ABSTRACT

Title of thesis: THE EFFECT OF HURRICANES ON BURGLARY IN NORTH CAROLINA COUNTIES, 1999-2003

Amber L. Beckley, Master of Arts, 2008

Thesis Directed by: Professor Laura Dugan
Department of Criminology and Criminal Justice

Hurricanes and tropical storms cause much harm and extensive damage. Their effect on crime is interesting as their precise timing is unpredictable. Yet, there is a limited body of research on this effect. This thesis examines the effect of hurricanes on burglary in North Carolina counties for a five year period between January 1999 and December 2003. It considers both routine activity theory and social disorganization theory to explain how crime may change after a disaster. The results indicate that some social disorganization components interact with a hurricane to produce an effect on burglary. The routine activity proxies used were not significant, but this could have been the result of numerous limitations. Future directions for research include improving and expanding data sources and incorporating alternate theories.

THE EFFECT OF HURRICANES ON BURGLARY IN NORTH CAROLINA COUNTIES, 1999-2003

by

Amber L. Beckley

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Advisory Committee:
Professor Laura Dugan, Chair
Professor Raymond Paternoster
Professor David Kirk

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I. Introduction

Researchers have occasionally studied whether special events, such as holidays, have an effect on patterns of criminal offending (Cohn and Rotten, 2003; Zimring, Ceretti, and Broli, 1996). However, very few have investigated patterns of offending surrounding a relatively unexpected event. One such type of event is a weather disaster. A weather disaster is a natural meteorological phenomenon that causes physical destruction and social disruption. The government is primarily responsible for maintaining social control and alleviating the many problems that a disaster brings with it. Unfortunately, policymakers have little empirical research from which to draw upon when forming policy for such an event. This can cause them to rely on myths and anecdotal information.

Two commonly held beliefs are that mass panic and looting occur in the wake of a disaster. According to Dynes and Tierney (1994), the mass panic phenomenon has been proven to be inaccurate. Looting, however, is more complicated. While narrowly defined as theft, it connotes a crowd of people wildly stealing from abandoned businesses and residences. Using the standardized definition of burglary, "the unlawful entry of a structure to commit a felony or theft" (Department of Justice, Federal Bureau of Investigation,
http://www.fbi.gov/ucr/cius_04/offenses_reported/property_crime/burglary.html,
accessed on June 13, 2007) looting would be a post-disaster surge in burglary.

To further complicate policy formation, research indicates that media portrayals of crime problems following a disaster are inaccurate (Drabek, 1986; Wenger and

Friedman, 1986). This effect is likely heightened by a scarcity of empirical evidence regarding crime in the wake of a disaster. This leads one to question what exactly disaster-crime policy is based upon. Drabek (1986:47) notes that "the greater the degree that disaster plans reflect myths about social behavioral responses, the greater the likelihood they will be ineffective." Ineffective policies can lead to a waste of resources and distract attention from more urgent concerns. The goal of this thesis is to help eliminate myths surrounding the effect of weather disasters on burglary through empirical analysis. I specifically consider the relationship between burglary and hurricanes/tropical storms (here forward referred to as "hurricanes") in North Carolina counties over a 60 month period to answer the question: what is the effect of a hurricane on burglary?[1] In the first section, I discuss weather disasters and responses. In sections II and III, I incorporate criminological theory into weather disaster response. In section IV, I discuss the data and method. The results and discussion of the analysis are covered in sections V and VI, respectively. Section VII discusses the limitations of this study and Section VIII contains the implications and conclusion.

[1] Hurricanes and Tropical Storms differ in terms of wind speed. Hurricanes have sustained winds of greater than 73 miles per hour. Tropical storms have sustained winds of 39-73 miles per hour (http://www.nhc.noaa.gov/HAW2/english/basics.shtml). Upon reviewing the events in the proposed thesis I found that most tropical storms resulted in or from hurricanes and were sufficiently destructive. The term "hurricane" will be used to generically capture all of these events unless a specific event is being discussed.

II. Weather Disasters

There is a wide body of literature concerning the social impact of disasters. What is known about the effects of disasters is that they have a severe psychological impact on individuals (Sowder, 1985). In this section I discuss the government response to hurricanes and how crime policy can be incorporated into that response. I then outline a few examples of disaster preparation efforts that could impact crime. I also discuss broad social effects of a disaster, and then consider the specific effects a disaster has on crime. I conclude with a summary of the implications for this proposed thesis.

Government Policy and Hurricanes

According to Schneider (1992), the government's general response to weather disasters should have three objectives: (1) preparing areas for potential emergency situations; (2) providing immediate relief after a disaster strikes; and (3) helping individuals and communities recover from the effects of a disaster. If crime does in fact increase following a disaster, then its prevention should be a priority throughout these objectives. If, however, crime levels are not affected by a disaster more emphasis can be placed on providing other types of aid to disaster victims. In order for the government response to achieve these objectives it is important that each response be tailored to the specific type of the disaster as each disaster presents a unique situation.

Perry (1985) developed a disaster classification scheme which combined the work of Barton (1970) and Anderson (1969). His five dimension scheme covers the scope of the impact of the disaster, the speed of onset, the duration of impact, the secondary impact, and social preparedness. The scope of the impact refers to the size of the affected area. The speed of onset is the amount of time between when warning of the event is received and when the event begins. The duration of the impact is the length of time that the disaster persists. The secondary impact includes other effects of the disaster such as physical destruction, health risks, and environmental hazards. Social preparedness refers to the predictability of the disaster (Perry, 1985:18).

Hurricanes present unique situations when classified with Perry's (1985) typology. Hurricanes affect very large areas; the track of an entire storm system can range thousands of miles. Hurricanes are detected well in advance of their landfall providing ample warning time for reaction. During the time between the initial warning and the onset of the hurricane people can prepare for the deleterious conditions and act in ways to prevent loss. Hurricanes typically last for a few days, and can cause damage that takes weeks or even months to repair. Finally, hurricanes usually occur during "hurricane season" – the six month period between June and November (North Carolina Division of Emergency Management, http://www.nccrimecontrol.org/index2.cfm?a=000003,000010, accessed on June 13, 2007) – and generally only affect specific areas. In other words, people generally know where and when a hurricane may occur and may use this information to make preparations far in advance.

Some preparation efforts, such as choosing not to vacation during hurricane season, stocking up on emergency items, and boarding up homes may affect crime after a hurricane occurs. Yet, it is questionable whether citizens consider their vulnerability to crime while preparing for a hurricane. It has become the responsibility of the government to take the unique circumstances presented by each hurricane into consideration and prepare appropriately in order to minimize damage and loss.

Disaster Preparation

Disaster preparation includes a variety of actions aimed at reducing harm via actions prior to the onset of the disaster. I consider three specific factors that are administered by the government: warnings, mobilization of emergency relief, and evacuation protocol and procedure. I discuss these factors in order to describe a few of the major processes that go on prior to a disaster. I have not included these processes in the data analysis because there is no systematic documentation of the actions taken prior to each hurricane. I discuss the possible effects of the exclusion of these variables in the limitations section.

Warnings

It is important to include a discussion of warnings because they could have an effect on burglary. Both potential burglars and potential victims are able to receive warnings. Warnings can draw burglars to an area or make them shy away. Burglars may be drawn to an area if they believe that the danger is minimal and know that people have left their homes vacant. Conversely, they may heed the warning and also be concerned by the danger caused by the threat. Potential burglary victims may heed warnings and hastily leave their houses in an unsecured state. However, potential victims may be wrought with concern about damage to their homes and board up windows, making them more difficult to penetrate. While the potential effects of a warning are apparent on the surface, the process of warning response is complex and not easily predicted.

Fitzpatrick and Mileti (1994) describe ten aspects to warning dissemination that create different responses depending on how they are combined and carried out. They are: (1) the source of the message, (2) the consistency of the information, (3) the accuracy of the message, (4) the clarity or understandability of the message, (5) the level of certainty of the impending disaster conveyed by the message, (6) the completeness of the information, (7) the guidance provided by the message, (8) the frequency with which the message is relayed, (9) identification of the level of risk for specific locations, and (10) the method of message delivery.

In addition, warning response consists of a two step process. First, the individual evaluates the situation. This step consists of five stages. First, the person is first made aware of the warning. He or she must then understand and believe the warning. After this, he or she must evaluate the risk. In the fifth stage the individual chooses what to do and proceeds into the second step of the warning response – reaction.

People choose among two main courses of action: to remain in the area or to evacuate. The type of action they choose is affected by five factors (Fitzpatrick and Mileti, 1994). The first factor is environmental cues. Environmental cues are personal evaluations of the potential harm of a disaster based on the state of the environment at the time. Second is the social setting in which the warning is received. The third factor is social ties; these connections to others operate to push people to stay in an area or leave. Fourth, the receiver's sociodemographic characteristics (such as age and sex) influence how the individual evaluates the warning. Finally, psychological factors (such as variation in mental capacity) affect reaction to warnings.

These many factors can lead to many different variables that may impact burglary: whether an individual evacuates, when an individual evacuates, the amount of time spent inside the home if the individual remains, and the measures taken to protect a home. Again, the effect of not including the many aspects of a warning is discussed in the limitations section.

Emergency Relief

Emergency relief efforts are important procedures that serve to return the community to normal functioning as quickly as possible. These efforts can also provide an opportunity to practice crime reduction, should crime be a disaster-related problem. There are two types of emergency relief: pre-disaster and post-disaster. Pre-disaster efforts are intended to lessen the overall physical and social impact of the disaster prior to its occurrence. Pre-disaster efforts consist of mobilization of the National Guard, preparation of shelter sites, and mobilization of volunteers, for example. Pre-disaster relief is likely to occur for a hurricane because of the substantial amount of warning received.

Post-disaster relief serves to return the community to normal functioning as quickly as possible Post-disaster relief can encompass the aforementioned actions and also includes providing funds. Funds are allocated to repair public facilities, provide victims with subsidies, and support shelters. Provisions for post-disaster relief can be included in preparation efforts.

Pre- and post-disaster efforts that draw numerous volunteers and emergency relief workers to the area may dissuade burglars from coming into the area for fear of being detected. However, if burglars are aware that many have abandoned their houses for shelters, they may be encouraged to target the abandoned area. Finally, if post-disaster funds are used to acquire new goods, burglars may again be drawn to the area. Pre-disaster and post-disaster efforts that may help reduce crime are citizen education on potential victimization and increased police presence.

Evacuation

There are two types of evacuations: post-impact and pre-impact. Evacuations can be mandatory, voluntary, or recommended. The type of evacuation is determined by the expected or actual harm of the hurricane. Evacuations are either short- or long-term. Short-term evacuations are less socially disruptive. Long-term evacuations can produce severe social consequences (Perry et. al. 1981) and can lead to permanent vacancy (Smith and McCarty, 1996). Like warnings, evacuations are not simple processes and it is important to consider each decision point.

Perry (1994) notes that six variables affect the decision to evacuate: confirmation that the warning is real, confirmation that the warning comes from a reliable source, information about the nature of the threat, the perception of the amount of danger posed by the threat, possession of an evacuation plan, whether all family members are accounted for. An additional variable, not mentioned by Perry, is the ability to evacuate.

Evacuation may have an effect on burglary in an area. First, evacuations leave many homes unguarded. Those residing in affected areas are required to leave and eventually the police must leave the area to avoid danger as well. Police typically set up road blocks to prevent people from entering evacuated areas. However, police may also be forced to evacuate, leaving the area unguarded. Second, the mass exodus of refugees is likely to have a social impact both in- and outside of the affected area. Inside the area, residents that ignore evacuation orders may form a social network that serves to protect property and ward off intruders. Outside of the affected area, shelters are set up. Shelter areas may experience increased burglary as a result of the social disruption caused by the influx of many evacuees.

The extent to which people evacuate may depend on the composition of the affected area. Research indicates that minorities are more likely to have lower perceptions of threat and less likely to believe warnings (Perry and Mushkatel, 1984). As such they are less likely to evacuate (Perry and Mushkatel, 1984). This finding is bolstered by evidence that as people's perception of danger increases, the probability that they will comply with an evacuation order increases (Drabek, 1986). Thus, predominantly minority neighborhoods may retain many of its residents during a disaster.

Social Outcomes of a Disaster

In general, research has found two competing outcomes of a disaster. Either chaos occurs in the form of panic, riots, mass exodus etc.; or there is increased community cohesion – people form an altruistic community with goals of reparation. These outcomes also vary in their duration.

Increased Cohesion

Studies that report increased cohesion do not find that these effects persist over the long-term. Friesema and colleagues (1979) reviewed multiple weather disaster sites and found that, in general, cohesive communities did form briefly, but the immediate changes following the disaster did not survive over the long-term. They also found a short-term decrease in divorce rates immediately following the disaster; however, within five months the rates returned to their previous levels.

Drabek and colleagues (1975) analyzed Topeka, Kansas after a tornado. They found that disaster victims were happier in their marriage and had improved their immediate family interactions. But, interaction with extended family members decreased. Drabek and colleagues also found a decrease in divorce rates immediately following the disaster; however, that effect only lasted for a short period of time.

Increased Chaos

In contrast to research that finds cohesion, studies that find negative outcomes note that these outcomes persist. Two studies found that there were permanent changes in the community following a disaster. Erikson (1994, 1976) found that community social disorganization is permanently affected after a disaster. Smith and McCarty (1996) found that 33 percent of the population permanently left the area after a disaster.

In addition, Siegel and colleagues (1999) conducted a series of interviews with independent samples of residents in Los Angeles County for two years following the Northridge Earthquake in 1994. They found no increases in social disorganization or community cohesion. Rossi and colleagues (1983) also found no long-term demographic changes at the county level. In summary, there are conflicting results as to what occurs following a disaster and also in how long these outcomes persist.

Crime Outcomes of a Disaster

The crime-related research following a disaster is no more conclusive than the research that considers general social outcomes. Siegel (1999) in the aforementioned study, found no change in crime. Lemieux (2004) looked at rates of crime during Quebec's ice storm and found a significant rise in property crime. He attributed this to an increase in the opportunity to commit crime.

Friesema and colleagues (1979) analyzed crime after a hurricane in Galveston, Texas and found that the number of assaults reported decreased for approximately four months after the disaster. They stated that this result could have occurred for two different reasons. First, increased ties to family could have prevented assaults from occurring. Alternately, they realized that the finding could be an artifact of the data. The police may have been unable to detect and properly record assaults because the disaster disrupted their activity. Friesema and colleagues also found that auto theft increased. This increase, however, persisted for more than six months. They explain that the disaster could have damaged vehicles, making them easier to steal. They do not formally test this assertion and do recognize that this is only one of many plausible scenarios.

LeBeau (2002) looked at police calls for service following Hurricane Hugo in North Carolina. He found that the police calls for service drastically shifted to other times of the day and argued that it was a result of changed routine activities. He separated routine activities into two types: discretionary and obligatory. Discretionary activities were activities that people chose to engage in, like going to the movies. Obligatory activities were activities that people were generally obligated to do, like going to work or school. LeBeau stated that when the hurricane struck there was an anomalously high amount of calls for service during the time when people would normally be involved in obligatory activities (e.g. on a weekday morning) and a decrease in the amount of calls during typical discretionary time when calls for service peak (e.g. throughout the weekend). LeBeau also analyzed the overall number of calls for service and found an increase in all categories at least two standard deviations above the daily mean on at least one occasion in the ten days following Hurricane Hugo. He concluded that Hurricane Hugo altered routine activities, patterns in calls for service, and the number of calls for service.

Cromwell and colleagues (1995) analyzed crime following Hurricane Andrew and also took a routine activity theory perspective. They found no change in the amount of reported crime. They observed that the community increased its self-reliance and individuals served as their own guardians. Cromwell believed that official crime statistics may be distorted because the entire police department had been destroyed and officers were not available (personal communication, November 2007).

Implications

The government plays an important role in disaster response. I have demonstrated in this section that policies and procedures can have an impact on citizen action both before and after the disaster. Evacuation policies are probably the most important policies affecting burglary. First, evacuations leave many homes unguarded. Those residing in affected areas are required to leave and eventually, due to rising danger levels, the police must evacuate as well. Police typically set up road blocks to prevent people from entering evacuated areas. However, after they too have evacuated, anyone is able to access the area. Second, the mass exodus of people is likely to have a social impact in affected areas as well as the areas to which victims flee. Inside the area, residents that ignore evacuation orders may form a social network that serves to protect property and ward off intruders. Outside of the affected area, shelters are set up. Shelter areas may experience increased burglary as a result of the social disruption caused by the influx of many evacuees.

There are mixed results as to the type of social impact a disaster has upon the community. In addition, there are inconsistencies as to whether the effect is long- or short-term. Also, evacuation rates may differ according to the racial composition of an area. The mixed results may indicate that social processes vary across communities. Therefore, I consider two theories to assess the hurricane-burglary relationship. I begin with a discussion of routine activity theory in order to explain how crime could occur after a hurricane. Then I incorporate social disorganization theory to explain how the effect of a hurricane may differ across counties.

III. Routine Activities and Hurricanes

Routine activity theory was first proposed by Cohen and Felson (1979) in order to explain how crime rates increased after World War II. They theorized that there is always a pool of motivated offenders: people waiting for the "right" situation to commit a crime. The right situation has unguarded suitable targets. In this section I summarize routine activity theory and establish the ties between changing routine activities and burglary. I also discuss how routine activities can change after a hurricane.

In addition, I tie routine activity theory into social disorganization theory in order to provide a more comprehensive explanation of criminal behavior. One of the primary difficulties with finding full support for routine activity theory is that all of its components are not tested. I discuss this and other weaknesses. Finally, I discuss the implications for this proposed thesis.

Routine Activity Theory

Cohen and Felson (1979:593) state that routine activities are, "any recurrent and prevalent activities which provide for basic population and individualistic needs." These include work, school, and other activities both in- and outside the home. They assert that three things are necessary for the commission of a crime: a motivated offender, a suitable target, and the lack of a capable guardian. On a macro-level, any gross changes in these elements will produce a change in crime rates. Cohen and Felson analyzed crime statistics from an approximately twenty-year period after World War II. They found that burglary (among other crimes) had increased. They attributed this to a macro-level shift in how people spent their time and the increased portability of goods.

During the post-World War II period more women went to work during the day, people got married later in life, and divorce rates increased. As a result, the number of homes left vacant during the daytime, the time when burglary occurs most often (Reppetto, 1974), increased. This gave burglars more unguarded targets as they prefer to avoid contact with victims/guardians (Shover, 1991).

At the same time, the number of suitable targets increased because of changes in the nature of goods. Appliances and electronics became smaller and more valuable. They were more portable and easier to steal. Cohen and Felson (1979) empirically demonstrated that changes in targets and how guardians spend their time was related to increases in crime.

Hurricanes and Routine Activity Theory

A hurricane could affect all of the elements in routine activity theory. Motivated offenders may be drawn to an area if they are aware that homes will be abandoned (Decker et. al, 2007). Conversely, offenders may be forced from an area if the weather is too severe.

Reppetto (1974) found that, in general, burglars were not especially skilled and often chose targets based on ease of access. A hurricane may damage homes in ways that make them more accessible, increasing the number of suitable targets. Alternatively, the number of suitable targets could decrease if people made efforts to protect their homes from damage by, for example, boarding up windows. If the only reasonable access point is the door, certain rare skills, such as lock picking, may be necessary to enter.

Three types of capable guardians may be available during a hurricane. First, the police are formal capable guardians. During a hurricane they may be present in high numbers. They may, however, be forced to leave if the weather is too severe. Also, it is questionable whether police can guard against burglary as it often occurs inside a private residence. At a minimum, police have been trained to look for and recognize criminal behavior and they are available around the clock.

Second, homeowners are also potential guardians. They may evacuate, leaving their home empty or, if they choose to stay, they may spend more time at home than they would under normal circumstances. Finally, community groups can form during a hurricane. These groups may engage in "neighborhood watch" activities and step in when police are unavailable. These groups may be better at policing burglary because they are likely more aware of the whereabouts of the homeowners. However, these groups are unable to perform in the same capacity as police; they are not likely to operate 24 hours per day and also do not have police training.

Routine Activity and Social Disorganization

Routine activity and social disorganization theory have been linked on the individual level. Researchers theorize that characteristics of social disorganization that are found in individuals can be combined with routine activities to alter individual predisposition to crime. Miethe and colleagues (1987) observed that routine activity patterns were correlated with demographic variables and both affected victimization for property crimes. One component of social disorganization theory is lack of control of minors. This component was incorporated into routine activity theory by Osgood and Anderson (2004) who found that unsupervised juveniles who were involved in unstructured activity had both increased delinquency and increased victimization. Smith and colleagues (2000) also made an empirical connection between the two theories by interacting them in a statistical model. They found that the interactions were significant.

Weaknesses of Routine Activity Theory

Meier and Miethe (1993: 485) identify a few weaknesses of routine activity theory. The first weakness, also present in many other criminological theories, is what they term "theoretical indeterminacy, or the ability of the same indicator to serve more than one theoretical master". Proxies are often used which capture more than the construct they are attempting to measure. For example, population density, which is often used as a proxy for the number of offenders and targets, can also indicate levels of social control. This problem is related to the second problem of relying on secondary data. Meier and Miethe state that secondary data can be problematic when it is not collected with the sole intent of looking at routine activities. The variables in these datasets were not intended to measure constructs of routine activity theory and therefore may not be capturing the constructs. The third problem is that all relevant variables are often not included in research designs and statistical models. Researchers often only look at one or two of the elements of routine activity theory. When they exclude elements, they fall short of testing the full theory. This raises questions about the reliability of the theory.

Implications

Routine activity theory has been successfully applied to burglary, making its application in the present study appropriate. It has also been successfully applied in previous research on weather disasters and crime. In addition, the theorized changes that could occur in the three elements provide support for its use. The present study builds on previous routine activity research by adding a new proxy to measure a change in routine activity theory. This study does not, however, resolve some of the other weaknesses of routine activity theory.

While routine activity theory may explain increases or decreases in burglary after a hurricane, it fails to explain the divergent outcomes of community cohesion and chaos and how these outcomes affect crime. The issue of "theoretical indeterminacy" can also be resolved by incorporating specific measures of related theories, like social disorganization theory. For these reasons, I next consider social disorganization theory and its potential effects on post-hurricane burglary rates.

IV. Social Disorganization Theory

Shaw and McKay (1942) developed social disorganization theory after tracing patterns of delinquency over 30 years in Chicago neighborhoods. They used a social ecology perspective and the idea of concentric zones developed by Park and Burgess (1924) to develop their theory. Shaw and McKay tracked delinquency by concentric zone and noticed that it remained relatively stable despite changing demographic characteristics of the neighborhood inhabitants. They concluded that the stable crime rate was an inherent property of the area itself. These areas were socially disorganized and social disorganization was an endemic property of the location that did not go away even if there was a change in the residency. Social disorganization consists of a breakdown in community institutions. Shaw and McKay were quite vague as to exactly how or through what process social disorganization contributed to delinquency. They were, however, very clear that actual social disorganization is something that cannot be quantified (1942). The social interactions in a neighborhood have to be qualitatively observed and evaluated.

Sampson (1987) and Kornhauser (1978) have since clarified how social disorganization affects crime. Social disorganization impedes the formation of social networks. Social networks serve to control crime; according to Sampson they provide a supervisory function. Hence, areas that are socially disorganized have few or limited social networks and higher crime. Social disorganization theory typically uses the neighborhood or standard metropolitan statistical area as its unit of analysis. However, Osgood and Chambers (2000) have successfully applied the theory to counties.

In order to facilitate empirical studies, researchers have developed quantifiable constructs. There are many variations of these constructs. Those most commonly used capture socioeconomic status, residential instability, racial and ethnic heterogeneity, urbanization, and “supervision” (Jacob, 2006). These constructs typically use some type of spatial measurement as a unit of analysis (i.e. a city block or a standard metropolitan statistical area). In general research has supported linking these constructs to social disorganization and crime. They are, however, not without their problems.

Social Disorganization Constructs

Socioeconomic Status

Socioeconomic status consists of far more than monetary factors; however, measures typically include income or poverty. Lander (1954) produced very controversial evidence that indicators of socioeconomic status (e.g. average education, average rent) were not statistically significant predictors of delinquency. His research was highly criticized and was essentially discredited for multiple methodological reasons (see Chilton 1964; Bordua 1958-59; Rosen and Turner 1967). More recent studies have found support for socioeconomic status as a contributing factor to social disorganization and increased crime.

Land, McCall, and Cohen (1990) investigated inconsistent results across multiple studies testing social disorganization covariates. They considered studies that used census data from 1950 thru 1980. They found that relative deprivation was consistently associated with homicide across the four decades.

Sampson and Groves (1989) also found that socioeconomic status was an explanatory factor in differential involvement in crime in Great Britain. They used self-report surveys to assess both violent and non-violent crime and found correlations with the constructs for both types of crime. However, some of the differences in crime rates due to social disorganization were quite small.

Smith and Jarjoura (1988) studied the impact of social disorganization on burglary using victimization data. They found that socioeconomic status was not a significant factor in burglary when other social disorganization variables were included in the model.

Bursik and Grasmick (1993) found that economic factors significantly affected crime. They also concluded that contradictory findings regarding socioeconomic status may be the result of looking at measures that do not capture economic deprivation, which they claim to be the more relevant factor. They argue that economic deprivation is more sensitive to variation at the low end of the socioeconomic scale than other general measures of socioeconomic status.

Residential Instability

The stability of a neighborhood is often measured by the rates of in- and out-migration or by average length of residency. Residential instability prevents neighbors from forming social networks, which in turn causes a loss of control. According to Kornhauser (1978), social networks suffer because residents fail to communicate with one another. Communication is hampered by the short amount of time people stay in the neighborhood. Residents are unable to form strong lines of communication because they do not stay in the area long enough. Some residents are also aware that they will only be temporary residents and avoid commitment to the neighborhood.

Kasarda and Janowitz (1974) found a significant positive effect of length of residence on informal network formation in Great Britain. Tittle and Paternoster (1988) also found that mobility has an indirect effect on crime; it lowers commitment to neighborhood morals and thus increases crime. Sampson and Groves (1989) also found that residential instability significantly inhibited informal social networks.

Crutchfield and colleagues (1982) analyzed crime in the 65 largest standard metropolitan statistical areas. They found that residential mobility was significantly and positively related to violent and property crime; the effect was strongest for burglary. They concluded that social integration broke down in those areas (Crutchfield et al.: 475). Smith and Jarjoura (1988) also found that residential mobility significantly impacted burglary.

South (1987) and Messner (1986) both found that in-migration was significantly and positively related to crime. South considered out-migration as well but found that the effect lost significance when in-migration was incorporated into the model.

Racial and Ethnic Heterogeneity

Racial and ethnic heterogeneity is typically measured by the proportion of non-whites living in an area. Racial and cultural differences cause distance between residents and impedes the creation of informal social networks. Language barriers also prevent residents from communicating with one another in an efficient and productive manner. It can also be a basic inability to find commonalities among people of different cultures.

Sampson and Groves (1989) found that ethnic heterogeneity hindered the formation of informal social networks in Great Britain. Markowitz and colleagues (2001) also used data from the British Crime Survey and found a significant positive relationship between ethnic heterogeneity and crime.

One consistent problem with determining the effect of racial and ethnic heterogeneity on crime is its confluence with poverty. This issue has lead researchers to draw different conclusions on the function of these variables. For example, in his study of Chicago neighborhoods, Small (2007) found that poverty was confounded with racial composition. He concluded that in neighborhoods where minorities were the majority, poverty, not the predominantly minority population, was prohibiting the formation of informal social networks.

Urbanization

Shaw and McKay (1942) postulated that urban areas would have higher social disorganization and hence higher crime. Researchers have found that urbanization is a valid construct in social disorganization and crime. Hartnagel and Lee (1990) looked at Canadian cities with populations greater than 25,000 people. They found that larger cities have both higher property and violent crime rates. Markowitz and colleagues (2001) also found that urbanization was a significant factor in explaining crime in Great Britain.

There has been some research questioning the uniqueness of social disorganization to urban areas. For example, Osgood and Chambers (2000) analyzed over

250 non-metropolitan counties and found social disorganization. They also found that social disorganization affected crime in those areas. Shannon (1998) looked at the small town of Racine, Wisconsin and found that it was socially disorganized as well.

Control of Minors

Control of minors is the final construct and is often measured by the number of single-parent households or by a ratio of adults to children. Shaw and McKay (1942) stated that the ability to control teenage peer groups was an important part of being socially organized. They failed, however, to specify how minors are to be controlled. As such this construct has been called many different names. For example, Jacob (2006) used the term “supervision”; Sampson (1987), “family disruption”; and Korbin (1991), “loss of trans-generational control.”

Markowitz and colleagues’ (2001) and Jacob’s (2006) research supports family disruption as a positive significant factor in crime. The legitimacy of this construct is rarely disputed because of the abundance of research in many fields indicating that children from single-parent households are at a higher risk of engaging in delinquent behavior (see for example Demuth and Brown, 2004; Thomas et al., 1996; Antecol and Bedard, 2007).

Problems with Social Disorganization Theory

Despite substantial support for social disorganization theory, it still has weaknesses. Bursik (1988) identified five problems with social disorganization theory. Some of these problems have implications for this proposed thesis.

Bursik (1988) first noted that criminology shifted from a macro to a micro level approach. Individual level characteristics were used to explain criminality, not environmental factors. This shift in emphasis indicates that social disorganization theory lacks the explanatory power in explaining crime that individual level theories do. The shift however, does not mean that environmental explanations of criminal behavior have been discredited. Taking a macro-level perspective is still appropriate and still receives a significant amount of scholarly attention.

Bursik (1988) also identified the assumption of stable ecological structures as a problem. Researchers often used demographic data to determine whether an area is socially disorganized. Unfortunately, demographic data that is gathered too infrequently to reflect changes in the population could be related to social disorganization. To combat this problem, researchers have used longitudinal data. In addition, Kubrin and Weitzer (2003) recommend using growth curve models to assess how neighborhoods vary in their level of social disorganization over time.

Third, Bursik (1988) recognized problems with how crime and delinquency are measured. This is a persistent problem in official data. In order to be included in the Uniform Crime Reports a crime must first be reported to the police. The police must then corroborate the incident and properly record it. Mosher, Miethe, and Phillips (2002) identify attempts to deflate statistics by misclassifying crimes and manipulating data. This problem is not unique to social disorganization theory. All research that uses official data is subject to this flaw. However, the issue still persists.

According to social disorganization theory, crime is more prevalent in areas with high levels of social disorganization. Perhaps these areas are subject to more attention from the police and more stringent reporting by the police. Also, citizens in disorganized areas may be more likely to use the police as a means to solve problems because, by definition, they are unable to effectively do so themselves. Hence, higher rates of crime could in reality be an artifact of social disorganization. However, studies that compare official and unofficial data still find support for social disorganization theory (Sampson, 1985; Sampson and Groves, 1989; Elliott et al., 1996; Gottfredson et al., 1991)

Bursik (1988) identifies the difficulty in measuring social disorganization as a fourth problem. While many of the concepts have been quantified, researchers have not reached a consensus on how to operationalize some of them. Sampson and Groves (1989) point out that an important reason why measurement has been a problem is because there is a lack of usable data. Data from official sources are often ill-suited for the measurement of social disorganization and gathering data independently requires funds. This is most clear with the constructs of cross-generational control and socioeconomic status (Bursik and Grasmick, 1993).

Finally, Bursik (1988) finds fault in the normative assumption of social disorganization theory. The normative assumption states that a collective consensus must exist in order to solve problems. Bursik (1988:535) points to research by Rossi and colleagues (1974) and Sellin and Wolfgang (1964) that indicates that a reasonable assumption is that residents want a life-style free from the threat of serious crimes. In other words, the community can have heterogeneous norms and values and still be crime free.

Implications for the Present Study

The literature supports social disorganization as a factor that influences crime. It operates by hindering the formation of informal social networks. As a result, communities are unable to informally control crime prone residents and crime increases. Research has been fairly consistent in finding support for the factors associated with social disorganization and their subsequent influence on crime.

Social disorganization theory may help explain why there are different outcomes after a disaster. Communities that are socially disorganized are unable to maintain social control under normal circumstances. When a catastrophic event is introduced, social disorganization may compromise the small amounts of social control in those communities. Those who are of low socioeconomic status will be unable to vacate or properly protect their homes. The lack of communication formed by cultural divisions and shifting populations will likely dissuade people from relying on their neighbors during a time of crisis. Single mothers will be consumed with the responsibility of protecting their children and taking care of their homes, rendering them unable to help the community after a hurricane. As such, an altruistic community is unlikely to form and mass panic may result. This state of chaos could mean more opportunities to steal.

Conversely, in a community with well-formed networks, neighbors may find it natural to rely on one another during a disaster. Most residents are financially able to repair damages as well as offer aid to their neighbors. Since the neighborhood is ethnically homogenous there is an increased chance that residents share culture as well. Thus, during a hurricane, it is more likely that those involved will have similar priorities and concerns. Intact families are able to share the responsibilities of protecting the household and managing the children; they may even be able to help others due to their increased efficiency. It is easy to envision how, during a disaster, a socially organized community could pull together and discourage crime through increased social control.

Hypotheses

I have developed two hypotheses that apply routine activity theory and social disorganization theory to a hurricane. As the literature has established, hurricanes affect routine activities. I assert that the threat of being harmed is what causes people to change their patterns of behavior and that the more severe the weather disaster, the more people will alter their routine activities. To the extent that routine activities move away from their norm, crime will increase because of the new patterns create new opportunities and targets for crime. Hence, the first hypothesis is that *the amount of damage caused by a hurricane is positively related to the rate of burglary.* I expect that this relationship will be curvilinear with diminishing returns as the severity of the storm – as measured by the amount of damage – increases. This is likely to occur for two possible reasons. First, if a disaster causes billions of dollars worth of damage, it is likely that there will be few objects left to steal. Second, disasters with extreme amounts of damage are often very dangerous and force everyone, including would-be thieves, from the area.

The second hypothesis attempts to address the issue of different post-disaster community responses and the effect that such responses may have on crime. In this study, I assume that residents want a relatively crime-free environment. I also assume that the extent to which such an environment is achieved depends on the formation of informal social networks. This, in turn, requires some level of social organization. I argue that in locations with high social disorganization, post-hurricane rates of burglary will increase. The disaster introduces more chaos into the environment and, after the hurricane, residents that are typically unable to control crime experience a more pronounced level of crime. Thus, the second hypothesis is that: *the interaction of social disorganization and a hurricane is positively related to the rate of burglary*.

V. Data and Method

This section provides an overview of the proposed data and methodology that will be used in the thesis. First, I describe the sources of the data and give a qualitative account of the hurricanes that are in the dataset. Next, I state the proposed model. I follow this with a description of the variables. Finally, I address pre-estimation issues.

Description of the Data

The data from this thesis includes North Carolina's 100 counties over a 60 month period between January 1999 and December 2003; totaling 6000 observations. I comprised the dataset from three sources. The crime data come from the Uniform Crime Reports (UCR). Only crimes reported to and corroborated by the police are in the UCR. The UCR data is assembled by the Federal Bureau of Investigation (FBI) from police departments on an annual basis. The UCR includes information on burglaries as one of its index crimes. For this thesis, the number of burglaries has been summed across all of the reporting departments in each county for each month.[2]

The data on social disorganization comes from the United States Census Bureau, which is responsible for conducting the Census.[3] The Census is delivered in questionnaire form and is conducted decennially. It captures basic information on the entire population and also generates imputed data for an extended questionnaire. This extended

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[2] The County figures were calculated from the jurisdiction data and the Census population as opposed to using the UCR County Data because of the population and imputation problems with UCR county-level data identified by Maltz and Targonski (2002). They noted that the population figures in the UCR county-level data were often incorrect and noted significant problems with the imputation procedures used by the FBI which have not yet been fully resolved.

[3] The exception to this is the number of non-white residents which was obtained from the North Carolina Office of State Budget and Management.

questionnaire contains more detailed information on income, education, and employment, for example. The census variables are assumed to be constant across all time periods. The problems with this restriction are discussed in the limitations section.

Information on the control variables comes from North Carolina's Office of State Budget and Management. This office estimates county populations by age and sex. A complete description of how the estimates are derived is included in the first Appendix.

The hurricane data come from the National Oceanic and Atmospheric Administration (NOAA), a federal body responsible for the National Weather Service and other ocean and weather related agencies. There were 5 hurricanes/tropical storms in North Carolina recorded by NOAA during the period of observation (see Table 1).[4] Figure 1 displays the path of the hurricanes included in the analysis. The eastern region of the state was primarily affected. The second Appendix contains color-coded maps of the specific counties affected by the storm.

The first, Hurricane Dennis, made landfall on August 30, 1999. After a brief stay on land Dennis went out to sea and returned some days later (September 4, 1999) as a tropical storm. Reports state that no one was injured and that the biggest losses were to commercial crab fishermen (Pressley, 1999a). Some areas had washed out roads and

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[4] The North Carolina State Climate Office (NCSCO) provides different information on the number of storms that affected North Carolina during this time period. Their data states that nine hurricanes/tropical storms affected North Carolina and two made landfall between January 1999 and December 2003. Their information excludes the specific counties affected, narratives of the events, estimates of damage, or estimates of injury and death. Because this data was less comprehensive, the data from NOAA was used. The six additional events that are included in the NCSCO data set were all non-landfalling, category one hurricanes or lower, with winds no higher than 75 miles per hour. The NCSCO states that this type of storm typically causes minor damage to vegetation. The strongest storm was hurricane Kyle which was classified as a tropical depression – sustained surface winds of less than 39 miles per hour – for the majority of the time it passed over the eastern coast of North Carolina.

flood waters up to four feet deep (Fallis and Perlstein, 1999). In Carteret County, located on the coast, approximately 400 people went to shelters (Pressley, 1999a).

Table 1. Distribution of Hurricanes over time in North Carolina

Hurricane Name	Month & Year Occurred
Hurricane Dennis	August 1999
Hurricane Floyd	September 1999
Hurricane Irene	October 1999
Tropical Storm Gustav	September 2002
Hurricane Isabel	September 2003

Hurricane Floyd came shortly after on September 14, 1999. Hurricane Floyd was much more devastating than Dennis, with losses estimated at six billion dollars (Brooks, 1999). Over one-half of the state was affected and the entire eastern third of the state was impassable (Firestone, 1999). A state of emergency was declared and coastal islands were evacuated (Pressley, 1999b). Over one-thousand people had to be rescued from the roofs of their homes after being forced there to escape flood waters (The Sun, 1999a). Thirty-thousand people's homes were flooded, and 10,000 people had to go to shelters (The Sun, 1999b). One million people lost power (Fisher, 1999) and a few factories shut down (Matthews and Hagerty, 1999). Over one million livestock perished and there was an estimated 1 billion dollars in agriculture losses (Kilborn, 1999). A twelve hour curfew, between seven pm and seven am, was ordered in the city of Rocky Mount in order to prevent looting (Kilborn, 1999).

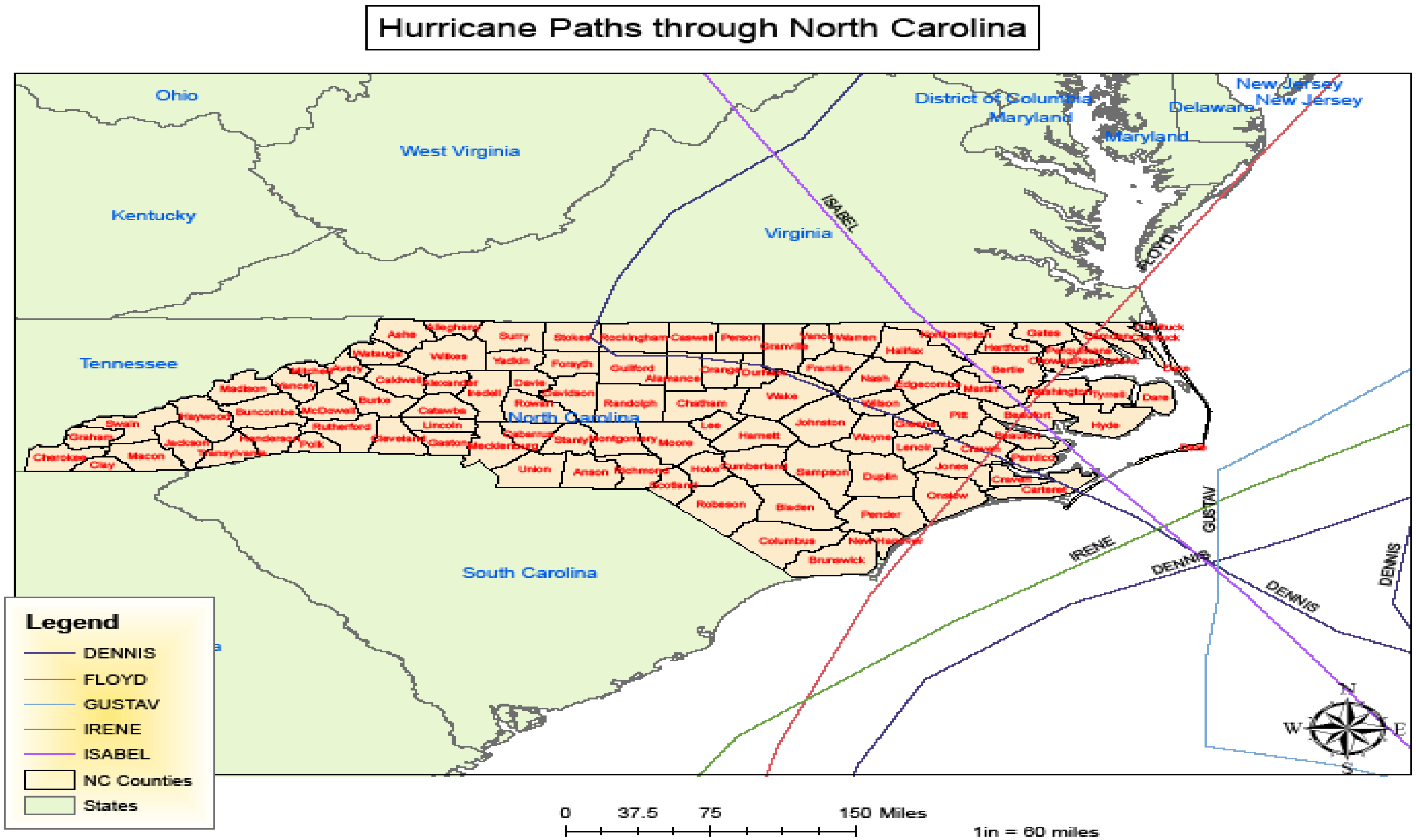

Figure 1. North Carolina Hurricane

Just over a month later, on October 17, 1999, Hurricane Irene hit North Carolina. Fortunately it was not as destructive as Floyd had been. However, likely as a result of the devastation caused by Floyd, a state of emergency was declared and 300 National Guard troops were mobilized (New York Times, 1999). Flooding was the primary problem brought on by Irene, as the ground was already saturated from the floods caused by Floyd and Dennis (Nakamura, 1999)

The next event, Tropical Storm Gustav, did not occur until September 2, 2002. Although it was only a tropical storm, it was the biggest storm in North Carolina since Dennis (New York Times, 2002). Gustav's primary target was the Outer Banks (the eastern coastal counties of North Carolina) where areas were flooded (New York Times, 2002). Power was knocked out on Hatteras Island, located in Dare County's southern Outer Banks (St. Petersburg Times, 2002).

The final hurricane in the time period under consideration, Hurricane Isabel, made landfall on September 18, 2003. A state of emergency was declared and National Guard troops were mobilized (Leinwand and Parker, 2003). The Outer Banks were most affected. Three people were killed in the disaster (Fears, 2003). All of Hatteras Island, located in Dare County on the southern Outer Banks, was inaccessible due to flooding and washouts (Cooperman and Walsh, 2003). President Bush declared a federal disaster (Kennedy, 2003).

Model

I use a random effects panel model with maximum likelihood estimation to evaluate my hypotheses. The distribution of the dependent variable does indicate that a

Tobit model (Tobin, 1958) would also have been appropriate due to the truncation of the data at zero (see Figure 2). However, after comparing the results of the Tobit and the least squares panel models, the findings were similar and the least squares panel model was chosen for ease of interpretation. I have selected a random effect model in order to account for variation over time in omitted variables (Hsaio, 2003). I have no reason to assume that the variables that I am not capturing remain constant over time or across each county. By choosing a random effects model I allow variation in the error across both time and county (Hsaio, 2003). One caveat of a random effects model is that I assume that the errors have a normal distribution. To make sure that I was not erroneously choosing the random effects model, I conducted Hausman tests (1978). When significant, the Hausman test indicates that the fixed effects model should be used, of all of the models indicated that using a random effects model was acceptable. The model is as follows:

Burglary Rate = f(Hurricane, Financial Severity , Corporal Severity, Social Disorganization, Social Disorganization x Hurricane, Controls) (1)

Where "social disorganization" and "controls" are comprised of multiple variables. The variables in the models are described below.

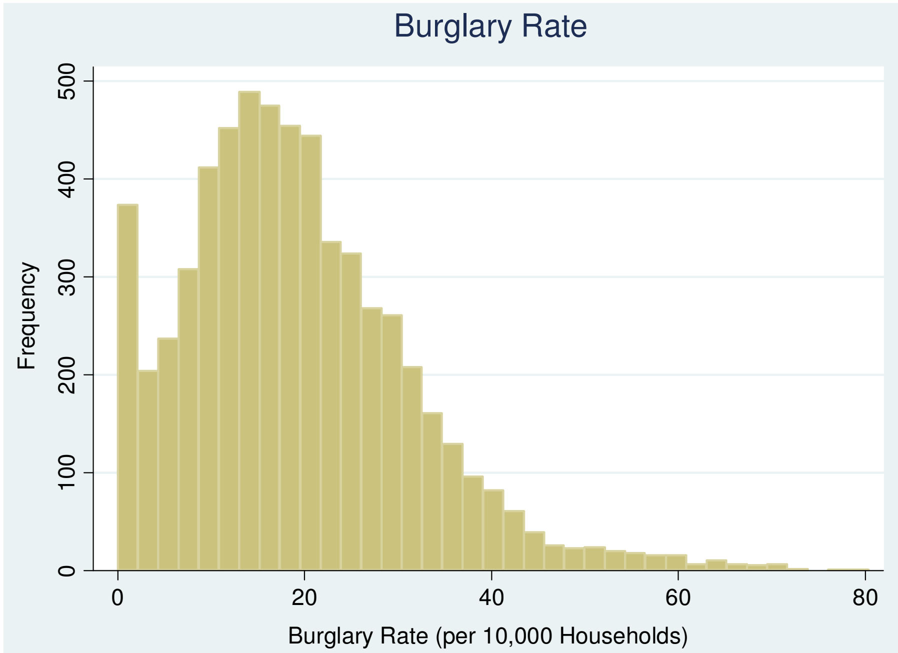

Figure 2. Frequency Distribution of Burglary Rate

Variables

The following variables have been selected for inclusion in the proposed model. Their descriptive statistics are summarized in Table 2.

Burglary Rate

Number of Burglaries per 10,000 households is the outcome variable. It takes the form:

$$B = ((b_c / u_c) \text{ x } 10{,}000) \qquad (2)$$

Where the number of burglaries in a given county, b_c, is divided by the number of "housing units", u_c, in that county. Housing units, as opposed to population, is used in the denominator in order to account for the proportion of properties that could be burglarized.[5] The mean number of burglaries was 19.18 per 10,000 with a standard deviation of 12.20.

Hurricane Measures

The first two measures of the capture the amount of damage, death, and injury caused by the hurricane and are proxies of the impact on routine activities. In theory, the more damage a hurricane causes, the more it alters routine activities. For example, if schools and offices are destroyed, people cannot engage in their routine of going there during the week. The first measure is financial severity. It is defined as:

$$F = ((p + c)/l_c) / 1000 \quad (3)$$

Where p is the estimated amount of property damage in dollars, c is the estimated amount of crop damage in dollars, and l_c is the total land area of the county in square miles. The figure is measured in thousands of dollars. The mean amount of damage is $7.9544 per square mile with a standard deviation of $85.2001. NOAA calculates the dollar estimate from "all available data at the time of publication" (http://www.ncdc.noaa.gov/oa/climate/sd/sdfaq.html, accessed on May 3, 2007). This includes police, media, and private corporations. This measure does exclude water area.

Corporal severity of the hurricane is another key independent variable. It indicated the number of deaths and injuries per 10,000 county residents. It is defined as:

$$C = ((i + d)/h_c) \times 10{,}000 \quad (4)$$

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[5] According to the US Census Bureau: A housing unit is a house, an apartment, a mobile home, a group of rooms, or a single room that is occupied (or if vacant, is intended for occupancy) as separate living quarters. Separate living quarters are those in which the occupants live and eat separately from any other persons in the building and which have direct access from the outside of the building or through a common hall.

Where i is the number of injuries caused by the hurricane, d is the number of deaths caused by the hurricane, and h_c is the number of habitants in the county. The mean amount of deaths and injuries was 0.0208 per 10,000 habitants. The maximum was 31.2876 per 10,000 habitants[6].

NOAA's unit of analysis is the National Weather Service Forecast Zone. In North Carolina, each zone is a county. However, in the storm database some of the counties are grouped together under one event.[7] For example, Brunswick, New Hanover, and Pender County are one grouping of counties for Hurricanes Dennis, Floyd, and Isabel. Therefore, the occurrence of a hurricane is a dichotomous variable with 1 indicating the occurrence of at least one hurricane in a given county during a given month. The hurricane is recorded by individual National Weather Service Forecast Offices and that information is then transferred to NOAA. The National Weather Service Forecast Offices determine whether or not a hurricane occurs in a county based on wind speed. In order for a county to be classified as having had a hurricane winds must reach a speed of 74 miles per hour. Approximately two-percent of the county-months had at least one hurricane (see Table 3).

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[6] Corporal severity was not squared because the squared values became very small and were of little contribution to the analysis.

[7] See Appendix 2 for a complete guide of how the counties are grouped together.

Table 2. Descriptive Statistics of the Variables.

Variable Name	Mean	Standard Deviation	Minimum	Maximum
Dependent Variable				
Burglary Rate	19.1800	12.2000	0.0000	80.41
Independent Variables				
Routine Activity				
Financial Severity	1.6606	18.8958	0.0000	435.7384
Financial Severity^2	359.7495	5493.3700	0.0000	189868.0000
Corporal Severity	0.0208	0.5707	0.0000	31.2876
Hurricane	0.0183	0.1342	0.0000	1.0000
Social Disorganization				
Proportion Urban	0.3487	0.2757	0.0000	0.9613
Proportion Non-white	0.2455	0.1751	0.0109	0.6673
Linguistic Isolation	0.0136	0.0098	0.0000	0.0554
Born Outside US	0.0353	0.0240	0.0065	0.1125
Female Headed Household	0.0695	0.0221	0.0270	0.1243
Relative Deprivation	0.4171	0.0227	0.3733	0.4662
Proportion Non-professional employment	0.7380	0.0558	0.5024	0.8095
Average Education*	3.5330	0.4578	3.0027	6.0000
In-migration	0.1889	0.0591	0.0986	0.3855
Out-migration	0.1481	0.0476	0.0890	0.3831
Control Variables				
Proportion Age 15 – 24	0.1319	0.0334	0.0857	0.3206
Proportion Male	0.4905	0.0150	0.4581	0.5540
Coastal County	0.2000	0.4000	0.0000	1.0000

* -- variable is reverse coded

Table 3. Distribution of Hurricanes across County-months.

Hurricane	Frequency	Percent
None	5890	98.17
One or more	110	1.83
Total	6000	100

Social Disorganization Variables

The social disorganization variables selected have been linked to their theoretical constructs. Table 4 shows which variables measure each specific construct. A description of the variables and how they are measured follows.

Proportion of urban residents is the operationalization of urban, one of the components of social disorganization. It is defined by the following function:

$$U = h_u / h_c \tag{5}$$

where h_u is the number of habitants classified as urban by the US Census. The average proportion of a county that was urban was 0.3487 with a standard deviation of 0.2757.

Proportion of nonwhite residents is one indicator of racial and ethnic heterogeneity. The formula is:

$$\overline{W} = h_{nw} / h_c \tag{6}$$

where h_{nw} is the number of residents classified as non-white in a county. This number includes Hispanics and multi-racial individuals.

Linguistic isolation is the second indicator of racial and ethnic heterogeneity. It is defined as:

$$L = H_{esl} / H_c \tag{7}$$

where H_{esl} is the number of households in a county where English is not spoken "very well" by all adults in the household, as determined by the US Census. And, H_c is the total number of households in the county. The average proportion of linguistically isolated households was 0.0136 with a standard deviation of 0.0098.

Proportion of people born outside of the United States is the third indicator of racial and ethnic heterogeneity. It takes the form:

$$N = h_f / h_c \tag{8}$$

where h_f is the total number of foreign born residents in a county.[8] The average proportion of non-US natives in a county was 0.0353 with a standard deviation of 0.0240. Supervision of minors is operationalized by the proportion of female headed households.

It takes the following form:

$$S = H_f / H_c \tag{9}$$

where H_f is the proportion of female headed, single parent households. The average proportion of single parent, female headed households is 0.0695 with a standard deviation of 0.0221.

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[8] Foreign born does not include those born in Puerto Rico, US island areas, or born those born abroad to citizens of the United States.

Table 4. Social Disorganization Constructs and the Census Variables Assigned to the Construct.

Construct	Variables
Urbanization	Proportion Urban
Racial and Ethnic Heterogeneity	Proportion Nonwhite
	Total Linguistic Isolation
	Total Born Outside of the US
Supervision of Minors	Proportion Single Parent Female Headed Household
Socioeconomic Status	Relative Deprivation
	Proportion in Non-professional Occupation
	Average Educational Attainment for those over 25*
Residential Instability	In-migration over 5 year period (1995-2000)
	Out-migration over 5 year period (1995-2000)

* -- variable is reverse coded

Relative deprivation is one indicator of socioeconomic status. It is determined by the Gini coefficient, which is a measure of income inequality. Possible values range from zero to one with higher values indicating more income inequality. I use Abounoori and McCloughan's (2003) adaptation of the formula for grouped data which is as follows:

$$G = C\sum_{k=1}^{K} w_k \left(1 - \frac{\bar{y}_k}{\bar{y}}\right) \tag{10}$$

where $C = 2 / n(n + 1)$, n is the the number of individuals, K is the total number of groups, w_k is the weight corresponding to each group, $\bar{y}$ is the mean income, and $\bar{y}_k$ is the mean income of a group. I apply this formula to the 2000 Census data on income. There are 16 different groups of income in this data, measured in dollars.[9] I used the midpoint of the category multiplied by the frequency of the category in order to calculate group mean income.[10] I compared the aggregate income using this formula to the aggregate income given by the Census and there was a small error that was never higher than 2 percent. This error was consistently positive indicating that my estimates of income are slightly high. This may have had a slight impact on the accuracy of the figures. The fourth appendix contains the complete derivation of Abounoori and McCloughan's equation. The average relative deprivation is 0.4171 with a standard deviation of 0.0227.

Another indicator of socioeconomic status is the proportion of people in a non-professional occupation. It is defined as:

$$\overline{P} = e_{\overline{p}} / e \tag{11}$$

where $e_{\overline{p}}$ is the number of people employed in a non-professional occupation and e is the total number of people employed. [11]

The final indicator of socioeconomic status is average education. It takes the form:

$$E = \frac{\sum_{g=1}^{G} n_g g}{\sum_{g=1}^{G} n_g} \tag{12}$$

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9 The 16 categories are as follows: less than 10,000; 10,000 to 14,900; 15,000 to 19,900, 20,000 to 24,900, 25 to 29,900; 30,000 to 34,900; 35,000 to 39,900; 40,000 to 44,900; 45,000 to 49,900; 50,000 to 59,000; 60,000 to 74,900; 75,000 to 99,900; 100,000 to 124,900; 125,000 to 149,900; 150,000 to 199,000; greater than 200,000.

10 For the greater than $200,000 category, $200.000 was used.

11 Refer to Appendix 5 for a complete listing of job categories.

where n_g is the number of people in group g of educational attainment ($g = 1,2,\ldots,G$). Educational attainment ranges from one nine (see Table 5 for a description of the categories). This variable is reverse coded so that higher values indicate less educational attainment. The mean average educational attainment is 3.533 with a standard deviation of 0.4578.

Table 5. Educational Attainment Levels and Assigned Values.

Level of Education	Value
No Education	9
No High School	8
Some High School	7
High School Graduate	6
Some College	5
Associate's Degree	4
Bachelor's Degree	3
Master's/Professional Degree	2
Doctorate	1

In-migration is the first measure of residential mobility. It is calculated by:

$$I = m_i / h_c \tag{13}$$

where m_i is the total number of people that moved into a county over a five year period between 1995 and 2000. The mean in-migration is .1889 with a standard deviation of 0.0591.

Out-migration is the second measure of residential instability. The formula is as follows:

$$O = m_o / h_c \tag{14}$$

where m_o is the total number of people that moved into a county over a five year period between 1995 and 2000. The mean out-migration is 0.1481 with a standard deviation of 0.0476.

Control Variables

The following three control variables are included in the model: proportion aged 15-24, proportion male, and coastal county. The first two, proportion aged 15-24 and proportion male, will be used to control for known correlates of crime. Including whether or not the county is coastal will control for any unique effect being in a coastal county will have on burglary. These could include the effects of: vacation homes, different weather patterns, and population flows. North Carolina has a total of 20 counties designated as coastal by NOAA.

Pre-estimation Issue

All of the social disorganization variables for the data are more correlated with each other than with the dependent variable (see Table 6), a violation of the guideline established by Klein (1962). When the variables are highly correlated, it indicates that they are related. Models that suffer from multicollinearity have inflated standard errors which can possibly lead to a Type II error, in which a false null fails to reach significance. This problem is common in studies with variables measuring social disorganization theory and has been previously addressed by principal component analysis (see Land et al., 1990; De Coster et. al, 2006). I also conduct principal component analysis in order to address the multicollinearity issue.

Table 6. Correlation Matrix of Social Disorganization Variables.

Variable	1	2	3	4	5	6	7	8	9	10
Burglary Rate (1)	1.0									
Proportion Urban (2)	0.4087	1.0								
Proportion Non-white (3)	0.4732	0.0652	1.0							
Linguistic Isolation (4)	0.2664	0.3381	-0.0219	1.0						
Born Outside US (5)	0.2790	0.4517	-0.0196	0.9417	1.0					
Proportion Female Headed Household (6)	0.5928	0.2613	0.8294	-0.0021	-0.0190	1.0				
Relative deprivation (7)	0.0814	-0.2885	0.4595	-0.1362	-0.2207	0.3831	1.0			
Proportion in Non-professional Employment (8)	-0.0932	-0.5548	0.0708	-0.3693	-0.5417	0.0780	0.0860	1.0		
Average Education (9)	0.0201	0.5306	-0.2271	0.2529	0.4112	-0.1886	-0.2861	-0.7285	1.0	
In-migration (10)	-0.0986	0.2222	-0.2186	0.0384	0.2265	-0.2222	-0.3249	-0.5710	0.5174	1.0
Out-migration (11)	0.0104	0.3555	0.1035	0.0414	0.1881	0.0986	-0.0086	-0.4301	0.3845	0.6690

I extracted 3 factors with Eigenvalues over one (see Table 7). Visual analysis of the scree plot also indicated that there were three possible factors (see Figure 3). The loadings on the factors shown in Table 8, the rotated loadings shown in Table 9, as well as the loading plot after rotation (see Figure 4). Both the orthogonal varimax and oblique rotation described three general components: disadvantage, non-national, and migration. Disadvantage was comprised of proportion nonwhite, female headed household, and relative deprivation. Non-national was a combination of linguistic isolation and born outside of the U.S. Migration consisted of both in-migration and out-migration. Notice that these variables are not linked to the components in the same manner they are linked to the theoretical constructs in Table 4. The components were created by summing across the relevant variables.

Table 7. Component Eigenvalues for the Principal Component Analysis of the Social Disorganization Variables.

Component	Eigenvalue
1	3.8925
2	2.2010
3	1.6287
4	0.8651
5	0.6886
6	0.3831
7	0.1749
8	0.0932
9	0.0444
10	0.0285

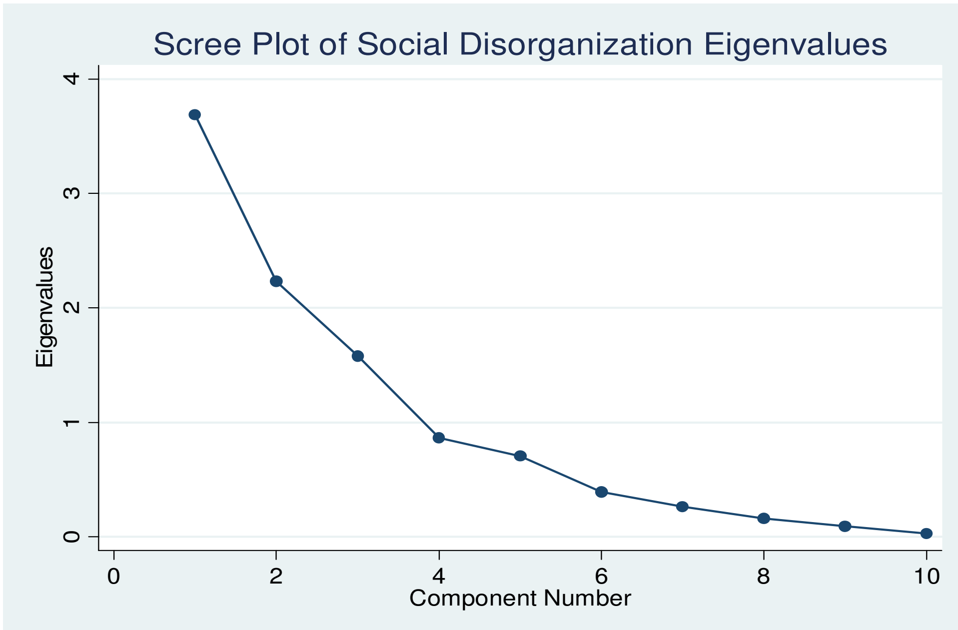


Figure 3. Scree Plot of Eigenvalues

Table 8. Component Loadings from the Prinicpal Component Analysis of the Social Disorganization Variables.

Variable	Comp 1	Comp 2	Comp 3
Proportion Urban	0.3414	0.2268	0.0377
Proportion Non-white	-0.1175	0.5990	-0.0956
Linguistic Isolation	0.2747	0.1521	0.5862
Born Outside of US	0.3616	0.1494	0.4761
Proportion Female Headed Household	-0.0939	0.6085	-0.0737
Relative Deprivation	-0.1963	0.3567	-0.1400
Proportion Non-professional Employment	-0.4391	-0.0902	0.0920
Average Education	-0.4595	0.0222	0.1752
In-migration	0.3561	-0.1323	-0.3930
Out-migration	0.2922	0.1439	-0.4478

Table 9. Orthogonal Varimax and Oblique Rotated Component Loadings of the Social Disorganization Variables.

Variable	Orthogonal Varimax Rotation			Oblique Rotation		
	Comp 1	Comp 2	Comp 3	Comp 1	Comp 2	Comp 3
Proportion Urban	0.2755	0.2674	0.1483	0.3344	0.3889	0.1412
Proportion Non-white	-0.0020	0.0040	0.6179	-0.1056	0.0944	0.6695
Linguistic Isolation	-0.0931	0.6585	-0.0000	0.0077	0.6919	0.0907
Born Outside of US	0.0402	0.6149	-0.0014	0.1520	0.6809	0.0604
Proportion Female Headed Household	0.0058	0.0366	0.6189	-0.0913	0.1322	0.6730
Relative Deprivation	-0.0586	-0.1324	0.4055	-0.1577	-0.1009	0.4344
Proportion Non-professional Employment	-0.4197	-0.1814	-0.0184	-0.5053	-0.3158	0.0349
Average Education	-0.4756	-0.0979	0.0809	-0.5712	-0.2256	0.1617

Table 9 (continued)

Variable	Orthogonal Varimax Rotation			Oblique Rotation		
	Comp 1	**Comp 2**	**Comp 3**	**Comp 1**	**Comp 2**	**Comp 3**
In-migration	0.5054	-0.1604	-0.1325	0.5693	-0.0551	-0.2520
Out-migration	0.5026	-0.1725	0.1560	0.5154	-0.0268	0.0594

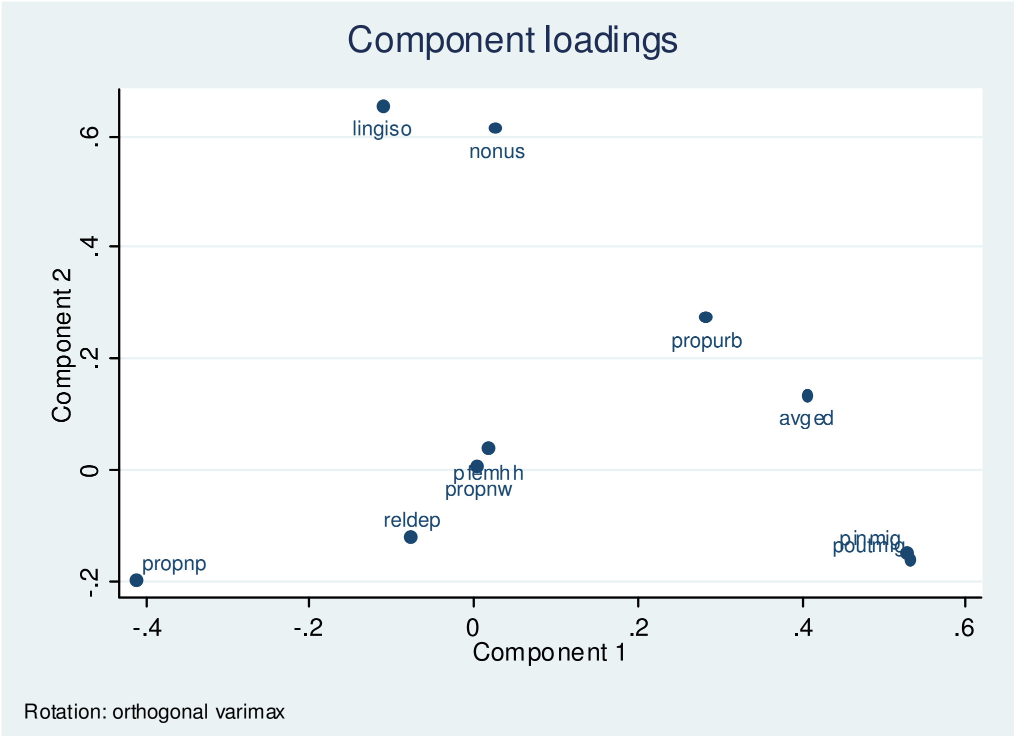


Figure 4. Loading Plot of Social Disorganization Variables after Orthogonal Varimax Rotation

The Cronbach's alpha for Disadvantage was only 0.3720, which is relatively low. However, I found that the Eigenvalue of this component was 1.8986 after re-rerunning a factor analysis with maximum likelihood estimation, indicating that these three variables together explain more than they would independently. The Cronbach's alpha for migration was 0.7904 and 0.7942 for non-national. The three remaining variables (proportion non-professional, average education, and proportion urban) did not fit with any of the components and were retained as separate variables. The correlations of the social disorganization variables and components improved. However, average education and proportion non-professional were still highly correlated (see Table 10). I proceeded to conduct preliminary analysis in order to see what the effects of each of these variables were in the model. The results of this analysis are described in the next section.

Table 10. Correlation Matrix of Social Disorganization Components and Remaining Social Disorganization Variables.

Component/ Variable	1	2	3	4	5
Non-national (1)	1.0000				
Mobility (2)	0.1773	1.0000			
Disadvantage (3)	-0.0410	-0.1014	1.0000		
Proportion Non-Professional (4)	-0.4978	-0.5556	0.0783	1.0000	
Average Education (5)	0.3698	0.5010	-0.2457	-0.7285	1.0000
Proportion Urban (6)	0.4239	0.3079	0.0519	-0.5548	0.5306

VI. Results

This section contains the results of the least squares panel regression models. There are two main analyses. The first group of models assesses the effect of the routine activity proxies on the rate of burglaries per households. The second assesses the impact of the social disorganization variables and their interaction with a hurricane on burglary. The results include the variance of the person-specific error, Sigma *i*, the variance of the general error, Sigma *u*, and the total variance contributed by the county level variance component, Rho. In addition, three types of fit statistics are included. First, the likelihood ratio test is the difference in the log-likelihood of the present model and, in this case, the constant only model. The statistic has a chi-square distribution with the degrees of freedom equal to the difference in the number of parameters estimated. Second and third are the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). Both of these statistics penalize for additional parameters. In both of these cases, the lowest value indicates the best model. .

The routine activity results (see Table 11) also include the constant only model which indicates that the average rate of burglary is approximately 19 per 10,000 households. The routine activity proxies are not significant when added consecutively or concurrently. But, their direction indicates that increased financial impact increases burglary rate, financial impact squared decreases burglary rate and corporal harm decreases burglary rate. The magnitude of the results is fairly small, with each additional 100,000 dollars of damage contributing very little to the rate of burglary. Each additional death or injury per 10,000 people decreases the rate of burglary by less than one household per 10,000. The dichotomous coastal county variable was significant ($p<.01$), indicating that coastal counties had approximately five fewer burglaries per 10,000 households than non-coastal counties. None of the models with the theoretically relevant variables are best fitted to the data according to the likelihood ratio test, AIC, and BIC.

Many iterations of the social disorganization models were tested. As previously noted, problems arose with the correlations of proportion non-national, mobility, proportion non-professional, average education and proportion urban as indicated by the increased standard errors.

In order to determine which variables were most problematic I conducted collinearity diagnostics on the five variables above. Table 12 contains the results of this analysis. The variance inflation factor (VIF) was highest for proportion non-professional and average education, but was not extreme. However, the tolerance for both of these variables is low, which is problematic as a tolerance of zero indicates multicollinearity. The figures for non-professional indicate that this variable is more problematic than average education. Yet, from a social disorganization theory perspective, removing this variable and retaining average education is not sensible. In areas where average education is low, residents may still able to support themselves financially and invest in the community as well. In areas with higher proportions of non-professional employment, the average income is likely to be lower. Residents in these areas may have a decent education, but may be unable to find employment that meets their qualifications. These people may be divested in the community and be simply looking to transition out of their employment predicament and the community. Thus, retaining proportion of non-professional employment and dropping average education is more appropriate for assessing social disorganization.

After this issue was resolved, I added each social disorganization variable to the model with the dichotomous hurricane variable. The hurricane variable remained significant throughout all of the models and was positive, indicating that a hurricane increased the rate of burglary. The magnitude of this increase, however, was only approximately one additional burglary per 10,000 households. The non-national and disadvantage components and the proportion urban also remained significant. Proportion non-professional and mobility seemed to still present some multicollinearity issues. A consequence of multicollinearity is that standard errors are large and failure to reject the null hypothesis is more likely. The non-professional variable is significant in the final model, but the mobility variable is not. Both of these variables were retained for the next portion of the analysis.

Table 11. Panel Analysis Results for Routine Activity Proxies on Burglary Rate (Standard Errors in Parentheses).

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Financial Severity		0.0009	0.0016		0.0045	0.0047
		(0.0010)	(0.0045)		(0.0052)	(0.0052)
Financial Severity ^{2}			-6.73×10^{-7}		-3.24×10^{-6}	-3.42×10^{-6}
			(4.22×10^{-6})		(4.81×10^{-6})	(4.82×10^{-6})
Corporal Severity				-0.0991	-0.1866	-0.1932
				(0.1432)	(0.1617)	(0.1678)
ProportionAge 15-24						-3.2487
						(9.9870)
Proportion Male						-18.1280
						(41.9551)
Coastal County						-5.8650**
						(2.1779)
Constant	19.1829***	19.1758***	19.1750***	19.1850***	19.1745***	29.6689
	(1.0544)	(0.9403)	(0.9228)	(1.0393)	(0.9024)	(20.8325)
Sigma *i*	10.5134	9.4374	9.1682	10.3593	8.9588	8.5920
Sigma *e*	6.2786	6.2787	6.2792	6.2789	6.2792	6.2781
Rho	0.7371	0.6891	0.6807	0.7313	0.6706	0.6519

Table 11 (continued)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Loglikelihood	-19792.6	-19792.27	-19791.75	-19792.36	-19791.07	-19788.26
LR Test (df)		0.66 (1)	1.70 (2)	0.48 (1)	3.06 (3)	8.68 (6)
AIC	39591.21	39592.53	39592.53	39592.73	39594.15	39594.51
BIC	39611.31	39613.33	39613.33	39619.53	39634.34	39654.81

* -- < .05
** -- < .01
*** -- <.001

Table 12. Variance Inflation Factor (VIF), Tolerance, and R-squared of the Correlated Social Disorganization Components and Variables.

Variable	VIF	Tolerance	R-squared
Non-national	1.42	0.7064	0.2936
Mobility	1.52	0.6580	0.3420
Proportion Non-Professional	2.90	0.3450	0.6550
Average Education	2.31	0.4328	0.5672
Proportion Urban	1.59	0.6298	0.3702

Next, I incorporated the interaction between social disorganization and the hurricane. Table 13 contains selected model results. The only interaction variable that was significant was that of the hurricane interacted with mobility ($p<.05$). Further additions of variables to the model produced a worse fit. Thus the final and best fitting model contains only the hurricane-mobility interaction with the addition of the control variables. The hurricane-mobility interaction is negative, indicating that when a hurricane hits an area, the level of mobility in the area causes the rate of burglary to decrease. Specifically, a one unit increase in mobility causes burglary to decrease by approximately 9 burglaries per 10,000 households. In these models, the hurricane variable alone came close, but failed to reach significance in all models. Disadvantage, proportion non-professional, and proportion urban all had a significant positive impact on the rate of burglary.

Table 13. Selected Results from the Panel Model with Social Disorganization Variables Interacted with the Dichotomous Hurricane Variable (Standard Errors in Parentheses).

Variable	Model 1	Model 2	Model 3	Final Model
Hurricane	0.3309	0.5862	0.4765	0.3276
	(2.5354)	(2.5579)	(2.5810)	(2.5363)
Non-national	65.5827**	65.6067**	65.4782**	36.7917
	(24.0372)	(24.0318))	(24.0343)	(25.7746)
Mobility	-11.0001	-11.0029	-10.9975	-0.2314
	(8.4229)	(8.4210)	(8.4207)	(10.1375)
Disadvantage	26.5346***	26.5688***	26.5703***	29.4421***
	(3.3168)	(3.3163)	(3.3162)	(3.3224)
Proportion Non-professional	32.2763*	32.2397*	32.2403*	32.0759*
	(17.9613)	(17.9573)	(17.9566)	(18.5150)

Table 13 (continued).

Variable	Model 1	Model 2	Model 3	Final Model
Proportion Urban	18.3352***	18.3282***	18.3345***	18.2102***
	(3.0241)	(3.0234)	(3.0233)	(2.9306)
Hurricane x Non-national			-5.7731	
			(18.1110)	
Hurricane x Mobility	-9.8447*	-10.9683*	-11.1935	-9.5990*
	(5.4806)	(5.6758)	(5.7240)	(5.4836)
Hurricane x Disadvantage		-2.6581	-2.8204	
		(3.5337)	(3.5702)	
Hurricane x Proportion Non-professional	5.2446	8.3491	8.5387	5.2100
	(3.8964)	(5.6758)	(5.7068)	(3.8998)
Hurricane x Proportion Urban	1.7407	2.0903	1.8724	1.7069
	(2.2116)	(2.2598)	(2.3609)	(2.2112)

Table 13 (continued)

Variable	Model 1	Model 2	Model 3	Final Model
Proportion 15-24				-9.4459*
				(10.1344)
Proportion Male				19.6810
				(42.5060)
Coastal County				-6.2828***
				(1.8889)
Constant	-30.5488	-30.5453*	-30.5448*	-41.9217*
	(15.7149)	(15.7113))	(15.7107)	(21.0500)
Sigma *i*	6.6969	6.6954	6.6951	6.4080
Sigma *e*	6.2746	6.2743	6.2742	6.2732
Rho	0.5325	0.5324	0.5324	0.5106
Log-likelihood	-19744.62	-19744.34	-19744.28	-19739.00
Degrees of Freedom	12	13	14	15
LR (df)		0.56 (1)	0.68 (2)	11.24 (3)**
AIC	39513.24	39514.67	39516.57	39507.99
BIC	39593.63	39601.77	39610.36	39608.48

* -- < .05

** -- < .01

*** -- <.001

VII. Discussion

Neither of the routine activity proxies that I identified were significant. Hence, my first hypothesis was not supported. The direction of the variable was correct for financial severity, but the magnitude was small. The direction for corporal severity was not as I had hypothesized. In fact, increased death and injury drastically decreased the number of burglaries. These proxies may not have been accurate enough to capture the effect (if any) on the rate of burglary. Conversely, there could be an issue with construct validity in that these proxies are not in fact measuring an effect on routine activities. This idea may be somewhat supported by the early tests of the social disorganization models where the dichotomous hurricane variable reached significance. However, as these models grew in complexity, the variable lost its significance.

My second hypothesis was onlysomewhat supported in once instance. One of the social disorganization variables, mobility, significantly interacted with a hurricane. However, the direction of effect of the hurricane-mobility interaction on burglary was not correctly hypothesized. This interaction indicated that more mobility during a hurricane resulted in lower rates of burglary. This is contradictory to social disorganization theory. I assert that what I have in fact captured with this result is not social disorganization decreasing crime, but that people in highly mobile areas move out following a disaster - thus leaving nothing to take nor anyone to do the taking. While the notion that residents permanently leave an area has been empirically supported (Smith and McCarty, 1996), the remainder is pure speculation. This study contains no measures of permanent migration after a hurricane. However, in highly unstable areas, it seems likely that the residents will simply pick-up and leave following a disaster.

VIII. Limitations

There are many limitations to the present study. First, routine activities were not directly measured. Also, like other studies using routine activity theory, only two components of the theory were actually captured: guardians and targets. While some of the factors affecting motivated offenders may be captured by the amount of destruction, there is no direct measure of how many potential thieves moved into an area following a hurricane. Obtaining this type of information is highly unlikely since a large portion of it is unofficial.

In addition, the financial and injury/death information was compounded across many counties. This certainly deteriorated some of the accuracy in the effect of the two proxies on burglary. The potential problem is, for example, that the majority of damage occurred in one county, but the estimate was pooled across three counties. This would cause the other two counties to be attributed with more damage than actually occurred. If burglary rates did not change in these counties, or went in the opposite direction of the county where the most damage occurred, the relationship between this figure and burglary would be obscured. Perhaps a county specific measure of financial and corporal severity would have resulted in a significant relationship with the rate of burglary.

The second major limitation of this study is the measures of the social disorganization constructs. While annual data was used where possible, it was not used on many of the important variables like annual income. ESRI, a private corporation that provides geographic information system and mapping software, does provide an annual book of interpolated county demographic figures for each state. However, upon investigating this as a potential resource for this study, it was determined that their unique data was unusable. Their population demographic information was acceptable, but had already been obtained from North Carolina's State Office of Budget and Management. They offered annual interpolations on income but only provided five different categories of income. The limited amount of categories did not allow for an accurate calculation of relative deprivation.

The potential problem with having used data collected decennially is that it could be insignificant in predicting crime. Since this data remained stable while crime fluctuated, it would appear that it had no effect on crime. In the present study, this did not prove to be a problem in terms of the significance. However, it is likely that the estimators are not accurate.

Another limitation of this study is the lack of information on disaster responses. As previously mentioned, evacuations, warnings and disaster relief all have the potential to affect burglary rates. However, there is no information on evacuations and warnings that is regularly recorded or gathered by one body. This is complicated by the fact that any jurisdiction can issue a warning, ranging from one village to the entire state, and these can be done simultaneously. Another problem with measuring evacuation orders is that some counties may refuse to issue them under any circumstances. For example, Onslow (a sparsely populated coastal county), never issues evacuation orders. This is because the responsibility for the well-being of the citizens then falls upon the county. Onslow does not want this liability. The county may recommend that citizens evacuate, but never issue an official order. It is unknown whether other counties follow this same policy.

Another restriction is the reliance on official data. This problem is especially important for the present study because police may be unable to respond to citizens during and after a hurricane. Should there be increased rates of burglary during that time they would not be reflected in official data. In addition, official data is also dependent on citizens being aware of their victimization. Residents may never know if they have been burglarized if there are large amounts of damage. It is also possible that a burglary may not be evident for some time. Even then, should a homeowner recognize that a burglary has occurred it is impossible to say whether or not they would report it. The problem of non-reporting may be further exacerbated by insurance. If an individual can simply compound stolen items into insurance claims of disaster loss, it is unlikely that they would go through the hassle of contacting the police as well.

These limitations are extensive and do serve to weaken the results. However, they do not compromise the findings entirely. Despite these limitations, this study still has important implications which are discussed in the final section.

IX. Implications and Conclusion

The most important finding in this study is that the effect of a hurricane on burglary is dependent on social components. This implies that policies should be tailored to the needs of the specific area in order to effectively impact burglaries following a hurricane. One blanket policy will not be sufficient. In areas where additional burglary prevention measures are needed, a more conservative policy would not be effective. In areas that are socially organized, a more comprehensive policy would be wasteful.

The other main implication of this research is that more data needs to be collected on disasters, important disaster related demographic factors, and variables that measure social disorganization and routine activity theory. Disaster research would be greatly improved if there were official records on all of the aspects of a disaster. This includes - but is not limited to - whether a warning was issued, whether a curfew was issued, the amount of damage caused, and the amount of money put into disaster relief and the source of those funds. In addition, estimates of damage that are gathered in a more systematic fashion would be desirable.

The abandonment of areas following a hurricane should also be recorded. It has only been assumed in this study that people permanently vacating an area caused the rate of burglary to decline. This hypothesis should be formally tested, but to do so requires appropriate data. This again, leads to the major limitation of this study, the lack of regularly collected data. The state of North Carolina does do an impressive job estimating some figures on an annual basis, but there are a number of important factors that are not regularly measured. While private groups, such as ESRI, do gather some of this information, they do not provide the finite data that is needed to thoroughly address the complex issue of social disorganization.

There are also many areas for future research. First, the routine activity proxy is worthy of future research. The proxy used in the present study should be re-evaluated with better data and new proxies should be tested. Police calls for service, as used by LeBeau (2002) may be helpful in determining the impact on routine activities. Second, a re-test of the models in this study using data that has been collected more regularly is important. The results contained in this study must be replicated prior to any policy formation. Third, a different theoretical framework could be used. For example, rational choice theory may be more appropriate in explaining how individuals choose to commit or not commit a burglary following a disaster. In theory, an individual may weigh the potential of getting caught in a city that has been abandoned and a typical non-offender may choose to steal. In an alternate scenario, burglary may be a rational choice if the only other choice is to go hungry. Fourth, multiple sources of crime data should be explored. This would be helpful for determining the nature of discrepancies between official and unofficial data during a disaster. In addition, it would provide direction as to the type of data that should be used in future analysis. Finally, this idea could be expanded to other crimes and other types of disasters. As stated in the second section, each type of disaster can be analyzed using Perry's (1985) typology. This means that different factors occur for each type of disaster. A closer study of the effects that various types of disaster have is important for the creation of disaster specific responses. In addition, the type of crime is important to consider as well. One type of crime prevention policy will not target all types of crime, thus policies need to be crime specific and should be research based.

Hurricanes have a detrimental effect on many things. While this study has many limitations it provides insight as to how a hurricane affects burglary. It helps to explain past mixed results on whether an altruistic community forms or social disorganization occurs following a hurricane. It shows that the effect of a hurricane is dependent upon the nature of the community prior to the disaster. Society does not drastically change because an unexpected factor is introduced. While mobility, an otherwise negative factor, may act in a way to decrease crime after the disaster, the "bad" area does not suddenly become "good" as a consequence of the tragedy. Future research using improved data and methods is necessary in order to formulate comprehensive policy.

Appendix 1. Method for Estimating County Totals.

Note: This is the method used for 2003. The methods for previous years are the same, with the obvious exception that the corresponding census estimate is used. The description below has been reproduced from:
http://www.osbm.state.nc.us/ncosbm/facts_and_figures/socioeconomic_data/population_estimates/demog/revmet3.html
A complete listing of the annual methodologies can be found at:
http://www.osbm.state.nc.us/ncosbm/facts_and_figures/socioeconomic_data/population_estimates/county_estimates.shtm

Revised July 1, 2003 County Population Estimates

Methodology --- County Totals

For these estimates, the county boundaries are those in effect for the 2000 federal census, including changes released by the Census Bureau through the middle of March of 2007. The state estimate was produced by adjusting the 2003 state estimate for North Carolina released in March of 2007 by the United States Bureau of the Census for changes in major institutional populations at both July 1, 2003 and April 1, 2000. The county estimates are averages of two sets of estimates, a set of modified Census Bureau estimates, and a set of alternative estimates produced by this office.

Modified Census Bureau Estimates

In March of 2007, the Population Division of the United States Bureau of the Census released their revised 2003 state and county population estimates for North Carolina. They used an administrative records technique similar to the 1990's technique of the same name. I made a few corrections to their April 1, 2000 county institutional populations and their July 1, 2003 county institutional populations based on corrections to individual institutions.

Alternative Estimates

Two basic procedures were used to build these estimates. First, I estimated the population 65 years of age and older. In the past, changes in the number of MEDICARE enrollees during the estimate period were used to measure changes in the population 65 years of age and older. This year, because of problems getting consistent MEDICARE data for years after 2003, I just used the 65+ population from the modified Census Bureau estimates mentioned above.

Second, I used a standard ratio/correlation method to estimate the population aged 0-64. The data series used were automobile and truck registrations (**X1**), school enrollment in grades 1 through 8 (**X2**), and a three year sum of births (**X3**). For 2003, the three year sum of births was the sum of final calendar year values for 2001, 2002, and 2003; for 2000, the sum of final calendar year values for 1998, 1999, and 2000. The prediction equation for each North Carolina county is given by

$$\mathbf{y} = -0.00391 + 0.52214 * \mathbf{X1} + 0.27868 * \mathbf{X2} + 0.19735 * \mathbf{X3},$$

where **y** represents the estimated ratio of percentage shares of nongroup quarters population and each of the series indicators (**X1**, **X2**, and **X3**) represents the ratio of percentage shares of the associated variable. The equation coefficients were derived by least squares regression, using series indicator and population values for 1990 and 2000. The results of this equation were adjusted for the extra 1/4 year of the estimate period by linearly expanding the change in **y** from the assumed 2000 value of 1.0. The nongroup quarters 0-64 population estimate derived from this equation was combined with independent estimates of the population of military barracks, college dormitories, and other institutions to yield the estimate of the total 0-64 population.

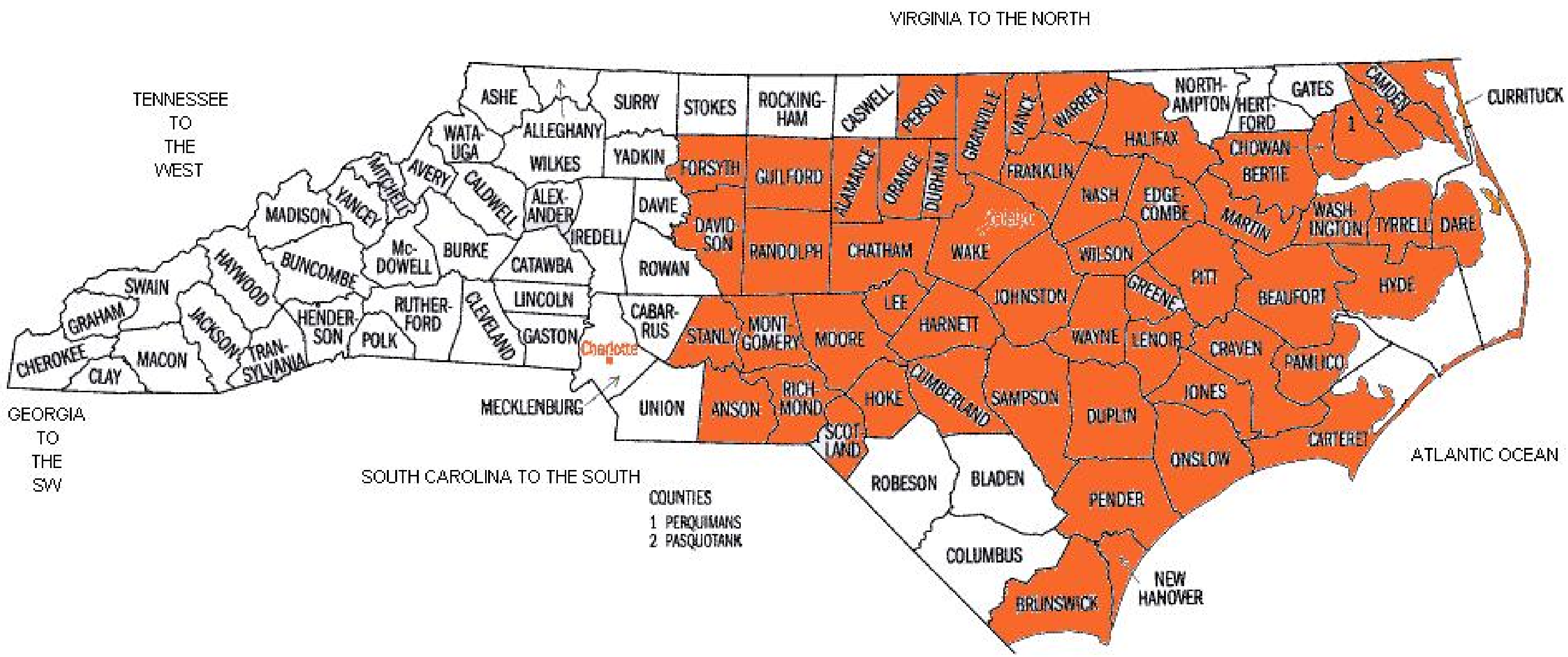
The state estimate for 2003 was the adjusted one mentioned above. Subtraction of the sum of the county populations 65 and older from this estimate produced a control for the 0-64 population estimates.

Methodology --- Age, Race, and Sex Detail

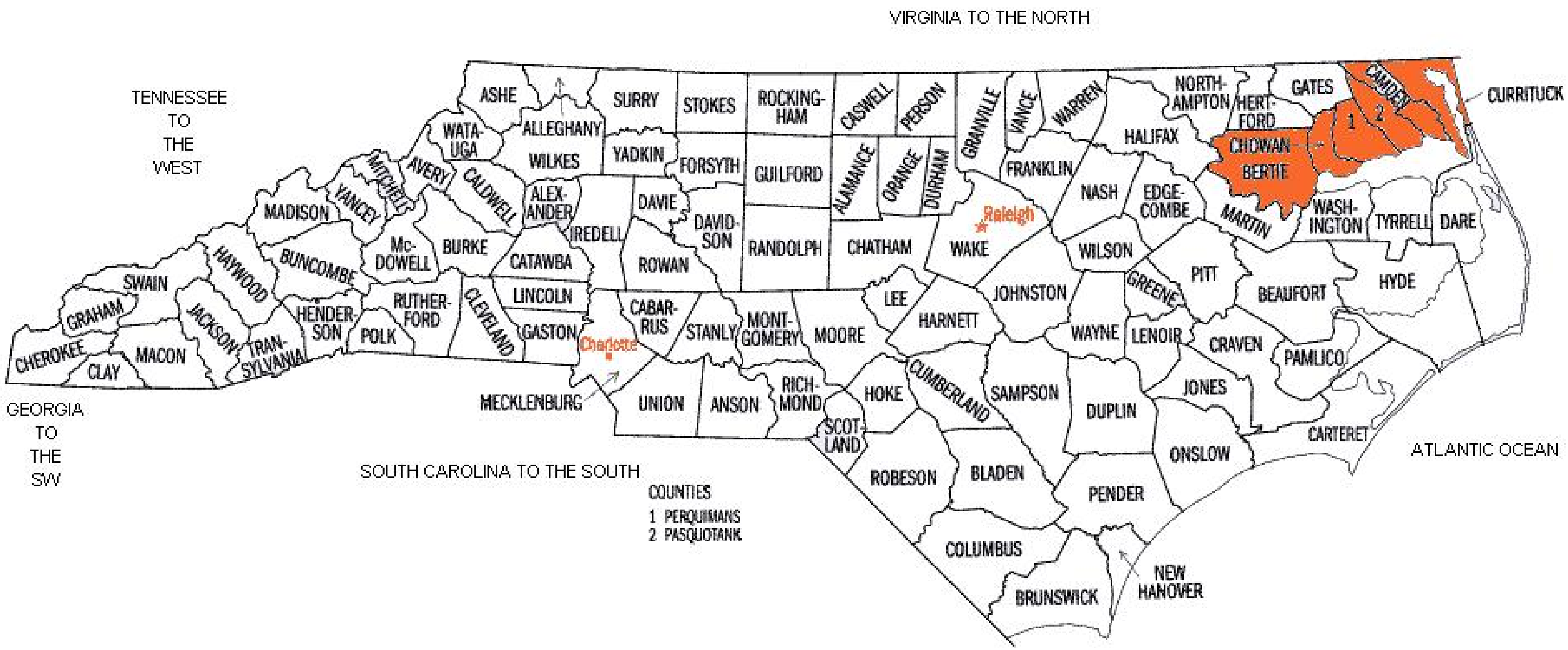
To calculate the populations for the different age, race, and sex groups, I used a relatively simple process. First, projections were made for each county by 384 age, race, and sex cells (96 age values: 0,1,2,...,94, and 95+; white/other; male/female) to April 1, 2010. Then, these values were interpolated (<u>age cohort</u> interpolation for non-institutional populations; <u>age group</u> interpolation for institutional populations) to July 1, 2003 using the April 1, 2000 Census values as a base. Next, the 384 cells for each county were proportionately adjusted to sum to the county total population. Finally, the appropriate age cells were summed to form each group.

Appendix 2. Storm Specific Maps of Affected Counties.

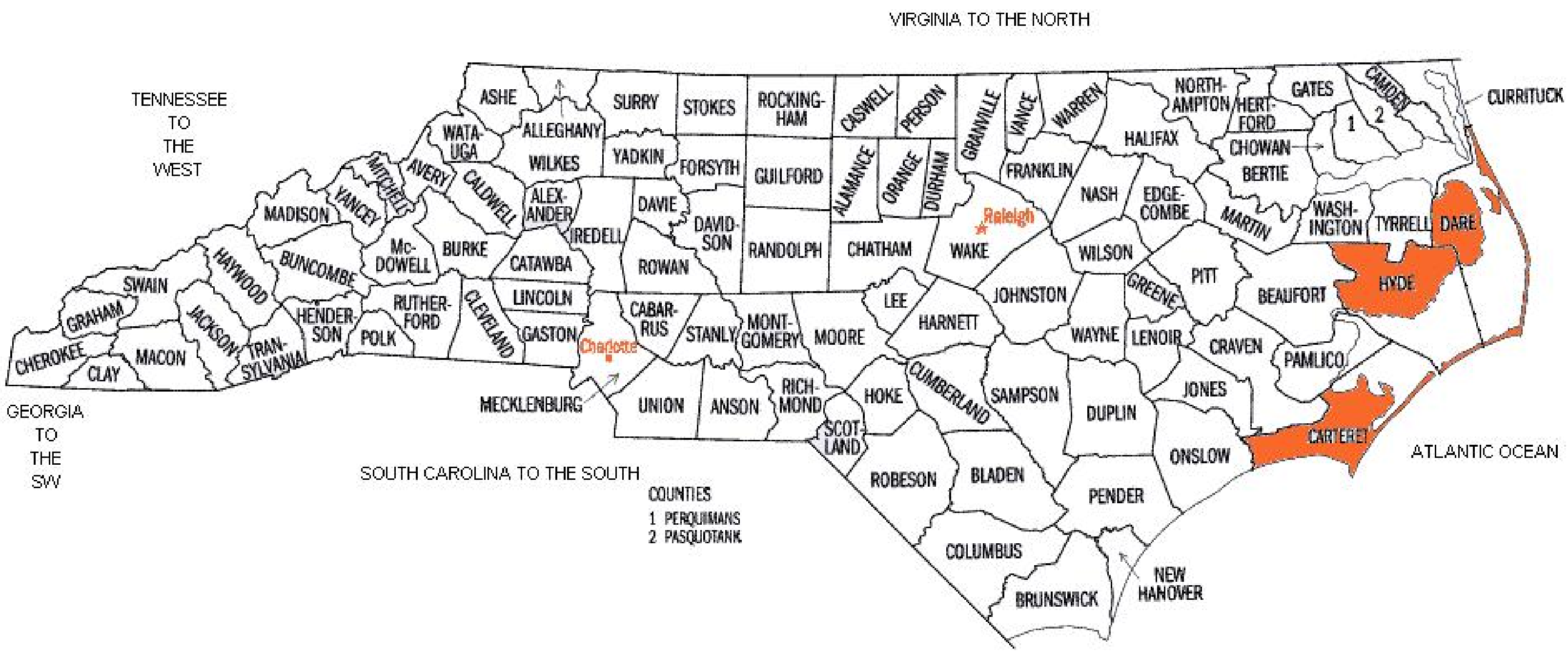
Hurricanes Dennis (August 1999) and Hurricane Floyd (September 1999). Note: The same counties were affected for each storm



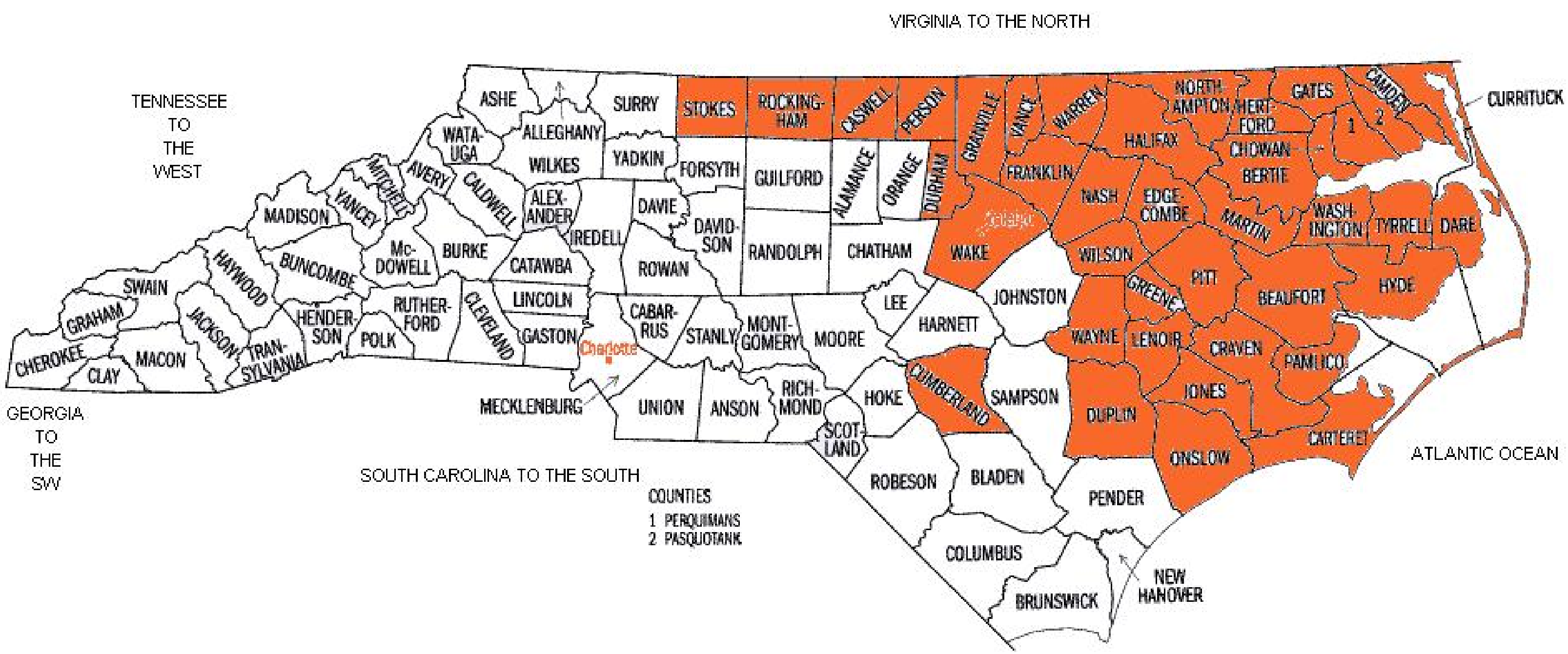
Hurricane Irene (October, 1999)



Tropical Storm Gustav (September 2002)



Hurricane Isabel (September 2003)



Appendix 3. County Groupings for Hurricanes.

Group 1
Bertie, Camden, Chowan, Currituck, Pasquotank, Perquimans

Events
Hurricane Dennis, Hurricane Floyd, Hurricane Irene, Hurricane Isabel

Group 2
Beaufort, Carteret, Craven, Duplin, Dare, Hyde, Greene, Jones, Lenior, Martin, Onslow, Pamlico, Pitt, Tyrell, Washington

Hurricane Dennis, Hurricane Floyd, Hurricane Isabel

Group 3
Brunswick, New Hanover, Pender

Event
Hurricane Dennis, Hurricane Floyd

Group 4
Alamance, Anson, Chatham, Cumberland, Davidson, Durham, Edgecombe, Forsyth, Franklin, Granville, Guilford, Halifax, Harnett, Hoke, Johnston, Lee, Montgomery, Moore, Nash, Orange, Person, Randolph, Richmond, Sampson, Scotland, Stanly, Vance, Wake, Warren, Wayne, Wilson

Event
Hurricane Dennis, Hurricane Floyd

Group 5
Carteret, Dare, Hyde

Event
Tropical Storm Gustav

Group 6
Gates, Hertford, Northampton

Event
Hurricane Isabel

Group 7
Caswell, Rockingham, Stokes

Event
Hurricane Isabel

Group 8
Cumberland, Durham, Edgecombe, Franklin, Granville, Halifax, Nash, Person, Vance, Wake, Warren, Wayne, Wilson

Event
Hurricane Isabel

Appendix 4. Abounoori & McCloughan's (2003) Gini Coefficient

This appendix provides an extended description of Abounoori and McCloghan's (2003) derivation of the Gini Coefficient. For their complete article see the 2003, 8th issue of *Applied Economics Letters*.

The formula for the orginal Gini coefficient is:

$$G = 1 - 2\int_0^1 l(z)\,\mathrm{d}\,z \tag{1}$$

where z is the proportion of people receiving a certain income and l is the proportion of total income received by those people. Essentially, it produces a figure indicating disparity between proportion of the population and proportion of income earned.

This formula was simplified by Milanovic (1994). His derivation is as follows:

$$G = \left(\frac{2}{n(n+1)}\right) \cdot (n, n-1, n-2, ...1) \cdot \left\{ \begin{pmatrix} 1 \\ 1 \\ 1 \\ . \\ . \\ . \\ 1 \end{pmatrix} - \frac{1}{\overline{y}} \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ . \\ . \\ . \\ y_n \end{pmatrix} \right\} \tag{2}$$

where n is the number of individuals and y is income. This derivation cannot be used with grouped data which is missing information on individual incomes. Hence, Abounoori and McCloghan's (2003) formula. They weight each group by the formula:

$$w_k = \frac{1}{2}\left\{ \sum_{k=k}^{K} n_k \left(\sum_{k=k}^{K} n_k + 1 \right) - \sum_{k=k+1}^{K} n_k \left(\sum_{k=k+1}^{K} n_k \right) \right\} \tag{3}$$

where k is the group (k = 1,2,…..K). They then plug this into the formula on page 31:

$$G = C \sum_{k=1}^{K} w_k \left(1 - \frac{\overline{y}_k}{\overline{y}} \right) \tag{4}$$

Appendix 5. Occupational Categories

- Management, professional, and related occupations:
  - Management, business, and financial operations occupations:
    - Management occupations, except farmers and farm managers
    - Farmers and farm managers
    - Business and financial operations occupations:
      - Business operations specialists
      - Financial specialists
  - Professional and related occupations:
    - Computer and mathematical occupations
    - Architecture and engineering occupations:
      - Architects, surveyors, cartographers, and engineers
      - Drafters, engineering, and mapping technicians
    - Life, physical, and social science occupations
    - Community and social services occupations
    - Legal occupations
    - Education, training, and library occupations
    - Arts, design, entertainment, sports, and media occupations
    - Healthcare practitioners and technical occupations:
      - Health diagnosing and treating practitioners and technical occupations
      - Health technologists and technicians
- Service occupations:
  - Healthcare support occupations
  - Protective service occupations:
    - Fire fighting, prevention, and law enforcement workers, including supervisors
    - Other protective service workers, including supervisors
  - Food preparation and serving related occupations
  - Building and grounds cleaning and maintenance occupations
  - Personal care and service occupations
- Sales and office occupations:
  - Sales and related occupations
  - Office and administrative support occupations
- Farming, fishing, and forestry occupations
- Construction, extraction, and maintenance occupations:
  - Construction and extraction occupations:

Supervisors, construction and extraction workers
Construction trades workers
Extraction workers
Installation, maintenance, and repair occupations

Production, transportation, and material moving occupations:
Production occupations
Transportation and material moving occupations:
Supervisors, transportation and material moving workers
Aircraft and traffic control occupations
Motor vehicle operators
Rail, water and other transportation occupations
Material moving workers

References

Abounoori, E. & McCloughan, P. (2003). A simple way to calculate the Gini Coefficient for grouped as well as ungrouped data. *Applied Economics Letters, 10* (8), 505-509.

Anderson, W.A.(1969). (in Perry, 1985). Disaster warning and communication in two communities. *Journal of Communication, 19*, 92-104.

Antecol, H. & Bedard, K. (2007). Does single parenthood increase the probability of teenage promiscuity, substance use, and crime?. *Journal of Population Economics, 20*(1), 55-71.

Barton, A. (1970). (in Perry, 1985). *Communities in disaster.* New York: Raven Press.

Bordua, D.J. (1958-59). Juvenile delinquency and "anomie": An attempt at replication. *Social Problems, 6* (3), 230-238.

Brooks, R. (1999, September 21). North Carolina hurricane damages rise --- loses are expected to hit at least $6 billion total; new storm is awaited. *Wall Street Journal,* p. A2

Bursik, R.J. (1988). Social disorganization and theories of crime and delinquency: Problems and prospects. *Criminology, 26*(4), 519-551.

Bursik, R. J. & Grasmick, H.G. (1993). Economic deprivation and neighborhood crime rates. *Law & Society Review, 27*(2), 263-283.

Chilton, R. J. (1964). Continuity in delinquency area research: A comparison of studies for Baltimore, Detroit, and Indianapolis. *American Sociological Review, 29*(1), 71-83.

Cohn, E.G. & Rotten, J. (2003). Even criminals take a holiday: Instrumental and expressive crimes on major and minor holidays. *Journal of Criminal Justice, 31*(4), 351-260.

Cohen, L.E. & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*(4), 588-608.

Cooperman, A. & Walsh, E. (2003, September 21). In N.C., cleaning up after Isabel. *The Washington Post,* p. A1.

Cromwell, P., Dunham, R., Akers, R., & Lanza-Kaduce, L. (1995). Routine activities and social control in the aftermath of a natural catastrophe. *European Journal on Criminal Policy and Resarch, 3*(3), 56-69.

Crutchfield, R.D., Geerken, M.R., & Gove, W.R. (1982). Crime rate and social integration. *Criminology, 20*(3&4), 467-478.

Decker, S.H., Varano, S.P., Greene, J.R. (2007). Routine crime in exceptional times: The impact of the 2002 Winter Olympics on citizen demand for police services. *Journal of Criminal Justice, 35*(1), 89-101.

De Coster, S., Heimer, K., Wittrock, S.M. (2006). Neighborhood disadvantage, social capital, street context, and youth violence. *The Sociological Quarterly, 47* (4), 723-753.

Demuth & Brown (2004). Family structure, family processes, and adolescent delinquency: The significance of parental absence versus parental gender. *Journal of Research in Crime & Delinquency, 41*(1), 58-81.

Department of Justice, Federal Bureau of Investigation. *Crime in the United States, 2004*. Retrieved June 13, 2007 from http://www.fbi.gov/ucr/cius_04/offenses_reported/property_crime/burglary.html.

Drabek, T.E. (1986). *Human system responses to disaster: An inventory of sociological findings.* New York: Springer-Verlag.

Drabek, T.E., Key, W.H., Erickson, P.E., Crowe, J. L. (1975). The impact of disaster on kin relationships. *Journal of Marriage & Family Therapy, 37* (3), 481-494.

Dynes, R.R. & Tierney, K.J. (Eds.). (1994). *Disasters, collective behavior, and social organization.* Cranbury, New Jersey: Associated University.

Elliott, D.S., Wilson, W.J., Huizinga, D., Sampson, R.J., Elliott, A., Rankin, B. (1996). The effects of neighborhood disadvantage on adolescent development. *Journal of Research in Crime and Delinquency, 33*, 389-426.

Erikson, K.T. (1976). *Everything in its path: Destruction of community in the Buffalo Creek flood*. New York: Simon and Schuster.

Erikson, K. T. (1994). *A new species of trouble: Explorations in disaster, trauma, and community*. New York: W.W. Norton.

Fallis, D.S. & Perlstein, L. (1999, September 6). Dennis rains more trouble as it fades. *Washington Post,* p. A01.

Fears, D. (2003, September 21). In North Carolina, a paradise lost; Hurricane Isabel ravages the historic coastal community of Edenton.

Firestone, D. (1999, September 18). High water strands 1,000 and closes roads in state. *New York Times,* p. B5.

Fisher, M. (1999, September 17). No barrier to Floyd; islands windblown; floods as far as you can see. *The Washington Post*, p. A15.

Fitzpatrick, C. & Mileti, D.S. (1994). Public risk communication. In Dynes, R.R. & Tierney, K.J. (eds.) *Disasters, collective behavior, and social organization* (71-84). Cranbury, New Jersey: Associated University.

Friesema, H.P., Caporaso, J., Goldstein, G., Lineberry, R., McCleary, R. (1979). *Aftermath: Communities and natural disasters*. Beverly Hills, CA: Sage Publications.

Gottfredson, D.C., McNeil, R.J. III, Gottfredson, G.C. (1991). Social area influences on delinquency: A multilevel analysis. *Journal of Research in Crime and Delinquency, 28*, 197-226.

Hartnagel, T.F. & Lee, G.W. (1990). Urban crime in Canada. *Canadian Journal of Criminology, 32*, 591-606.

Hausman, J.A. (1978). Specification tests in econometrics. *Econometrica, 46* (6), 1251-1271.

Hsaio, C. (2003). *Analysis of Panel Data* (2^{nd} ed.). United Kingdom: Cambridge University Press.

Jacob, J.C. (2006). Male and female youth crime in Canadian communities: Assessing the applicability of social disorganization theory. *Canadian Journal of Criminology and Criminal Justice, 48*(1), 31-60.

Kasarda, J.D. & Janowitz, M. (1974). Community Attachment in Mass Society *American Sociological Review, 39*(3), 328-339.

Kennedy, H. (2003, September 20). Isabel's toll: $1B, 17 dead. *Daily News (New York)*, p. 2.

Kilborn, P.T. (1999, September 19). North Carolina reeling in hurricane's aftermath. *New York Times*, p. A1.

Klein, L.. (1962). *An introduction to econometrics*. Englewood Cliffs, NJ: Prentice-Hall.

Korbin,S. (1971). in Voss, H.L. & Peterson, D.M. (eds.). *Ecology, crime, and delinquency.* New York: Appleton Century Crofts.

Kornhauser, R. (1978). *Social sources of delinquency.* Chicago: University of Chicago Press.

Kubrin, C. E. & Weitzer, R. (2003). New directions in social disorganization theory. *Journal of Research in Crime and Delinquency, 40* (4), 374-402.

Land, K.C., McCall, P.L., & Cohen, L.E. (1990). Structural covariates of homicide rates: Are there any invariances across time and space?. *The American Journal of Sociology*, *95*(4), 922-963.

Lander, B. (1954). Towards an understanding of juvenile delinquency. New York: Columbia University.

Leinwand, D. & Parker, L. (2003, September 18). Isabel comes ashore today. *USA Today,* p. 1A.

LeBeau, J.L. (2002). The impact of a hurricane on routine activities and on calls for police service: Charlotte, North Carolina, and Hurricane Hugo. *Crime Prevention and Community Safety: An International Journal, 4,* (1), 53-64.

Lemieux, F. (2004). L'impact d'une perturbation sociale majeure sur les occasions criminelles et la frustration relative: une étude de cas. *Canadian Journal of Criminology & Criminal Justice, 46*(1), 45-72.

Maltz, M.D. & Targonski, J. (2002). A note on the use of county-level UCR data. *Journal of Quantitative Criminology, 18*(3), 297-318.

Markowitz, F.E., Bellair, P.E., Liska, A.E., Liu, J. (2001). Extending social disorganization theory: modeling the relationships between cohesion, disorder, and fear. *Criminology, 39*(2), 293 – 320.

Matthews, R.G., & Haggerty, J.R. (1999, September 16). Hurricane Floyd: Companies close southeast factories due to hurricane. *Wall Street Journal*, p. A17.

Messner, S.F. (1986). Modernization, structural characteristics, and societal rates of crime: An application of Blau's macroosociological theory. *Sociological Quarterly, 27*(1), 27-41.

Meier, R. F. & Miethe, T.D. (1993). Understanding theories of criminal victimization. *Crime and Justice, 17*, 459-499.

Miethe, T.D., Stafford, M.C. & Long, J.S. (1987). Social differentiation in criminal victimization: A test of routine activities/lifestyle theories. *American Sociological Review 52*(2), 184-194.

Mosher, C., Miethe, T.D., Phillips, D. (2002). *The mismeasure of crime*. Thousand Oaks, CA: Sage Publications.

Nakamura, D. (1999, October 18). For North Carolina, another deluge; Hurricane Irene likely to bring new floods in Floyd's wake. *The Washington Post,* p. A3.

National Hurricane Center. *Hurricane preparedness.* Retrieved May 3, 2007 from http://www.nhc.noaa.gov/HAW2/english/basics.shtml.

National Oceanic and Atmospheric Administration. *NCDC storm events page – FAQ.* Retrieved May 3, 2007 from http://www.ncdc.noaa.gov/oa/climate/sd/sdfaq.html.

New York Times. (1999, October 17). Storm heads for Carolinas after soaking south Florida. *New York Times,* p. 1.36.

New York Times. (2002, September 11). Outer Banks inundated. *New York Times,* p. A24.

North Carolina Division of Emergency Management. Retrieved June 13, 2007 from http://www.nccrimecontrol.org/index2.cfm?a=000003,000010.

Osgood, D.W. & Anderson, A.L. (2004). Unstructured socializing and rates of delinquency. *Criminology, 42*(3), 519-549.

Osgood, D.W. & Chambers, J.M. (2000). Social disorganization outside the metropolis: An analysis of rural youth violence. *Criminology, 38*(1), 81-115.

Park & Burgess (1924). *Introduction to the science of sociology. 3rd Ed.* New York: Greenwood.

Perry, R.W. (1985). *Comprehensive emergency management: Evacuating threatened populations*. Greenwich, Connecticut: Jai Press.

Perry, R.W. (1994). A model of evacuation compliance behavior. In Dynes, R.R. & Tierney, K.J. (eds.) *Disasters, collective behavior, and social organization* (85-98). Cranbury, New Jersey: Associated University.

Perry, R.W., Lindell, M.K. & Greene, M.R. (1981). *Evacuation planning in emergency management*. Lexington, Massachusetts: Lexington Books.

Perry, R.W. & Mushkatel, A.H. (1984). *Disaster management: Warning response and community relocation*. Westport, Connecticut: Greenwood Press.

Pressley, S.A. (1999a, September 6). Welcome long wore out, Dennis leaves NC. *The Washington Post*, p. A18.

Pressely, S.A. (1999b, September 15). Floyd roars toward U.S.; huge flight from coast. *The Washington Post,* p. A1.

Reppetto, T.A. (1974). *Residential Crime*. Cambridge, MA.: Ballinger Publishing Company.

Rosen, L. & Turner, S. H. (1967). An evaluation of the Lander approach to ecology of delinquency. *Social Problems, 15* (2), 189-200.

Rossi, P. H., Waite, E., Bose, C. E. and Berk, R. E., 1974. The seriousness of crimes: Normative structure and individual differences. *American Sociological Review*, 39, 224–237.

Rossi, P.H., Wright, J.D., Weber-Burdin, E., & Pereira, J. (1983). *Victims of the environment: Loss from natural hazards in the United States, 1970-1980*. New York: Plenum Press.

Sampson, R.J. (1985). Neighborhood and crime: The structural determinants of personal victimization. *Journal of Research in Crime and Delinquency, 22*, 7-40.

Sampson, R.J. (1987). Communities and crime. In Gottfredson, M. & Hirschi, T. (eds.) *Positive criminology* (91-114). Newbury Park, CA: Sage Publications.

Sampson, R.J. & Groves, W.B. (1989). Community structure and crime: Testing social disorganization theory. *The American Journal of Sociology, 94*(4), 774-802.

Schneider, S.K. (1992). Governmental response to disasters: The conflict between bureaucratic procedures and emergent norms. *Public Administration Review, 52*(2), 135-145.

Sellin, T. & Wolfgang, M.E. (1964). *The measurement of delinquency.* New York: Wiley and Sons.

Shannon, L. W. (1998). *Alcohol and drugs, delinquency and crime: Looking back to the future.* New York: St. Martin's Press.

Shaw, C.R. & McKay, H.D. (1942). *Juvenile delinquency and urban areas.* Chicago: University of Chicago.

Shover, N. (1991). Burglary. *Crime and Justice, 14*, 73-113.

Siegel, J.M, Borque, L.B., Schoaf, K.I. (1999). Victimization after a natural disaster: Social disorganization or community cohesion. *International Journal of Mass Emergencies and Disasters, 17*(3), 265-294.

Small, M.L. (2007). Racial differences in networks: Do neighborhood conditions matter?. *Social Science Quarterly, 88*(2), 320-343.

Smith, D.A. & Jarjoura, G.R. (1988). Social structure and criminal victimization. *Journal of Research in Crime & Delinquency, 25*(1), 27-51.

Smith, S.K. & McCarty, C. (1996). Demographic effects of natural disasters: A case study of Hurricane Andrew. *Demography, 33*(2), 265-275.

Smith, W.R., Frazee, S. G., & Davidson, E.L. (2000). Furthering the integration of routine activity and social disorganization theories: Small units of analysis and the study of street robbery as a diffusion process. *Criminology, 38*(2), 489-523.

South, S.J. (1987). Metropolitan migration and social problems. *Social Science Quarterly, 68* (1), 3-18.

Sowder, B.J. (1985). *Disasters and Mental Health.* Rockville, MD: Department of Health and Human Services.

St. Petersburg Times (2002, September 11). Storm brushes by N.C. islands. *St. Petersbur Times*, p. 4A.

The Sun. (1999a, September 19). Hundreds rescued from Floyd flooding; in North Carolina and New Jersey people plucked from roofs, trees. *The Sun,* p. 8A.

The Sun. (1999b, September 22). Villages of trailers, campers created for Floyd refugees; families whose homes are still under water can leave N.C. shelters. *The Sun,* p. 11A.

Thomas, G., Farrell, M.P., & Barnes, G.M. (1996). The effects of single-mother families and nonresident fathers on delinquency and substance abuse in black and white adolescents. *Journal of Marriage & Family, 58*(4), 884-894.

Tittle, C.R. & Paternoster, R. (1988). Geographic mobility and criminal behavior. *Journal of Research in Crime & Delinquency, 25*(3), 301-343.

Tobin, J. (1958). Estimation for relationships with limited dependent variables. *Econometrica, 26*(1), 24-36.

Wenger, D. & Friedman, B. (1986). *Local and national media coverage of disaster: A content analysis of the print media's treatment of disaster myths.* Disaster Research Center University of Delaware.

Zimring, F.E., Ceretti, A., & Broli, L. (1996). Crime takes a holiday in Milan. *Crime & Delinquency, 42*(2), 269-278.