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Natural Disasters and Social Order: Modeling Crime Outcomes in Florida

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This study analyzes the spatial distribution of crime outcomes at the county scale in Florida as a function of natural disasters. Geographic Information Systems (GIS) and conditional fixed effects negative binomial statistical techniques are used. Four crime outcomes are analyzed: index crimes, property crimes, violent crimes, and domestic violence crimes. Adjusting for socio-demographic and social order variables, we find that natural disasters significantly decrease levels of reported index, property, and violent crimes, but significantly increase the expected count of reported domestic violence crimes.

Key words: Natural disasters, crime, domestic violence, social order, therapeutic community

Introduction

Natural disasters constitute a major threat to the health, safety, and property of American communities (Mileti 1999). While comprehensive data are difficult to collect, one study estimates the overall costs of natural hazards at $54 billion per year or approximately $1 billion per week (van der Vink et al. 1998). Data from the Centers for Disease Control and Prevention indicate that almost 32,000 Americans were killed by forces of nature from 1979 to 2003 (Zahran, Peek and Brody 2008). Natural hazards not only cause human casualties and property loss, but also disrupt social order and community life. Indeed, Fritz (1961, p. 654) argues that natural disasters offer a real world laboratory for testing basic questions on how individuals and communities respond and adapt to conditions of loss and dispossession. While news media frequently cover natural disasters as agents of social disorder, panic, looting, and criminal deviance (Fischer 1998), the empirical link between disasters and crime is disputed in mass emergency and disaster research. Disagreement among researchers is understandable. What research exists on the relationship between natural hazards and crime is limited to case studies of single events, small sample descriptive analyses, or statistical accounts of behavior in one location during a single point in time. As a result, little can be concluded scientifically on the degree to which disasters affect criminal behavior.

We address this lack of systematic research by examining natural disasters and crime in Florida longitudinally, at a large spatial scale, while statistically controlling for multiple socioeconomic and social order characteristics that may condition the relationship between natural disasters and crime outcomes. Specifically, we spatially assess the occurrence of several types of crime for every county in Florida from 1991 to 2005. This research approach enables us to understand with greater precision and certainty the degree to which disasters influence criminal behavior in a particularly hazard-prone region of the United States. Results advance the debate on disasters and crime, and also provide important guidance for decision makers that guard the safety of residents in the aftermath of a disaster event.

Our study is organized into four sections. First, we review the literature on postdisaster criminal behavior. We divide existing studies into two propositions that represent a long standing debate in the hazards and disaster research field: one proposition maintains that disasters strengthen social bonds and increase prosocial behavior, ultimately leading to a decrease in crime; the other proposition argues that natural disasters lead to an increase in crime as social cohesion and mechanisms of social control decline. Second, we detail elements of the research design. We explain the logics of unit selection and universe, discuss variable operations, data sources, and statistical procedures. Third, using Geographic Information Systems (GIS) and conditional fixed effects negative binominal statistical regression, we analyze four crime outcomes: index crimes, property crimes, violent crimes, and domestic violence crimes. Our predictors of crime outcomes are organized into three categories: baseline demographic variables, social order variables, and disaster variables. Fourth, we conclude by discussing the theoretical and applied implications of this research.

Literature Review

On the question of the likelihood of postdisaster criminal behavior, the research literature is divided into two propositions. *Proposition 1* holds that natural disasters give rise to altruism and norms of reciprocity that either reduce or stabilize rates of reported crime. *Proposition 2* holds that natural disasters weaken agencies of formal and informal social order, giving rise to criminal opportunities and behavior. Both propositions flow logically from different theoretical stances, supported by case studies and some empirical evidence.

Proposition 1

Many studies of postdisaster deviance and antisocial behavior draw on Fritz's (1961) concept of the *therapeutic community* to explain why rates of crime decline (or increase only modestly) after a disaster event. Fritz (1961) argues that postdisaster behavior is adaptive, prosocial, and aimed at promoting the safety of others and restoration of community life. Many reasons account for postdisaster altruism and other community-oriented behaviors. First, social divisions tend to dissolve in the aftermath of a disaster. Risk, loss, and suffering become public rather than private phenomena (Fritz 1961, p. 685). This relative equality of suffering promotes solidarity among disaster victims and sympathizers.[1] Second, human survival needs are widespread and visible in the aftermath of a disaster (Fritz 1961, p. 684). Visible suffering increases empathy, inducing social cooperation to solve immediate problems like rescue and debris clearance. Third, natural disasters enable groups to introduce desired reforms into a social system (Fritz 1961, p. 685). For social entrepreneurs, disasters represent opportunities for social change.

Much empirical research, *in support of Proposition 1*, focuses on the question of looting. Although there is no formal definition of looting, the concept is generally understood as widespread theft of property in the context of a disaster (Quarantelli 2007). According to Fischer (1998), looting is the most expected criminal response to a natural disaster. Logically, opportunities for widespread theft are said to increase following a disaster because private property is unprotected. Contrary to logical expectations, scholars find that incidences of looting in the aftermath of a disaster are empirically rare (Barsky 2006; 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).

For example, in a National Opinion Research Center (NORC) report on the 1952 White County, Arkansas tornado, researchers found that only 9 percent of the most affected residents reported that they, or members of their immediate household, had lost property to looters (Dynes and Quarantelli 1968). One third of those who had lost property were uncertain whether the loss was due to looters, or whether the missing items had been blown away or buried in debris. Similarly, Gray and Wilson (1984) note that only 9.5 percent of residents in Xenia, Ohio reported stolen property following a tornado event in 1974. In both cases, even the most pessimistic estimated increase in property theft fell considerably short of widespread looting.

Other studies, *in support of proposition 1*, find that measures of property and violent crime decrease below or remain equal to routine rates in the aftermath of a disaster, both in terms of what is reported to police and the number of arrests made[2] (Quarantelli 1994;

Quarantelli and Dynes 1972; Taylor 1977). Siegel et al. (1999), in a study of crime, victimization, and traumatic stress before and after the 1994 Northridge earthquake, found relatively stable crime rates. Siegel and colleagues theorize that the stress and disorder caused by the disaster were offset by increases in community cohesion (and positive other-regarding behaviors) observed in the data. Similarly, Lemieux (1998) discovered that occurrences of property crime decreased modestly during the Quebec ice storm of 1998. In both cases—the Northridge earthquake and the Quebec ice storm—the increased presence of police and agencies of formal control partially account for the behavior of crime rates (see Decker, Varno, and Greene 2007).

Proposition 2

Many studies reporting an increase in postdisaster criminal activity draw on two ecological theories of crime: *routine activities theory* (Cohen and Felson 1979) and *social disorganization theory* (Shaw and McKay 1942). Routine activities theory posits that crime will occur if three key elements converge in time and space: the availability of suitable targets (i.e., property to steal or individuals to victimize), the absence of capable guardians (police, neighbors, or technologies of surveillance), and the presence of motivated offenders (Cohen and Felson 1979). A disaster event changes local "routine behaviors" and increases the likelihood that motivated offenders will identify suitable targets in the absence of capable guardianship. Vacated (or insufficiently guarded) residential and commercial properties represent *suitable targets*. Levels of guardianship decline as people evacuate their homes and law enforcement officials focus on rescue and emergency response activities. Survivors of a disaster may become targets for criminal victimization during recovery, evacuation, and relocation efforts. In the words of Cromwell and colleagues (1996, p. 58): "The destruction brought on by a large scale disaster has the capacity to increase crime by increasing the vulnerability of both persons and places to victimization and by rendering guardians less capable or fewer in number."

Social disorganization theory posits that communities characterized by residential instability, low socioeconomic status, and poor collective efficacy (social networks that represent the willingness to participate in social control) have impaired capacity to informally control crime (Sampson and Groves 1989; Sampson, Morenoff, and Earls 1999; Sampson and Raudenbush 1999; Sampson, Raudenbush, and Earls 1997; Shaw and McKay 1942). Thus, disaster events are said to aggravate social conditions that cause social disorganization and crime (Davila et al. 2005). Natural disasters can fracture community cohesion, impairing a community's ability to respond to and sanction antisocial conduct or crime (Berkowitz 1993; Curtis, Miller, and Berry 2000; Erikson 1976; Siman 1977; Taylor 1989).

In *support of Proposition 2*, a number of studies have reported increases in postdisaster criminal behavior. Friesema et al. (1979) observed a 30 percent increase in auto theft following Hurricane Carla in Galveston, Texas. Siman (1977) noted a 40 percent rise in property crime and a 14 percent increase in drinking-related offenses following a flood disaster in Wilkes Barre, Pennsylvania. Adams and Adams (1984) compared police data in Othello, Washington seven months before and after the eruption of Mount Saint Helens, finding a 27 percent increase in the number of assaults, a 10 percent increase in disorderly conduct, and a 23.7 percent increase in acts of vandalism and malicious mischief. Frailing and Harper (2007) maintain that preexisting socioeconomic conditions explain why the burglary rate in New Orleans soared by an estimated 403 percent following Hurricane Katrina.

The empirical link between natural disasters and crime appears particularly salient for domestic and family violence (Enarson, Fothergill and Peek 2006; Fothergill 1996). Curtis and colleagues (2000) note that reports of child abuse increased following Hurricane Hugo in South Carolina and the Loma Prieta Earthquake in California. Following the eruption of Mount Saint Helens, incidents of domestic violence reported to the police increased 46 percent (Adams and Adams 1984). Drawing on data from the Centers for Disease Control and the Florida Department of Rehabilitative Services, Peacock and colleagues (1997) report substantial increases in domestic violence injunctions following Hurricane Andrew. In fact, the surge in post-hurricane domestic violence cases necessitated the hiring of additional judges (Swarns 1992). Proponents of *Proposition 2* reason that because disasters impose significant stress on households and families, communities are likely to observe increased counts of domestic violence.

While the debate on the relationship between disasters and crime cannot be resolved in a single study, the differences in the theoretical propositions and the empirical findings described above may be explained in part by variation in pre- and postdisaster conditions. Sociodemographic and economic characteristics, such as population, income, education, age, and community-level wealth may account for differences in behavior following a disaster. Also, social order attributes including the level of law enforcement and the degree of social cohesion may help explain the variation among results associated with disasters in crime. A better understanding of this relationship is important because it provides signals to residents, the media, and decision makers regarding what to expect after a disaster event and how to most effectively work with local communities and individual survivors of trauma. Large scale, longitudinal studies that control for multiple confounding factors are perhaps the most effective line of research in terms of addressing the topic in a scientific manner, yet none of the aforementioned studies have undertaken this level of analysis.

Research Design

Unit of Analysis

Florida is an excellent laboratory for testing the relationship between natural disasters and crime for many reasons. First, Florida leads the country in major disasters that warrant federal involvement. According to Federal Emergency Management Agency records, Florida endured 34 separate *major* disasters from 1990 to 2005. Second, Florida is exposed to many hazards, including tropical storms, hurricanes, tornadoes, wildfires, severe flooding, high winds, abnormally high tides, and freezing. Third, from a population geography standpoint, Florida is highly heterogeneous—localities vary considerably in terms wealth, measures of social cohesion, and crime outcomes. This demographic and spatial variability permits sound statistical analyses.

We analyze crime outcomes at the county scale for many practical reasons. First, the finest spatial resolution for longitudinal data on crime outcomes in Florida is at the county scale. Second, data for critical predictors in our model – disaster frequency and intensity – are only available at the county scale or higher. This is true of disaster data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), data from the National Weather Service, and data from the Public Entity Risk Institute on presidential disaster declarations. Third, though census tracts and block groups have the advantage of greater homogeneity with regard to population characteristics, these smaller units are not political or administrative entities. Law enforcement decisions that influence crime outcomes are made at city or county levels and these levels are more theoretically appropriate for estimating the effect of formal social order measures like police density.

Dependent Variables

Four crime outcomes are measured and analyzed at the county scale: *index crimes, property crimes, violent crimes,* and *domestic violence crimes*. All crime data are derived from the Florida Department of Law Enforcement's Uniform Crime Reports (see Table 1). First, *index crimes* are measured as the annual count of murders[3], forcible rapes[4], robberies, aggravated assaults, burglaries, larceny thefts, and motor vehicle thefts known to police that occur in a county. Second, *property crimes* are measured as the annual number of burglaries, larceny thefts, and motor vehicle thefts known to police that occur in a county. Third, *violent crimes* are estimated as the annual total of murders[5], forcible rapes, robberies, and aggravated assaults known to police that occur in a county area. For the index, property, and violent crimes, data are collected for the years 1991-2002. Fourth, *domestic violence crimes* are measured as the annual sum of domestic related criminal homicides, manslaughters, forcible rapes, acts of forcible sodomy, forcible fondling, aggravated assault, aggravated stalking, simple assault, threat or intimidation, and stalking known to police that occur in a county. Domestic violence data are collected for the years 1992-2005[6]

Table 1: Variable Operations, Data Sources, and Expected Direction

Variable Name/Sign	Variable Operation	Data Source [b]
Baseline Variables [a]		
Population (+)	Total county population (10,000 increments).	US Census, 1990, 2000
Economic capital (+/-)	Sum of standardized scores of median household income and median home value ($100 increments).	US Census, 1990, 2000
Social Order Variables		
Law enforcement density (-)	Total number of law enforcement personnel divided by the population size and then multiplied by 10,000.	FDLE Police Personnel Data, 1991-2005
Nonprofit density (-)	Number of tax-exempt non-profit organizations with $25,000 dollars in gross receipts required to file IRS Form 990, divided by population and multiplied by 10,000.	NCCS Core Files, 1991-2005
Disaster Variables		
Disaster frequency (+/-)	Number of natural disasters recorded in a county in a given year (18 natural hazard types are inventoried).	SHELDUS, 1991-2005
Presidential declarations (+/-)	Number of major and emergency disaster declarations made by the President in a given year.	Public Entity Risk Institute, 1991-2005
Dependent Variables		
Index crimes	Total annual number of reported murders, forcible rapes, robberies, aggravated assaults, burglaries, larceny-thefts, and motor vehicle thefts.	FDLE Uniform Crime Reports, 1991-2002
Domestic violence crimes	Total annual number of reported domestic violence crimes, including criminal homicides, manslaughters, forcible rapes, acts of forcible sodomy, forcible fondling, aggravated assault, aggravated stalking, simple assault, threat or intimidation, and stalking.	FDLE Uniform Crime Reports, 1992-2005
Property crimes	Total annual number of reported burglaries, larceny-thefts, and motor vehicle thefts.	FDLE Uniform Crime Reports, 1991-2002
Violent crimes	Total annual number of reported murders, forcible rapes, robberies, and aggravated assaults.	FDLE Uniform Crime Reports, 1991-2002

[a] Values for the 1990 and 2000 Censuses are used to estimate intervening years, assuming uniform rate of change.
[b] FDLE = Florida Department of Law Enforcement; NCCS = National Center for Charitable Statistics

Independent Variables

Predictors of crime outcomes are organized into three categories: baseline sociodemographic variables, social order variables, and disaster variables. Two baseline sociodemographic variables are used: *population size* and *economic capital*. *Population size* is the total number of people residing in a country area (in increments of 10,000). Values for the 1990 and 2000 Censuses are used to derive an average annual linear growth rate used to estimate population size for intervening years and extrapolation beyond 2000. *Economic capital* is measured as a summary index of standardized scores of median household income and median home value. Median home value is an estimation of how much a property (house and lot) would bring in the marketplace. Income is the sum of all reported household earnings. Median value calculations are rounded to the nearest hundred dollars. Again, county values for the 1990 and 2000 Censuses are used to estimate intervening years, assuming equal interval of change.

Two social order variables are used: *law enforcement personnel density* and *nonprofit organization density*. Our law enforcement density variable estimates the level of formal guardianship that exists in a given county, measured as the total number of law enforcement personnel divided by the total population and multiplied by 10,000. The county average is 325 law enforcement officers per 10,000, with a standard deviation of 250. Data are derived from the Florida Department of Law Enforcement Police Personnel database.

Our *nonprofit organization density* variable estimates the level of social cohesion[7], measured as the total number nonprofit organizations of tax exempt status with $25,000 dollars in gross receipts required to file Form 990 with the Internal Revenue Service (IRS) in a county, divided by the population size and multiplied by 10,000. Data are derived from the National Center for Charitable Statistics (NCCS), Core Files 1992, 1994, 1997, and 2001. The NCSS Core File merges descriptive information from three cumulative files compiled by the IRS: the Business Master File, the Return Transaction File, and the Statistics of Income file. The NCCS conducts standardized checks on all information, making the Core File the most complete and highest quality data source ever available on nonprofit organizations (Lampkin and Boris 2002, 1683).

Last, two disaster variables are measured: *disaster frequency* and *presidential disaster declarations*. *Disaster frequency* is measured as the annual total number of natural disasters recorded in a county. As indicated in Table 2, the average county in Florida is struck by six natural disasters per year. Data on disaster frequency are from the SHELDUS database at the Hazards and Vulnerability Research Institute at the University of South Carolina. SHELDUS inventories 18 natural hazard types, including hurricanes, floods, wildfires, and drought. The database is formed by culling numerous public data sources including National Climatic Data Center monthly releases. Data records include the start and end date of the hazard event, as well as the county areas affected.

Table 2: Descriptive Statistics of Dependent and Independent Variables

Variable	Mean	Std. Dev.	Min	Max
Baseline Variables				
Population	222947.8	371506.9	5714.2	2320847
Economic capital	-1.43E-09	1.715611	-2.8257	5.415072
Social Order Variables				
Enforcement density (10,000)	325.0255	249.7463	138.7925	2148.885
Nonprofit density (10,000)	48.66373	35.99205	0	272.2216
Disaster Variables				
Disaster frequency	6.027363	6.486637	0	50
Presidential declarations	0.449005	0.742676	0	4
Dependent Variables				
Index crimes	15524.43	33510.44	19	258874
Domestic violence crimes	1847.471	3052.313	1	20408
Property crimes	13943.18	30332.13	6	235057
Violent crimes	2188.098	5030.182	3	43722

To estimate whether high intensity disasters affect crime outcomes, we measure the number of disaster events declared an emergency situation by the President of the United States. *Presidential declarations* are measured as the number of major and emergency disaster declarations made by the President in a given year, from 1991 to 2005. Results in Table 2 show that the average county in Florida experiences a major disaster necessitating federal assistance about once every two years. The Disaster Relief and Emergency Assistance Act allows the President to provide federal assistance to disaster afflicted counties for emergency work, repair or replacement of disaster damaged facilities, and to prevent or reduce long term risk to life and property from natural hazards. Though the President has considerable discretion[8] on when to release federal monies for disaster relief, assistance is typically provided for high impact disasters that overwhelm the capabilities of local and state disaster response agencies. Data on presidential declarations are from the Public Entity Risk Institute, 1991-2005.

Modeling Procedure and Scale

Crime data have three properties that dictate the appropriate modeling procedure: they are count variables, measured over time, exhibiting significant overdispersion. Approaches based on a Poisson regression assume that the conditional variance of a crime outcome is equal to the expected value. All crime outcomes examined violate this assumption—in such cases a negative binomial regression approach is favored (King 1989; Long 1997). The longitudinal structure of county crime data violates the independence assumption of conventional negative binomial regression, causing problems of autocorrelation and heteroscedasticity that produce spuriously low standard error estimates. Cross-sectional time series modeling procedures are available to account for problems of observational nonindependence. Conditional fixed effects negative binomial models (with standard error estimates adjusted for clustering within counties) are estimable using the *xtnbreg* function in *STATA* 9.1. We opt for fixed over random effects for two reasons: counties in Florida are not representative of the population of counties nationally; and no time invariant vectors are used to predict crime outcomes.

Descriptive Results

We begin our analysis with a series of maps (generated in *ArcGIS* 9.1) to illustrate spatial variation in crime outcomes and measures of disaster frequency and intensity (presidential declaration). The spatial distribution of the annual average index crimes and domestic violence crimes (per 10,000) are displayed in Figures 1 and 2 respectively. Both distributions are divided into quintiles, with higher values in dark blue and lower values in yellow and green. As shown in Figure 1, the index crime rate is generally higher in southern Florida, with higher values also clustering spatially in the east Atlantic tip and the Tampa Bay region stretching east into the Florida interior. The Tampa Bay region is also high in domestic violence crimes (as illustrated in Figure 2). The east Atlantic tip is comparatively low on domestic violence crimes.

Figures 3 and 4 illustrate the geography of the average annual number of natural disasters (frequency) and major disasters (necessitating federal assistance) experienced by Florida counties. Figure 3 shows high average annual disaster counts in the Tampa Bay region, the northeast coast, and the southern tip of the state. Figure 4 shows the distribution of presidential declaration events, or high intensity disasters. For the years examined, the Florida panhandle and neighboring counties are particularly susceptible to high intensity disaster events, as are the northeast coast and southern tip of Florida. Taken together, these maps suggest some spatial overlap between natural disasters and crime outcomes. In fact, bivariate correlation tests show that disaster frequency is positively and significantly correlated (where $p = .000$) with all four crime outcomes. In the next set of analyses, we test whether observed positive correlations between disaster frequency and crime outcomes hold with the addition of statistical controls.

Regression Results

Table 3 presents the matrix of intercorrelations among the independent and dependent variables. First, as one would expect, the dependent variables are all extremely highly intercorrelated with one another so they are likely to produce similar results. Second, however, the independent variables have minimal correlations with each other, so multicollinearity is unlikely to be a threat to the interpretation of the regression coefficients. Third, population size is highly correlated with all four dependent variables so it is logical to enter it first into all regression models. Finally, the number of disasters has a strong positive correlation with all dependent variables.

Figure 1: Spatial Distribution of Average Annual, Index Crimes (per 10,000) in Florida, 1991-2002, by County

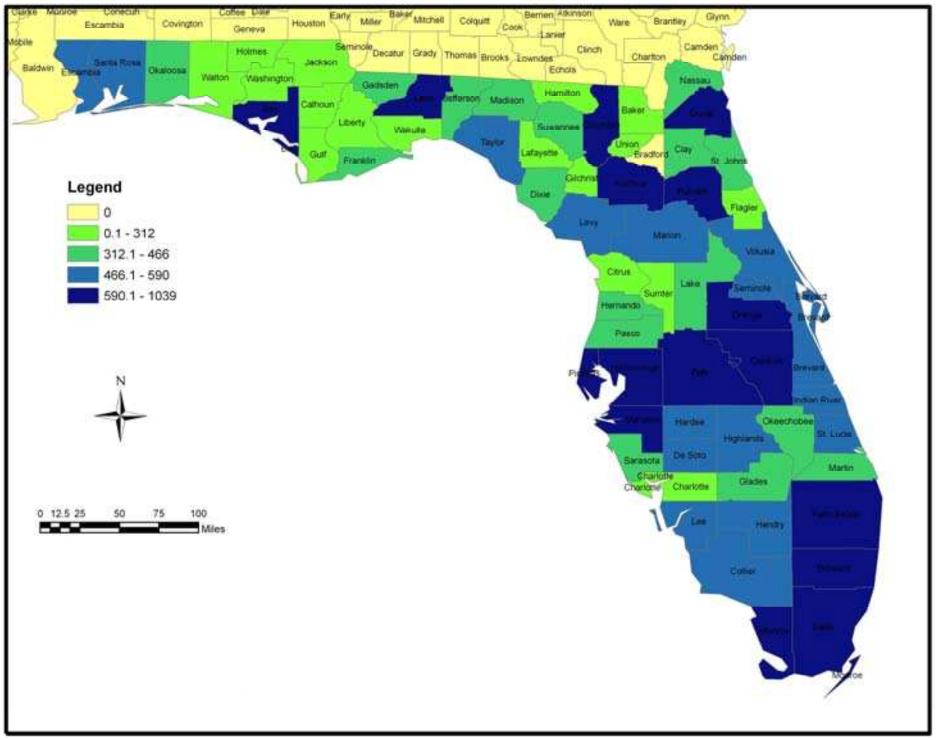


Figure 2: Spatial Distribution of Average Annual Domestic Violence Crimes (per 10,000) in Florida, 1991-2002, by County

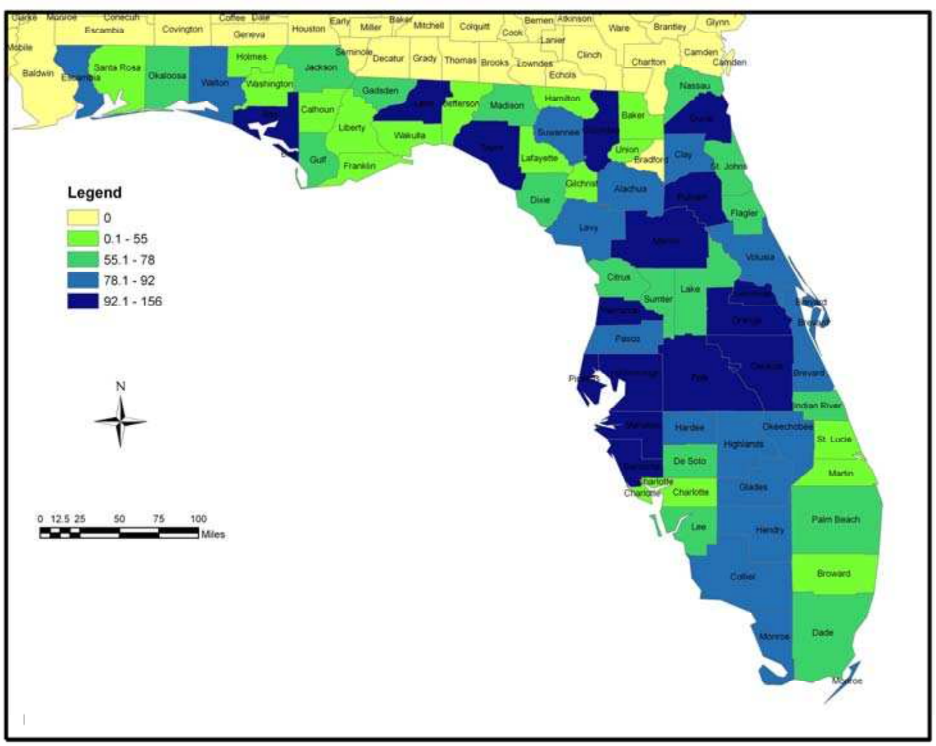


Figure 3: Spatial Distribution of Average Annual Natural Disasters in Florida, 1991-2002, by County

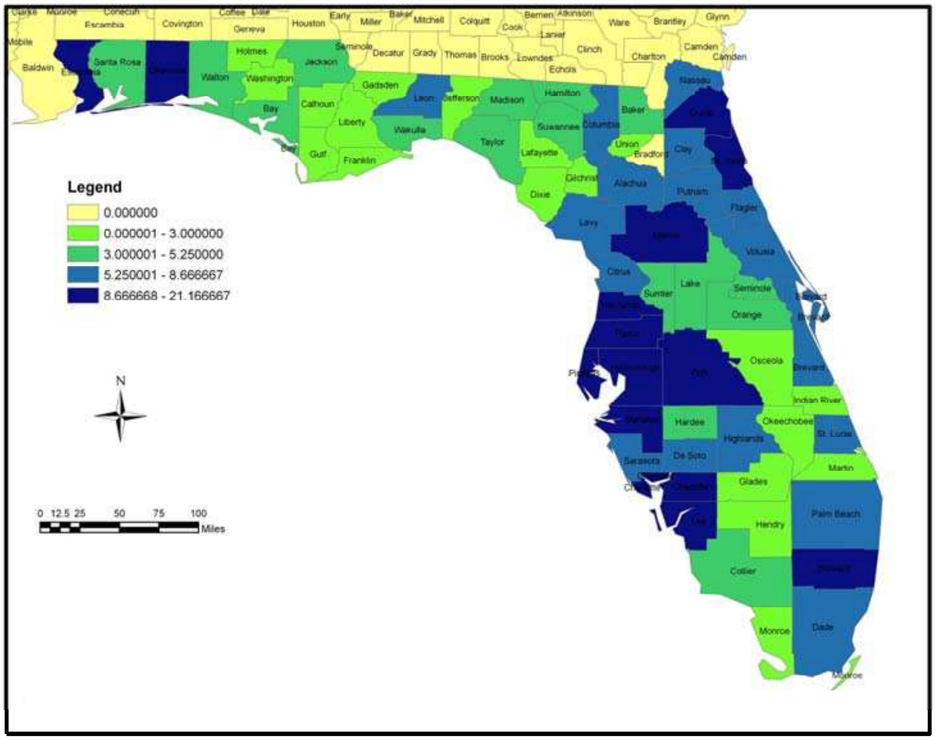


Figure 4: Spatial Distribution of Average Annual Presidential Disaster Declarations in Florida, 1991-2002, by County

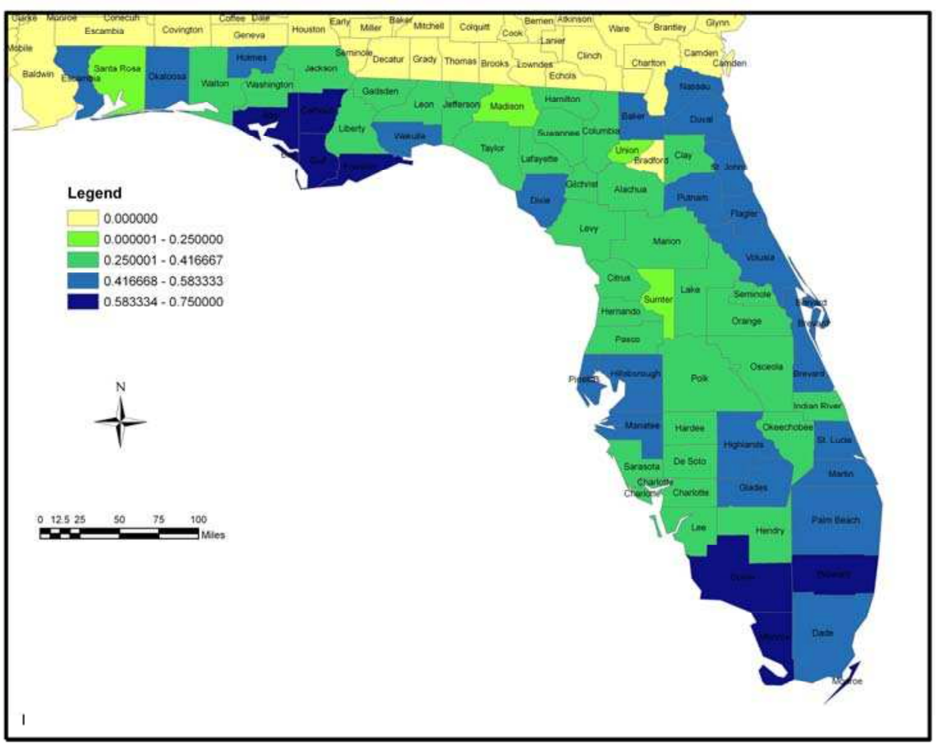


Table 4 presents conditional fixed effects negative binomial regression results for index crimes.[9] The raw coefficients reported in Table 4 give the direction and statistical significance of effects. The antilog of a parameter yields the net effect of a unit change in a covariate on the predicted *count* of index crimes experienced by a county. Odds ratios are reported in neighboring columns. We model index crimes incrementally, beginning with baseline demographic and social order variables. Model 2 in Table 4 shows that index crimes increase with population (b = .00272, p <.01) and economic capital (b = .00272, p < .01). As expected, both informal (nonprofit density) and formal (law enforcement density) social order measures significantly decrease index crimes. A unit change in law enforcement density decreases the expected count of index crime arrests by .0004 percent, where p <.01.

With index crimes adequately modeled by demographic and social order variables, we introduce our disaster frequency and intensity measures in Model 3. As suggested by *Proposition 1,* an increase in the number of disasters experienced by a county decreases the number of index crimes observed (b = -.00371, p < .05). This negative regression coefficient might seem to conflict with the positive zero-order correlation reported in Table 3. However, the number of disasters is highly correlated with both index crimes (r = .240) and population size (r = .339) and the latter two variables are extremely highly correlated with each other (r = .956). Consequently, the partial correlation of hazard frequency with index crimes, when controlling for population (r = -.301), reverses the sign of the zero order correlation. Controlling for demographic and social order variables, a single natural disaster reduces the expected count of index crimes by .0037 percent (= 100 [exp (.00371) − 1]), roughly equal to 57 index crimes (.0037 * 15,524). Disaster intensity is statistically insignificant, where p > .05. The Wald χ^2 statistic (99.87) at the bottom of Table 4, Model 3 provides a measure of model fit—accordingly, we reject the null hypothesis that all 6 coefficients are simultaneously equal to zero.

Next, we disaggregate the index crime measure into property and violent crime components. Each component is modeled independently, with results presented in Tables 5 and 6. We deploy the same procedure of loading variable domains incrementally. Table 5 shows that both social order variables negatively predict property crime outcomes—a unit change in nonprofit density, for example, decreases the expected count of property crimes by .0049 percent. Disaster frequency is a significant negative predictor of property crimes (b = -.00356), where p > .05.

Table 3: Intercorrelations Among Independent and Dependent Variables

Variable	1	2	3	4	5	6	7	8	9	10
1. Index crime	1.000									
2. Property crime	.999[b]	1.000								
3. Violent crime	.990[b]	.986[b]	1.000							
4. Domestic violence crime	.936[b]	.935[b]	.929[b]	1.000						
5. Population	.956[b]	.935[b]	.926[b]	.955[b]	1.000					
6. Economic capital	.080[b]	.087[b]	.040[b]	.071[b]	.140[b]	1.000				
7. Law enforcement per capita	-.046	-.047	-.043	-.078[b]	-.086[a]	-.025[b]	1.000			
8. Nonprofits per capita	.077[*]	.078[a]	.073[a]	.137[b]	.103[b]	.281[b]	.226[b]	1.000		
9. Number of disasters	.240[b]	.242[b]	.228[b]	.399[b]	.339[b]	.036	-.104[b]	.185[b]	1.000	
10. Presidential declarations	.033	.033	.030	.044	.052	.081[a]	-.020	.040	.300[b]	1.000

[a] $p < 0.05$, 2-tailed; [b] $p < 0.01$, 2-tailed.

Table 4: Conditional Fixed Effects Negative Binomial Regression of Index Crimes, 1991-2002

	Model 1		Model 2		Model 3	
	b	IRR	b	IRR	B	IRR
Baseline Variables						
Population (10,000)	.00271[b] (.00098)	1.0027	.00272[b] (.00097)	1.0027	.00312[b] (.00098)	1.0031
Economic capital	.0924[b] (.018)	1.0968	0.161[b] (.023)	1.1749	0.170[b] (.024)	1.1854
Social Order Variables						
Enforcement density (10,000)			-.000390[b] (.00014)	.9996	-.000382[b] (.00014)	.9996
Nonprofit density (10,000)			-.00395[b] (.00089)	.9961	-.00386[b] (.00088)	.9962
Disaster Variables						
Disaster frequency					-.00371[a] (.0018)	.9963
Presidential declarations					.0113 (.012)	1.0113
Constant	2.715[b] (.059)		3.084[b] (.084)		3.092[b] (.084)	
Observations	798		798		798	
Number of FIPS	67		67		67	
Avg. Obs. per FIPS	11.9		11.9		11.9	
Log Likelihood	-5890.25		-5873.65		-5871.57	
Wald χ^2 (vs. Null)	56.07		94.07		99.87	

Standard errors are in parentheses. [a] $p < 0.05$, [b] $p < 0.01$

On the prediction of violent crime outcomes in Table 6, our law enforcement density measure is statistically insignificant (b = -.00011). Our results indicate that an increase in law enforcement density does more to reduce property crime than violent crime outcomes. In Table 6, results also show that disaster frequency reduces the expected count of violent crime by .0051 percent (where $p < .05$), roughly equal to a reduction of 11 reported violent crimes per disaster. In both property and violent crime models, disaster intensity (as measured by the number of presidential disaster declarations) is statistically insignificant.

Table 5: Conditional Fixed Effects Negative Binomial Regression of Property Crimes, 1991-2002

	Model 1		Model 2		Model 3	
	b	IRR	b	IRR	B	IRR
Baseline Variables						
Population (10,000)	0.00283 [b]	1.0028	0.00281 [b]	1.0028	0.00319 [b]	1.0032
	(0.00098)		(0.00097)		(0.00098)	
Economic capital	0.0877 [b]	1.0917	0.156 [b]	1.1690	0.164 [b]	1.1787
	(0.018)		(0.024)		(0.024)	
Social Order Variables						
Enforcement density (10,000)			-0.000504 [b]	.9995	-0.000497 [b]	.9995
			(0.00015)		(0.00015)	
Nonprofit density (10,000)			-0.00405 [b]	.9960	-0.00396 [b]	.9961
			(0.00091)		(0.00091)	
Disaster Variables						
Disaster frequency					-0.00356 [a]	.9964
					(0.0019)	
Presidential declarations					0.0123	1.0124
					(0.012)	
Constant	2.667 [b]		3.086 [b]		3.092 [b]	
	(0.060)		(0.087)		(0.087)	
Observations	798		798		798	
Number of FIPS	67		67		67	
Avg. Ob. per FIPS	11.9		11.9		11.9	
Log Likelihood	-5806.30		-5787.31		-5785.42	
Wald χ^2 (vs. Null)	52.15		92.68		97.95	

Standard errors are in parentheses. [a] $p < 0.05$, [b] $p < 0.01$

Table 6: Conditional Fixed Effects Negative Binomial Regression of Violent Crimes, 1991-2002

	Model 1		Model 2		Model 3	
	b	IRR	b	IRR	B	IRR
Baseline Variables						
Population (10,000)	.00319[b]	1.0032	.00331[b]	1.0033	.00390[b]	1.0039
	(.00096)		(.00096)		(.00096)	
Economic capital	.0933[b]	1.0978	0.153[b]	1.1651	0.169[b]	1.1839
	(.021)		(.026)		(.026)	
Social Order Variables						
Enforcement density (10,000)			-.000116	.9999	-.000108	.9999
			(.00014)		(.00014)	
Nonprofit density (10,000)			-0.00317[b]	.9968	-0.00310[a]	.9969
			(.00091)		(.00090)	
Disaster Variables						
Disaster frequency					-.00515[a]	.9949
					(.0020)	
Presidential declarations					.00716	1.0072
					(.013)	
Constant	2.598[b]		2.815[b]		2.832[b]	
	(.065)		(.089)		(.089)	
Observations	798		798		798	
Number of FIPS	67		67		67	
Avg. Obs. per FIPS	11.9		11.9		11.9	
Log Likelihood	-4579.67		-4572.49		-4569.09	
Wald χ^2 (vs. Null)	50.93		69.73		79.10	

Standard errors are in parentheses. [a] $p < 0.05$, [b] $p < 0.01$

Finally, we model the count of reported domestic violence crimes in Florida counties (in Table 7). By separating domestic violence crimes (from violent crimes in general), one can analyze disaster effects within domestic contexts. Beginning with social order variables, Table 7, Model 3 shows that law enforcement density is an insignificant predictor of domestic violence outcomes. On the other hand, our measure of informal social order—nonprofit density—is a negative partial correlate of domestic violence. A unit change in the density of voluntary associations decreases the expected count of domestic violence crimes by .0042 percent (where $p < .01$).

Table 7: Conditional Fixed Effects Negative Binomial Regression of Domestic Violence Crimes, 1992-2005

	Model 1		Model 2		Model 3	
	b	IRR	b	IRR	B	IRR
Baseline Variables						
Population (10,000)	.00780 [b]	1.0078	.00776 [b]	1.0079	.00719 [b]	1.0072
	(.00079)		(.00077)		(.00083)	
Economic capital	.155 [b]	1.1680	.229 [b]	1.2575	.228 [b]	1.2555
	(.018)		(.025)		(.025)	
Social Order Variables						
Enforcement density (10,000)			.0000698	1.0001	.0000524	1.0001
			(.00014)		(.00014)	
Nonprofit density (10,000)			-.00311 [b]	.9969	-.00319 [b]	.9968
			(.00075)		(.00075)	
Disaster Variables						
Disaster frequency					.00732 [b]	1.0072
					(.0021)	
Presidential declarations					-0.0147	.9854
					(.012)	
Constant	1.846 [b]		2.014 [b]		2.015 [b]	
	(.055)		(.078)		(.078)	
Observations	931		931		931	
Number of FIPS	67		67		67	
Avg. Obs. per FIPS	13.9		13.9		13.9	
Log Likelihood	-5740.96		-5732.37		-5726.32	
Wald χ^2 (vs. Null)	282.37		308.56		325.04	

Standard errors are in parentheses. [a] $p < 0.05$, [b] $p < 0.01$

Interestingly, disaster frequency is a significant positive predictor of domestic violence crime (b = .00732, $p < .01$). With an odds ratio of 1.0072, on average, a natural disaster increases the expected count of domestic violence by about 13 crimes (.0072 * 1,847). We arrive at the same result if we model domestic violence outcomes as a rate (using the *xtreg* function in *STATA*), and adjusting for numerous other population and housing variables. In fact, the coefficient on disaster frequency is even stronger when domestic violence outcomes are modeled as a rate.

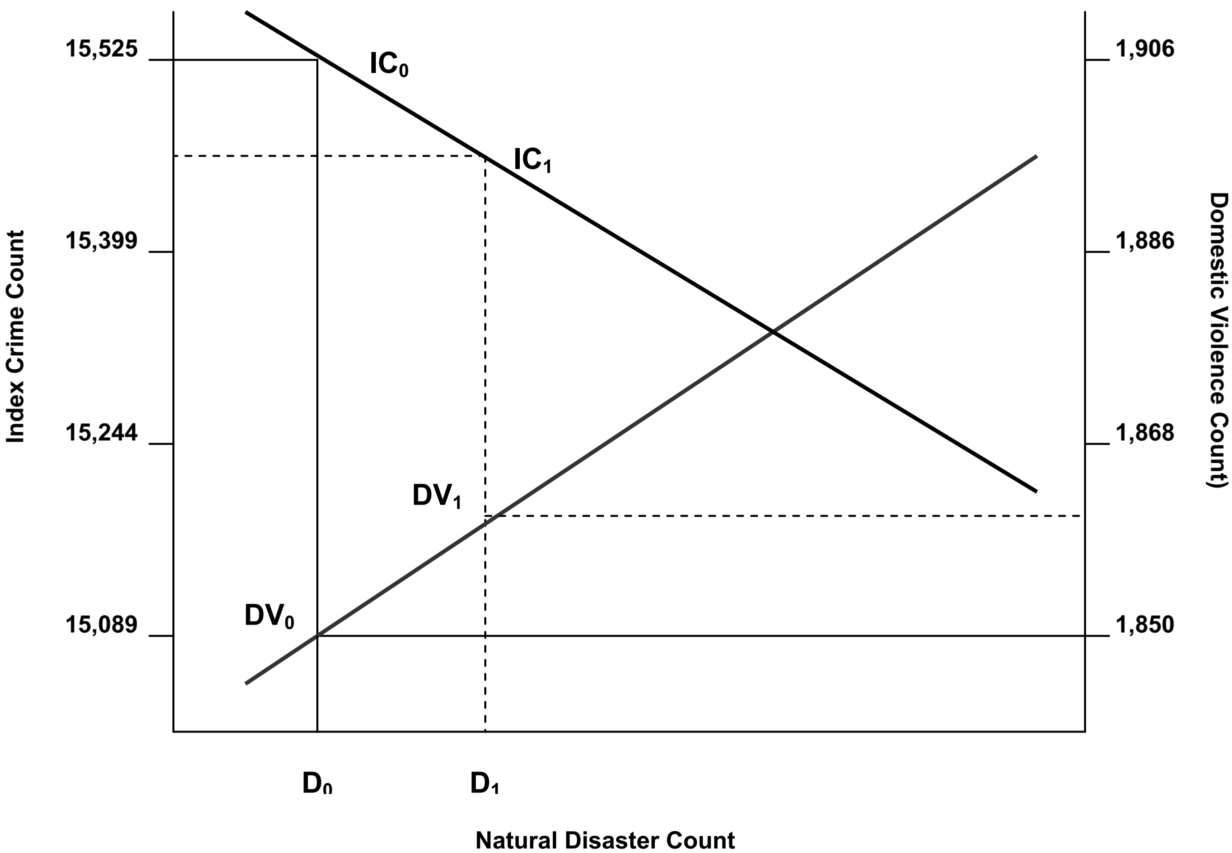
Taken together, our results suggest that natural disasters decrease the volume of crime generally, but increase reported violence in the domestic context. Our regression results are summarized in Figure 5. On the left vertical axis, the count of index crime (IC) is shown. The figure of 15,525 at the top of the left axis is the average annual count of index crimes for Florida counties. On the right vertical axis domestic violence (DV) crimes are plotted. The figure of 1,850 at the bottom of the right axis is the average annual count of domestic violence crimes in Florida counties. Both vertical axes are numbered in equal percent change intervals (.010 percent). On the horizontal axis we find the count of natural disasters (D). Slope coefficients for both lines are derived from fully saturated regression models (in Table 4 for index crimes, and Table 7 for domestic violence crimes). The graph shows that a unit change in natural disaster count (D_0 to D_1) decreases the expected count of index crimes by about 57 ($IC_1 – IC_0$, -0.0035 percent), and increases the expected count of domestic violence crimes by about 13 (DV_1 - DV_0, 0.0075 percent).

Discussion and Conclusion

This research empirically tested two competing propositions that represent a long standing debate in the disaster research literature. Adherents to *Proposition 1* claim that in the worst of scenarios, natural disasters negligibly increase rates of reported crime (Fischer 1998; Lepointe 1986; Quarantelli 1993; Tierney et al. 2001). Moreover, instances of widespread property theft are "nonexistent or numerically rare… covertly undertaken in opportunistic settings, done by isolated individuals or very small groups, and socially condemned" (Quarantelli 2007, p. 3). The more common social outcome in natural disasters, according to proponents of *Proposition 1*, is an increase in prosocial behaviors that significantly offset opportunities to steal and cheat others. Conversely, adherents to *Proposition 2* assert that natural disasters increase crime by shocking routine activities and patterns of social organization. Proponents of *Proposition 2* also argue that because disasters impose significant stress on households, communities are likely to observe increased counts of domestic violence. Our spatial and statistical results indicate that natural disasters significantly decrease levels of reported index, property, and violent crimes, but significantly increase the expected count of reported domestic violence crimes. Thus, our results lend support to both *Proposition 1* and *Proposition 2,* depending on the type of crime considered.

For example, in the case of index, property, and violent crimes, the theory of the altruistic or therapeutic community (Barton 1969; Fritz 1961) applies as these acts of illegal deviance are reduced in the aftermath of disaster. During this period, disaster survivors are focused on immediate survival needs, and they tend to rely on one another to address those needs. As survivors bind together to collectively overcome the social trauma and physical destruction caused by the extreme event, feelings of altruism, acts of prosocial behavior, and levels of informal social control increase. Although the media tends to portray images of "chaos" and subsequently perpetuate the notion that disasters lead to a breakdown of the social order, our study shows that disasters diminish most forms of criminal activity.

Figure 5: Model of Disaster Frequency and Reported Index and Domestic Violence Crimes



These altruistic norms, however, do not extend to the most private and intimate sphere of social life: the domestic context. Our findings indicate that disasters contribute to a significant increase in the count of domestic violence crimes, which include acts such as domestic related criminal homicide, rape, aggravated assault, stalking, and violent threat or intimidation. Postdisaster stress may overwhelm intimate partners as they attempt to cope with their own or their family members' traumatic reactions to disaster, the loss of material possessions and valued family memorabilia, financial strains, and increased demands for carework between partners and between adults and children.

Turning to *Proposition 2*, our results provide limited empirical support. Adherents to *Proposition 2* have traditionally relied on ecological theoretical frameworks that include routine activities and social disorganization theories. Of the two ecological frameworks, routine activities theory may best explain why domestic violence incidents increase as a result of disasters while other forms of crime decrease.

Under the routine activities perspective, three elements must converge in time and space for crime to occur: a motivated offender, suitable target, and lack of capable guardianship (Cohen and Felson 1979). In the case of domestic violence, the motivated offender is the batterer while the suitable target is the victim. Adherents to *Proposition 2* often argue that guardianship declines or is less capable in disaster events thereby making crime events more likely to occur. It is equally plausible, however, to consider the idea that, although some forms of guardianship may decline in disasters, alternative forms of guardianship may also emerge in disasters that serve as a deterrent for motivated offenders who have contact with suitable targets. One of these alternative forms of guardianship may come in the form of the therapeutic community. Indeed, the therapeutic community may function as a powerful form of guardianship given our findings that disaster events decrease index, property, and violent crime.

The question remains, however, why this alternative form of guardianship (hereinafter referred to as therapeutic guardianship) does not decrease the occurrence of domestic violence. Three possibilities may help explain this result. First, disaster events may *increase the number of motivated offenders* willing to engage in domestic violence. Second, the number of motivated offenders may remain unchanged but disaster events cause existing offenders to *increase the frequency of their offences.* Either possibility could be explained by the unique stresses associated with disaster incidents that influence offending behavior coupled with the inability of therapeutic guardianship to penetrate into the private sphere of domestic violence. Third, disaster events may have little impact on the frequency of domestic violence but the variation of guardianship that comes in the form of the therapeutic communities allows for heightened detection and reporting of domestic incidents.

A central tenet of routine activities theory is that that guardianship must be "capable." Indeed, therapeutic guardianship applies to most crime contexts. However, therapeutic guardianship is ineffective in reducing the most private forms of crime that occur within the family unit—domestic violence. The idea that therapeutic guardianship is unable to mitigate the occurrence of domestic violence is hardly surprising given that the crime of domestic violence has always presented distinct challenges for criminal justice system actors who have historically struggled with how to respond to, control, and adjudicate cases as part of their guardianship responsibilities.

While our research demonstrates important relationships between natural disasters and crime, it should be considered only a starting point in what should be a more thorough empirical investigation of the topic. First, crime data is sensitive to changes in crime reporting protocols, selective enforcement of laws due to alterations in law enforcement priorities, and inability or unwillingness of citizens to report crime due to a belief that the police are too busy to effectively respond to crime during disaster events

(Mueller and Adler 1998; Siman 1977; Wenger et al. 1975). Future research should therefore use multiple indicators for crime outcomes. Prior research on exceptional events indicates that one must explore a number of crime indicators before making definitive conclusions about the relationship between exceptional events and crime (Decker et al. 2007). Second, UCR data is comprised of crime reports, which are contingent on the ability of the police to respond to and document crime incidents. Future work should examine other sources of data such as public demand for police services (via calls for service) before, during, and after disaster events to gauge the extent of crime as reported by the community. Third, our nonprofit organization density measure is an imperfect estimate of local social cohesion. Because NCSS Core Files undercount religious organizations, future studies may profit from inclusion of church membership data from *Association of Religious Data Archives.* Finally, additional research is needed to further dissect the impact of disaster characteristics on levels of crime. For example, disaster events differ in their degree of predictability, probability, and controllability; in the nature of the precipitating agent (flood, fire, explosion, tornado, hurricane, earthquake, etc.); in their origin (natural, technological, or willful acts of violence); in their speed of onset (instantaneous, progressive); in their scope (focalized, diffused); and in their destructive effects on people and physical objects. By delving more deeply into specific disaster characteristics and human responses to these events, we can better understand the likelihood of an emergent crime problem and provide useful information to residents and decision makers on what to expect after a disaster event.

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Notes

1. More recently, statements on social vulnerability and inequality question the assumption of disasters as “status levelers” (Enarson and Morrow 1998; Hewitt 1997; Peacock et al.1997; Wisner et al. 2004). Scholars find that socially vulnerable or disadvantaged populations have lower levels of disaster preparedness (Edwards 1993; Farley 1998; Russell, Goltz, and Bourque 1995), are less likely to receive and act on official disaster warnings (Fothergill and Peek 2004; Perry and Lindell 1991; Perry and Mushkatel 1986), and suffer more in property damage, injury, and death from disaster events (Enarson et al. 2006; Wright et al. 1979).

2. Studies of unplanned events like blackouts also show how the forces of social cohesion (and therapeutic behavior) may reduce crime and victimization. For example, Genevie et al. (1987), in a neighborhood comparison of looting behavior in the New York City blackout of 1977, report that looting was strongly correlated with levels of neighborhood socioeconomic characteristics, fear, trust, and social cohesion.

3. This includes nonnegligent manslaughter.

4. Florida uses a *Forcible Sex Offense* (FSO) category that is not used in federal statistics. FSOs include forcible rape, attempted rape, forcible sodomy, and forcible fondling. When the forcible rape category is presented it includes rape and attempted rape only, while forcible sodomy and forcible fondling are included in aggravated assault.

5. This includes nonnegligent manslaughter.

6. Data were collected for all publicly available years.

7. As with all data sources the NCSS Core File has flaws. Limitations include: 1) no data are collected on organizations with less than $5,000 in annual gross receipts; 2) data on religious organizations are incomplete because such entities are not required to register with the IRS; and 3) because organizations with multiple locations may file under one consolidated Form 990, the count of nonprofits operating locally is underestimated (Salamon and Dewees 2002). Such limitations—particularly the lack of information of small groups—weaken the validity of our nonprofit organization density variable as a measure of informal social processes that may reduce observed levels of reported crime."

8. There is some evidence to suggest that the decision to release federal monies to disaster affected areas may be motivated by political calculation (Downton and Pielke 2001; Reeves 2007).

9. We also model crime outcomes as rates (crime outcome / population size) using the x*treg* function in STATA. In the *xtreg* model the coefficient on disaster frequency performing even stronger as a negative correlate ($b = -.0002511$, $p < .01$). No matter the specification, the disaster frequency measure is a significant predictor of crime outcomes. Results are available from authors on request.

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