18e+08	-3.18e+07
HerfRaceXt~e	.0467671	.0108538	4.31	0.000	.025494	.0680402
herfEthXtime	.038475	.0134486	2.86	0.004	.0121162	.0648338
lnNP_coXtime	-.0117852	.0010179	-11.58	0.000	-.0137802	-.0097901
vlag_lnXtime	.0035678	.0013437	2.66	0.008	.0009343	.0062013
HR_DEMIxTime	.0002708	.0178639	0.02	0.988	-.0347419	.0352835
_cons	8.231711	.2299272	35.80	0.000	7.781062	8.682359

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0048582	.0002052	.0044721	.0052776
var(_cons)	.8037851	.0265198	.7534522	.8574805
cov(time,_cons)	-.0294673	.0018673	-.0331271	-.0258075
var(Residual)	.4918047	.0038687	.4842803	.499446

Table A.18: Model H: HLM Interaction of *lnDEMI* and *Ethnic Heterogeneity* (Violent Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0671575	.1114259	0.60	0.547	-.1512333	.2855482
lnEvents	-.0342082	.0116407	-2.94	0.003	-.0570236	-.0113929
pctMale15_24	-.0007015	.0100101	-0.07	0.944	-.0203209	.0189178
theil	2.13e+08	2.42e+08	0.88	0.379	-2.61e+08	6.87e+08
herf_race	-3.021327	.1162772	-25.98	0.000	-3.249226	-2.793428
herf_ethnic	-1.798565	.1585577	-11.34	0.000	-2.109332	-1.487798
lnNP_count	.1531909	.0123488	12.41	0.000	.1289876	.1773941
vlag_ln	.1473918	.0105439	13.98	0.000	.1267261	.1680574
HE_DEMI	-.030176	.1297638	-0.23	0.816	-.2845083	.2241564
time	-.1029675	.0214389	-4.80	0.000	-.1449869	-.0609481
lnDEMIxtime	-.0068834	.0161523	-0.43	0.670	-.0385413	.0247744
lnEventsXt~e	.0063696	.0013983	4.56	0.000	.0036289	.0091102
pctMale15_~e	.0028868	.0009409	3.07	0.002	.0010427	.0047309
TheilXtime	-7.47e+07	2.20e+07	-3.40	0.001	-1.18e+08	-3.17e+07
HerfRaceXt~e	.0468278	.0106009	4.42	0.000	.0260504	.0676052
herfEthXtime	.0379891	.0138102	2.75	0.006	.0109216	.0650565
lnNP_coXtime	-.0117961	.0010181	-11.59	0.000	-.0137915	-.0098007
vlag_lnXtime	.0035614	.0013435	2.65	0.008	.0009283	.0061945
HE_DEMIxTime	.0004462	.0187524	0.02	0.981	-.0363079	.0372003
_cons	8.225027	.2313024	35.56	0.000	7.771683	8.678372

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0048582	.0002053	.0044721	.0052777
var(_cons)	.8037747	.026515	.7534507	.8574599
cov(time,_cons)	-.029465	.001867	-.0331242	-.0258057
var(Residual)	.491801	.0038687	.4842767	.4994422

Table A.19: Model I: HLM Interaction of *lnDEMI* and *lnNProfit* (Violent Crime Rate)

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0583338	.0468813	1.24	0.213	-.033552	.1502195
lnEvents	-.0347011	.0116337	-2.98	0.003	-.0575027	-.0118994
pctMale15_24	-.0006376	.0100108	-0.06	0.949	-.0202584	.0189831
theil	1.94e+08	2.44e+08	0.79	0.427	-2.85e+08	6.73e+08
herf_race	-3.021409	.1162927	-25.98	0.000	-3.249338	-2.793479
herf_ethnic	-1.805515	.1557527	-11.59	0.000	-2.110785	-1.500246
lnNP_count	.1537775	.0124596	12.34	0.000	.129357	.1781979
vlag_ln	.1472778	.0105438	13.97	0.000	.1266123	.1679432
NPxDEMI	-.0044981	.0115806	-0.39	0.698	-.0271957	.0181995
time	-.103259	.0212768	-4.85	0.000	-.1449608	-.0615572
lnDEMIxtime	-.0076147	.0053517	-1.42	0.155	-.0181037	.0028744
lnEventsXt~e	.006414	.0013981	4.59	0.000	.0036738	.0091541
pctMale15_~e	.0028818	.0009408	3.06	0.002	.0010379	.0047258
TheilXtime	-7.34e+07	2.22e+07	-3.31	0.001	-1.17e+08	-2.99e+07
HerfRaceXt~e	.0468931	.0105991	4.42	0.000	.0261192	.0676669
herfEthXtime	.0383495	.0134483	2.85	0.004	.0119913	.0647076
lnNP_coXtime	-.0118324	.0010346	-11.44	0.000	-.0138602	-.0098046
vlag_lnXtime	.0035689	.0013435	2.66	0.008	.0009358	.0062021
NPxDEMIxTime	.000296	.0013529	0.22	0.827	-.0023556	.0029477
_cons	8.229809	.2297777	35.82	0.000	7.779453	8.680165

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0048584	.0002053	.0044723	.0052778
var(_cons)	.8040411	.0265273	.7536939	.8577515
cov(time,_cons)	-.0294829	.0018676	-.0331434	-.0258224
var(Residual)	.4917961	.0038687	.4842718	.4994374

Table A.20: Model J: Full Model and Variance Components for Aggravated Assault Rate

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0280372	.0248695	1.13	0.260	-.0207062	.0767806
lnEvents	-.027674	.0126381	-2.19	0.029	-.0524441	-.0029039
pctMale15_24	-.0120818	.0109069	-1.11	0.268	-.033459	.0092953
theil	6.57e+08	2.63e+08	2.50	0.012	1.42e+08	1.17e+09
herf_race	-2.974402	.1264557	-23.52	0.000	-3.222251	-2.726554
herf_ethnic	-1.995079	.1692916	-11.78	0.000	-2.326884	-1.663274
lnNP_count	.1499456	.0134837	11.12	0.000	.123518	.1763732
vlag_ln	.1572642	.0115031	13.67	0.000	.1347186	.1798099
time	-.1150718	.0232647	-4.95	0.000	-.1606697	-.0694739
lnDEMIxtime	-.0047416	.0033369	-1.42	0.155	-.0112818	.0017986
lnEventsXt~e	.0049766	.0015194	3.28	0.001	.0019986	.0079545
pctMale15_~e	.0034022	.0010294	3.30	0.001	.0013846	.0054198
TheilXtime	-6.81e+07	2.39e+07	-2.85	0.004	-1.15e+08	-2.13e+07
HerfRaceXt~e	.0519362	.0115947	4.48	0.000	.029211	.0746614
herfEthXtime	.0462997	.0147132	3.15	0.002	.0174624	.0751371
lnNP_coXtime	-.0117057	.001112	-10.53	0.000	-.0138852	-.0095263
vlag_lnXtime	.0028383	.0014657	1.94	0.053	-.0000344	.0057109
_cons	8.078476	.2499477	32.32	0.000	7.588587	8.568365

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.005859	.0002412	.0054049	.0063512
var(_cons)	.9492277	.0308192	.8907051	1.011596
cov(time,_cons)	-.0362468	.0022058	-.0405702	-.0319235
var(Residual)	.5813137	.0045663	.5724324	.5903327

Table A.21: Model K: Full Model and Variance Components for Forcible Rape Rate

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0444543	.0302726	1.47	0.142	-.0148789	.1037876
lnEvents	-.0908589	.015066	-6.03	0.000	-.1203877	-.0613301
pctMale15_24	.0681406	.0112571	6.05	0.000	.046077	.0902042
theil	1.53e+09	2.63e+08	5.82	0.000	1.01e+09	2.04e+09
herf_race	-1.187996	.1261647	-9.42	0.000	-1.435274	-.9407179
herf_ethnic	-.4242182	.1688283	-2.51	0.012	-.7551157	-.0933207
lnNP_count	.337891	.01422	23.76	0.000	.3100204	.3657617
vlag_ln	.1361025	.0130785	10.41	0.000	.1104691	.161736
time	-.0352144	.0263452	-1.34	0.181	-.0868501	.0164213
lnDEMIxtime	-.010702	.0040663	-2.63	0.008	-.0186717	-.0027323
lnEventsXt~e	.0171895	.0018117	9.49	0.000	.0136386	.0207404
pctMale15_~e	.001223	.0011573	1.06	0.291	-.0010453	.0034912
TheilXtime	-1.35e+08	2.66e+07	-5.07	0.000	-1.87e+08	-8.28e+07
HerfRaceXt~e	.0312727	.0130436	2.40	0.017	.0057076	.0568377
herfEthXtime	-.002192	.0165642	-0.13	0.895	-.0346572	.0302732
lnNP_coXtime	-.0228396	.0012036	-18.98	0.000	-.0251987	-.0204805
vlag_lnXtime	.0083279	.0016914	4.92	0.000	.0050128	.011643
_cons	1.959529	.2565063	7.64	0.000	1.456786	2.462272

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0066651	.0003043	.0060946	.0072891
var(_cons)	.8189513	.0294645	.763191	.8787856
cov(time,_cons)	-.0387268	.0024544	-.0435373	-.0339162
var(Residual)	.8797978	.0068979	.8663816	.8934218

Table A.22: Model L: Full Model and Variance Components for Homicide Rate

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0609498	.0256339	2.38	0.017	.0107083	.1111914
lnEvents	-.0559161	.0119428	-4.68	0.000	-.0793237	-.0325086
pctMale15_24	-.0113783	.0071303	-1.60	0.111	-.0253535	.0025969
theil	1.16e+08	1.62e+08	0.72	0.473	-2.02e+08	4.35e+08
herf_race	-2.419501	.0786836	-30.75	0.000	-2.573718	-2.265283
herf_ethnic	-.4345706	.1051603	-4.13	0.000	-.6406811	-.2284602
lnNP_count	.1222144	.0091352	13.38	0.000	.1043097	.1401192
vlag_ln	.0720293	.0092913	7.75	0.000	.0538187	.09024
time	-.044496	.0172208	-2.58	0.010	-.0782481	-.0107439
lnDEMIxtime	-.0058766	.0034265	-1.72	0.086	-.0125924	.0008392
lnEventsXt~e	.0102359	.0013944	7.34	0.000	.007503	.0129688
pctMale15_~e	.0003534	.0007393	0.48	0.633	-.0010956	.0018025
TheilXtime	-7.64e+07	1.67e+07	-4.58	0.000	-1.09e+08	-4.37e+07
HerfRaceXt~e	.0262989	.0082486	3.19	0.001	.0101319	.042466
herfEthXtime	-.0035436	.0106014	-0.33	0.738	-.024322	.0172348
lnNP_coXtime	-.0076638	.000818	-9.37	0.000	-.009267	-.0060605
vlag_lnXtime	.0022626	.0011509	1.97	0.049	6.95e-06	.0045183
_cons	2.914518	.1649571	17.67	0.000	2.591208	3.237828

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0010164	.0001187	.0008085	.0012779
var(_cons)	.2070982	.0109395	.1867298	.2296884
cov(time,_cons)	-.0080046	.0009893	-.0099435	-.0060657
var(Residual)	.6858206	.0053642	.6753871	.6964153

Table A.23: Model M: Full Model and Variance Components for Robbery Rate

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0608682	.0271007	2.25	0.025	.0077518	.1139846
lnEvents	-.0413672	.0131428	-3.15	0.002	-.0671266	-.0156079
pctMale15_24	.0199082	.0102437	1.94	0.052	-.0001691	.0399854
theil	-1.43e+09	2.48e+08	-5.74	0.000	-1.91e+09	-9.38e+08
herf_race	-5.160013	.1216684	-42.41	0.000	-5.398479	-4.921548
herf_ethnic	-1.433126	.1633269	-8.77	0.000	-1.753241	-1.113011
lnNP_count	.2908512	.0119715	24.30	0.000	.2673874	.314315
vlag_ln	.0853689	.0109936	7.77	0.000	.0638219	.1069159
time	-.0735182	.020676	-3.56	0.000	-.1140424	-.0329939
lnDEMIxtime	-.0101434	.0036426	-2.78	0.005	-.0172827	-.0030041
lnEventsXt~e	.0108715	.0015662	6.94	0.000	.0078017	.0139413
pctMale15_~e	.0024117	.0008973	2.69	0.007	.0006529	.0041704
TheilXtime	-1.81e+08	2.12e+07	-8.53	0.000	-2.22e+08	-1.39e+08
HerfRaceXt~e	.0360552	.0102064	3.53	0.000	.0160511	.0560593
herfEthXtime	.032195	.0128304	2.51	0.012	.0070479	.057342
lnNP_coXtime	-.0215566	.0009939	-21.69	0.000	-.0235047	-.0196086
vlag_lnXtime	.0055822	.0013918	4.01	0.000	.0028544	.0083101
_cons	6.837717	.2395521	28.54	0.000	6.368203	7.30723

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0030398	.0001947	.0026811	.0034465
var(_cons)	.8432501	.0327765	.7813954	.9100013
cov(time,_cons)	-.0040948	.0017064	-.0074393	-.0007503
var(Residual)	.7287168	.0057176	.7175962	.7400097

Table A.24: Model A: HLM Model for Index Crime and Disaster for Police Guardianship, without Controls.

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
time	-.0109831	.0033868	-3.24	0.001	-.0176212	-.0043451
lnDEMI	-.0017705	.0379261	-0.05	0.963	-.0761043	.0725633
lnEvents	-.0130952	.0187984	-0.70	0.486	-.0499394	.0237491
lnDEMIxtime	.0020733	.0058479	0.35	0.723	-.0093884	.013535
lnEventsXt~e	.0028206	.0020527	1.37	0.169	-.0012026	.0068438
_cons	7.677524	.0345512	222.21	0.000	7.609805	7.745243

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0030364	.0002186	.0026367	.0034966
var(_cons)	.8239779	.0363249	.7557715	.8983398
cov(time,_cons)	-.0276298	.002319	-.0321749	-.0230847
var(Residual)	.0853756	.0025375	.0805444	.0904967

Table A.25: Model B: HLM Model for Index Crime and Disaster for Police Guardianship, with Controls

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
time	-.1369473	.0251613	-5.44	0.000	-.1862626	-.087632
lnDEMI	.0039141	.0389832	0.10	0.920	-.0724916	.0803197
lnEvents	-.0175767	.0190689	-0.92	0.357	-.0549511	.0197976
pctMale15_24	.0234283	.011369	2.06	0.039	.0011456	.0457111
ln_police	.0352953	.0146995	2.40	0.016	.0064848	.0641059
theil	1.41e+09	2.34e+08	6.03	0.000	9.54e+08	1.87e+09
herf_race	-1.356714	.1326323	-10.23	0.000	-1.616669	-1.09676
herf_ethnic	-1.161963	.1766619	-6.58	0.000	-1.508214	-.815712
lnNP_count	.2140462	.019254	11.12	0.000	.176309	.2517833
inlag	.0382125	.0127076	3.01	0.003	.0133061	.0631189
lnDEMIxtime	-.0011711	.0060326	-0.19	0.846	-.0129947	.0106526
lnEventsXt~e	-.0001217	.0020907	-0.06	0.954	-.0042195	.0039761
pctMale15_~e	-.0001819	.0010409	-0.17	0.861	-.002222	.0018582
lnPoliceXt~e	-.001228	.0013498	-0.91	0.363	-.0038736	.0014176
TheilXtime	1.09e+07	2.21e+07	0.49	0.622	-3.25e+07	5.43e+07
HerfRaceXt~e	.023119	.0119003	1.94	0.052	-.0002052	.0464432
herfEthXtime	.0443065	.015362	2.88	0.004	.0141975	.0744156
lnNP_coXtime	.0009343	.0018043	0.52	0.605	-.0026019	.0044706
InLagXtime	.00873	.0014963	5.83	0.000	.0057973	.0116627
_cons	8.723424	.2757204	31.64	0.000	8.183022	9.263826

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0031422	.0002224	.0027352	.0036097
var(_cons)	.5470633	.0266733	.4972048	.6019215
cov(time,_cons)	-.0267612	.0021037	-.0308844	-.0226379
var(Residual)	.0855939	.0025424	.0807533	.0907248

Table A.26: Model C: HLM Model for Property Crime and Disaster for Police Guardianship, without Controls

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
time	-.0114009	.0037448	-3.04	0.002	-.0187406	-.0040612
lnDEMI	-.005944	.0420766	-0.14	0.888	-.0884126	.0765246
lnEvents	-.0049527	.0208181	-0.24	0.812	-.0457555	.0358501
lnDEMIxtime	.002622	.0064826	0.40	0.686	-.0100837	.0153277
lnEventsXt~e	.0022733	.0022715	1.00	0.317	-.0021788	.0067254
_cons	7.55432	.0379453	199.08	0.000	7.479948	7.628691

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0037046	.0002749	.0032032	.0042845
var(_cons)	.9466401	.0437584	.8646456	1.03641
cov(time,_cons)	-.03311	.0028625	-.0387205	-.0274995
var(Residual)	.105592	.003184	.0995324	.1120206

Table A.27: Model D: HLM Model for Property Crime and Disaster for Police Guardianship, with Controls

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0012841	.0432699	0.03	0.976	-.0835233	.0860916
lnEvents	-.0123295	.0210966	-0.58	0.559	-.0536781	.0290191
pctMale15_24	.0311154	.0124672	2.50	0.013	.0066801	.0555507
ln_police	.036081	.016224	2.22	0.026	.0042825	.0678795
theil	1.53e+09	2.56e+08	5.97	0.000	1.03e+09	2.03e+09
herf_race	-1.198424	.1452565	-8.25	0.000	-1.483122	-.9137264
herf_ethnic	-1.020614	.193491	-5.27	0.000	-1.39985	-.6413787
lnNP_count	.2344029	.0211719	11.07	0.000	.1929067	.275899
plag_ln	.0427964	.0141119	3.03	0.002	.0151377	.0704552
time	-.1318852	.0275448	-4.79	0.000	-.185872	-.0778984
lnDEMIxtime	-.0010248	.0066954	-0.15	0.878	-.0141477	.012098
lnEventsXt~e	-.0006568	.0023142	-0.28	0.777	-.0051925	.003879
pctMale15_~e	-.0008222	.0011485	-0.72	0.474	-.0030732	.0014287
lnPoliceXt~e	-.001268	.0014914	-0.85	0.395	-.0041912	.0016551
TheilXtime	1.33e+07	2.45e+07	0.55	0.586	-3.46e+07	6.13e+07
HerfRaceXt~e	.0239741	.0131114	1.83	0.067	-.0017236	.0496719
herfEthXtime	.0398055	.0169207	2.35	0.019	.0066416	.0729694
lnNP_coXtime	.0010434	.0019931	0.52	0.601	-.002863	.0049498
plag_lnXtime	.0092236	.0016623	5.55	0.000	.0059655	.0124816
_cons	8.192095	.301231	27.20	0.000	7.601693	8.782497

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.003783	.0002785	.0032747	.0043701
var(_cons)	.6464298	.0329049	.5850501	.7142491
cov(time,_cons)	-.0315859	.0026057	-.036693	-.0264788
var(Residual)	.1060959	.0031979	.1000097	.1125525

Table A.28: Model E: HLM Models for Violent Crime and Disaster for Police Guardianship, without Controls

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
time	-.0075199	.0057182	-1.32	0.188	-.0187275	.0036876
lnDEMI	-.0656827	.0656472	-1.00	0.317	-.1943488	.0629833
lnEvents	-.0195255	.0321643	-0.61	0.544	-.0825662	.0435153
lnDEMIxtime	.0124777	.0100491	1.24	0.214	-.0072182	.0321735
lnEventsXt~e	.0049633	.0034852	1.42	0.154	-.0018676	.0117941
_cons	5.141714	.0572237	89.85	0.000	5.029557	5.25387

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0079606	.0006556	.006774	.0093551
var(_cons)	1.848664	.090438	1.679642	2.034695
cov(time,_cons)	-.0686067	.0063528	-.0810579	-.0561555
var(Residual)	.2675532	.0080434	.2522439	.2837916

Table A.29: Model F: HLM Models for Violent Crime and Disaster for Police Guardianship, with Controls

Variable	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	-.070653	.0682641	-1.03	0.301	-.2044483	.0631423
lnEvents	-.0251403	.0325628	-0.77	0.440	-.0889621	.0386816
pctMale15_24	.0054044	.0178888	0.30	0.763	-.0296571	.0404659
ln_police	.0560264	.0246166	2.28	0.023	.0077788	.1042741
theil	1.15e+09	3.61e+08	3.20	0.001	4.46e+08	1.86e+09
herf_race	-2.84562	.2153058	-13.22	0.000	-3.267612	-2.423628
herf_ethnic	-1.52231	.2773896	-5.49	0.000	-2.065983	-.9786362
lnNP_count	.1788133	.0310267	5.76	0.000	.118002	.2396246
vlag_ln	.1452686	.0252461	5.75	0.000	.0957871	.1947501
time	-.1737334	.0423544	-4.10	0.000	-.2567466	-.0907203
lnDEMIxtime	.0072869	.0105105	0.69	0.488	-.0133133	.0278871
lnEventsXt~e	.0008385	.0035706	0.23	0.814	-.0061598	.0078367
pctMale15_~e	.0022196	.0017572	1.26	0.207	-.0012244	.0056636
lnPoliceXt~e	-.0032276	.0022831	-1.41	0.157	-.0077023	.0012472
TheilXtime	3.31e+07	3.79e+07	0.87	0.383	-4.12e+07	1.07e+08
HerfRaceXt~e	.0554505	.0207344	2.67	0.007	.0148117	.0960892
herfEthXtime	.0363009	.0259162	1.40	0.161	-.014494	.0870957
lnNP_coXtime	.0039773	.0030346	1.31	0.190	-.0019703	.0099249
vlag_lnXtime	.0125517	.0027998	4.48	0.000	.0070642	.0180393
_cons	7.511955	.4437571	16.93	0.000	6.642207	8.381703

Random-effects Parameters

	Estimate	SE	95% CI	
var(time)	.0085362	.0006927	.0072809	.0100079
var(_cons)	1.109522	.0650922	.989005	1.244724
cov(time,_cons)	-.0653578	.0060198	-.0771563	-.0535592
var(Residual)	.2777106	.0083974	.2617301	.2946668

Table A.30: Model A: HLM Model for Index Crime Utilizing Disaster Types, without Controls

	Coefficient	SE	Z	P-value	95% Confidence Interval	
time	-.0147343	.0014762	-9.98	0.000	-.0176275	-.0118411
lnDEMI	.0342211	.012763	2.68	0.007	.0092061	.0592362
lnEvents	-.0125911	.0110923	-1.14	0.256	-.0343317	.0091495
geoBinary	-.2244253	.261234	-0.86	0.390	-.7364345	.2875838
massBinary	-.0289481	.0331937	-0.87	0.383	-.0940065	.0361104
wildfireBi~y	.0263597	.0362323	0.73	0.467	-.0446543	.0973736
coastalBin~y	.0742537	.0384416	1.93	0.053	-.0010905	.1495978
hurBinary	.0321799	.0221512	1.45	0.146	-.0112355	.0755954
heat_drBin~y	.0267907	.0127833	2.10	0.036	.001736	.0518455
lightBinary	.0045722	.0120408	0.38	0.704	-.0190274	.0281718
torBinary	-.0109668	.0118043	-0.93	0.353	-.0341028	.0121692
windBinary	-.0052274	.0109944	-0.48	0.634	-.026776	.0163212
winterBinary	.0035627	.0107567	0.33	0.740	-.0175201	.0246454
floodBinary	.0236025	.0105933	2.23	0.026	.00284	.0443649
severeBinary	-.0187401	.01233	-1.52	0.129	-.0429065	.0054263
lnDEMIxtime	-.0058353	.0016682	-3.50	0.000	-.009105	-.0025656
lnEventsXt~e	.0036007	.0013351	2.70	0.007	.0009839	.0062174
geoBiXtime	.0232302	.0277983	0.84	0.403	-.0312534	.0777138
massBiXtime	.0026523	.0041185	0.64	0.520	-.0054197	.0107243
fireBiXtime	-.0028608	.004155	-0.69	0.491	-.0110045	.0052828
coastBiXtime	-.0072148	.0043262	-1.67	0.095	-.0156941	.0012645
hurBiXtime	-.0003926	.0025768	-0.15	0.879	-.0054431	.0046579
ht_drBiXtime	-.0056366	.0018512	-3.04	0.002	-.0092649	-.0020083
lightBiXtime	.0002312	.0015894	0.15	0.884	-.002884	.0033463
torBiXtime	.0003779	.0014978	0.25	0.801	-.0025576	.0033135
WindBiXtime	-.0009975	.0013679	-0.73	0.466	-.0036786	.0016836
winterBiXt~e	-.0021758	.0013629	-1.60	0.110	-.0048471	.0004955
floodBiXtime	-.0018909	.0013347	-1.42	0.157	-.004507	.0007251
seversBiXt~e	.0017604	.001582	1.11	0.266	-.0013402	.004861
_cons	7.68732	.017677	434.88	0.000	7.652673	7.721966

Random Effects Parameters

	Estimate	SE	95% CI	
var(time)	.0025948	.0000882	.0024276	.0027735
var(_cons)	.6824343	.0193657	.6455145	.7214657
cov(time,_cons)	-.0172042	.0010183	-.0192001	-.0152083
var(Residual)	.128432	.0010073	.1264728	.1304216

Table A.31 Model B: HLM Model for Index Crime Utilizing Disaster Types, with Controls

	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0301529	.0128025	2.36	0.019	.0050604	.0552453
lnEvents	-.0210598	.0111116	-1.90	0.058	-.0428381	.0007186
geoBinary	-.2605572	.2609307	-1.00	0.318	-.771972	.2508577
massBinary	-.0336038	.0331459	-1.01	0.311	-.0985685	.0313609
wildfireBi~y	-.0007995	.0361829	-0.02	0.982	-.0717167	.0701177
coastalBin~y	.0376977	.0384563	0.98	0.327	-.0376754	.1130707
hurBinary	.0209788	.0222191	0.94	0.345	-.0225699	.0645275
heat_drBin~y	.029005	.0128214	2.26	0.024	.0038754	.0541345
lightBinary	-.0031986	.0120645	-0.27	0.791	-.0268446	.0204474
torBinary	-.0053269	.0117823	-0.45	0.651	-.0284199	.0177661
windBinary	-.0112731	.0109926	-1.03	0.305	-.0328182	.010272
winterBinary	.0162732	.0108194	1.50	0.133	-.0049323	.0374788
floodBinary	.0227449	.0105851	2.15	0.032	.0019985	.0434913
severeBinary	-.0099341	.0123218	-0.81	0.420	-.0340844	.0142162
pctMale15_24	.0025718	.0066248	0.39	0.698	-.0104126	.0155563
Theil	-2.68e+08	1.72e+08	-1.55	0.120	-6.05e+08	6.99e+07
herf_race	-1.175542	.0824456	-14.26	0.000	-1.337132	-1.013952
herf_ethnic	-1.025862	.1107576	-9.26	0.000	-1.242943	-.808781
lnNP_count	.0989475	.0081119	12.20	0.000	.0830485	.1148465
Inlag	.0727284	.0051632	14.09	0.000	.0626087	.0828481
Time	-.0471229	.0134987	-3.49	0.000	-.0735799	-.020666
lnDEMIxtime	-.005991	.0016741	-3.58	0.000	-.0092722	-.0027097
lnEventsXt~e	.0048953	.0013455	3.64	0.000	.0022582	.0075323
geoBiXtime	.0264282	.0277874	0.95	0.342	-.0280341	.0808904
massBiXtime	.0043147	.0041166	1.05	0.295	-.0037536	.0123831
fireBiXtime	.0007393	.0041627	0.18	0.859	-.0074195	.0088982
coastBiXtime	-.0033491	.0043372	-0.77	0.440	-.0118499	.0051517
hurBiXtime	-.0006732	.002602	-0.26	0.796	-.0057731	.0044266
ht_drBiXtime	-.0061627	.0018696	-3.30	0.001	-.009827	-.0024984
lightBiXtime	.0009027	.0015954	0.57	0.572	-.0022242	.0040297
torBiXtime	-.0004611	.0014975	-0.31	0.758	-.003396	.0024739
WindBiXtime	-.0002575	.0013714	-0.19	0.851	-.0029455	.0024304
winterBiXt~e	-.0032647	.0013749	-2.37	0.018	-.0059595	-.0005698
floodBiXtime	-.001693	.001336	-1.27	0.205	-.0043116	.0009256
seversBiXt~e	.0003338	.001583	0.21	0.833	-.0027688	.0034364
pctMale15_~e	.0017992	.0006112	2.94	0.003	.0006013	.0029972
TheilXtime	-4.11e+07	1.46e+07	-2.81	0.005	-6.97e+07	-1.25e+07
HerfRaceXt~e	-.0031208	.0069249	-0.45	0.652	-.0166934	.0104518
herfEthXtime	.0241216	.0087416	2.76	0.006	.0069884	.0412548
lnNP_coXtime	-.0077195	.000658	-11.73	0.000	-.0090092	-.0064297
InLagXtime	.0018237	.0007095	2.57	0.010	.000433	.0032144
_cons	8.821308	.1561466	56.49	0.000	8.515266	9.12735

Random Effects Parameters

	Estimate	SE	95% CI	
var(time)	.0026183	.0000913	.0024453	.0028036
var(_cons)	.4742274	.0148158	.4460602	.5041733
cov(time,_cons)	-.0144522	.0008755	-.0161683	-.0127362
var(Residual)	.1280442	.001007	.1260856	.1300333

Table A.32: Model C: HLM Model for Property Crime Utilizing Disaster Types, without Controls

	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0332902	.0145745	2.28	0.022	.0047246	.0618557
lnEvents	-.0135115	.0108276	-1.25	0.212	-.0347333	.0077102
geoBinary	-.201659	.298788	-0.67	0.500	-.7872726	.3839547
massBinary	-.0241372	.0378476	-0.64	0.524	-.0983172	.0500428
wildfireBi~y	.03915	.0413401	0.95	0.344	-.0418752	.1201751
coastalBin~y	.0820814	.0437975	1.87	0.061	-.0037601	.1679229
hurBinary	.0284509	.0252537	1.13	0.260	-.0210455	.0779472
heat_drBin~y	.0253654	.014471	1.75	0.080	-.0029972	.0537281
lightBinary	.0052164	.0136535	0.38	0.702	-.021544	.0319767
torBinary	-.0108767	.0133905	-0.81	0.417	-.0371217	.0153682
windBinary	-.0007175	.0123176	-0.06	0.954	-.0248595	.0234245
winterBinary	.0029183	.0120289	0.24	0.808	-.0206579	.0264945
floodBinary	.0255864	.011898	2.15	0.032	.0022668	.0489059
severeBinary	-.0091501	.0073681	-1.24	0.214	-.0235913	.0052911
time	-.0152444	.0016448	-9.27	0.000	-.0184681	-.0120207
lnDEMIxtime	-.0061329	.0019054	-3.22	0.001	-.0098673	-.0023984
lnEventsXt~e	.0041849	.0011936	3.51	0.000	.0018455	.0065243
geoBiXtime	.0210295	.0317797	0.66	0.508	-.0412576	.0833166
massBiXtime	.0018947	.0046879	0.40	0.686	-.0072934	.0110827
fireBiXtime	-.0060063	.0047369	-1.27	0.205	-.0152904	.0032778
coastBiXtime	-.0082902	.0049218	-1.68	0.092	-.0179368	.0013564
hurBiXtime	.0007887	.002936	0.27	0.788	-.0049658	.0065432
ht_drBiXtime	-.0056998	.0020954	-2.72	0.007	-.0098066	-.0015929
lightBiXtime	.0003322	.0018001	0.18	0.854	-.0031959	.0038603
torBiXtime	.0000714	.0016951	0.04	0.966	-.003251	.0033938
WindBiXtime	-.0016823	.0015214	-1.11	0.269	-.0046642	.0012995
winterBiXt~e	-.0020507	.001518	-1.35	0.177	-.005026	.0009246
floodBiXtime	-.0021345	.0014929	-1.43	0.153	-.0050605	.0007915
_cons	7.56601	.0188981	400.36	0.000	7.528971	7.60305

Random Effects Parameters

	Estimate	SE	95% CI	
var(time)	.0031487	.0001097	.0029408	.0033712
var(_cons)	.7465403	.0216132	.7053586	.7901264
cov(time,_cons)	-.019291	.0011999	-.0216428	-.0169391
var(Residual)	.1682086	.0013216	.1656382	.1708189

Table A.33: Model D: HLM Model for Property Crime Utilizing Disaster Types, with Controls

	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0293847	.0146355	2.01	0.045	.0006997	.0580697
lnEvents	-.0204319	.0126821	-1.61	0.107	-.0452884	.0044246
geoBinary	-.2520806	.2986679	-0.84	0.399	-.8374589	.3332977
massBinary	-.0306337	.0378921	-0.81	0.419	-.1049009	.0436334
wildfireBi~y	.0074778	.0413323	0.18	0.856	-.073532	.0884875
coastalBin~y	.038508	.0439007	0.88	0.380	-.0475357	.1245518
hurBinary	.0146674	.0253798	0.58	0.563	-.0350761	.0644109
heat_drBin~y	.0287009	.0146521	1.96	0.050	-.0000167	.0574185
lightBinary	-.0056573	.0137862	-0.41	0.682	-.0326778	.0213631
torBinary	-.0057794	.013469	-0.43	0.668	-.0321782	.0206194
windBinary	-.0104346	.0125584	-0.83	0.406	-.0350486	.0141794
winterBinary	.0160442	.0123622	1.30	0.194	-.0081853	.0402737
floodBinary	.0233724	.012099	1.93	0.053	-.0003413	.047086
severeBinary	-.0064135	.0140748	-0.46	0.649	-.0339996	.0211726
pctMale15_24	.0078692	.007226	1.09	0.276	-.0062936	.0220319
theil	-1.16e+08	1.84e+08	-0.63	0.528	-4.77e+08	2.45e+08
herf_race	-1.038859	.0880021	-11.80	0.000	-1.21134	-.8663778
herf_ethnic	-.9883905	.1185421	-8.34	0.000	-1.220729	-.7560522
lnNP_count	.1173936	.0088828	13.22	0.000	.0999836	.1348037
plag_ln	.0782717	.005832	13.42	0.000	.0668411	.0897024
time	-.0445797	.014935	-2.98	0.003	-.0738518	-.0153076
lnDEMIxtime	-.006289	.0019144	-3.29	0.001	-.0100411	-.0025368
lnEventsXt~e	.0052511	.0015356	3.42	0.001	.0022415	.0082608
geoBiXtime	.0257294	.0317929	0.81	0.418	-.0365836	.0880425
massBiXtime	.0039654	.0047042	0.84	0.399	-.0052546	.0131854
fireBiXtime	-.001684	.0047559	-0.35	0.723	-.0110054	.0076374
coastBiXtime	-.0035948	.0049501	-0.73	0.468	-.0132967	.0061072
hurBiXtime	.0007526	.002973	0.25	0.800	-.0050744	.0065796
ht_drBiXtime	-.0064723	.0021374	-3.03	0.002	-.0106615	-.0022832
lightBiXtime	.001387	.0018232	0.76	0.447	-.0021865	.0049605
torBiXtime	-.0006674	.0017119	-0.39	0.697	-.0040225	.0026878
WindBiXtime	-.0004421	.0015671	-0.28	0.778	-.0035135	.0026293
winterBiXt~e	-.0031878	.0015715	-2.03	0.043	-.006268	-.0001077
floodBiXtime	-.0017562	.0015273	-1.15	0.250	-.0047497	.0012372
seversBiXt~e	-.0005052	.0018085	-0.28	0.780	-.0040497	.0030393
pctMale15_~e	.0018404	.0006797	2.71	0.007	.0005081	.0031727
TheilXtime	-5.54e+07	1.63e+07	-3.41	0.001	-8.72e+07	-2.35e+07
HerfRaceXt~e	-.0063389	.0077046	-0.82	0.411	-.0214396	.0087618
herfEthXtime	.0258506	.0097171	2.66	0.008	.0068055	.0448957
lnNP_coXtime	-.0090066	.0007232	-12.45	0.000	-.0104241	-.0075891
plag_lnXtime	.0019834	.0008015	2.47	0.013	.0004124	.0035543
_cons	8.434303	.1680007	50.20	0.000	8.105028	8.763578

Random Effects Parameters

	Estimate	SE	95% CI	
var(time)	.003185	.0001142	.0029688	.0034168
var(_cons)	.5278779	.0167561	.4960372	.5617624
cov(time,_cons)	-.0163139	.0010369	-.0183461	-.0142816
var(Residual)	.1679724	.0013232	.1653989	.1705859

Table A.34: Model E: HLM Model for Violent Crime Utilizing Disaster Types, without Controls

	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0477056	.0245652	1.94	0.052	-.0004413	.0958525
lnEvents	-.0245863	.0211874	-1.16	0.246	-.0661128	.0169403
geoBinary	-.3278998	.5080691	-0.65	0.519	-1.323697	.6678974
massBinary	-.0411729	.0640337	-0.64	0.520	-.1666766	.0843307
wildfireBi~y	.0331814	.0696688	0.48	0.634	-.1033669	.1697297
coastalBin~y	.0931636	.073352	1.27	0.204	-.0506036	.2369309
hurBinary	.0905749	.0424794	2.13	0.033	.0073168	.173833
heat_drBin~y	.0255851	.0246339	1.04	0.299	-.0226965	.0738667
lightBinary	.0258815	.0230881	1.12	0.262	-.0193704	.0711333
torBinary	.00288	.0227651	0.13	0.899	-.0417389	.0474989
windBinary	-.0458912	.0211054	-2.17	0.030	-.0872571	-.0045253
winterBinary	-.0362571	.0206855	-1.75	0.080	-.0768	.0042858
floodBinary	.0216441	.0204143	1.06	0.289	-.0183671	.0616554
severeBinary	.0189701	.023641	0.80	0.422	-.0273654	.0653057
time	-.0064582	.0024629	-2.62	0.009	-.0112853	-.001631
lnDEMIxtime	-.0052176	.0032074	-1.63	0.104	-.011504	.0010688
lnEventsXt~e	.0038547	.0025272	1.53	0.127	-.0010986	.0088079
geoBiXtime	.0340037	.0536913	0.63	0.527	-.0712292	.1392367
massBiXtime	.0039979	.0078596	0.51	0.611	-.0114066	.0194025
fireBiXtime	.0004051	.0079475	0.05	0.959	-.0151718	.015982
coastBiXtime	-.0068431	.0081641	-0.84	0.402	-.0228445	.0091583
hurBiXtime	-.0061966	.0049137	-1.26	0.207	-.0158273	.0034341
ht_drBiXtime	-.0044051	.0035597	-1.24	0.216	-.0113821	.0025718
lightBiXtime	-.001926	.0030291	-0.64	0.525	-.007863	.0040109
torBiXtime	.0001985	.0028752	0.07	0.945	-.0054367	.0058337
WindBiXtime	.0040263	.0026146	1.54	0.124	-.0010981	.0091508
winterBiXt~e	.0017487	.0026146	0.67	0.504	-.0033758	.0068732
floodBiXtime	-.0011704	.0025623	-0.46	0.648	-.0061924	.0038516
seversBiXt~e	.0001169	.0030165	0.04	0.969	-.0057952	.0060291
_cons	5.098448	.0279707	182.28	0.000	5.043627	5.15327

Random Effects Parameters

	Estimate	SE	95% CI	
var(time)	.0047577	.0001984	.0043844	.0051629
var(_cons)	1.452568	.0430853	1.370531	1.539517
cov(time,_cons)	-.0375161	.0023435	-.0421093	-.0329228
var(Residual)	.4914469	.0038582	.4839429	.4990673

Table A.35: Model F: HLM Model for Violent Crime Utilizing Disaster Types, with Controls

	Coefficient	SE	Z	P-value	95% Confidence Interval	
lnDEMI	.0276256	.0247239	1.12	0.264	-.0208325	.0760836
lnEvents	-.0468957	.0212079	-2.21	0.027	-.0884624	-.005329
geoBinary	-.3859051	.5083241	-0.76	0.448	-1.382202	.610392
massBinary	-.0551026	.0639943	-0.86	0.389	-.1805291	.0703239
wildfireBi~y	.0004484	.0695876	0.01	0.995	-.1359408	.1368375
coastalBin~y	.017564	.0734795	0.24	0.811	-.1264532	.1615812
hurBinary	.0478664	.0427271	1.12	0.263	-.0358772	.1316101
heat_drBin~y	.0368406	.024698	1.49	0.136	-.0115666	.0852477
lightBinary	.0055192	.0232144	0.24	0.812	-.0399803	.0510186
torBinary	.0131663	.022743	0.58	0.563	-.0314091	.0577418
windBinary	-.0463463	.0211286	-2.19	0.028	-.0877576	-.004935
winterBinary	-.0024215	.0208672	-0.12	0.908	-.0433204	.0384774
floodBinary	.0276176	.0204177	1.35	0.176	-.0124003	.0676356
severeBinary	.0308781	.023647	1.31	0.192	-.0154692	.0772254
pctMale15_24	-.0007496	.0100115	-0.07	0.940	-.0203717	.0188726
theil	2.13e+08	2.42e+08	0.88	0.378	-2.61e+08	6.87e+08
herf_race	-2.982665	.1172398	-25.44	0.000	-3.212451	-2.752879
herf_ethnic	-1.834869	.1558409	-11.77	0.000	-2.140312	-1.529427
lnNP_count	.1560805	.0124481	12.54	0.000	.1316827	.1804783
vlag_ln	.1449696	.0106126	13.66	0.000	.1241693	.1657699
time	-.1045482	.0213831	-4.89	0.000	-.1464582	-.0626382
lnDEMIxtime	-.0047564	.0032319	-1.47	0.141	-.0110908	.001578
lnEventsXt~e	.0072019	.0025496	2.82	0.005	.0022048	.0121989
geoBiXtime	.038878	.053799	0.72	0.470	-.0665661	.144322
massBiXtime	.0065416	.0078705	0.83	0.406	-.0088843	.0219675
fireBiXtime	.0040893	.0079798	0.51	0.608	-.0115509	.0197295
coastBiXtime	.0005618	.008218	0.07	0.945	-.0155452	.0166688
hurBiXtime	-.0043907	.0049939	-0.88	0.379	-.0141785	.0053972
ht_drBiXtime	-.0064866	.0035955	-1.80	0.071	-.0135338	.0005605
lightBiXtime	-.0004931	.0030571	-0.16	0.872	-.0064849	.0054987
torBiXtime	-.0013612	.0028805	-0.47	0.637	-.0070069	.0042846
WindBiXtime	.0046127	.0026276	1.76	0.079	-.0005373	.0097627
winterBiXt~e	-.0013865	.0026483	-0.52	0.601	-.0065771	.0038041
floodBiXtime	-.0014689	.0025706	-0.57	0.568	-.0065072	.0035694
seversBiXt~e	-.001969	.0030262	-0.65	0.515	-.0079003	.0039623
pctMale15_~e	.0028937	.000942	3.07	0.002	.0010473	.00474
TheilXtime	-7.26e+07	2.20e+07	-3.30	0.001	-1.16e+08	-2.95e+07
HerfRaceXt~e	.0436585	.010831	4.03	0.000	.0224302	.0648868
herfEthXtime	.0416084	.0135466	3.07	0.002	.0150575	.0681594
lnNP_coXtime	-.0118702	.0010291	-11.54	0.000	-.0138871	-.0098533
vlag_lnXtime	.0038455	.0013522	2.84	0.004	.0011952	.0064958
_cons	8.226614	.2298072	35.80	0.000	7.7762	8.677027

Random Effects Parameters

	Estimate	SE	95% CI	
var(time)	.0048607	.0002054	.0044743	.0052805
var(_cons)	.8005743	.0264485	.7503789	.8541275
cov(time,_cons)	-.0294573	.0018669	-.0331164	-.0257982
var(Residual)	.4919758	.0038717	.4844456	.499623