# ECOLOGICAL PREDICTORS OF LOCAL MOTOR VEHICLE THEFT AND CHANGES OVER A DECADE: 1990-2001

by

JEFFREY A. WALSH

A Dissertation
submitted to Graduate Faculty in Criminal Justice
in partial fulfillment of the requirements for the degree Doctor of Philosophy,
City University of New York
2005

COPYRIGHT PAGE

Approval Page

This manuscript has been read and accepted by the Graduate Faculty in Criminal Justice in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

1/11/05 ______ Dr. Andrew A. Karmen

Date — Chair of Dissertation Committee

1-11-05 ______

Date — Executive Officer

Dr. Mangai Natarajan Ph.D. ______

Dr. Eli Silverman Ph.D. ______

Dr. Ralph Taylor Ph.D. ______

Supervisory Committee Members

The City University of New York

Abstract

ECOLOGICAL PREDICTORS OF LOCAL MOTOR VEHICLE THEFT AND CHANGES OVER A DECADE: 1990-2001

by

Jeffrey A. Walsh

Advisor: Professor Andrew Karmen

There are more than one million motor vehicles stolen in the United States each year worth an estimated eight billion dollars. National motor vehicle theft rates decreased each year during the 1990s but have begun to climb again in the new millennium with each year since 1999 experiencing an increase.

This dissertation is a study of rising motor vehicle theft and the effects of ecological change over a decade in the medium size Midwestern city of Peoria, Illinois. The study employs both a series of two-wave cross-sectional analyses and a series of longitudinal lagged ecological effects analyses to study the impacts of community structure on motor vehicle theft. The study addresses three specific areas of shortcomings in the existing literature: 1) reliance on relatively large units of analysis; 2) prevalence of single-wave cross-sectional designs; 3) and use of macro level data to explain micro level community processes derived from a limited number of theoretical perspectives. The study draws upon the underpinnings of multiple theoretical models of

crime including social ecology, routine activities, human territorial functioning, and the subcultural diversity model. Additionally, the study identifies alternative theoretical perspectives by which motor vehicle theft could be explored. The research utilizes two unique sources of data: police department records of motor vehicle thefts, and the 1990 and 2000 decennial censuses. Regression analyses are used to identify predictors of motor vehicle theft. The cross-sectional analyses found several differing significant relationships when compared to the results of the longitudinal analyses suggesting that the pattern of relative change is different. For example, SES is a significant predictor when studied cross-sectionally but is less so when studied longitudinally. Heterogeneity has a greater predictive impact longitudinally than it does cross-sectionally. Census block group instability has a paradoxical relationship to motor vehicle theft when studied longitudinally that is not present in cross-sectional analyses.

The findings support the assertion that there are multiple theoretical explanations of motor vehicle theft available when studied at the macro level and that micro level data collection is necessary to fully operationalize the social processes that are directly related to vehicle theft.

ACKNOWLEDGEMENTS

I would like to thank the members of my dissertation committee for their support, guidance, and patience throughout this project. Without their insight, oversight, and tutelage this project would not have been possible. Each committee member offered unique contributions and their collective efforts are what made this project a success.

I would like to thank Dr. Andrew Karmen, the Chair of my committee, who assisted with the original conceptualizations of the project and the many editorial revisions throughout the research effort. His insights and research experience studying various aspects of motor vehicle theft and victimization were invaluable. He also gave me a new appreciation for the methodical process that is research.

Dr. Mangai Natarajan helped me delve into the early aspects of crime mapping and taught me how to conceptualize this study from a geo-spatial perspective. She first introduced me the Environmental Criminology perspective providing a wealth of new literature for me to become acquainted with. She was always available to discuss the various twists and turns that the project took along the way and guided me through the many revisions. She was also instrumental in my professional development.

Dr. Eli Silverman assisted with the early conceptualization of the project and was encouraging throughout its completion. He, too, assisted with the editorial process and helped create a better final product.

A very special thank you goes to Dr. Ralph B. Taylor of Temple University who spent countless hours providing tireless instruction, advice, and unwavering support for this project in both a mentoring capacity and as a friend. He imparted upon me a whole new appreciation for research methodology and quantitative analysis and taught me the true value of being thorough. Dr. Taylor was also instrumental in my professional development not only as a scholar but also as an instructor in the classroom providing advice and feedback. I am appreciative of his willingness to help in all aspects of the process of doctoral education. I will strive to pay his generosity forward.

I would like to thank Dr. Todd Clear and Dr. Ned Benton for their early support of the project and their resounding sentiment at the proposal defense that this study "must" be done.

I would like to thank Maggie Smith for her willingness to listen along the way and the unfettered access to the Law and Police Science Computer Lab. It was there that much of the early crime mapping and data entry took place.

I would also like to thank Peoria Police Officer, Joe Benko, without Officer Benko's support there would not have been such a rich dataset of vehicle thefts to study and analyze.

Dr. Ellen Kurtz helped me refine some of the early spatial issues of this study and provided technical instructions for calculating several of the spatial formulas as well as early support for the "daunting parts" of the project.

Thank you to Dr. Josh Freilich, Dr. Dina Rose and the many other friends and supporters who were always encouraging and most optimistic when the challenge seemed its greatest.

A very special thank you goes to Christina Czechowicz who helped me navigate the waters of doctoral education and was a true friend and confidante from the very beginning. She helped get me in to the program, and she helped get me through the program. Her belief in my ability to complete what I had started kept me going at challenging times and for that I cannot say thank you enough. Every doctoral student should be so lucky to have such tremendous support.

Lastly but certainly not least, I would like to thank my family including my wife Jane, my daughter Lauren, and my parents for their support, and willingness to endure throughout this process. Without their feigned interest in the project and sincere heart felt support this truly would not have been possible. We did it; we finished the dissertation and earned a Ph.D.

– Thank you

# TABLE OF CONTENTS

# LIST OF TABLES

Table Page

# LIST OF FIGURES

# CHAPTER 1

# INTRODUCTION TO THE CRIME OF MOTOR VEHICLE THEFT

## Scope of the Problem and Recent Trends

The crime of motor vehicle theft is a very serious problem in the United States and consistently ranks as the single most expensive property crime in the country with victims suffering both significant financial losses and personal hardships. As FBI UCR statistics have revealed, there have been over one million vehicles stolen each year since the late 1970s and the associated costs of the thefts have continued to climb annually. This trend continued through the 1980s and 1990s and is evident even now in the new millennium (FBI, 2002). For example, in the year 2000 alone, the economic value of the nearly 1.2 million stolen vehicles was approximately $7.8 billion, or an average of more than $6,000 per stolen vehicle (FBI, 2001). The estimated value of all motor vehicles stolen in 2001 was $8.2 billion dollars, or an average of more than $6,500 per vehicle (FBI, 2002). The cumulative value of motor vehicles stolen is showing an upward trend.

The 2003 FBI Uniform Crime Report (UCR), released October 25, 2003, states that motor vehicle thefts in 2001 were up 5.7 percent over thefts in 2000, and in 2002 vehicle thefts were up an additional 1.2 percent over thefts in 2001. In sum, motor vehicle thefts have risen by 10 percent since 1999. Simply stated, despite significant efforts the crime of motor vehicle theft and its consequent monetary and social costs continue to stubbornly increase by modest proportions.

Interestingly, the high numbers of annual motor vehicle thefts accounted for in these UCR statistics, while considered extremely accurate, do not include the category of crime referred to as car jacking - involving the theft of motor vehicles at gunpoint. According to Rengert (1997), who cites Fried (1991), carjackings are counted as robberies according to UCR recording practices and are not represented in the official annual vehicle theft statistics that are reported by the FBI, were they to be counted the vehicle theft numbers would be even higher.

### *Direct Costs Incurred*

The crime of motor vehicle theft is a vast problem of both national and international scale affecting nearly every community in the United States and many abroad. While individual motor vehicle theft victims experience much of the excessive financial losses directly many others in society also suffer. The direct costs to the theft victim were estimated at more than $240 after accounting for recoveries, reimbursements, and insurance payouts according to Harlow (1988). This number must certainly be adjusted upward to keep it in context given the lapse in time from when the research was conducted to today. In fact, simply factoring in a 3% annual inflation rate raises that victim cost incurred amount to $385 in 2004. The vehicle owners are only one entity in a chain of victims who suffer both financially and socially from motor vehicle theft.

Insurance companies absorb a significant amount of financial loss from vehicle theft as well. Although, it is noteworthy to mention that since most states in the U.S. require motorists to be insured, theft losses are largely passed on to every insured motorist in the form of increasing insurance costs, inflated insurance premiums and higher insurance deductibles. According to the Federal Bureau of Investigation, vehicle thefts have added an average of $85 to every family's annual auto insurance premium (Ragavan and Kaplan, 1999).

*Indirect Costs Incurred*

Additionally, there are a profound number of indirect costs associated with stolen automobiles. The investigation of vehicle thefts by law enforcement personnel draws on already significantly limited police resources; prosecution and adjudication are expensive to the courts and consequently to the taxpayers; victims often experience inconveniences and costs that far exceed the monetary value of their vehicles; worker productivity is lost due to unplanned absences from work associated with the inconvenience of not having a vehicle as well as time spent filling out police reports (Henry and Bryan, 2000).

Also, as new and innovative efforts at theft prevention are developed and implemented, citizens must bear the additional costs associated with these devices and heightened security features. Occasionally insurance premium reductions are offered to vehicle owners who implement these various theft prevention devices but the reduction is often nominal and the initial savings rarely covers the cost of the device. Another hardship of vehicle theft is that stolen automobiles are routinely used in the commission of a multitude of other crimes occasionally resulting in the injury and death of innocent citizens caught unsuspecting as the events unfold. Vehicle thieves, in an effort to evade law enforcement, are occasionally involved in injurious accidents involving themselves, the police, and innocent third parties. Direct victims of motor vehicle theft are clearly not the only ones impacted by this crime as it occurs in communities throughout the United States and abroad.

National crime victimization research suggests that households of lower socioeconomic status bear a disproportionate amount of the cost associated with the crime of motor vehicle theft. These vehicle owners are often unable to afford full-coverage insurance that would compensate them for the loss of their automobile and they are also less likely to live in areas providing indoor facilities such as garages to protect their property and are more apt to park on edges of streets or in driveways. They are also less likely to be able to afford the optional additive theft prevention devices like the LOJAC service or sophisticated car alarms (Brill, 1982). The social costs of motor vehicle theft are far reaching in today's society and extend well beyond the simple economics of the actual criminal event.

Although national motor vehicle theft rates declined for much of the 1990's the frequency and cumulative costs are still startling. While vehicle theft rates had been declining modestly during the 1990's, the overall cost of theft was actually increasing due to the fact that new cars in the marketplace have become more and more expensive and thus their monetary loss is much greater when they are stolen and/or damaged. Ironically, some of the technological "improvements" that have been contributing to increasing vehicle costs come in the form of a variety of theft prevention devices from coded keys and engine shut off switches to alarm systems and GPS tracking programs.

A wide variety of vehicle theft prevention products, escalating in technological sophistication, have been marketed to vehicle owners over several decades in an effort to combat thefts and reduce the high costs associated with this crime. There are generally two aspects to vehicle security: improving perimeter security to prevent break-ins, and the installation of systems that, in one way or another, disable a vehicle while parked to prevent it from being driven away (Webb, 1994).

*A Brief History of Motor Vehicle Theft*

Early motor vehicles had very few security features built-in, in fact they often were void of even the simplest safety and security features such as enclosed passenger compartments, windows, and even roofs. The benefit was that this allowed vehicles that routinely obstructed traffic due to emerging metropolitan congestion to be moved by anyone when they were parked in public spaces. Eventually sealed passenger compartments with doors, windows, and a roof became the norm. However, citizens were prohibited by law from locking their cars when they were parked in public spaces in order to allow them to be moved when necessary. Between 1910 and 1950, major safety and security improvements were made, including incorporating lock mechanisms into doors, changing the shape of vehicle door handles, and switching from push-button ignition to key ignition (Webb, 1994).

The growing problem of motor vehicle theft and the ease at which motivated thieves could compromise the existing theft prevention devices led Congress to pass the Motor Vehicle Theft Act of 1919. This act is commonly referred to as the Dyer Act The Dyer Act addressed an issue that had been plaguing local law enforcement for some time, how to apprehend motor vehicle thieves when they cross over state jurisdictional boundaries, which was common, especially in cities and communities near state borders.

The Dyer Act made interstate transport of stolen motor vehicles a federal crime and authorized the Federal Bureau of Investigation (FBI) to investigate vehicle thefts that crossed over state jurisdictional lines (Lowenthal, 1950).

Additional legislation followed that required vehicle manufacturers to include anti-theft devices in their cars. A variety of developments were entertained and the method of choice became the steering wheel lock. In 1970, Federal Motor Vehicle Safety Standard 114 became effective after its passage into law in 1966. Standard 114 required all vehicle manufacturers to outfit their passenger vehicles with a key-lock system that would prevent the car from being steered without the necessary and unique ignition key, consequently rendering it un-drivable. An analysis of pre and post key-lock trend data for a brief period of time in 1974 suggested that the ignition key-lock systems were moderately effective. The cars with the key-lock system represented nearly 58 percent of the cars on the road in 1974 but accounted for only 45 percent of vehicles stolen at the time (Webb, 1994).

The products currently incorporated into vehicle theft prevention efforts range from basic target hardening techniques such as putting steering column locks in vehicles at the time of manufacturing to placing a Club on the steering wheel of a car or having a basic alarm installed. There are even more sophisticated preventive measures like installing a commercial vehicle tracking device that uses a global positioning system (GPS) or installing engine cut-off switches that render the vehicle immobile.

The utility and success of many of these products is debatable because deterrence is difficult to measure. Steering column locks, car alarms, and the Club were all once very common target hardening techniques with widespread support and implementation.

However, at this point in time, loss prevention specialists often regard these techniques as on the verge of extinction – that is, car thieves are largely undeterred by the presence of any of these devices and know relatively easy ways of "beating" them. Steering column casing and locks are easily "cracked", car alarms result in too many false alarms to generate much suspicion when a theft is actually underway, and the Club can be breached by cutting the steering wheel, often with a strong pair of gardening sheers or a small hand saw.

*Modern Era of Motor Vehicle Theft*

The new era of sophisticated and more costly tracking systems using GPS is catching on and vehicle manufacturers are incorporating these features in their newer, more expensive models of vehicles. The most common tracking system on the market is the LOJAC system which serves the exclusive function of a vehicle theft recovery system. The OnStar system has multiple use tracking purposes, including aiding a stranded motorist, unlocking vehicles that have been accidentally locked, and locating missing vehicles. Despite these many and varied attempts at prevention, motor vehicle theft is still a very lucrative criminal act with more and more vehicles going missing each year.

According to data from the UCR reporting program, nearly 43 million vehicles were stolen from 1960 through 1999. The data trend suggests that, although not annually sustained, motor vehicle theft increased significantly during those four decades. Research conducted by Clarke and Harris (1992), suggested that between 1958 and 1989 motor vehicle theft increased by nearly 400 percent. National crime statistics show that motor vehicle theft had been decreasing consistently for several recent years during the 1990's. However, new data compiled by the National Insurance Crime Bureau (NICB) indicate that motor vehicle theft is once again on the rise. As previously mentioned, statistics compiled by the Federal Bureau of Investigation show that auto theft rates have been increasing as society has moved into the new millennium with more thefts occurring in each successive year.

### *Stolen Vehicle Recovery*

Despite continued efforts to combat motor vehicle theft, the number of motor vehicles that are recovered has remained somewhat debatable yet surprisingly low for decades. According to Karmen (1996) the vehicle theft recovery rate dropped from more than 90 percent in the 1940s to approximately 73 percent in 1992 based on NCVS nationwide figures. In 1977 only 59 percent of stolen vehicles were recovered according to McCaghy, Giordano, and Henson (1977), and in 1982 an FBI motor vehicle theft study found that 77 percent of stolen vehicles were recovered but stated that the rate of recovery today is much less.

The year 2000 Uniform Crime Report (UCR) Supplementary Analysis addendum of motor vehicle theft, relying on National Based Incident Reporting System (NIBRS) and National Crime Information Center (NCIC) records, indicated that the current recovery rate was 53 percent and 51 percent respectively (FBI, 2000). Recent estimates by the F.B.I. (UCR, 2001) suggest that in 2001 approximately 62 percent of stolen vehicles were recovered. It is worth mentioning that "recovered" gives no indication of the condition of the vehicle upon its return to the legal owner.

There are several reasons for the continued low rate of recovery for stolen vehicles. First, more cars are being stolen for their parts and as a result they are stripped to accommodate the lucrative illegal parts trade both in this country and abroad leaving virtually nothing to be recovered except a vehicle chassis with the VIN number attached. Secondly, sophisticated factions of highly organized criminals are stealing more cars for the sole purpose of illegal exportation to foreign countries. This is possibly the fastest growing area of motor vehicle theft (Miethe and McCorkle, 2001). Regardless of the reason, this fluctuating recovery rate also greatly contributes to the overall cost of motor vehicle theft since it means that when there are low recovery rates insurance companies will deem more vehicles a complete and total loss and will be forced to make costly payouts to owners accordingly. It is also important to note that recovering a vehicle does not necessarily preclude a costly insurance claim. In fact, many vehicles that are recovered each year have been stripped of their valuable parts and/or destroyed intentionally or in an accident and must undergo costly repairs or be deemed "totaled".

### *Case Clearance*

On another note, there are also extremely low motor vehicle theft case clearance rates and arrests of suspects. According to the UCR statistics for 2002 there were 1,246,096 vehicles stolen in 2002, a 1.4 percent increase over the 1,228,391 number stolen in 2001. Unfortunately, in 2002 there were only 148,943 arrests made for motor vehicle theft and only 13.8 percent of all cases were cleared by arrest or exceptional means. In 2001 there were only an estimated 147,451 perpetrators arrested for the 1,228,291 thefts, or slightly more than ten percent. The low case clearance rate and consequently even lower arrest rates of offenders make it difficult to study who the actual offenders are. Occasionally one arrest aides in the clearance of multiple vehicle theft cases (FBI Report, Crime in the United States, p. 4-7).

Comparisons by regions show that the Northeast had the highest clearance rate, 15.7 percent, followed by the South with 15.6 percent clearance, then the Midwest with 14.9 percent clearance rate , and lastly, the West had a 10.8 percent clearance rate. In 2000 only 14 percent of the cases nationwide were cleared by law enforcement.

Low clearance rates are not surprising given the case clearance trend that has emerged over the last several decades. In 1953 an estimated 26 percent of vehicle theft cases were cleared. However, since 1953 the trend showed a marked decrease and by 1973 the clearance rate had dropped to 16 percent and in 1993 the clearance rate had dropped to a mere 14 percent (Karmen, 1996).

Many researchers agree that there are several different types of motor vehicle thieves ranging from experienced professionals to joyriding teens. Slightly differing typologies of motor vehicle thieves have been created and explored by a number of researchers over the years (Clarke and Harris, 1992; Clarke, 1991; Karmen, 1996; Giordano, and Henson, 1977). The general consensus among researchers has been that joyriding thieves, seizing opportunities provided by careless motorists, have been the most prevalent group of offenders. However, more recent research has suggested the burgeoning problem of professional thievery, largely for purposes of international exportation.

Research by Clarke and Harris (1992) suggests that motor vehicle theft is predominantly an urban crime with 37 percent of auto thefts occurring on the street in front of the victim's residence. Additionally, non-commercial parking lots accounted for 19 percent, followed by 16 percent in other street locations (Krimmel and Mele, 1988).

The exorbitant cost to the public in terms of lost property is a serious concern for victims, insurance agencies, policy makers, community organizations, and law enforcement, to name a few of the entities impacted by this crime. Understandably, the law enforcement community and beyond has tried to understand, prevent, and solve this crime for decades.

### *Previous Approaches of Explaining Motor Vehicle Theft*

Much of the previous research on the phenomenon of motor vehicle theft has been void of much sound theoretical basis or foundation. In fact, much of the previous research has been merely descriptive in nature and has focused more on the demographic characteristics of the offenders who steal the vehicles - an interesting endeavor given the paucity of information available about these individuals due to the previously mentioned small number of clearances and arrests. And yet other studies have explored vehicle theft victims (see Karmen, 1996) and descriptions of the most popular makes and models of vehicles stolen, vehicle design and target hardening theft prevention strategies often in the absence of sound theoretical support (see Copes, 1999). An important exception to this includes a series of studies on rational choice conducted by Ron Clarke (1986). Clarke's research has focused on target hardening techniques and auto theft prevention from a choice structured cost/benefit analysis on the part of the potential thief.

Additionally, several existing studies have drawn conclusions about the applicability of various theoretical models to explain motor vehicle theft without actually testing the major tenets of the theory in question. For example, macro level data has been used to make assertions regarding micro level processes. The fundamental problem arising from this line of inquiry is known as the ecological fallacy – the drawing of inferences about individuals and individual level behaviors based on interpretations of aggregate level data.

A more comprehensive understanding and deeper knowledge of the systemic processes and sociodemographic/ecological factors that impact the occurrence of motor vehicle theft in our communities over time could greatly help to reduce the risk and subsequent incidence of this pervasive crime in the United States and contribute greatly to identifying theoretical orientations that suitably explain this pervasive crime phenomenon.

Much like other criminal events occurring within the social landscape, motor vehicle theft generally is not randomly distributed in space and time and tends to have an uneven concentration and density throughout the spatial layout of a city with some areas having tremendous amounts of theft while others have none. The reasons for these disparities in theft density and the nonrandom spatial patterning are largely dynamic and it is believed that they can be traced to the social environment and the sociodemographic structure of the city.

The environmental criminology paradigm holds that crime is not randomly distributed and that social change in the social environment contributes to and structures the opportunities for crime and criminality. "The ecological study of human behavior is built upon the assumption that the geographical surroundings, the man-made milieu, and the demographic characteristics of the population can shape and influence the development of communities" (Faggiani, 1994, p.8).

Certain places (locations) and spaces (areas) tend to provide a high-risk setting for a disproportionate number of criminal events (Block and Block, 1995). Criminal events become concentrated in places or spaces for a number of reasons. Potential offenders may prefer certain locations or areas. Some places in the community may have characteristics that serve as crime generators or crime attractors for type specific crimes. For example, previous research suggests that the following community places are "target locations": taverns, bars or liquor stores, abandoned buildings, public housing, high schools, and certain types of businesses and homes (Block and Block, 1995). "It is not always recognized, however, that different types of crime may cluster in different areas of the city" (Block and Block, 1995, p.148). Block and Block (1992) found that areas of Chicago where instrumental homicide was most dense were not necessarily the same areas where gang related homicide was densest (Block and Block, 1995). Therefore, it is important to study crime types individually rather than simply studying the aggregate of all property crimes or violent crimes.

It is also important to note that motor vehicle theft is a qualitatively unique property crime with numerous attributes that distinguish it from other property crimes. For instance, motor vehicle theft, or car theft as it is synonymously referred, is the only property crime where the target also usually provides the getaway opportunity for the offender. Motor vehicles are uniquely vulnerable items of property in that they are often left unattended, without adequate guardianship, in full view of potential offenders for extended periods of time, and their monetary value is often substantial creating immediate offender motivation. Interestingly, auto theft victims are occasionally facilitators of the thefts and a peculiar pattern of victim blaming has developed. The same interest groups that blame the offender for committing the crime also blame the victim for making the crime too easy for the offender. Research conducted by Karmen (1990) has suggested that owner negligence is actually overblown and not the smoking gun that many in law enforcement, insurance, and the motor vehicle manufacturing industry would have us believe. Nonetheless, vehicle theft victim blaming remains common, possibly as a diversionary tactic to shield those - other than the owner - who are partly responsible for the safety and security of our vehicles, namely law enforcement who patrol and protect our communities and the motor vehicle manufacturing industry who sell cars that are too easily stolen (Karmen, 1996).

Motorists' concerns for the loss of their vehicles coupled with many statewide laws mandating that owners insure their vehicles in order to file insurance claims for monetary loss has helped to keep the reporting rates high (McCaghy et al., 1977; Clarke and Harris, 1992). In fact, research by Karmen (1996) found that the percentage of vehicle thefts that were reported to both the NCVS and the police increased over the last several decades from approximately 68 percent in 1973 to more than 75 percent in 1992. Karmen (1996) also notes that motor vehicle theft is reported more often these days than in past decades. As a result researchers may safely assume that the officially reported completed motor vehicle thefts are in very high concordance with the actual number of thefts in a particular location, as well as where, when, and which cars were stolen (Hollinger and Dabney, 1999).

Despite the high frequency and staggering costs, both direct and indirect, motor vehicle theft has been rather neglected in the criminological/criminal justice literature. In fact, a study by Clarke and Harris (1992) indicated that despite the significant costs associated with motor vehicle theft, and the exceptionally high reporting rates of victims of completed thefts, not a single academic book about motor vehicle theft had been published in the twenty years preceding their study. Even more surprising, this author has not discovered one written since then either with the exception of the recently published Crime Prevention Studies volume 17, titled Understanding and Preventing Car Theft (2004). The volume contains several articles on car theft research from around the country. So, while motor vehicle theft is the most reported of all property crimes and the most expensive it is also one of the least solved and least researched. As a result, this situation provides an abundance of opportunities for empirical study and exploration. Insight into the phenomenon of vehicle theft is greatly needed in order to protect our communities and our property from this encroaching criminal event.

## Statement of the Problem

There are several shortcomings in the existing research and literature on motor vehicle theft. For example, much of the existing literature has tended to focus on and address issues or characteristics pertaining to the offender and/or the victim and details pertaining to the criminal event itself. Limited research has focused on the social ecology of the community or the social structure of the environment where the thefts occurred in an effort to study vehicle theft from a structural perspective. The current research contributes to the literature on motor vehicle theft and community crime and goes beyond much of what has previously been studied, especially with regard to the unit of analysis and subsequent level of aggregation, the novelty of the methodology and analyses, and the expansion of theoretical inquiry.

### *Problem Number One: Research Design*

The vast majority of existing studies of motor vehicle theft have primarily been single-wave cross-sectional research designs capturing information related to vehicle thefts at one specific point in time, commonly one year of data or less. The reasons for conducting cross-sectional analyses of motor vehicle theft have largely been two-fold: 1) single-wave cross-sectional analyses only require crime data and community level data for one point in time making data acquisition considerably easier and cheaper than longitudinal research; 2) geographic units of analysis have a tendency to undergo boundary changes over time and as a result make longitudinal analyses more difficult. However, newly emerging data products are able to control for some of this boundary change making longitudinal research more possible and reliable today.

The over reliance on cross-sectional studies of motor vehicle theft have told us very little about changes over time in either vehicle thefts patterns and trends or the impact of community structure and change on vehicle theft patterns and trends. The cross-sectional approach only provides a snapshot of the actual crime phenomenon at one specific point in time thereby neglecting dynamic processes that could be having an impact on the incidence of theft over time. The incorporation of longitudinal research on the crime of motor vehicle theft would provide a new avenue by which to study and further understand this complex crime.

*Problem Number Two: Units of Analysis*

Much of the existing research has tended to use relatively large geographic units of analysis with large levels of sociodemographic aggregation, namely regional comparisons, state and/or city comparisons, county comparisons, parish comparisons, and census tract comparisons. Cross-sectional studies at large levels of aggregation have a tendency to obscure the nuances of community structure that are only observable at a more micro level and over time. For example, large units may be half Black and half White and seem heterogeneous when in actuality the area is highly segregated (Davison and Smith, 2000). Smaller levels of aggregation would capture local factors that may be impacting the criminal event being studied. In fact, it is the opinion of this author that of the more micro units of analysis used for community crime research, the most common unit of analysis tends to be conducted at the meso level using census tracts, not the more finite block group or even face block. This trend is likely due to the limited Census data available at the more micro levels of aggregation as well as changes in geographic boundaries among the smaller units. With the advent of new data products to the marketplace provided by commercial data vendors issues of uniformity in geographic units and levels of aggregation are much less of an obstacle than they once were. Researchers are now finding it possible to use normalized census data across time comparing like units of analysis.

*Problem Number Three: Macro Level Analysis of Micro Level Processes*

Lastly, many of the existing motor vehicle theft studies that do purport to study the phenomenon by testing specific theories do not adequately isolate and operationalize the micro level social processes necessary for a full and true test of the specific theory. For example, the effectiveness of resident efforts at informal social control to direct the behaviors of others is a micro level process. Rather, it is argued here that many of the existing studies simply test for the presence of macro level antecedent factors or preconditions that might set in motion micro level processes that could then lead to a higher incidence of criminal events, specifically motor vehicle theft. The point is that many of these studies have actually studied levels of association between crime and sociodemographic predictors without establishing a clear causal link (Bursik, 1986). This ill-advised tradition became a very common modality in the ecological literature, especially in the years since Shaw and McKay first postulated social disorganization theory. As previously mentioned, one problem arising from this approach is the drawing of erroneous conclusions based on data at larger levels of aggregation, also known as an ecological fallacy.

Several of these existing studies have operationalized theoretical propositions by choosing proxy measures that are at large levels of aggregation and not mutually exclusive to the specific theory being tested. These proxy measures could easily be interpreted /adapted to fit alternative theoretical models, thereby confounding assertions regarding the explanatory power of the specific theory/theories in question without addressing potential alternative explanations. A model linking traditional theoretical approaches of explaining motor vehicle theft in combination with several alternative theoretical perspectives can be seen in figure 13. A comprehensive exploration of motor vehicle theft would ideally consist of a meso level analysis such as the present study combined with micro level analysis of social processes present in the environment

The current study addresses some of the previously mentioned limitations by employing methodologies and techniques of analyses that are largely absent in the existing literature on motor vehicle theft. Specifically, this study contributes to and expands upon both the motor vehicle theft literature and the communities and crime literature by looking at the impact of community structural change in ecological predictors over time and the effects on motor vehicle theft counts.

## Summary

This study breaks from tradition and employs a two-wave cross-sectional research design allowing for the analysis of motor vehicle theft at two points in time providing for a comparative analysis of the predictors at an earlier and later date spanning a decade of time. Also, this study adds a longitudinal dimension to the analyses of motor vehicle theft by taking into account a longitudinal lagged effects model in order to study the relationship between ecological predictors and vehicle theft over time and to study the relationship between ecological change over time and motor vehicle theft.

This study relies on a comparatively small geographic unit of analysis, the census block group, resulting in a meso level of aggregation from which the ecological predictors have been drawn. The term meso was developed by Brantingham and Brantingham (1984) to imply an intermediate level of spatial aggregation including census tracts, street blocks, zip codes, and the like. As previously mentioned, the use of a small unit of analysis allows for a more thorough examination of community structure and the nuances of ecological change taking place in a more finite area. According to Harries and Kovandzic (1999), geographers interested in studying crime have strongly suggested that the census block group is a better unit of analysis than the larger census tract because they provide better spatial definition and context (Lockwood, 2004). In support of this idea, there have been several recent ecological studies of crime that have successfully used the census block group as the operational definition of a neighborhood (see McNulty and Holloway, 2000; Lockwood, 2004).

This research, similar to some of the existing studies, tests antecedent structural predictors of motor vehicle theft that have been shown to be associated with ecological theories of crime and micro level social processes. This study tests for the predictive power of these variables and then offers several potential alternative theoretical explanations of motor vehicle theft that might be suitable when studied at the micro level to assess the presence or absence of specific social processes. The objective is to identify if the ecological predictors that have often been used in other community crime studies show a meso level relationship to motor vehicle theft and then to demonstrate the need for follow-up micro level data collection and analysis that are necessary in order to truly identify and discern the underlying social processes at work. As previously stated, micro level data collection is necessary to definitively test most theories of social ecology, community structure, and environmental criminology.

The following chapter (Chapter Two) is a brief review of the literature detailing some of what has previously been studied with regard to motor vehicle theft and why the current study is needed. Chapter three identifies the theoretical underpinnings of the study of motor vehicle theft based on what has been done in the past as well as alternative approaches that should be considered as vehicle theft research moves forward. Chapter four details the methodology used to guide the current study including the unit of analysis and the research design. Chapter five provides a discussion of the community profile of the study area. The intention is to give the reader some context when thinking about vehicle theft in Peoria, Illinois. Chapter six outlines the analysis plan that was followed in the current study detailing the two unique series of analyses that were conducted. Chapter seven details the results that were found, both the anticipated findings as well as a few that were unexpected. Finally, chapter eight is the discussion chapter which attempts to draw conclusions about motor vehicle theft, identify strengths and weaknesses of the present study, and suggest avenues for future inquiry.

# CHAPTER 2

# REVIEW OF THE LITERATURE

## Defining the Crime: Motor Vehicle Theft

Before the discussion of the literature on motor vehicle theft it is important to provide a working definition of the crime. Motor vehicle theft (MVT) is a common larceny offense that involves the completed or attempted theft of a self-propelled vehicle that travels on a surface not on rails. Specifically excluded from this category are boats, heavy construction equipment, airplanes, and farming equipment (UCR, 1998). The vast majority of stolen motor vehicles are, as one would expect, automobiles (Miethe and McCorkle, 2001).

Despite being a common larceny offense and due to its frequency and seriousness, motor vehicle theft is classified as a separate FBI Type I Index Offense. An important distinction needs to be made between motor vehicle theft and thefts from motor vehicles. The theft of items from within motor vehicles such as, stereos, airbags, CD players, radar detectors, and personal property are classified exclusively as larceny offenses, and not as motor vehicle thefts. The distinction is the theft of the actual motor vehicle rather than the theft of contents from within the motor vehicle (Miethe and McCorkle, 2001; Clarke and Harris, 1992). Again, there are auto related crimes that do not constitute official motor vehicle theft, even crimes where the vehicle goes missing, for example "car jacking" is technically classified as a robbery according to URC reporting practices according to Rengert (1997).

*Review of the Motor Vehicle Theft Literature*

Motor vehicle theft is a socially unique property crime that has largely been ignored by both the criminological and sociological literature. The lack of available empirical information on auto theft is surprising given the role of the automobile in both the American economy and culture (McCaghy, Giordano and Henson, 1977).

The automobile has single-handedly changed the American landscape from coast-to-coast and forever altered the demographic composition of U.S. cities. Given the plight of the automobile in the U.S., Clarke and Harris (1992) suggest that the principal reason for conducting more criminological research on this pervasive crime is to develop prevention tactics and reduce the nation's crime statistics.

The various types of motor vehicle theft range from joyriding to professional thievery and the differing rates show significant variation based on region of the country, size of the population, and demographics of the geographic area in question. Motor vehicle theft is not a random event and tends to be unevenly distributed with a spatial and temporal pattern throughout a geographic unit (Henry and Bryan, 2000).

*Seasonal, Regional, and Daily Difference in Vehicle Theft*

Henry and Bryan (2000) found that Fridays and Saturdays had the highest concentration of motor vehicle thefts and Tuesdays and Wednesdays had the lowest. Motor vehicle theft showed little variation for different months of the year. However, a seasonal effect could be noticed with the month of August shown to have the highest rate of theft while the month of December was reported as having the lowest. The findings of this study lend some support to the theory of routine activities. For example, the convergence in space and time of suitable targets with windows rolled down, tops open, keys in the ignition and motivated offenders would likely be more plentiful in the warmer months than in the colder months.

In a preliminary report of the UCR (2003) crime data suggested that in 2002 the South had the highest percentage of motor vehicle thefts or 35.5 percent of total estimates of the four regions of the country with the West coming in second with 30.5 percent of total estimates and the Northeast experiencing the smallest percentage of motor vehicle thefts or 14 percent of total estimates.

In a manuscript published just two years prior to the preliminary UCR (2003) report, Miethe and McCorkle (2001) found results somewhat contrary to that of the later published preliminary UCR (2003) report. They found that the states on the West Coast, not in the South, had the highest rate of motor vehicle theft, but their descriptive analysis concurred with the UCR and also found that the lowest rates occurred in the Northeast.

Plouffe and Sampson (2004) in their study of auto theft from parking lots in Chula Vista, CA found unique differences between local and regional theft trends. They found that areas in closer proximity to the U.S./Mexico border were more likely to be targeted for exportation thefts where as cities further north were more likely to be plagued by joyriding theft. The authors conclude that regional crime trends may offer a broad understanding of crime but differences within regions are best examined and analyzed at the local level of the problem.

*Opportunity, Choice, Social Structure and Motor Vehicle Theft*

Clarke (1992, 1987, 1983) has studied automobile theft quite extensively from a rational choice perspective. "The rational choice perspective, the central premise of which is that offenders choose to commit crimes for the benefits they confer, is a theory of both crime and criminality" (Clarke and Harris, 1992, p.25). Clarke and Harris (1992) draw on the research of Cornish and Clarke (1987) in applying the "choice structuring properties" of crime to the study auto theft. They propose that the choice to commit auto theft is structured by several elements: availability (how common, where parked, etc.); security (quality of locks, alarm systems, convertible top, etc.); and attractiveness in terms of profitability for professionals or enjoyment for joyriders (value of parts, image, power, etc.). These three areas of choice structuring are believed to correspond to the major determinants of rational choice theory – effort, risk, and reward as originally discussed by Cornish and Clarke (1987), (Clarke and Harris, 1992).

The findings of the Clarke and Harris (1992) study suggest that the differing motivations for auto theft structure the choices pertaining to which vehicles are stolen. For example, cars stolen for stripping tended to be European and industry sources had identified that the radios of these models were particularly attractive to thieves. Also, the Volkswagen Golf Cabriolet had a strip rate twice that of any other vehicle in the study. Interestingly, the vehicle is a soft-top convertible and could easily be entered without a key. Many of the European models are often manual shift, which may explain why they are not kept for short-term use. Inexperienced American drivers may find these vehicles more difficult to operate.

Temporary use vehicles (those stolen for temporary transport) tended to be powerful American made cars that conveyed a "macho" image, such as the Camaro or the Firebird. Surprisingly foreign made cars like the Porsche was relatively unpopular, possibly due to the inability to blend in. Flashy cars with a youth at the wheel would raise the suspicion of both law enforcement and community members in poorer areas (Clarke and Harris, 1992).

Vehicles stolen for permanent retention tended to be luxury cars like Mercedes and Porsche due to their profit potential and general appeal to professional thieves and others not conflicted about owning a stolen vehicle (Clarke and Harris, 1992).

Clarke and Harris (1992) suggest that understanding offender motivation and decision making is a benefit of the rational choice perspective that is not offered by other theories addressing the phenomena of motor vehicle theft.

Plouffe and Sampson (2004) in a study of vehicle thefts from parking lots in California devised their study to test aspects of choice, routine activities, and pattern theories. They found that motivated offenders actively sought out and identified parking lots that drew large numbers of vehicles with limited or no parking lot controls. Most of the lots tended to be within close proximity to the Mexican border and offer an ample number of suitable targets for extended periods of time.

Copes (1999) conducted a study of motor vehicle theft in a small Parish in Louisiana to test the merits of routine activities theory at explaining crime specific measures. He asserted that motor vehicle theft has never been directly tested using routine activities theory but that many previous findings make it conducive to this pursuit. Copes states that research by Gould, (1969) concluded that as the number of motor vehicles available between 1921 and 1925 increased, so did the number of thefts. This is a tenet supported by routine activities theory similar to the portability of goods proposition of Cohen and Felson (1979). Also, urban areas that have a large pool of potential offenders tend to have higher rates of motor vehicle theft. Copes (1999) cites research by Roncek and Bell (1981) and Roncek and Faggiani (1985) who found that city blocks with bars and blocks adjacent to high schools have increased levels of motor vehicle theft.

Copes (1999) used the census tracts in each Parish as his unit of analysis (n = 41). The dependent variable in the study is the motor vehicle theft rate computed using vehicle theft incident report data for the years 1994-1996 as the numerator and the number of registered vehicles in each tract as the denominator. The predictor variables operationalizing the major elements of the theory were gathered from the 1990 decennial census and consisted of: percent poor and percent young males for motivated offenders; road density and car density for suitable targets; and multiple housing units and population density for lack of suitable guardianship. The study consisted of one-wave of cross-sectional data analyzed using ordinary least squares regression (OLS).

The findings of the study suggest that the number of motor vehicle thefts vary directly with the supply of potential offenders. Also, the percentage of poor people in the population contributed in explaining variations in the rate of motor vehicle theft. As the percentage of poor increased, so did the rate of motor vehicle thefts, even after controlling for other intervening variables. The number of roads, expressed in the study as road density, was another variable significantly related to the rates of motor vehicle theft. The availability of more roads provides thieves with more get-away opportunities once they have stolen an auto, presumably increasing the desirability of the location.

Copes (1999) did not find any direct relationship between the number of young males in the population and the rate of motor vehicle theft. Also, multiple unit housing was expected to reduce motor vehicle theft by providing more surveillance, but this was not the case and the predictor was not significant. The findings, while supportive of some of the antecedent constructs of routine activities theory, also show support for some alternative antecedent theoretical explanations of vehicle theft like rational choice and even some of the preconditions of social disorganization and human territorial functioning.

Hollinger and Dabney (1999) conducted a study of motor vehicle thefts from shopping center parking lots employing a routine activities theory model. The unit of analysis in the study was shopping centers in the U.S. (n = 265). The dependent variable in the study was the number of vehicle thefts occurring at each shopping mall, ranging from 0-150 with a mean of 14.1 and a standard deviation of 23.1. The independent variables were gathered from a survey instrument that was sent to the security directors of the individual malls. The study was a single-wave cross-sectional design that looked at the aggregate number of motor vehicle thefts that had occurred at each shopping center in 1992.

The analysis consisted of OLS regression techniques to test the effects of various predictor variables used to operationalize the main tenets of routine activities theory. The suitable targets variable was operationalized using the average number of vehicles that frequented the mall each day. The motivated offender variable was derived based on the responses to three questions: 1) the presence of loitering groups, 2) presence of public transportation at the center of the mall, 3) the presence of organized street gangs. The absence of capable guardians variable was operationalized using the number of weekly security guard man hours, percentage of guards on the outside versus on the inside of the mall, the presence of a security vehicle for exterior patrols or not.

The findings only suggest moderate support for explaining vehicle theft with an $R^2$ value 21.2 percent. The motivated offender variables had a significant impact on the dependent variable in the direction expected. Only two of the capable guardian predictors supported the routine activities thesis – presence of police patrols and the use of security vehicles to patrol the parking lots. The suitable target variable was not significant and did not support the routine activities thesis.

In sum, the Hollinger and Dabney (1999) study found that the presence of motivated offenders both in the community and at the shopping center, coupled with the absence of capable guardians in the form of security personnel and police patrolling the shopping center created the optimal conditions for auto theft to occur. Interestingly, these findings did not depend on the size or the physical design of the shopping center, "…nor an assortment of socio-economic status characteristics of the community" (Hollinger and Dabney, 1999, p.73). Their study, although not testing for spatial autocorrelation, found that the single most significant predictor of vehicle theft in the shopping center was the UCR vehicle theft rate found within the areas of the community surrounding the mall (Hollinger and Babney, 1999).

Saville and Murdie (1988) conducted a case study of the spatial analysis of motor vehicle theft in Peel, a municipality on the Western edge of Toronto. The authors examined the role of place in the criminal event of vehicle theft using vehicle thefts during 1984. They employed a rational choice opportunity model to study vehicle thefts and calculated a theft rate for each of 47 patrol zones based on the number of thefts and the population density. They then gathered data on several independent variables including: parking spots per square mile, percent single family households in the population, persons per square mile, population between 15 and 19, population between 20 and 24, population between 25 and 29, and population between 15 and 29.

The results of their study suggest that the age categories of 20-24, and 15-24 correlated significantly with the dependent variable. Multiple regression techniques were used and only age 20-24 and coming from a single-family household emerged as statistically significant variables. The full model explained 40 percent of the variance in motor vehicle theft. Further analyses suggested that age 20-24 was the most useful explanatory variable accounting for 31 percent of the variance in motor vehicle theft (Saville and Murdie, 1988).

A final analysis was run whereby the extreme positive regression residuals for the two patrol zones with the most vehicle thefts were mapped showing 'hot spots' of motor vehicle theft. Analyses of the mapped residuals lead to the hypothesized possibility that the two areas with extremely high positive residuals represent patrol areas where professional motor vehicle thieves may be active. A qualitative analysis of the two patrol zones was conducted and revealed that these were areas of easy availability with vehicle rental and leasing companies present as well as car dealerships. The areas were also mixed-use – residential and commercial (Saville and Murdie, 1988).

From an offender perspective Miethe and McCorkle (2001) point out that there are two divergent and competing views about how an individual's social class impacts the likelihood that they will commit motor vehicle theft. "According to the "favored-group" perspective, white middle-class youths are thought to commit high rates of car theft because of the early development of car consciousness and driving skills among suburban youth (Miethe and McCorkle, 2001, p.153).

Research by McCaghy, Giordano and Henson, (1977) suggests that unlike practically any other crime, motor vehicle theft is concentrated among the socially advantaged supports the favored group hypothesis. Additionally, according to Rice and Smith (2002), contrary to other street crimes, motor vehicle theft has been believed to be most prevalent among the socially advantaged. On the other hand, the "disadvantaged-group" perspective suggests that lower-class minority youth are the disproportionate number of offenders because they lack legitimate access to vehicles and success and use them as a sign of status and a means of needed transport (Miethe and McCorkle, 2001).

Miethe and McCorkle (2001) also state that, "[C]ities and geographic areas within them with higher levels of ethnic and racial diversity, higher population mobility, low per capita income, higher unemployment, and higher proportions of single parent families have the highest rates of motor vehicle theft" (Miethe and McCorkle, 2001, p. 152).

Ley and Cybriwsky (1974), drawing on the work of the early ecologists, studied the spatial ecology of stripped automobiles in Philadelphia. Their interest was in relating the spatial location of individual stripped cars to the physical and social characteristics of the immediate setting where the event occurred. Their general thesis was that, "locations which suffer from weak sociospatial control are locations with an ecology favorable to criminal behavior" (Ley and Cybriwsky, 1974, p.54). While they don't specifically outline their hypothesis as such, it is conducive to the theoretical tenets of human territorial functioning and stems from the presence or absence of community social control.

A sample of 138 unambiguously stripped cars were gathered and analyzed in 1972. Specific interest was paid to the location points where these vehicles were stripped. Their results indicate that institutional land use was the most frequent location of recovery, consisting of railroads, factories, schools, and hospital structures. These locations make no territorial claim to adjacent street space. Institutional/industrial land use locations do not have territorial markers in place beyond their actual physical location. For example, there is no community watch group discouraging crime in an industrial park. The second most common group of locations were vacant structures, houses, stores, and empty lots. These locations were also absent any enduring claim on space by local controls. The investment of resources and capital is unlikely in vacant areas and as a result territorial control are lacking. Finally, the third most common locations were near intersections, beside doorless and often windowless flanks of residential housing. These locations were apparently free of immediate opportunities for surveillance (Ley and Cybriwsky, 1974, p.61). These areas are also often low in territorial functioning and control by local area residents creating opportunities for the encroachment of crime. Residents spend their limited time and resources protecting their immediate surroundings and living space.

A more recent study of automobile theft by Rice and Smith (2002) explores causes in the variations of auto theft rates integrating the constructs of routine activities theory and social disorganization theory to improve the predictive power of their model.

The unit of analysis in the study is a micro unit, the census face block (n = 7931), in a community in North Carolina. The dependent variable is the number of motor vehicle thefts (n = 1049) in the study year 1993. The predictor variables were collected from county tax assessor data and 1990 U.S. Census data. The study is a single-wave cross-sectional design using 1990 demographics and community data to study motor vehicle thefts that occurred in 1993.

Their research relied on multiple sources of data to operationalize the primary variables of the two theories. Census data were used to measure several social disorganization concepts including: number of Blacks, racial heterogeneity, the average percentage below median property value, distance from city center, and number of single parent households. Census data were also used to measure several routine activities concepts: number of vacant/parking lots, number of hotels or motels, number of commercial establishments, number of stores, number of multifamily buildings, number of restaurants and gas stations, and number of youth places (Rice and Smith, 2002).

The findings of the study, using ordinary least squares regression techniques, suggest that the social disorganization model explained 18 percent of the variance. The routine activities model explained 24.5 percent of the variance and a model combining all of the variables of both theories explained 28.3 percent of the variance. "All of the variables in the social disorganization model were statistically significant except for the percentage below median building value and racial heterogeneity" (Rice and Smith, 2002, p.319).

In addition, the direction of influence for all of the significant variables was in the expected direction. It is important to note that all of the routine activities variables were statistically significant and in the predicted direction as well. A third model with 22 interaction terms improved the explained variance to 32.1 percent with 13 of the interaction terms being statistically significant. The only interaction term that was contrary to the stated hypothesis was the interaction between the presence of single parent families and commercial places (Rice and Smith, 2002).

In conclusion, the authors found that each theory had its own independent role in explaining the spatial distribution of auto theft and that there was even greater utility in integrating the theoretical perspectives. By explaining the crime of motor vehicle theft using a small unit of analysis the authors have, "...captured the context of the crime more so than previous spatial studies. Moreover, the relationship of nearly every independent variable to auto theft hints at potential practical application" (Rice and Smith, 2002, p. 328).

Davison's (1995) ecological analysis of crime was another study combining a statistical model incorporating both routine activity and social disorganization variables. The unit of analysis in the study was the street segment (n = 2,207). The model accounted for a total of 35 percent of the variance in motor vehicle thefts in Raleigh, North Carolina. Davison found that the greater the population of the street segment the lesser the impact on auto theft in all three of the equations. However, the number of potential places in the street segment tended to contribute to the auto theft problem.

Interestingly, with regard to the social disorganization variables, the presence of African Americans in the population increased the likelihood of auto thefts. However, heterogeneity decreased the chances of auto theft occurring. Also, auto theft was more likely to occur in areas closer in proximity to the downtown of the city. "When all of the routine activity measures are added to the model, the presence of owner-occupied places, average values of apartments, and business/offices decreases the impact of social disorganization variables on auto theft on a street segment" (Davison, 1995, p. 126).

As is evident from the literature, the results are often contradictory from one study to the next particularly with regard to the ecological structural predictors such as: heterogeneity, percent of young people in the population, and SES. The present study will attempts to address some of these inconsistencies as well as approach the study of motor vehicle theft from a meso level of analysis using a smaller unit of analysis than is common in the existing literature. This study will also employ unique techniques of analyses, some of which have not been used in the study of motor vehicle theft before. Finally, this study will identify alternative theoretical approaches by which to study and explore motor vehicle theft, beyond traditionally approaches present in the literature.

# CHAPTER 3

# THEORETICAL ORIENTATION TO MOTOR VEHICLE THEFT

## Explaining Motor Vehicle Theft

As previously mentioned, while there have been several studies discussing the various typologies of offenders and victims, as well several that look at theft prevention strategies, there is a conspicuous void in the literature detailing research that looks specifically at community composition, social structure, ecology, and demographic characteristics that explain or show a relationship to motor vehicle theft.

One of the primary objectives of this study is to incorporate facets of community structure to identify ecological relationships and links to motor vehicle theft. To this end, the following discussion will provide a brief orientation to the theoretical models that have traditionally been applied to the crime of motor vehicle theft and after each orientation specific studies that have applied the theory being summarized will be reviewed.

### *Rational Choice and Routine Activities Theory*

The theoretical perspectives reviewed in the following section are rational choice and routine activities theory. These theories can be linked to the ecological study of crime due to its emphasis on the geographic distribution of victims, criminal opportunities, and motivated offenders. The human ecology perspective "...facilitates an investigation into the way in which social structure produces convergence, hence allowing illegal activities to feed upon the legal activities of everyday life" (Cohen and Felson, 1979, p.588). In addition, the two perspectives are linked borrowing from the economists of the late 1970s, rational choice theory was developed and came to be known in terms of opportunities, costs, and benefits. These terms are used when assessing offenders' decisions to commit crimes. "In a sense, the economic approach brought us full circle to the two-hundred-year-old classical position that individual behavior is a calculation of gain and pain" (Williams and McShane, 1999, p. 235). There is a common theme among rationalist theorists that criminal rationality is hedonistic and certain background factors lead to pleasurable indulgences.

The beginnings of contemporary rational choice theory were largely sociological in orientation and were strongly influenced by newly developed victimization interests and statistics methods of inquiry. There are several sub-theories within the broader perspective of rational choice theory, one of which is routine activities theory. This theory combines rational choices made by offenders with the lifestyle behaviors of victims.

Routine activities theory was first developed by Cohen and Felson (1979) to explain rising crime rates via increased criminal opportunities. Increases in criminal opportunities result in consequently higher victimization rates as well. The theory combines elements of human ecology, deterrence, and rational choice structuring. Originally, it was viewed as a practical way to evaluate crime and victimization as rates rose throughout the 1970s, and gained popularity and became commonplace during the 1980s. "One reason for its popularity was the easy connection with the burgeoning interest in victimology and a new ecological crime-prevention approach" (Williams et.

al., 1999, p. 235). However, the primary reason for its popularity was the resurgence of beliefs about the nature of humans as rational beings motivated by choices that impact their behaviors. Cohen and Felson (1979) believe that crime is distributed unevenly in space and time and therefore is non-random and fluctuates based on the presence or absence of three social conditions: the availability of suitable targets, the presence of motivated offenders, and the absence of capable guardians (Hollinger and Dabney, 1999). The theory is only indirectly a theory of offender motivation and is more directly a theory of criminal opportunity that is structured by complex and dynamic social changes.

"Routine activities theory basically states that the volume of criminal offenses is related to the nature of everyday patterns of social interaction. As the pattern of social interactions changes so do the number of crimes" (Williams, et. al., 1999, p. 236). Cohen and Felson (1979) believe that the structure of a society's work, leisure, education and entertainment patterns increases crime opportunities without necessarily increasing the number of offenders in the environment. A neighborhood can have a high rate of crime even when the supply of motivated offenders is held constant simply by providing increased opportunities (Copes, 1999).

Most people realize that there are certain places, types of people, and social situations that threaten personal property and safety. This understanding is instrumental to the notion that criminal victimization is generally not a random event and that actions can be taken to remove oneself from harm's way (Massey, Krohn and Bonati, 1989). The study of victimological risk assessment stems from two related and complementary areas of research. The first area of research was discussed by Hindelang (1978) who outlined the lifestyle and exposure to risk perspective. The other area was routine activities theory. "Routine activities theory focuses on the social circumstances that generate high rates of crime" (Copes, 1999, p. 125). In particular, the theory tries to offer an explanation for how three social elements (motivated offenders, suitable targets, and the absence of capable guardians) come together in time and space resulting in criminal events. First, there must be a motivated offender. This is only briefly discussed, though, because the presence of motivated offenders is taken as a given or known fact. Also, there are a multitude of existing criminological theories that focus on the offender and the influencing factors that motivate him or her to commit an offense. However, the theory does posit that crime rates will correspond to the number of motivated criminals in the population. Examples of motivated offenders are young males, drug users, and unemployed individuals (Akers, 2000).

Second, Cohen and Felson (1979) postulate that there must be suitable targets: that is a victim, something worth stealing, taking, assaulting, burglarizing, or killing. According to Cohen and Felson, criminal choices are influenced by the perception of target vulnerability, opportunity and accessibility. The acronym VIVA (value, inertia, visibility, and access) best characterizes a target's suitability. The value of the target is calculated by the offender from his point of view based on his wants and needs. Inertia refers to the physical aspects of the target that make it either more or less suitable (i.e. how much energy must be expended to victimize the target). Visibility refers to how many individuals the target is exposed to. The more people the target is exposed to the greater the likelihood it will be victimized. Finally, access refers to the amount of people who have contact with the target. The more people with access to the target the more likely a motivated offender will eventually victimize the target (Felson, 2000).

Third, they state that there must be an absence of capable guardians: the lack of someone or some thing present that could prevent or deter the incident from occurring (Williams et. al., 1999). The theory suggests that the presence of capable guardians may deter criminal behavior. "Evidence is accumulating that predatory criminals are aware of law enforcement's capability; communities with the reputation of employing aggressive "crime fighting" cops are less likely to attract potential offenders than areas perceived to have passive law enforcers" (Siegel, 1999, p.118).

Routine activities theory discusses the role of offenders and targets and their convergence in time and space. The three elements of the theory consist of motivated offenders, suitable targets, and absence of capable guardians. If one component of the theory is missing, crime is not as likely to occur. However, if all components are present, crime is highly likely to occur. The theory functions on a continuum and more of one component may compensate for less of another (Hollinger and Dabney, 1999). Possibly the most important contribution of the theory is the argument that crime rates are not only based on the amount of motivated offenders, suitable targets, and guardians in the population. Rather, crime rates are a product of the factors affecting the frequency of the convergence in time and space (Sherman, Gartin and Buerger, 1989). People's suitability as targets depends upon the routine activities they engage in on a daily basis. For example, the convergence of motor vehicles in a mall parking lot over the Holiday shopping season creates a glut of suitable targets, especially if there is an absence of capable guardians. Motivated offenders would be wise to seek out this type of setting where by to perpetrate the crime of motor vehicle theft.

The nature of routine activities theory implies that suitable targets are found more frequently in some areas than in others and at certain times as opposed to others. Therefore, the use of crime mapping for the identification of hot spots in certain parts of the community may be an effective tool for the development of crime control initiatives. In fact, Cohen and Felson (1979) argue that American society has changed over the years resulting in increased interaction with motivated offenders, more suitable targets, and greater absence of guardians. "Even if the number of motivated offenders does not increase, crime will be greater because of the increase in the latter two elements" (Williams et. al., 1999, p. 237).

There are a number of appealing qualities to routine activities theory. The three necessary elements of the theory have a symbiotic, conceptual relationship. The "... conceptual framework incorporates all of the logically necessary elements required in the crime causation nexus, namely, the presence of a victim target, perpetrator, and minimal certainty of detection" (Hollinger and Dabney, 1999, p.64). The characteristics of the theory allow scholars flexibility in terms of offense types, offenders, victims, and the geographic unit of analysis from which they can choose to apply the theoretical perspective. A review of the relevant literature shows that the theory has been relatively successful in explaining variations across diverse types of crimes and among diverse geographic locations (Hollinger and Dabney, 1999).

Historically, routine activities theory has been used to study categories of crimes in their aggregate, such as violent crimes or property crimes collectively. However, there is some criticism associated with this type of application of the theory. "By doing so they assume that the underlying causes of crime are the same for different types of crimes"

(Copes, 1999, p.126). For example, routine activity variables do a better job explaining property crimes than they do violent crimes (Meithe and Meier, 1990). There is a need to develop more crime specific models to test and develop the theory, especially at the micro levels of the community structure.

Recent research has begun to test the theory using a crime-specific approach. The theory has been applied to the study of larceny, (Mustaine and Tewksbury, 1998), burglary (Robinson and Robinson, 1997), homicide (Kennedy and Silverman, 1990) as well as several other crimes like motor vehicle theft (Copes, 1999). "The routine activity approach has also been used to explain criminogenic "hot spots" – the concentration of crime in specific locations" (Copes, 1999, p.127).

Based on individual differences in their routine activities, some individuals and property will be more prone to certain types of victimization than others. Similarly, certain geographic locations are more susceptible to crime because of the geographic landscape, the type of activities taking place in the area, and the amount of social interaction present (Williams et. al., 1999). Contemporary routine activities theory has evolved from a theory of personal victimization to one that now also explains the various differences in criminal offending based on geography and mobility.

## Previous Studies of Routine Activities and Their Findings

Routine activities theory has been tested widely and applied to a number of crimes and contexts resulting in varying amounts of empirical support. The original study by Cohen and Felson (1979) reviewed crime trends in the United States from 1947-1974 in order to show that the dispersion of activities away from the home increases the opportunity for crime and therefore generates higher crime rates. The findings suggest numerous levels of support for this hypothesis including increased labor force participation by females and single-adult households. Burglary and robbery victimization rates were twice as high for people living in single-adult households. They also found that the consumer electronics market was serving to manufacture more portable electronics that were quickly deemed suitable targets. Also, unemployed persons were more likely to be victimized than the employed, possibly reflecting the residential proximity to high concentrations of potential offenders.

Research by Witterbrood and Nieuwbeerta (2000) examined the effects of prior victimization and routine activities on future victimization. They found that individuals who had once been victimized suffered a substantially higher risk of subsequent victimization. They attribute these findings in part to the effects of previous victimization but more so to the patterns of routine activities the individuals engaged in.

A study by Roncek and Maier (1991) examined the relationship between recreational liquor establishments and crime. Their findings suggest that the number of such establishments had a significant effect on the amount of crime. In addition, the amount of crime is compounded when the liquor establishments are located in anonymous areas with low guardianship. The location of the establishment and the surrounding physical characteristics impacted the amount of crime that was facilitated.

Kennedy and Forde (1990) conducted an extensive telephone interview victimization survey. They studied the relationship between lifestyle and criminal victimization and found that risky settings produced greater rates of victimization and age, sex and income level are related to rates of victimization. Males spending large amounts of time in bars contributed to more risk of criminal victimization, while increased age and marriage reduced the risk. They found that the routine activity of leaving home and frequenting bars made some individuals more vulnerable and suitable to victimization and less capable guardians over their person and property.

Sherman, Gartin, and Buerger (1989) used routine activities theory to study hot spots of predatory crime. This was the first study employing spatial data to operationalize and test the theory. They analyzed 323,979 calls for service throughout Minneapolis' 115,000 addresses and intersections and found that 50 percent of the calls were received from just 3 percent of the addresses in the population. The study revealed that all robberies occurred at 2.2 percent of places, all rapes at 1.2 percent of places, and all 3,908 auto thefts occurred at 2.7 percent of places. The hot spots usually included large department stores, bars, convenience stores, public housing, and apartment buildings. Most of these establishments, as well as others in the area, facilitate routine activities and are conducive to bringing unacquainted individuals together in space and time. In addition, they attract young males, those most likely to offend (Copes, 1999). Routine activities create the potential for hot spot formation where all three necessary elements of the theory exist in one location.

## Social Structure and Social Disorganization

Crime in our communities is a pervasive problem affecting nearly every facet of society and researchers have long been interested in its distribution and concentration. Furthermore, a considerable portion of the communities and crime research has attempted to develop an understanding of what factors lead to changes in these distributions and concentrations over time. An essential area of inquiry addresses community level social control and the informal social processes that inhibit law violating behavior and serve to promote order maintenance. The contemporary communities and crime research trend stems from the pioneering ecological work of the Chicago School.

Robert Park and Ernest Burgess (1924) largely pioneered the social ecology perspective by developing the concentric zone model for studying the ecology and growth of American cities. They proposed that cities, in the absence of opposing factors, expand radially from the central business district out to the commuter zone in a succession of five distinct concentric zones with dramatic differences being evident from one zone to the next.

In their original study, residential neighborhoods nearest the central business district were the least desirable because they suffered from poor upkeep by landlords, were the least attractive, and provided relatively inexpensive substandard housing. These areas typically provided initial residence to immigrant ethnic groups that moved into the city (Bursik and Grasmick, 1993).

In addition, as the immigrants began to integrate into the economic structure of the city they would seek a better quality of life and a better residence further from the inner/central city. As a result, high population mobility and rapid transition made it difficult to establish informal social controls among the residents occupying the least attractive areas of the city, those closest to the central business district. These neighborhoods had no control over the movement of incoming unwanted residents and often had high rates of population heterogeneity (Bursik and Grasmick, 1993). "Park and

Burgess theorize that the condition of social disorganization in a zone of the city limits the community's ability to resist invasion" (Veysey and Messner, 1999, p.157).

The study of social ecology seeks to understand a person's relationship with his/her social environment. The geographic surroundings as well as the social context of the environment can transform and shape a community. Social ecology from a criminological perspective involves the study of an individual's relationship with his environment and the geospatial distribution of crime and delinquency within that environment.

The work of Park and Burgess unleashed a torrent of ecologically oriented research between 1920 and 1940 interested in furthering the understanding of the intricacies of the community and the impacts of community members on the social structure (e.g. Anderson, N. *The Hobo*; Zorbaugh, H. *The Gold Coast and the Slum;* Cressey, P. *The Taxi-Dance Hall).* While subsequent research designed to validate their findings was greeted with mixed results, their original efforts were responsible for a new era of intellectual thought and theory development (Brown, Esbensen, Geis, 2001).

The acclaimed "Chicago School" sociologists, Clifford Shaw, a student of Burgess' at the University of Chicago, and Henry McKay (1942), further developed the ecological work of Park and Burgess in their seminal work designed to study juvenile delinquency rates throughout Chicago. Their research was one of the first efforts to employ the use of maps to assist in understanding the changing rates and spatial orientation of delinquency in the urban environment. "Spot" maps were used to identify the residences of all juvenile arrestees throughout the city, "rate" maps were used to report the percentage of juveniles with arrest records in each of the 431 census tracts, and "zone" maps displayed delinquency rates for juveniles in each of the five concentric zones as they fanned out radially from the center of the city (Brown, Esbensen and Geis, 2001).

Their research led them to conclude that delinquency could be associated with the differing environments and the social organization of the city. This finding was contrary to much of the popular research of the previous era that had focused on crime as a result of psychological imbalances, biological traits, and personal choices void of outside influences. They believed that delinquency was produced by deteriorated neighborhoods rather than by the individuals who lived there. Crime and deviance in these deteriorated neighborhoods were seen as the normal responses of normal people to abnormal social conditions. The occurrence of industrialization, urbanization, and a numerous other social changes in modern society were seen by many of the Chicago School sociologists as causing social disorganization by undermining community social controls that are traditionally exercised through social order and common values (Akers, 2000).

The theoretical construct of social disorganization as explained by Shaw and McKay centered around three independent variables: poverty, residential mobility and racial heterogeneity. Their choice of variables was also greatly influenced by the work of Wirth (1938) who was studying the impact of urbanization on human relations. The notion is that poor communities serve to foster social disorganization because they do not have the resources to address their problems. They also lack the funds to develop recreation areas for children and adults. Increased levels of residential mobility and instability contribute to anonymity. Community social control diminishes because residents do not know who belongs and who does not. This inhibits the necessary development of a sense of community. The problem is exacerbated in heterogeneous communities where natural divisions occur and people do not come to know one another and common values fail to emerge. The absence of a strong set of community values allows a tradition of delinquent behavior to foster that is passed down from one generation to the next through the process of cultural transmission. Of particular interest was what factors contributed to the enduring nature of deviance in certain areas of the city. Kornhauser (1978) refers to the breakdowns in community social control as a group-level analog of control theory.

According to Shaw and McKay's (1942) interpretation, if Burgess was correct, then delinquency should be higher in inner-cities. The synergy of poverty, rapid population growth, heterogeneity, and mobility would disrupt the community's social institutions like the family and cause social disorganization (Cullen and Agnew, 2003). The classic formulation of social disorganization established by Shaw and McKay (1942) holds that crime happens in neighborhoods characterized by low income, racial/ethnic heterogeneity, and residential mobility (Smith, Frazee, and Davison, 2000).

A community's weakened ability to impose formal and informal controls over residents decreases the costs of deviance within the community, making crime and delinquency more likely. Transgressors have less to fear and know that the risks associated with negative behavior are lessened. Stated this way, it is easy to view social disorganization theory as a systemic theory of neighborhood crime control (Bursik and Grasmick, 1993).

According to Taylor (2001) social disorganization refers to a community's inability "...to 'govern' the behavior of its residents, including children and teens; or to work toward common goals for the betterment of the neighborhood. Disorganized communities also lack sufficient ties to governing agencies and resources outside of the community itself" (Taylor, 2001, p. 7).

Shaw and McKay's original work has been further amended and elaborated upon over the years by a number of scholars seeking to strengthen its empiricism and broaden its application beyond what was once prevalent among the early theorists (e.g., Bursik, 1988; Bursik and Grasmick, 1993; Sampson and Groves, 1989; Taylor, 1997; Veysey and Messner, 1999). Stark (1987) points out that there are several aspects or factors of urban environments that characterize high deviance areas and that these aspects permeate all of the Chicago school literature. The factors that permeate the research include: density, poverty, mixed land use, transience, and dilapidation. Many of these factors continue to be a focus of ecological crime research even today.

What has unfortunately been neglected in much of the subsequent ecological research that has followed in the wake of Shaw and McKay's seminal work is that urban processes that impact upon and are related to crime can only be studied effectively over time (Bursik, 1986). Much of the subsequent research in the ecological tradition has been cross-sectional at a macro level with minimal inquiry into ecological change and its impact on crime over time.

As previously discussed, several motor vehicle theft studies have drawn heavily on Shaw and McKay's theory of social disorganization for good reason. It is true, social disorganization does appear to offer a promising opportunity to study and explain motor vehicle theft over time. Unfortunately no research that this author is familiar with has attempted to capture the micro level community processes associated with social disorganization and the relationship between those processes and motor vehicle theft, nor has the impact of ecological change on motor vehicle theft been measured or analyzed. The current research identifies some of these limitations in the ecological literature and attempts to address several of the concerns.

According to Bursik (1986) ecological studies of community crime rates and delinquency have been one of the important continuing traditions in empirical criminology. Bursik (1986) further notes that Shaw and McKay (1931, 1942) provided one of the most significant theoretical advances in the interpretation of spatial distributions of crime and delinquency when they pointed out that, "...neighborhood differentials in delinquency rates could only be fully understood when considered within the context of broader urban dynamics" (Bursik, 1986, p.63).

## *Explication of Structural/Ecological Predictors*

### *Socioeconomic Status (S.E.S.)*

Some derivation of economic status has become an influential measure in most ecological studies dating back to the era of Shaw and McKay. For example, economic factors such as income level, poverty, property value, unemployment, and median rent paid have been shown to have some association with crime. The association that has been identified is that a community's economic status is negatively correlated with its crime rate (Sampson, 1983, Norman, 1996, Sampson and Groves, 1989). According to interpretations of the process explicated in the original social disorganization model, communities of low socioeconomic status lacked the money and resources to sustain widespread community social control. Additionally, socioeconomic status has been positively correlated with citizen participation in community organizations and consequently, low socioeconomic status communities will have weaker membership and participation in community organizations than higher status communities. "The effects of SES on crime and delinquency rates are thus hypothesized to operate primarily through formal and informal controls as reflected in organizational participation and community supervision..." (Sampson and Groves, 1989, p. 780).

> "Messner and Blau (1987) found evidence that the level of poverty in an area is positively related to the area's motor vehicle theft rate, and several other authors have claimed that auto theft increases as the legitimate availability of cars decreases" (Biles 1877; Gould 1969; Mansfield, Gould and Namenworth 1974; Mayhew 1990; Tremblay, Claremont, and Cusson 1994) (Rice and Smith, 2002, p. 306).

*Residential Mobility*

Residential mobility generally refers to frequent population turnover within a community. An area with low population mobility would have a high percentage of the population remaining within the community for an extended period of time providing much needed community stability. The ecological perspective contends that a high degree of mobility equates to increases in crime rates in the community. According to Shaw and McKay's original model, constant turnover in the population and the need to assimilate new members into the community undermines a community's network of social relationships and it's ability to enforce social control. "...[R]esidential mobility operates as a barrier to the development of extensive friendship networks, kinship bonds, and local associational ties" (Sampson and Groves, 1989, p. 780). The longer an individual resides in a community presumably the more associations they have and the stronger their social network is. The constant flow of people in and out of a community creates an internalized feeling of anonymity and prevents individuals from developing strong bonds to their community or the organizations and individuals within it (Crutchfield, Geerken, and Grove, 1982).

In addition, areas with higher mobility create increased opportunity for the infiltration of individuals with diverse characteristics and backgrounds, which could serve to further undermine the integrity of the existing system of social controls. Individuals are most likely to establish relationships and ties to those they share commonalities with. "The inability to establish new relations with people of diverse racial and cultural traits decreases the individual's involvement in close-knit social networks while increasing the potential for community instability" (Norman, 1996, p. 68). Also, undesirable and unwelcome individuals may slip into the community to perpetrate crimes. These individuals are more likely to go unnoticed in areas with high rates of mobility where no one is certain who belongs and who does not.

Finally, in highly mobile/transient populations there will be an increased number of individuals who simply are unknown to members of the stable local population. This increases the difficulty for legitimate law abiding community residents to effectively monitor and survail the landscape and to recognize which individuals legitimately "belong" with each motor vehicle in the area. As a result, motor vehicle thieves are effectively aided by the uncertainty and unfamiliarity that exists in highly mobile/transient populations.

*Heterogeneity*

The racial and ethnic composition of a community is another important focus of ecological theory and research. Existing research suggests that crime rates are correlated with heterogeneity. Generally, the more heterogeneous a community is the greater the crime rate will be (Sampson and Groves, 1989; Warner and Pierce, 1993). Shaw and McKay suggested that this outcome was the result of a lack of cohesiveness in the community. Interestingly, research by Davison (1995) found that motor vehicle theft was actually less likely in heterogeneous communities but was greater in Black communities. The association though is that communities that lack a common cohesiveness will be less able to control unwanted invading criminal activity. "Racial and ethnic heterogeneity is said to account for fear and mistrust among community members, resulting in defensive associations which, in turn, lead to disruptions in the social order (Norman, 1996, p. 62).

According to Kornhauser (1978) heterogeneous communities are not able to develop solidarity or group level consensus due to the difficulty of integrating diverse subculture values and norms. The presence of multiple racially and ethnically autonomous groups in the community makes defining common goals difficult and impedes solidarity between groups. In addition, in terms of motor vehicle theft and heterogeneity, Clarke and Harris (1992) found theft rates to be greater in areas characterized by increased racial and ethnic diversity.

As a result of these diverse groups permeating the community and the social landscape it becomes exceedingly difficult for culturally diverse residents to understand complex and confusing events, such as motor vehicle theft, even as they transpire and occur around them. In effect, there is a mild "culture shock" underway, whereby members of one diverse group of people do not understand the legality or illegality of the behavior of another group of people. Here again, motor vehicle thieves are aided, this time by the unfamiliarity of community residents to the behaviors and actions of those around them and the result is a break down in community social control.

Merry (1981), in her cultural diversity model, states that the social structure contributes to high crime rates and that crime results when poverty and anonymity coexist. Poverty is believed to create the incentive or the motivation to commit crime. Anonymity, on the other hand, is often caused by the heterogeneous ethnic composition of the neighborhood. Anonymity allows a criminal to commit crime in his own neighborhood without fear of identification. Heterogeneous communities and neighborhoods foster anonymity. "This means he can commit crimes in his home territory, one which to him is relatively safe, predictable, and familiar, while appearing to his victims as if he were a stranger from a distant area" (Merry, 1981, p. 123).

According to Merry (1981) cultural differences and language barriers across ethnic lines cause neighborhood residents to interpret the apparently inexplicable behavior of their anonymous neighbors through the lens of their own culture. This often inaccurate interpretation leads to further confusion, misunderstanding, mistrust and fear.

Individuals often deal with dangerous environments by withdrawing into isolated social relationships that they are comfortable with and they avoid people who are unfamiliar and unpredictable. This response to cultural differences is fundamental to the formation of ethnic boundaries (Merry, 1981).

A related construct of heterogeneity is the percentage of African Americans in the population being studied. This variable is important and has been included in numerous sociodemographic studies including Shaw and McKay (1942) and Kornhauser (1978), which have found that the percentage of African Americans in the population has been correlated with local crime rates. The high concentration of racial diversity in the community is believed to decrease participation in community organizations and subsequent social control in the community (Rice and Smith, 2002). The theory of social disorganization, much like Merry's (1981) cultural diversity model, asserts that heterogeneous neighborhoods will have reduced informal control resulting in elevated crime rates.

> "The 1999 statistics from the U.S. Department of Justice also indicate that 42 percent of auto thefts cleared by arrest were thought to have been committed by African Americans. The U.S. Department of Justice, Bureau of Justice Statistics (1994), also indicated that Blacks are the victims of auto theft at a rate approximately 244 percent higher than the rate for Whites" (Rice and Smith, 2002, p. 314).

*Family Disruptions and Family Structure*

Research by Sampson (1987) has suggested that family disruptions may have a negative impact on a community's ability to impose informal social controls. "The basic thesis was that two-parent households provide increased supervision and guardianship not only for their own children and household property, but also for general activities in the community (Sampson and Groves, 1989, p. 781). According to early ecological research delinquency was associated with high concentrations of foreign born, black, single, female-headed households. The suggestion was that crime was due to single-parents inability to supervise and maintain control over their children and a general wider acceptance of criminal activity. In addition, single parents have fewer economic resources than two-parent households and a high concentration of single parent households is considered an indication of socially disorganized areas (Davison, 1995).

The related concept of family structure has also been the focus of ecological research. Land, McCall and Cohen (1990) found that in their study of homicide rates, the percentage divorced (used to measure family disintegration) showed a strong relationship to homicide. According to McKean (1983) the number of divorces in a standard metropolitan statistical area is related to the number of motor vehicle thefts in the area (Rice and Smith, 2002). According to Sampson (1978) family disruption manifests itself in a community through reduced participation in community organizations and activities. This increases the anonymity of community members and undermines efforts at social control.

One possible explanation is that individuals heading up single parent families, despite many who have a desire and vested interest in participation, are simply unable to due to existing work and family commitments that leave little time for outside affiliations and participation in community organizations. Also, single-parent families are in a particularly difficult situation when it comes to juggling employment and other commitments with supervising their children. Their inability to provide adequate surveillance of their children or their motor vehicles may impact the theft rates in the community.

*Age*

The general consensus in criminology and criminal justice is that age is inversely related to criminality. Both official statistics and victimization surveys reveal that young people are arrested in disproportionate numbers to their representation in the population. Youths age 13 to 17 make up roughly six percent of the population yet they account for about 25 percent of index crime arrests and 17 percent of arrests for all crimes combined. In direct contrast, adults 45 years old and over, make up 32 percent of the U.S. population and account for a mere seven percent of index crime arrests (Siegel, 2001).

Despite the incomplete information available about motor vehicle theft offenders the general consensus is that the majority of offenders are youthful individuals. "The U.S. Department of Justice (1996) indicated that people under 18 years of age accounted for 42 percent of those arrested for auto theft, and people under age 21 accounted for 59 percent of arrests" (Rice and Smith, 2002, p. 317).

As previously indicated, the theory of social disorganization has emerged as the premier ecological theory of crime and deviance. In turn, it has also emerged as one of the few theoretical foundations by which motor vehicle theft is studied. The following discussion will provide a brief synopsis of some of the contemporary developments in the social disorganization literature. Additionally, the predictors gathered from census demographic data and tested in the current study are most in line with the tenets of social disorganization theory.

### *Developments in Social Disorganization*

"Social disorganization theory of crime and delinquency has seen a resurgence of interest in recent years" (Veysey and Messner, 1999, p.156). The environmental criminology paradigm is particularly conducive to furthering this revitalized theoretical framework. The current study integrates both the historical and the contemporary social disorganization research in an attempt to operationalize and identify the antecedent structural variables that are believed to contribute to the complex and dynamic processes that in turn lead to crime, particularly motor vehicle theft. These structural variables are seen as a component providing the foundation for community control and the aversion of community crime. It is the position of several community researchers that a true measure of social disorganization needs to include data pertaining to the relational networks of the community, the processes of control, and the organizational activities that are generally only available through extensive community surveys and interviews within each of the local neighborhoods of a study area (Bursik and Grasmick, 1993). As a result, improvised measures of the variables thought to lead to social disorganization have been developed to study the antecedent structural predictors of social disorganization.

While not all research has agreed with the findings of Shaw and McKay or their interpretation of the results, most subsequent research on social disorganization has been based, for the most part, on their original model. The following section will provide a review of several of the empirical studies that have extended and expanded the social disorganization thesis in a number of significant ways.

A study conducted by Sampson and Groves (1989) is widely regarded as one of the more important criminological studies to be produced in the last couple of decades. Their research, conducted in Great Britain, addressed some of the pressing concerns with social disorganization research and added an accounting of family disruptions to explain the breakdown of community social controls. Their thesis was that community level family disruptions would have a positive impact on street corner peer groups, and in turn, increase crime and delinquency. They also postulated that urbanization weakened local kinship and friendship networks and inhibited social participation in community events. Their findings suggested that "...communities characterized by sparse friendship networks, unsupervised teenage peer groups, and low organizational participation had disproportionately high rates of crime and delinquency" (Sampson and Groves, 1989, p.799). In addition, variations in urbanization and organizational participation were shown to mediate in large part the effects of low S.E.S., residential mobility, and population heterogeneity.

Research conducted by Fagen and Schwartz (1986) also examined census data and traditional social disorganization variables. However, their research included survey results pertaining to attachments of youth to institutions of conventional socialization, extent of local personal ties, sentimental attachment to the neighborhood, and organizational involvement within the community, as well as other community control variables. The findings of the study were mixed but residential stability and organizational participation were indirectly related to delinquency through their effects on the attachment to school variable (Bursik and Grasmick, 1993).

Smith, Frazee and Davison (2000) studied street robbery using an integrated model of social disorganization and routine activities theory. They included what they called "a general measure of social disorganization," the distance of various land uses from the geographic center of the city. They found that as the distance from the center of the city increased, the criminogenic effect of various land uses declined. In addition to the distance measurement the authors used variables of single parent household, racial heterogeneity, average value of buildings, number of African Americans, and percent of buildings in the lowest quartile to measure social disorganization. The first four variables were found to be statistically significant.

Moriarty and Williams (1996) conducted a study to examine the relationship between routine activities theory and social disorganization to study property crime victimization in two areas of the community, one labeled as high crime and one as low crime. With regard to social disorganization theory they tested the following exogenous and intervening variables: average number of years at current residence, number of adults living at home, percentage of people who own their homes, median value of homes, number of friends in the neighborhood, number of relatives in the neighborhood, organizational participation, and perceived problems with unsupervised teenage gang activity.

"The exogenous and intervening variables measuring social disorganization indicate that the high crime area is more socially disorganized than the low crime area" (Moriarty and Williams, 1996, p. 51). The high crime area was characterized by racial heterogeneity, less residential stability, lower property values, more family disruptions, fewer friendship networks, less participation in community organizations, and greater concern for teen gang activity.

A study longitudinal by Miethe, Hughes and McDowall (1991) was conducted to assess the relationship between social change and crime rates and the effects of variables measuring social disorganization. The authors looked at rates of homicide, robbery, and burglary for 584 cities in 1960, 1970, and 1980. The independent variables measuring social disorganization were gathered from multiple sources including the U.S. Census records and included: mobility, ethnic heterogeneity, institutional control, and low economic status.

According to the social disorganization perspective, changes in crime rates over time should correspond to changes in demographic variables that indicate decreased effectiveness in social control. The cross-sectional results showed that only ethnic heterogeneity, residential mobility, and a single measure of institutional control (household crowding) were consistently and significantly associated with changes in crime rates over time. In addition, cities with greater initial rates of mobility and lowered levels of institutional control showed greater net increases in robbery and burglary. However, over time these variables did not significantly influence crime rates. Unemployment was significantly related to homicide over time. "The only other result consistent with social disorganization theory was the association between increasing income and decreasing robbery rates (Miethe, Hughes and McDowall 1991, p. 178). The general findings suggested that there was limited support for social disorganization theory, but not enough to adequately explained changes over time in crime rates.

Land, McCall and Cohen (1990) examined eleven structural covariates to assess why some cities, metropolitan areas, or states have higher homicide rates. The study was intended to clear up some of the inconsistent findings in the literature and to determine whether or not structural covariates could be used to develop a generalizable theory to explain ecological structural effects on homicide, or any other type of crime. The study relied on census data from 1960, 1970, and 1980. The eleven covariates in the analysis were gathered from twenty-one previous studies on homicide and were as follows: population size, population density, percentage of the population that is black, percentage ages 15-29, percentage of males ages 15 and over that is divorced, percentage of children 18 and younger not living with both parents, median family income, percentage of families living below the poverty line, the Gini index of income inequality, unemployment rate, and geographic locations in the South (Land et al., 1990).

The findings of the study were somewhat mixed and it was concluded that homicide to a large extent was context specific. That is, occurrence of a homicide was largely dependent on a wide variety of factors that serve to structure the criminal event. However, their regression model did show that the affluence index explained the variance in homicide rates consistently across all four time periods and all three units of analyses. In addition, population-structure and percentage divorced showed a strong relationship at nearly all levels of the analysis and time periods. Areas with greater population density or greater percentages of divorced males have greater homicide rates. Additional structural covariates showed mixed results and at different levels and times of the analysis (Land et al., 1990).

A study by Sampson and Wilson (1995) posits that macro-social patterns of community inequality lead to social isolation and the ecological concentration of the "truly disadvantaged" that subsequently leads to structural impediments and cultural adaptations that undermine community organizations and social control which cause crime rates to increase. A combination of historical and contemporary factors has created an environment in the inner cities that is characterized by a concentration of black poverty and family disruptions. These factors include racial segregation, economic transformation, black male joblessness, class-linked out-migration, and housing discrimination (Ibid.)

> "Boiled down to its essentials, then, our theoretical framework linking social-disorganization theory with research on urban poverty and political economy suggests that macro social forces (e.g., segregation, migration, housing discrimination, structural transformation of the economy) interact with local community-level factors (e.g., residential turnover, concentrated poverty, family disruption) to impede social organization" (Sampson and Wilson, 1995, p. 114).

Sampson and Wilson (1995) have attempted to combine both structural and cultural arguments into a theoretical explanation of the possible links between crime, race and inequality in America's cities.

In another important study by Sampson, Raudenbush, and Earls (1997) the issue of collectivity and crime is reviewed. In this study the authors assert that variations in crime rates are not solely attributable to structural demographic characteristics. Rather, collective efficacy – the willingness of community residents to intervene for the common good- can mediate the negative impact of the macro-economic and neighborhood stratification that is taking place in cities.

Their results suggest that collective efficacy is an important community element that can reliably be measured at the neighborhood level. The three dimensions of neighborhood stratification (concentrated disadvantage, immigration concentration, and residential stability) explained 70 percent of the variation in collective efficacy at the neighborhood level. Additionally, collective efficacy did have a mediating effect on, "… residential stability and disadvantage with multiple measures of violence, which is consistent with a major theme in neighborhood theories of social disorganization" (Sampson et al., 1997, p. 122).

*Criticisms of the Ecological Framework and Social Disorganization Theory*

The following section provides a review of several of the most common and salient criticisms of the ecological social disorganization theory. Despite the existing criticisms the perspective remains an influential perspective that has been gathering increased attention over the last several decades. In addition, as evidenced by the preceding review, there are means of conceptualizing and applying the theory that have been developed that offer varying degrees of solution to the following criticisms.

The greatest area of concern that has been raised numerous times in the ecological literature and has caused a great deal of confusion in the existing literature pertains to the operationalization and measurement of social disorganization. Bursik (1988) points out that one clear indication of the confusion around this issue is that there exists no fewer than four extended efforts attempting to explain the assumptions of the Shaw and McKay approach (e.g. Kornhauser, 1978). This criticism is two-pronged. One issue is the conceptualization of social disorganization and the other is how to measure it.

Much of the confusion over conceptualization stems from the fact that even Shaw and McKay occasionally did not differentiate the presumed outcome of social disorganization from disorganization itself. "This tendency led some to equate social disorganization with the phenomena it was intended to explain…" (Bursik, 1988, p. 526). The confusion over cause and effect led to difficulties in interpretation, replication and evaluation. Drawing on the original work of Park and Burgess, for which the impetus for social disorganization was based, an operational definition has been established defining it in terms of a neighborhoods ability to regulate itself through formal and informal processes of social control (Bursik, 1988). It is now a widely held belief that the ecological change that takes place in the social structure is part of the process contributing to the outcome of social disorganization. "Such an operational definition has made it much easier to differentiate social disorganization conceptually from the ecological processes that make internal self-regulation problematic and from the rates of crime and delinquency that may be a result" (Bursik, 1988, p.527).

The second facet of this area of criticism stems from study design and measurement. Most studies of social disorganization have relied upon local community areas demarcated by large aggregations of census boundary land parcels to establish the presence of disorganization. Individual crimes and crime rates are then calculated for these large geographic areas. The ecological structural dynamics relevant to the social disorganization model are then gathered for each area from available census data and occasionally supplemental sources. However, these are not complete measures of social disorganization as it has been operationalized and they do not capture the relational networks or systemic bases of control (Bursik and Grasmick, 1993).

Rather, extensive surveys, interviews and fieldwork need to be conducted in the entire community to measure a neighborhood's ability to regulate itself through formal and informal processes of social control over time. As previously noted, the logistic and economic complications associated with this sort of endeavor have limited the attempts. As a result, many studies linking social ecology to crime rates tend to miss the processes and focus more on the presence or absence of certain demographic characteristics.

The resulting conclusions concerning the dynamics of social disorganization are consequently based on "conjecture and speculation" (Bursik and Grasmick, 1993, p. 40). Unfortunately, a full test of the model ... will be impossible without an enormous outlay of funds.... Nevertheless, the results of these smaller scale analyses are very supportive of the predictions made by the Shaw and McKay model" (Bursik, 1988, p.532).

Another issue that has been raised is the use of cross-sectional research and the consequent reliance on stable ecological structures. The vast majority of ecological research attempting to following in the footsteps of the early work has studied the effects of structural characteristics on crime at one point in time. This is contrary to the basic premise of the classic ecological theory that was concerned with the processes of ecological change in urban areas. Most contemporary ecological studies have largely avoided this time consuming and costly endeavor of longitudinal micro level data collection (Byrne and Sampson, 1986; Faggiani, 1994). With few exceptions the subsequent studies following in this tradition have typically relied on cross-sectional data and it very rarely has been at what would be considered the micro level. It is simply impossible to study and assess the impacts of ecological change on crime from a single wave cross-sectional design at a macro level of aggregation.

Finally, an area of criticism that plagues many crime studies is the sources of data the studies are based on, particularly the reliance on official crime data. Shaw and McKay used law enforcement sources to determine that higher rates of delinquency exist in impoverished neighborhoods. "Critics claim official data distorts the real crime problem due to possible class biases on the part of the criminal justice system that may misrepresent crime rates in lower-class areas" (Davison, 1995, p. 11).

In addition, researchers have long been concerned with the reporting and recording accuracy of official crime data. There are a number of opportunities for human error and manipulation along the long chain of custody of official crime data.

Fortunately, researchers are aware of the problems that can exist and efforts are constantly being undertaken to improve the quality, integrity, reliability and validity of such data.

It is unknown at this point if the class bias argument is impacting the data in the current study. While it is true and in concert with the previously mentioned Shaw and McKay findings that crime (ex. motor vehicle theft) is in fact more prevalent in lower-class areas, there is no reason to believe that this is due to a criminal justice system class bias. Also, with regard to human error and reporting accuracy, efforts were made to clean the data and to carefully examine questionable cases. Human error is a reality and it is hoped that the systematic data management efforts implemented in this study were sufficient to address these concerns.

The several criticisms discussed here are not intended to be a comprehensive or exhaustive list of the criticisms of ecological research or social disorganization theory. Rather they are intended to provide the reader with insight regarding some of the complications that have arisen over the years as researchers have attempted to develop a means of conducting community crime research employing ecological underpinnings.

### *Alternative Potential Theoretical Explanations of Motor Vehicle Theft*

Much of the empirical motor vehicle theft research that has been conducted has tended to focus on a select few theoretical perspectives. As previously discussed here, repeatedly cropping up in the literature is the relationship between the early social ecology perspective, specifically social disorganization, and the victimization theory of routine activities theory. "Neighborhood characteristics provide the context in which delinquent and criminal behaviors emerge that would not otherwise be observed" (Smith, Frazee, Davison, 2000, p.489).

Below is a discussion of two alternative theoretical perspectives that are not articulated in the motor vehicle theft literature at present. However, many of the macro level antecedent demographic predictors that are commonly measured when studying communities and crime from a traditional ecological perspective could also be applied as antecedent factors leading to complex social processes pertinent to the following two theoretical approaches.

*Human Territorial Functioning*

"Human Territorial Functioning encompasses a class of environmental-behavior transactions concerned with issues of personal and group identity, cohesiveness, control, access, and ecological management" (Taylor, 1988, p. 3). Areas with greater territorial functioning will be more successful in discouraging crime and presumably will also then have fewer motor vehicle thefts.

Several of the common themes in the traditional ecological literature that can also apply to human territorial functioning are outlined in the follow discussion. For example, population increases are related to group size and as group size increases overall knowledge of and positive sentiment for others decreases. It is important to note that one may not necessarily dislike others but the general lack of knowledge of others and about others due to the size of the group leads to neutral opinions and an absence of friendly familiarity. An important dynamic of this is the willingness, or unwillingness as it might be, to contribute to the public good and protect mutually shared territory. A participatory attitude and willingness to contribute is believed to stem from liking others in the group (Taylor, 1988). As the population increases and contribution to the public good decreases opportunities for MVT will increase.

Additionally, individuals in low SES areas are presumed to withdrawal from the community due to perceived limited territorial control over what happens in their surrounding environment due to limited means available for protection. Withdrawal, it is believed sends cues and signals that the area is "up for grabs".

A study by Rainwater (1966) found that residents at the lower strata of the social class experienced minimal levels of territorial control. They instead were concerned only with what went on within their on households and withdrew any efforts to control the external events around their homes (Taylor, 1988).

Taylor's (1981) study of Baltimore neighborhoods found that residents occupying the middle class, as opposed to the lower class, strata of the social structure reported a wider domain of concern and control over their exterior property and their neighborhood. They reported stronger levels of territorial responsibility outside of the home in the surrounding environment. It is also proposed that the upper strata of the social structure may exert such strong territorial control that it may extend well beyond the immediate vicinity of the home and may encompass an entire neighborhood and beyond. In other words, lower SES residents living in areas with limited stability and high levels of disorder have limited territorial control whereas high income areas are occupied by residents with stability and strong territorial control over entire neighborhoods (Taylor, 1988). Areas low in SES and limited territorial functioning can result in increased crime, including more motor vehicle theft.

Individuals who have resided in the area for an extended period of time (low mobility) are more likely to feel strongly about the setting and to invest and exercise more territorial control. Areas with high concentrations of renters tend to have high population turnover. Also, renters tend feel less commitment to the community than owners who have an economic interest in protecting their territory. These assertions can be confounded by gentrification and must be explored more thoroughly in the social environment.

Homeownership is a construct that has been shown to have an impact on territorial functioning – that is, a study of Baltimore neighborhoods found that homeowners had more extensively marked and better kept properties than home renters and also had fewer problems and more social legibility than renters. Their housing units were in better condition, their yards neater and residents reported more responsibility/control of near-home public spaces (Taylor, 1988).

As cited by Taylor (1988), a study conducted by Festiger, Schachter and Back (1959) found that household units occupied by families also tend to have stronger ties to the environment in which they live as opposed to single person housing units which tend to have weaker ties to the community. Multiple unit housing units have been found to be individually isolated from the surrounding community. Essentially, areas with high concentrations/cluster of bounded multiple unit housing tracts are insulated from one another reducing the expanse of territorial control.

Human territorial functioning is best assessed through the micro level data collection of proxy measures that are indicative of links to social processes that in turn lead to diminished levels of social control increasing the likelihood of crime. The human territorial functioning perspective also has links to the incivilities perspective which too is best assessed through micro level data collection. The point here is that many of the macro level tenets of the prevailing ecological theories that have been used to explain motor vehicle theft can also be applied to the theory of human territorial functioning and this further illustrates the need for micro level data collection in studying crime and the related social processes impacting community social control. For example, it could be argued, CBGs with low SES are occupied by residents who lack the resources to adequately protect and target harden their surrounding territory. Aslo, it could be argued, CBGs of elevated instability are occupied by individuals who experience difficulty in establishing long standing territorial control due to the constant flow of people through the social environment. A lack of interest in community cohesion could lead to less territorial control within the community.

*Defensible Space*

Efforts that would seemingly promote territorial control and functioning have been discussed extensively by Newman (1972) in his defensible space manuscript. The most basic principle of defensible space is the restructuring of the physical layout of communities to facilitate community member control in the areas surrounding homes. The effort is intended to promote and preserve the communal areas in which they can realize their mutual lifestyles and values (Newman, 1996). Newman's (1972) primary findings were based upon differences in housing structure and the associated differences in crime. He found that high rise public housing facilities made it nearly impossible for residents to defend their space and the structure was soon overcome by criminal elements. The resulting suggestion was that fostering collective feelings of ownership and responsibility promotes a feeling of duty to defend their environments. To that end, it was recommended that smaller housing structures would lend themselves to easier defense (Newman, 1996).

Newman (1996) further identified characteristics unique to low income families that serve to undermine territorial control in high rise housing complexes. Where middle class families can reside in high rise residential complexes throughout the urban environment lower class families struggle to do so. The reasons for this as identified by Newman are that middle class residents have the capital to employ doormen, porters, elevator operators, resident superintendents, and the like to control both the interior and exterior living space. However, lower class residents by and large have none of the following amenities. These amenities provide territorial control and order maintenance of the environment. Lower class housing complexes are lucky to have non resident maintenance workers and an occasional security guard patrolling the grounds for several hours during the evening.

Additionally, according to Newman (1996), ownership of living space increases territorial control and order maintenance. Territorial claim diminishes as the number of people who share the space increases. The more people sharing the space the less each individual feels they can claim the rights to it. When the number is small it makes little difference if it is the interior of a building or the exterior but informal understanding about acceptable use practices are more likely to emerge.

When the number of people using communal space increases without formal guardianship, the likelihood of reaching implicit understanding about how the space is to be used is dramatically diminished. Under these circumstances, noone feels that they have the right to exert control over the space and it is used for all sort of purposes, including those least desirable. Outsiders now even invade the space and use it for their own purposes. An example of this phenomenon was witnessed by this author in New York City. An unsecured, unmonitored playground was built for residents of a particular high rise apartment complex on the upper east side of Manhattan. Within a short time neighboring residents and their children came to use the park and eventually local teens were using the area to congregate after school and leave trash and debris behind. Dog walkers would allow their dogs to use the ground and drink of the water fountains. On warm summer weekends people from surrounding areas of the community could be witnessed bringing coolers with food and occasionally alcohol to the park, leaving much of it behind. Eventually, the residents for which the playground was built basically relinquished the space to the intruders who now dominated it and used it for their own purposes.

Another interesting aspect of defensible space is the control of traffic flow, both pedestrian as well as automobile. The use of sidewalks and one way streets to control how people navigate space is important and can have a profound impact on how space is used and by whom.

*Subcultural Diversity Model*

The second alternative theoretical perspective to be discussed is the subcultural diversity model developed by Mary (1981). The subcultural diversity model focuses upon the pervasive impact that diverse populations and heterogeneity can have on community structure and community cohesion.

Merry (1981) conducted an ethnographic study of a multicultural housing project in Boston, MA. Merry (1981) asserts that the social structure contributes to high crime rates and that crime results when poverty, a dimension of many SES indexes, and anonymity coexist. Poverty is believed to create the incentive or the motivation to commit crime. However, anonymity, on the other hand, is often caused by the heterogeneous ethnic composition of the neighborhood. Anonymity allows a criminal to commit crime in his own neighborhood without the fear of identification inhibiting his actions. Heterogeneous communities and neighborhoods foster anonymity. "This means he can commit crimes in his home territory, one which to him is relatively safe, predictable, and familiar, while appearing to his victims as if he were a stranger from a distant area" (Merry, 1981, p. 123).

According to Merry (1981), cultural differences and language barriers across ethnic lines cause neighborhood residents to interpret the apparently inexplicable behavior of their anonymous neighbors through the subjective lens of their own culture and experiences. This often inaccurate interpretation leads to further confusion, misunderstanding and mistrust among residents living in close proximity to one another. The result is often the perception of a dangerous environment, both founded and unfounded.

Individuals often deal with dangerous environments by withdrawing into isolated social relationships that they are comfortable with and they avoid people who are unfamiliar and seemingly unpredictable. This response to cultural differences is fundamental to the formation of ethnic boundaries (Merry, 1981). This social withdrawal also creates an environment all the more conducive to crime. The withdrawal sends the message that the area lacks protection and sufficient guardianship.

Covington and Taylor (1991), in a study of fear of crime in urban residential neighborhoods in Baltimore found support for Merry's (1981) cultural diversity thesis. Covington and Taylor (1991), using 66 randomly sampled neighborhoods consisting of 562 blocks, found that regardless of a person's race, those that are more different racially from their neighbors tended to have more fear. "Thus, although it was originally developed in a multi-cultural subsidized housing project, the diversity model also applies to a large city composed largely of white and black residents" (Covington and Taylor, 1991, p. 243). The findings suggest generalizability of the subcultural diversity thesis beyond the housing project context in which it was originally developed.

Covington and Taylor (1991) suspect that the link between diversity and fear was driven primarily by micro level processes present in the racially changing neighborhoods, rather than the stably integrated ones. The existing subcultural differences and the "strangeness" of the "other" group inhibited territorial functioning and resulted in fear of crime (Covington and Taylor, 1988, p. 271). According to Covington and Taylor (1991), respondents in the Baltimore study who felt that they were more similar to their neighbors reported feeling more in control and consequently experienced a greater degree of territorial control.

Merry's (1981) cultural diversity model stems from structural neighborhood composition that serves to undermine community level social control and leads to processes that promote crime in the area. This said process is believed to contribute to greater amounts of motor vehicle theft. However, because the current data can not measure the micro level processes, proxy measures at a more meso level are being analyzed to determine the relationship between racial composition and motor vehicle theft. Further micro level exploration is necessary to discern the social processes at work in the environment.

In conclusion, the unique theoretical constructs reviewed here call for further exploration and articulation in order to discern micro level processes that could distinguish more comprehensively the differences between the complex theoretical relationships that have been discussed.

Many of the variables that have been operationalized in the current study have also been used as proxy measures in other studies to test a variety of theories. This study has assessed the applicability of several predictors to explain the occurrence of motor vehicle theft in communities. Additionally, potential connections have been discussed that may lead to complex theoretical processes in the social environment that may in turn cause motor vehicle theft. However, it is important to reiterate, demographic predictors gathered from census data sources are not sufficient to test for the presence of micro level processes that have been outlined in several of the theoretical models outlined here.

### *Environmental Criminology*

Studies in the ecology of crime helped spawn the rapidly growing field of environmental criminology, which emphasizes the significant role that space and place play in determining the time, location, and character of crimes. Environmental criminology is not an alternative approach but rather an inclusive complimentary approach to the other dimensions of crime inquiry. In fact, it is argued that to fully understand crime it must be studied from all dimensions. By concentrating on the crime-place and locational aspects of crime a more complete multidimensional analysis of crime can be accomplished, offering a greater understanding of criminal events (Brantingham and Brantingham, 1991).

The recent interest in environmental criminology has provided an opportunity for the development and implementation of new strategies in crime prevention such as GIS and crime mapping, "...and encouraged its use not only in the development of practical prevention programs but also in research about the etiology of crime" (Weisburd and McEwen, 1997, p. 14). Understanding the spatial relationship between crime and place became an integral part of the newly emergent focus. The emerging research sought to combine the elements of crime and place and so called "hot spots" of criminal activity in communities to further the understanding of crime place patterns and the effects of social structure. With the combined development and advances in computer technology and information systems, crime mapping emerged as a leading tool of research and practice in crime prevention strategies (Weisburd and McEwen, 1997).

Criminological theories are generally based on social theories and very little attention is paid to the spatial articulation of these theories. Brantingham and Brantingham (1984) have developed a typology of the major spatial approaches to human geography and crime. They divide spatial crime theories into three categories: (1) macro; (2) meso; and (3) micro approaches. "Macrotheories look at the spatial differentiation of large areas (countries or multicountry regions). Mesotheories explore spatial differentiation at an intercountry or regional level. Microtheories explore patterns within urban areas or cities or small regions" (Brantingham and Brantingham, 1984, p. 244-245). Many theories have application at multiple levels of inquiry and the categories are not mutually exclusive. "Many researchers cross the "boundaries" between theoretical approaches. Environmental criminology remains a growing and permeable field" (Brantingham and Brantingham, 1998, p.42).

Crime place theories suggest reasons why offenders commit crimes as well as where and when they strike. "In other words, they attempt to explain why crime incidences exhibit a particular spatio-temporal distribution" (Henry and Bryan, 2000, p. 2). Environmental criminology currently occupies a unique position within the broader disciplines of criminology and criminal justice. "The field explores how actual criminal events involve an interaction between motivated individuals and their surrounding social, economic, legal and physical environment" (Brantingham and Brantingham, 1998, p.31). Much of the emphasis of environmental criminologists is in exploring where and when different types of crime are concentrated in time and space and the social settings that facilitate that crime. This multidisciplinary area of study draws on and encompasses a number of the existing theoretical approaches stemming from social ecology, behavioral ecology, environmental psychology, and human geography to name a few. "All of the different theoretical approaches to the field share an interest in the interaction between people and what surrounds them" (Brantingham and Brantingham, 1998, p.32). The social environment of the community and its sociodemographic structure have become paramount to the exploration of criminal events.

Another important tenet of environmental criminology taken from the rational choice perspective, "...is that the location of crimes is determined through structured search and decision processed on the part of the offenders (and victims) shaped by perceptions of environmental cues that separate good criminal opportunities from bad criminal risks" (Brantingham and Brantingham, 1991, p. 3).

Environments that emit cues indicating that good criminal opportunities exist will develop concentrations of various crimes. Brantingham and Brantingham (1997) use the term "hot spot" to describe spatial concentrations of crime that can be visually recognized through pictures or maps, or events that can be mathematically recognized through the analysis of crime incident locations.

Accessibility is the key to most crimes and mobility is the key to accessibility. As can be seen from the previous discussion, hot spots have a significant impact on crime patterning analyses and crime mapping in particular. Their formation in the environment is dependent on community dynamics and social processes. Community structure and levels of social control are the factors that largely dictate crime concentration within the urban landscape.

### *Crime and Place*

It is important to now turn some attention towards a brief discussion of the physical locations of criminal events. Despite the voluminous community crime literature that exists in the wake of the early Chicago School research the following question continues to arise. "Might there exist a common set of spatial ecological conditions favorable to deviant behavior" (Ley and Cybriwsky, 1974, p.53)? A great deal of time has been spent studying this question and in response, several compelling answers have been offered.

Decades of research and policy pertaining to crime patterning, and the general ecology of crime had taken for granted that crime victims or targets were distributed evenly throughout the geographic landscape. Both scholars and practitioners debated the random distribution of criminal events among themselves for decades. "People victimized by crime near their homes often feel that there are no safe places and that danger lurks everywhere. Even many police often assume a random distribution of crime within areas" (Sherman, Gartin and Buerger, 1989, p. 27-28). However, contemporary research in crime analysis confirms that the non-random distribution of crime. It is well known that the distribution of the population, population dynamics, and the built environment (including commercial and residential development) exhibits clear spatial patterns. It is expected that the distribution of various types of crime will have identifiable spatial patterns as well (Chakravorty and Pelfrey, 2000). In fact, it can be argued that the spatial patterns of crime are related to the spatial patterns of population, community structure and the routine activities of individuals in their daily lives,.

The social milieu of a community is a complex organism with many internal and external factors impacting the behavior of residents in diverse ways. Localized areas of a community are often as diverse as the community itself and the ecology of an area and the sociodemographic composition of the residents who occupy the area have a significant impact on the events that transpire there, including the crimes that take place. The idea that a criminogenic environment can exist is not a new one and too harkens back to the work of the early social ecologists. Researchers have long attempted to understand what set of factors best predict the likelihood of various types of crime in a specific place.

Research suggests that crimes can be place specific, that is, an area of a community or city that has a high concentration of one type of crime will not necessarily have a high concentration of all crimes. The opportunity structure that is created by dynamic community events dictates what types of crime are most likely in specific areas of the community. With regards to motor vehicle theft there are a number of spatial and temporal factors that influence where thefts occur.

One thing that has been suggested by the existing literature is that, geographically speaking, motor vehicle theft has shown very little relationship to the spatial distribution for other crimes, suggesting a distinct etiology and a need for unique crime fighting initiatives and research approaches (Rice and Smith, 2002; Mayhew, 1990; Cornish and Clarke, 1986).

Our personal safety and risk of victimization from crime is shaped less by the many varied answers to the question, why do people commit crime, and more by the knowledge of dangerous and safe places in and around communities (Reiss, 1986).

Through the development of the emergent environmental criminology perspective drastic advances were made during the mid-1980s with the advent of computerized police records, relatively inexpensive personal computers, and manageable Geographic Information Systems (GIS). Such developments made it possible for researchers to begin to study the geographic distribution of crime and the related demographic composition of communities. "Spelman (1995) has summarized these findings as indicating that 10 percent of places in a city are likely to account for 60 percent of all calls for police service" (Brantingham and Brantingham, 1997, p. 10).

Sherman, Gartin, and Buerger (1989) found that when plotted on a map to identify calls-for-service hot spots, 50.4 percent of all calls to the police in their study were dispatched to a mere 3.3 percent of places throughout the city of Minneapolis. In addition, they also found that certain crimes were even more concentrated. Robberies were recorded in only 2.2 percent of places throughout the city, and all motor vehicle thefts occurred in 2.7 percent of places throughout the city. These locations have been labeled "hot spots" of crime and are the focus of many contemporary crime prevention efforts. Discoveries of this sort, for the most part, have helped disprove the notion that crime is a random event occurring where it does by happenstance.

Much of the contemporary community crime research has shown that communities can vary considerably in their structural stability over time and in the stability of their temporal crime rates suggesting that there might be sophisticated patterned changes in communities that better explain community crime. This is contrary to Shaw and McKay's original assumption of a stable set of ecological dynamics driven by the economic qualities of the community in which local communities have relatively permanent roles and potentials for social disorganization regardless of who occupies the space (Bursik, 1986).

Additionally, many contemporary ecological researchers have often instead clung to the assumption of communities being ecologically stable (Bursik, 1986). One reason for this could be due to data restrictions and the lack of longitudinal sources of community level data and the reliance on cross-sectional data sources and single-wave designs. However, a far back as 1950 Hawley asserted that the primary problem of ecological research is the neglected analysis of community adaptation to change.

Also, in the event that delinquency rates and community structure were ecologically stable during the Shaw and McKay era there is certainly no refuting that significant changes have taken place in cities and urban environments since World War II. Population mobility has increased, gentrification and urban renewal programs have become common, housing density, suburbanization, land use/zoning, urban sprawl and commercial and residential lending practices are common concerns often dramatically impacting community stability (Bursik, 1986; Kurtz, 2000). Both natural and planned changes are afoot and assumptions of inherent stability are a thing of the past, or at least they should be.

The general theme of much of the community crime literature that exists follows in the ecological tradition attempting to explain reasons for a community's failure to maintain informal or formal social controls, as well as uphold and in some cases improve, the integrity of the community social order. The causal argument holds that certain types of community structures can weaken controls that serve to dictate and maintain conformity (Reiss, 1986). The exploration of community controls and the processes that dictate and maintain that control as well as the processes that maintain community stability have enjoyed a revival in the ecological communities and crime literature. More recent research has moved away from the analysis of static relationships to the study of processual dynamic relationships in the urban environment to understand the effects of change on the incidence of crime (Bursik, 1986).

An example of the processual relationship leading to the breakdown of informal social controls follows. It has been asserted that high crime communities have a disproportionately high number of female headed households with dependent children, often with incomes below poverty level, living in low-cost, poor quality housing, in multi-unit buildings, with high vacancy rates. The weakened social controls in these situations lead to concentrations of similarly situated youth who come in frequent contact with one another creating a deviant subculture focused around antisocial conduct (Reiss, 1986).

Additionally, high crime areas tend to harbor other young, single, unattached persons, reducing familial controls. This concentration of single individuals might consist of drug dealers, prostitutes, alcoholics, addicts, and career offenders. These individuals serve as role models to youth in the community who come in contact with these adult networks (Reiss, 1986). "A neighborhood's structure and organization disproportionately select households and unrelated individuals who form networks that create and support delinquency and adult crime" (Reiss, 1986, p. 16). Similarly, selective out migration of conforming households and establishments is prevalent.

This study attempts to shed some light on the Ley and Cybriwsky (1974) question in relation to the crime of motor vehicle theft while studying community demographics, ecological composition, stability, and change. The current study draws on ecological models of crime to assess the presence of antecedent structural conditions that may set up for the systemic processes subsequently leading to motor vehicle theft. In addition, this study extends previous research, addressing the concern posed by Bursik (1981) regarding the need to study crime and change over time, by exploring how changes in the measures of social structural attributes commonly associated with future community disorganization are related to temporal changes in motor vehicle theft over a decade.

In large part, the primary interest of this study is to identify the ecological predictors within the community social structure that serve as crime attractors and crime generators for the crime of motor vehicle theft. It is believed that by identifying the ecological conditions - and changes in conditions - associated with the spatial distribution of motor vehicle theft that advances can be made not only in understanding this complex phenomenon of vehicle theft but also from a proactive policy perspective aimed at preventing its occurrence.

The following section identifies the salient ecological predictors that are hypothesized to have a relationship to the occurrence of motor vehicle theft. Each hypothesis is supported by an associated rationale which could be interpreted in light of the theoretical perspectives previously discussed.

## Hypotheses

Hypothesis 1: Census block groups with lower socioeconomic status (SES) will have high motor vehicle thefts.

> Census block groups of lower socioeconomic status will have fewer mechanisms of informal social control and will also have limited resources to fend off the invading criminal element. Low socioeconomic communities are more apt to withdraw from the neighborhood and concentrate their efforts on protecting their own residential unit. Furthermore, research suggests that many motor vehicle thefts are of the joyriding type perpetrated by poor low SES youths.

Hypothesis 2: Census block groups with greater community instability will have higher motor vehicle thefts.

Census block groups with greater instability are characterized as having a more transient and readily mobile population. Residents in areas of high instability lack emotional commitment to their neighborhoods and will be less likely, able, and willing to resist criminal activity, specifically motor vehicle thieves. With the increased mobility and transience in and out of the area residents will be less committed to their environment and consequently to their neighbors. Also, instability in the population will make it difficult to be certain about who belongs in the community and who is an outsider and as a result which motor vehicles belong to whom. Offenders that live in the area, as well as those coming into the area from the outside, will blend easily with existing residents due to the continual turnover of people in the community. Community cohesion and collective efficacy are perceived as lacking in instable communities thus providing opportunities for unfettered criminality.

Hypothesis 3: Census block groups with greater racial heterogeneity will have higher motor vehicle thefts.

More heterogeneous census block groups create increased opportunities for motor vehicle theft due to a general lack of cultural and ethnic cohesion among the differing groups and residents making up the population. Culturally diverse and unique groups of residents have a tendency to generate uncertainty of one another that often manifests as a fear of the unknown. This is especially true among those groups who are dissimilar. Heterogeneous block groups are less inclined to know who belongs in the area and who does not. Heterogeneity impedes the ability to ward off outsiders and establish collective community social controls on acceptable behavior. Also, residents will be less inclined to get involved and participate in community activities that could help prevent crime if they feel fearful of other community residents.

Hypothesis 4: Census block groups with large percentages of young males in the population will have higher motor vehicle thefts.

Research has shown that young males are responsible for a disproportionate amount of crime in general. Furthermore, research on motor vehicle theft has suggested that young males are among those arrested most often for the crime motor vehicle theft. The two age categories in this study (14-17 and 18-24) are used as a rough proxy measure of motivated offenders of crime, specifically motor vehicle theft.

Hypothesis 6: Census block groups with greater population will have higher motor vehicle thefts.

A greater number of people in the population of a block group will equate to more motivated offenders within the population. In addition, greater population, one could conclude, might also mean greater numbers of vehicles present in the population resulting in more targets.

Hypothesis 7: Census block groups that are more spatially autocorrelated will have higher motor vehicle thefts.

Spatial autocorrelation refers to the likelihood that the presence of a variable in one location makes its presence more likely in an adjoining area or in an area in closer proximity compared to an area of further proximity. CBGs with motor vehicle theft are presumed to be in close proximity to other CBGs with motor vehicle theft. Davison and Smith (2000) found that motor vehicle theft increases as the proximity to locations where other vehicle thefts have occurred increases.

Hypothesis 8: Block groups of the city that share a contiguous boundary to areas outside of the city will have fewer motor vehicle thefts.

This hypothesis applies to a dummy variable that was used to control for edge effects in the study area. The existing literature does not address the issue due to its uniqueness. The amount of motor vehicle theft in CBGs outside of the city is unknown and therefore, the impact on contiguously boundaried CBGs is unknown.

Hypothesis 9: Census block groups that straddle a city limits boundary will have fewer motor vehicle thefts.

Motor vehicle thefts occurring in a straddled CBG will effectively be diffused due to the fact that the full representation of the census predictor variables will be used in the analysis but only a partial incomplete representation of the CBGs vehicle theft count is available. The author is unaware of an accurate means of partialling the predictor variables to coordinate with the available motor vehicle theft data. In other words, the city boundaries and the census boundaries do not match up and as a result there is over representation of census demographics and under representation of motor vehicle thefts in the analyses.

## Research Objectives

The goal of this study is multi faceted and stems from an effort to address some of the limitations in the existing motor vehicle theft research. One objective is to identify the salient sociodemographic structural factors that make certain areas of the community more conducive to the crime of motor vehicle theft as predicted by the researchers previously cited. Specifically, in an attempt to understand the fluctuations in motor vehicle thefts over time throughout the social environment this research draws on the existing theoretical understanding of community crime to test a community stability model at the census block group level.

The study focuses on the changes in structural sociodemographics and their relationship to changes in motor vehicle thefts. The conceptual models incorporate several structural constructs (e.g., Population, S.E.S., Instability, heterogeneity, and young males) to determine their predictive power of explaining motor vehicle theft. Some of the variables used to operationalize the constructs in this study have been reviewed in previous research to test their effects on a variety of crimes other than motor vehicle theft. The changing composition of community settings has long been known to impact human behavior in a variety of ways, one of which is crime.

Another objective is to build upon previous ecological research in crime and delinquency by using both cross-sectional and longitudinal data to explore vehicle thefts at two points in time. The study also seeks to identify potential causal effects that are discernable with longitudinal data using smaller units of analysis beyond what is often encountered in the literature to answer the following question: what structural sociodemographic/socioecological factors make motor vehicle thefts more or less likely? (ex. Rice and Smith, 2002; Sampson, Raudenbush and Earls, 1997).

In addition, automated crime mapping techniques are used as a tool to pinpoint specific locations of motor vehicle thefts to visually represent the thefts in their spatial context within the city in order to conduct further analyses. Crime mapping technologies assist in understanding motor vehicle theft from a geography-of-crime perspective and help to develop proactive means for preventing it in the areas where it is concentrated. The use of crime mapping is growing in its application in the social sciences and is finding its way beyond law enforcement practitioners to city planners, academics, and other individuals involved and interested in the crime prevention and control process. This study seeks to contribute to this growing body of research.

A more profound understanding of the predictability of the spatial distribution of motor vehicle theft accompanied by effective means of reducing and preventing it will greatly help to reduce the overall costs incurred by all citizens and make society an altogether safer place by reducing the number of stolen motor vehicles and the subsequent associated crimes. The current study seeks to shed new light on a very costly crime, both economically and socially, that has thus far received little more than glancing attention by the fields of criminal justice and criminology.

## Conceptual Models

There are two conceptual models to be explored in this study with regard to the two distinct analytical approaches, a cross-sectional model (Figure 2) and a longitudinal lagged ecological effects model (Figure 3). As the cross-sectional model depicts there are two waves of motor vehicle theft data (1990/91 and 2000/01) and two waves of Census Bureau demographic data representing the beginning of two decades, 1990 and 2000. The objective is to use OLS regression analyses to test several models of ecological predictors for 1990 and 2000 and identify which of the predictors best explain motor vehicle theft at the block group level of aggregation for the two points in time, Time 1 (1990/9) and Time 2 (2000/01).

While there is quite an extensive and growing body of literature looking at the relationship between community structure and crime (see Taylor 2001, 1995, 1990; Bursik 1993, 1986, 1984) there are only a limited number of community crime studies looking specifically at motor vehicle theft and far fewer studies using the block group as the unit of analysis. It is important to note that analyzing the single 1990 wave of cross-sectional data can not be used to foretell which predictors will be significant in 2000 because there is no mechanism in place controlling for ecological change and its impact over the decade but, the coefficients for the two points in time can be compared to determine Time 1 and Time 2 consistencies and inconsistencies.

The second model is the longitudinal lagged ecological effects model (Figure 3). This model is a bit more complex and involves looking at how ecological lagged predictors of community structure at Time 1 (1990) and contemporaneous predictors at Time 2 (2000) actually impact motor vehicle theft at Time 2 (2000/01). The predicted values of a variable are referred to as "lagged" and the residuals are referred to as "unexpected change" predictors.

It is important to keep in mind that the dependent variable required adjustment for this series of analyses. The dependent variable was converted to a population weighted percentile variable representing unexpected change in logged motor vehicle theft - that is, it could not be predicted by 1990 vehicle thefts and it could not be predicted given, overall, how all CBGs changed in number of motor vehicle thefts from 1990 to 2000. The mechanics of this change process are discussed in the analysis plan.

As the model depicts, the objective is to again use OLS regression techniques to capture unexpected ecological change in community structure and population weighted logged motor vehicle theft over the decade to explain which predictors are impacting the outcome at Time 2. Stated another way, the research interest of the lagged effects model is two-fold: 1) to determine what ecological predictors of community structure from early in the decade (1990) are influencing or driving the motor vehicle thefts outcome late in the decade (2000/01); and, 2) to simultaneously identify predictors that are having a contemporaneous change effect on the outcome variable.

# CHAPTER 4

# METHODOLOGY

## *Study Design*

This is a unique and interesting case study analysis looking at motor vehicle theft over a decade in a location where vehicle theft rates were rising while national theft rates were declining over the same decade long period of time. The study employs the secondary analysis of motor vehicle theft data from Peoria, Illinois. The data were originally collected by the Peoria Police Department in the form of motor vehicle theft police reports for the period of time 1990-2001. In addition, secondary analysis of sociodemographic data collected by the United States Census Bureau has been used for the decennial census' survey 1990 and 2000 in an effort to identify and measure structural predictor variables of vehicle theft.

## *Unit of Analysis*

The units of analysis in this dissertation is the census block group. There are 90 block groups comprising the city of Peoria, Illinois (N=90). One of the prevailing criticisms in the existing ecological literature is the customary reliance on large geographic units of analysis to explain the variance among geographic regions, states, cities, SMSA's (standard metropolitan statistical areas), voting districts, and census tracts. The simple reason for this reliance on large units of analysis is that there is very little data available at the "neighborhood" level. "There are no existing, readily available data sources that account for neighborhoods within any given city. Since conducting a survey of existing neighborhoods in a city is often too cumbersome and too costly for most research projects, many researchers rely on the next best thing – census data" (Davison, 1995, p.35).

Census data are used in many ecological studies despite a few known limitations because these data are readily available, inexpensive, and provide detailed records for every city in the United States at several different levels of aggregation. The current study relies on one of the smaller levels of census aggregation, the census block group, and draws on the related sociodemographic characteristics of this unit of analysis to study the relationship between ecological community structure and motor vehicle theft.

According to the United States Census Bureau (2000) a block group is a cluster of census blocks all having the same first digit of their four-digit identifying numbers within a census tract and generally contain between 600 and 3,000 people, with an optimum size of 1,500 people. Block groups are used in tabulating data nationwide, as has been done for most block numbered areas since the 1970 census. It is important to note that Census Bureau levels of aggregation do not necessarily maintain informally created neighborhood boundaries that emerge within the social environment. For example, it is possible to have a census block group boundary cutting across neighborhood boundaries and visa versa.

Generally speaking, a smaller unit of analysis will also contain a smaller level of aggregation. When conducting ecological research and studying the underlying social structure, small levels of aggregation are usually considered most useful. One of the smallest unit of analysis and levels of aggregation in the census is the census face-block, unfortunately, the variables available at this smaller level of aggregation are limited, in part, due to an interest in protecting the anonymity of census respondents who could potentially be identified by cross referencing sociodemographic variables at this small individual block level of detail to actual locations on a street block segment.

This study looks at ninety (n = 90) census block groups comprising the city of Peoria, Illinois for both the 1990 and 2000 decennial census. The city census block groups are a small enough level of aggregation to identify and understand the composition of the city over time and they correspond to the jurisdiction that the Peoria Police Department patrols. The motor vehicle theft data collected for this study is from Peoria Police Department official reports, all of which have been gathered from incidents of vehicle theft from within the city limits of Peoria. Excluded from this study were all census block groups that fell outside of the city limits of Peoria (ex. Peoria Heights and West Peoria). These surrounding areas, while contiguous to the city of Peoria, are not patrolled by the Peoria Police Department and as a result no motor vehicle theft data is available. These areas are therefore not included in the study. Efforts were made to expand the study beyond the city limits and include these other police departments and the reported motor vehicle thefts within their jurisdictions but due to a variety of problems this was not possible. Figure 4 shows the Peoria city limits and the surrounding municipalities. The figure depicts the city of Peoria as the primary area on the map and shows two smaller municipalities – Peoria Heights to the East and West Peoria to the Southwest – both of which are inset within the larger landmass of Peoria. Several small contiguous municipalities are also viewable to the Southwest and the West.

*Modifiable Area Unit Problem*

One complication that is encountered when using data that has geographic boundaries, such as census data or voting districts, is that these boundaries have a tendency to change over time due to a variety of factors including redistricting and zoning. These boundary changes make it at the very least, difficult, and most likely, impossible, to compare census units and the associated sociodemographics over time. This is referred to as the modifiable area unit problem (MAUP) (Openshaw, 1984; Ratcliffe & McCullagh, 1999).

During the time between the 1990 decennial Census and the 2000 decennial Census the city of Peoria did in fact experience the modifiable area unit problem when the census boundaries in several areas of the city were altered. As a result, Census boundaries and the accompanying sociodemographic data for Peoria could not be matched up for exact comparison from one decade to the next.

In an effort to control for the modifiable area unit problem a commercial data vendor, Geolytics, was contacted and was able to provide a "new" data solution that "normalized" the underlying 1990 sociodemographic data to the geographic boundaries of the 2000 census for the entire county of Peoria in which the city of Peoria is located. More specifically, the data vendor was able to provide a product that reconstituted (normalized) all of the 1990 sociodemographic census variables and accompanying data within the newly designated 2000 Census boundaries. This unique solution allowed for the comparison of units of analysis that had identical geographic boundaries for both decennial census' 1990 and 2000. Furthermore, this allowed for the direct comparison of 1990 and 2000 sociodemographic census data without the negative effects of the modifiable area unit problem. The census boundary changes from the 1990 census to the 2000 census (before the data were normalized) can be seen by comparing the 1990 census boundary map (Figure 5.) with 2000 the census boundary map (Figure 6).

The boundary changes that occurred can be viewed in Figures 5 and 6. Figure 5 depicts the 1990 census tract boundaries and block group boundaries in bold black lines. Figure 6 also depicts the 2000 census tracts boundaries and block group boundaries in bold black lines. If the boundaries had not changed from 1990 to 2000 the 1990 boundary lines would match up perfectly in a comparison with the 2000 boundaries and would not show the changes that are visible.

This was clearly not the case and numerous boundary changes can be seen, especially when comparing the two sets of mapped boundaries on the south side of the city near the central business district (CBD). Solutions short of normalizing the data were considered, such as eliminating the CBG's that had extensive boundary changes over the decade from the sample. However, due to the extent of the boundary changes and their concentration in areas that also had substantial numbers of motor vehicle thefts, this was not a desirable or viable option and would have sacrificed a significant amount of valuable data.

## *Data Sources and Collection*

### *Motor Vehicle Theft*

The criminal event data used in this research is the Peoria Police Department motor vehicle theft incident level data from January 1, 1990 through December 31, 2001.

The period of twelve years was chosen because it corresponds to the two most recent decennial United States Census Bureau surveys (1990 and 2000) and allows for thorough analysis of vehicle thefts over the last decade, a time of marked vehicle theft increase in Peoria, Illinois. It is important to note that the majority of the statistical analyses of motor vehicle thefts actually utilizes a smaller subset of this twelve year span of time. The years of greatest statistical inquiry are 1990, 1991, 2000, and 2001. The full decade of data at this point is only used to track the vehicle theft trend in the study area over time.

According to Peoria Police Department records, from 1990 through 2001, there have been as few as 336 motor vehicle thefts to over 1,361 in a given year. Figure 7 shows the spatial layout of the 1990 motor vehicle theft point locations throughout the city or Peoria. Figure 8 shows the spatial layout of the 2000 motor vehicle theft point locations. As can be seen from a comparison of the two figures there is a greater concentration of theft in several areas of the city in 2000 as compared to the concentrations in 1990.

The intention of this study is not to attempt to explain the annual increases and decreases as they occurred over the decade but rather to study the impacts of ecological change over the decade on motor vehicle theft at the beginning and end of a decade. In order to accurately measure and account for the changes in the Census Bureau sociodemographic data and its potential relationship to motor vehicle theft, two populations for each unit of analysis have been created, one population for the beginning of each decade – 1990 and 2000. The details of the two populations are provided in the variable operationalization section. Table 1 shows the number of motor vehicle thefts by year along with the increases and decreases in thefts both annually and over the decade. Figure 14 shows the motor vehicle theft trend over the decade for both the local vehicle thefts and the national thefts. The divergent trend is interesting in that the local trend line is upward for the decade while the trend line for the national thefts is downward throughout the 1990s with a recent increase in thefts each year of the new millennium.

The official police reports for motor vehicle theft contain the following information: the make, model, year, color, incident report number, license plate number, date the vehicle was stolen, state in which it was registered, census tract from which it was stolen, police district from which it was stolen, the address where it was stolen from and, if available, where it was recovered. This study is particularly interested in the location of the vehicle theft, including the address, census tract, and census block group.

The data were collected through direct contact with Peoria Police Department (P.P.D.) personnel. All motor vehicle theft incident level data were entered into the mainframe computer system at the P.P.D. from official police reports. Some of this information was printed out to produce hard copies of the records while other parts were transmitted electronically and entered into a data file. All of the data were sent to the researcher for purposes of the current study. All of the motor vehicle police report variables have been entered into an SPSS data file and integrated with additional data from the U.S. Census Bureau creating a large and comprehensive data file combining vehicle thefts aver the decade and sociodemographic variables for further analysis.

The address locations of the thefts have all been recorded and then mapped using ArcView GIS 3.2. The mapped points have been integrated with census tract and block group maps and associated data to identify the number of thefts that have occurred within each unit of analysis. Also, the predictor variables have been collected from the U.S. Census Bureau at the block group level to facilitate the comparison of changes in ecological social structure characteristics over time.

In addition to mapping the locations of the thefts, the aggregate number of thefts in each census block group has been used to determine population weighted percentile scores for motor vehicle theft to assess the relative position of each block group at the two points in time and to control for spatial autocorrelation. Several of the ecological predictor variables have also been population weighted in order to assess their relative change in position over the decade. This process will be discussed in more detail in the analysis plan.

The only motor vehicle thefts that were not used in the current study were those thefts that did not have an address identifier associated or those that could not be mapped due to an incorrect or unmatchable address. Fortunately there was a minimal amount of unmatchable thefts and based upon careful review by the researcher there did not appear to be any pattern to the unmatched thefts. Table 2 shows the number of motor vehicle thefts that were accurately mapped each year, the number of thefts that were unable to be mapped each year the total number of cases for the year, and the associated annual "hit rate" – the percentage of accurately mapped thefts each year. The following discussion explains the geocoding process and the associated "hit rate" in more detail.

*Geocoding/Geoprocessing*

Geocoding is the procedure by which point locations, as defined by street addresses, latitude and longitude coordinates, or zip codes are matched to their proximate geographic location and are computer generated on an automated base map. The current study used various combinations of all three geocoding methods mentioned above. A "base map" of Peoria, Illinois was acquired from a commercial data vendor (GDT) and was loaded into ArcView GIS 3.2 for the address matching process.

ArcView GIS 3.2 was used to match the addresses of the motor vehicle thefts in Peoria, Illinois to their actual locations in the city using the base map through a process known as interactive batch-matching. During this process, all designated addresses associated with the motor vehicle theft locations are matched to their proximate locations on the automated base map. The results of the batch-match are represented by a "hit rate" – a number indicating the percentage of cases that were successfully matched to a point on the base map. For those addresses where a perfect match is not made, the researcher has the opportunity to review the individual address and make any necessary changes to improve the match score. Often the match score can be improved by simply correcting a misspelled street name in the address field. The annual "hit rates" over the decade for the current study show a successful match and subsequent point placement for over 95 percent of the cases each year.

Through the use of Monte Carlo simulation Ratcliffe (2004) was able to determine that an 85 percent hit rate is acceptable over 95 percent of the time across a varying range of spatial features. This finding suggests that the greater than 95 percent annual hit rates achieved annually in this study are more than acceptable and should be sufficient for the purposes of this study.

All records that could be plotted on the base map by using the address location identifier have been used in the present study and those cases missing this necessary information have been eliminated from the spatial aspects of the study. The final mapped product is a visual representation of the spatial distribution of motor vehicle theft data points accurately placed on a computer-generated map of the city of Peoria.

*Census Bureau Data*

Census data is collected on a national level and can be used to study very specific geographic/spatial attributes and community sociodemographics in select areas (e.g. Peoria, Illinois). For this study United States Census Bureau data were collected from both the 1990 and 2000 decennial census. Most of the relevant Census data were obtained from a commercial data vendor (Geolytics) using both 1990 and 2000 Census Summary File 3 (SF3) data. The Census sociodemographic data is being used to study the underlying social structure of the city of Peoria and its relationship to motor vehicle theft.

As previously discussed, the 1990 data were normalized to the 2000 census geographic boundaries and then all of the data were allocated to the ninety census block groups for Time 1 and Time 2. Further modifications were made to some of the data to get it into a more suitable form for further analysis, including logging, population weighting, and indexing z-scores.

Table 3 shows a complete list, at the larger city level of aggregation, of the Census Bureau demographic predictors that were drawn upon to study community structure at the census block group level in the current study. Percentage changes in the community structure variables over the decade can also be reviewed in the table. Several city wide demographics held quite constant over the decade with increases or decreases of less than five percent, for example: population (down .005 percent), individuals living below the poverty level (down .02 percent), males in the population between the ages of 14 and 17 (up 1.5 percent), and the number of vehicles available in the population (up 3 percent). Other demographics showed more dramatic increases and decreases, for example: median owner occupied property value (up 64 percent), median income (up 24 percent), percent of Black residents in the population (up 18 percent), percent of White residents in the population (down 11 percent), percent of residents in the labor force 16 years and older that who are unemployed (up 7 percent), and percent of the population living in a different house five years prior (up 8.4 percent).

As can be seen from the changes in citywide demographics, despite the fact that the city population has remained relatively stable there has been a great deal of demographic change in the city, some seemingly for the better – median income rose as did property values quite substantially - and some certainly for the worse – unemployment and the evidence of "White flight".

*Spatial Auto-correlation*

Spatial auto-correlation is a common problem that arises when studying spatial data that has been aggregated to political or administratively defined space. The concern is whether or not events in one location are affecting and having an impact on events in another location. In this instance we're concerned with the impact of motor vehicle theft in surrounding block groups impacting theft potential in other block groups, and how to control for this occurrence. This problem is of particular sensitivity to criminologists given the interdependent relationship that often exists between criminal events and geographic space. “Whatever boundaries are being used to delineate geographic areas, social phenomena are not likely to restrict themselves to those boundaries. This is particularly true of crime, which is likely to “spill over” from one neighborhood and effect adjoining neighborhoods” (Kurtz, 2000, p.74).

Unfortunately, many of the standard linear statistical models that have been developed rarely took geographical dependency into account (Land and Dean, 1991). By relying on standard linear regression models without taking into consideration any of the spatial interdependence that might exist, erroneous conclusions may be drawn. “In order to isolate the effect of crime on a particular neighborhood, it is necessary to control for the effects of crime from adjoining neighborhoods” (Kurtz, 2000, p.74).

The traditional methods that were employed to control for spatial autocorrelation involved only controlling for the events in locations with contiguous geographic boundaries. This approach did not take into account the effects of more distant locations or proximate locations of larger or smaller land areas or population sizes. Contemporary efforts to control for spatial autocorrelation now recommend taking into account all geographic units under analysis, contiguous and otherwise, within a study area and the potential impact of each on one another (Land and Dean, 1991; Roncek and Montgomery, 1984).

The method that was used in this study was described by Land and Dean (1992) and involved the creation of an instrument that measured motor vehicle theft potential in areas throughout the city in order to control for impacts of spatial autocorrelation in each block group. The instrument contained the inverse of the distance for each block group from each other as well as the latitude and longitude of each and the distance to the central business district. This method resulted in a spatial autocorrelation control variable that was subsequently entered into the regression equations as a predictor. The specific mechanics of the instrument and an explanation of the theft potential estimation variable and the instrumental variables that were used to create it can be reviewed in Appendix A.

### *Data Analysis*

The following discussion is very important to understanding the results section of this study. There are two parts to the statistical data analysis in this study. The first analysis involves a series of two-wave cross-sectional analyses using OLS regression techniques to look at logged motor vehicle theft at two points in time, the beginning of 1990 (Time 1) and the beginning of 2000 (Time 2). This analysis determined which predictors best explain logged motor vehicle theft at each of the two points in time and allows for comparisons of the significance levels and impacts of the predictor coefficients at both points in time looking at consistencies from the beginning of the decade, Time 1, to the end of the decade, Time 2. The predictor variables for both points of time were largely from the U.S. decennial census' and in some instances were manipulated by z-scoring several of the variables and adding up the scores to create indexes for SES and Instability. In addition, two dummy boundary variables were created as well as two age categories of young males. All of the resulting variables were then entered into their respective (Time 1 or Time 2) cross-sectional OLS regression analyses.

The second series of analyses are the longitudinal ecological effects models. These analyses required changing the dependent variable from a count variable into a population weighted percentile score for unexpected change logged motor vehicle theft. The population weighted percentile scores are based on cumulative population weighting with regard to the population in the CBG and the number of associated motor vehicle thefts (Taylor, 2001). The population weighting procedure is discussed more thoroughly in the analysis plan, Chapter 6.

This analysis allows for the assessment of change in relative ecological position from one point in time 1990/91 (Time 1) to the next 2000/01 (Time 2) and as Bursik (1986) notes, examining ecological change is not as straightforward as it might seem. Several approaches at measuring or capturing change have been used in a number of ecological studies and experts have often disagreed as to the best approach (Taylor, 2001). Hunter (1974) used gain scores, "...the proportional increase or decrease in the level of a variable in two successive periods of time" (Bursik, 1986, p. 42). Others have employed Bohrnstedt's (1969) residual change score recommendation. "To create such a measure, one regresses the level of a variable at time *t* on its level at time *t*-1. The residual for each community is the measure of change" (Bursik, 1986).

The lagged ecological effects regression analyses used here captures the amount of expected and unexpected change over the decade in an effort to explain how structural events at Time 1 impacted the outcome at Time 2. The technique was modeled after the approach used by Taylor (2001) to measure expected and "unexpected" change. The interest here is in the change that deviates from that which is expected (Taylor, 2001). "In a lagged model, the current value of the dependent variable is related to previous values of the independent or explanatory variables" (Brantingham and Brantingham, 1984, p. 114).

In preparation for the lagged effects analyses all of the requisite ecological predictors and the logged motor vehicle theft outcome variables were population weighted for Time 1 (1990/91) and Time 2 (2000/01). Next, the Time 1 population weighted logged motor vehicle theft outcome variable was regressed against the Time 2 population weighted logged motor vehicle theft outcome variable. The predicted values were saved as a new variable and the residuals were saved as a new variable. The predicted values correlate 1.0 with the 1990 scores on the motor vehicle theft outcome variable and are essentially the same. They are from this point on referred to as "lagged" and the residuals are from this point on referred to as "unexpected change" predictors. The lagged portion of the outcome variable was not retained for purposes of the analyses in this study. The "new" outcome variable for all of the subsequent lagged effects models became the "unexpected change" population weighted logged motor vehicle thefts variable.

Next, the Time 1 population weighted ecological predictors (IVs) were then regressed against the Time 2 population weighted predictors (IVs) and all of the predicted values and residuals were again saved as new variables. Again, the predicted values correlate 1.0 with the 1990 predictors. The predicted values are from this point on referred to as "lagged" predictors and the residuals are from this point on referred to as "unexpected change" predictors. In effect, the lagged predictors are representative of Time 1 (1990) effects on the outcome and the unexpected change predictors represent Time 2 (2000) unexplained contemporaneous effects on the outcome.

The interest is in seeing which ecological predictors best explain unexpected change population weighted logged motor vehicle theft. Are there significant co-occurring lagged and unexpected change predictors? Are there significant lagged predictors that are not associated with their contemporaneous unexpected change predictors? Also, are there significant predictors present or absent in the lagged ecological effects models that do not show congruence with the associated longitudinal models?

## Operationalization of Variables

This section describes and details the operationalization of each variable that is used in the study to test the previously specified hypotheses. The data sources for these variables, the decennial census survey for 1990 and 2000, have been previously discussed.

### *Outcome Variable (DV)*

#### *Motor Vehicle Theft*

For the purposes of this research the dependent variable is the number of completed motor vehicle thefts reported to the Peoria Police Department. This study does not include any attempted or incomplete thefts. Many attempted thefts are not reported to the police and therefore reliable incident information is unavailable. Rather than rely on a partial accounting of attempted motor vehicle thefts, the decision was made to include only reports of completed thefts because the number of reported thefts has been shown to be representative of the actual number of motor vehicle thefts that occur. As previously noted, vehicle thefts have an extremely high report rate largely due to the reporting requirements by insurance companies that require a police report to be filed in order to seek compensation through an insurance company. Attempted theft are not presumed to be as accurate due to the fact that potential victims did not suffer the financial loss of their vehicle and therefore may not take the time to file with the police.

As previously mentioned, in addition to the twelve year span of annual motor vehicle theft counts, two populations of motor vehicle thefts were created to represent two points in time, one for the beginning of the decade, Time 1, (1990/1991), and one to assess the end of the decade, Time 2, (2000/2001). The numbers of thefts in each of the units of analysis was summed for the years 1990/1991 and 2000/2001 and the mean calculated to produce the number of thefts for 1990/91 and 2000/2001 respectively. The mean number of thefts for each block group was natural logged to reduce the skew in the dependent variable. This was necessary because some CBGs in the city had no motor vehicle thefts and as a result did not resemble a normal distribution, a requirement of regression analysis. Figure 9 shows the 1990/91 data before it was logged to control for skewness and Figure 10 shows the 1990/91 data after it was natural logged. Figure 11 shows the 2000/01 mean motor vehicle theft data and shows the skewness before the data were natural logged. Figure 12 shows the improvement in the distribution after logging the mean number of motor vehicle thefts for 2000/01. This procedure created Time 1 (1990/1991) and Time 2 (2000/2001) mean motor vehicle theft counts. Table 4 shows the descriptive information for motor vehicle thefts for Time 1 and Time 2 before logging the variable and table 5 shows the descriptive information for mean motor vehicle thefts for Time 1 and Time 2 after logging.

The dependent variable was further altered for the longitudinal analyses from a simple count variable for the two periods in time to a population weighted percentile variable for the two points in time. This change was a necessary step in the process for doing the lagged effects analysis. This process is explained and discussed more thoroughly in the analysis plan.

Although the limitations of using police data are widely known, completed motor vehicle theft is a unique crime in many respects and the reporting rates are generally regarded as accurate. There are several explanations for this reliability in reporting accuracy. First, individuals who have had their vehicles stolen have a financial interest in having it recovered or filing an insurance claim to have it replaced. In fact, in most states, insurance companies require a police report before a motor vehicle theft claim can be filed.

A second reason that motor vehicle theft is accurately reported is that it tends to carry very little, if any, social stigma. It is well documented in the victimization literature that crime victims often refuse to report their victimizations due to any combination of a number of deeply emotional responses (ex., fear, guilt, shame, mistrust, outrage). Motor vehicle theft is not a crime for which most of these emotional reactions, besides outrage, are felt or internalized. These two reasons alone help to produce a more reliable reporting rate for motor vehicle theft than is available for most other crimes. It is worth noting though that victim-blaming is common in vehicle theft due to occasional and perceived motorist carelessness (ex. Leaving keys in car or vehicle running).

*Predictor Variables (IVs)*

The following section provides information pertaining to the operationalization and measurement of the ecological community structure predictor variables. Specifically, this section identifies and operationalizes the predictor variables that are relied upon in this study to attempt to explain high theft areas and changes in the number of motor vehicle thefts over the decade. These predictors have been gathered from existing census data sources for the decennial census survey's 1990 and 2000.

*Population*

The total number of people residing in each census block group has been collected from the respective decennial census survey and is used as a control variable in the cross-sectional models and as a population weighting tool in the lagged effects model. One of the rationales for using total population instead of total number of households is that total population takes account of the actual number of residents in an area where as a household measure does not account for households with large numbers of residents in them. Also, population density is thought to impact vehicle theft and total population is a better representation of density than total household number which takes no accounting of number of residents in the household. Additionally, it was determined that parts of the downtown area of the city tended to have a disproportionate number of people when compared to households suggesting that the household measure was probably not an accurate representation of population concentration and underestimated and even misrepresented the spatial layout of people in the population residing in the city of Peoria, especially the downtown area. In other words, the downtown area of the city tended to have larger households than other parts of the city. One explanation for this could be for example, the occurrence of multiple Bradley University students sharing a single household.

*S.E.S. Index*

The construct of socioeconomic status (S.E.S.) has a long history in the ecological literature. Socioeconomic status has been operationalized in this study by using several variables that were collected at the census block group level. Throughout the ecological literature a variety of variables have been used to create S.E.S. indexes including: median income, median property value, median rent, education level, poverty level, and occupational status, to name a few.

The current study, through a process of data reduction and scale reliability diagnostics, developed a block group level S.E.S. Index by summing the z-scores for the following sociodemographic variables of median household income level, median property level, and the percent of the population living below the poverty level. Median household income level and median property value have been natural logged in order to reduce the effects of any skew in the data. The SES Index variables were population weighted for the longitudinal lagged effects analyses.

*Instability Index*

Stability is another construct that reoccurs in the ecological literature. The current study developed a unique Instability index for use in the analyses comprising several salient stability variables. The Instability index was also operationalized using several demographic measures available in the census decennial survey. The following information has been gathered at the census block group level: the percentage of the population five years and older not living in the same house five years prior to participation in the census survey, in this instance 1985 and 1995; the percentages of occupied housing units that are renter occupied versus the percentage that are owner occupied; the percentage of single person households; and finally, the percentage of multiple unit housing as a percentage of the total number of housing units in the area. These individual predictors have been used to create the Instability Index by summing the individual z-scores. Again, these index variables were population weighted for the longitudinal lagged effects analyses.

*Heterogeneity*

The construct of racial heterogeneity has been operationalized using two measures available in the census decennial survey. The heterogeneity measure used in this study has also been used successfully elsewhere (see Miethe and McDowall, 1993; Rice and Smith, 2002). The index measures the percentage of the population that is White multiplied by the percentage of the population that is Black in each block group at both points in time – Time 1 and Time 2. The equation is represented by: (White/total pop.) x (Black/total pop.). It is worth noting that prior to creating the racial heterogeneity index a race variable, percentage of the population that is Black alone, was tried in the study. This predictor was highly correlated with other individual predictors in the model resulting in excessively high multicollinearity, especially with the SES predictor. The decision was made to use the heterogeneity index instead due to fewer collinearity concerns. In addition, the heterogeneity equation is a better measure of racial composition and integration.

*Young Males*

The percent of the population in each block group that is male between the ages of 14 thru 17 or 18 thru 24 have been operationalized by using several measures available in the census decennial survey. The total number of males represented in each of the two age categories were summed and the total number in each block group was used to determine what percentage of the population was represented by males in each of the two age categories. Young males in this study are viewed as motivated offenders of motor vehicle theft.

*Spatial Autocorrelation*

A measure of spatial autocorrelation has been created by taking the population weighted motor vehicle theft score, the centroid of each census block - consisting of the latitude and longitude, and distance of each block group from the downtown courthouse - a proxy measure for the center of the central business district. These variables were used to create the control measure for spatial autocorrelation (see Appendix A).

*Contiguous Boundary*

Two control variables for census boundary congruence with the municipal city boundaries were created in order to address the modifiable area unit problem (MAUP). The first dummy variable was created that would control for areas where the census block groups within city boundary limits were contiguous to census block groups outside of the city boundary limits where vehicle theft data were unavailable. This was necessary because information for the area outside of the city was absent creating a need to control for areas immediately contiguous to the city in case they were impacting events in block groups falling within the city limits.

*Straddle Boundary*

A second dummy variable was created to control for areas of the city where the geographic city limits boundary and the geographic census boundary did not coincide with one another. In several instances a city limit boundary line would cut through a census block group boundary, in effect greatly reducing the number of accounted for vehicle thefts while maintaining the full aggregation of demographic predictor data. The result was the potential for a diluted motor vehicle theft count and inflated demographic/predictor representation thereby creating the perception that vehicle theft was comparatively rare. The straddle boundary control variable made it possible to keep track of the impact this event had on the outcome.

In sum, a review of the predictor variables shows that each variable is actually a multidimensional predictor created to best capture ecological events in the social fabric of the community. Both the SES predictor and the Instability predictor are indexes containing unique demographic variables created by summing the z-scores for the included variables. The two young male age category variables were compiled as a representation of potential offenders in the population. The heterogeneity variable is an established heterogeneity index accounting for racial mix in the population of each CBG.

The remainder of the variables (population, spatial autocorrelation, contiguous boundary, and straddle boundary) were created to measure and control for specific events that could impact the results of the study.

# CHAPTER 5

# COMMUNITY CONTEXT AND RATIONALE OF THE STUDY LOCATION

## Vehicle Theft in Illinois

The number of motor vehicles stolen in the United States each year is high and the losses incurred are extremely costly. Motor vehicle thefts, while causing problems for the nation as a whole, are more troublesome in some states, cities, and communities than in others. Several of the states with a consistently high motor vehicle theft rate are: Florida, California, New Jersey, New York, and Illinois.

Based on crime statistics compiled by the Illinois State Police, Illinois ranked 5$^{th}$ in the United States for motor vehicle theft in 1996 and dropped to 7$^{th}$ in the nation in 1997. However, the decline did not continue and by the year 2000 Illinois motor vehicle thefts were up compared to most other states with Illinois ranking 4$^{th}$ in a national comparison. In 2001 things were not much better and Illinois was still strongly in the top 10 with a ranking of 6$^{th}$ place (UCR, 2001). In 2002 Illinois had again decreased its national standing to 7$^{th}$ place (UCR 2002). However, it is important to note that the number of motor vehicle thefts in Illinois throughout the decade of the 1990s did drop from 75,642 in 1991 to 45,262 in 2001, a decline of approximately 40 percent over the decade. According to the Illinois Criminal Justice Information Authority, motor vehicle theft costs Illinois residents nearly one million dollars a day, a staggering sum (Green, 2003).

According to Illinois arrest statistics in 2001 there were 10,687 arrests for motor vehicle theft. This is approximately 10 percent of the total number of arrests for motor vehicle theft reported in the United States in 2001. Motor vehicle theft arrests in Illinois have increased more than 15 percent since 1991. In 2002 there were 11,536 arrests for motor vehicle theft in the state. The national number of motor vehicle theft arrests actually decreased over the decade by approximately 36 percent.

In 2002, the average sentence length for the 866 motor vehicle theft offenders who were sentenced to serve time in the Illinois Department of Corrections was 4.1 years. Interestingly, although the total number of motor vehicle theft sentences imposed in 2002 increased from the year prior, the average sentence length actually decreased from 4.2 years to 4.1 years (Illinois Motor Vehicle Theft Prevention Council, 2003).

*Motor Vehicle Theft in Peoria, Illinois*

As noted, the current study addresses the motor vehicle theft phenomenon in Peoria, Illinois. The city of Peoria has been chosen as the study location for several reasons. First, Peoria has struggled to combat and control motor vehicle theft over the last decade. Although the vast majority of the country experienced a reduction in the rate of motor vehicle thefts throughout the 1990's, including many parts of Illinois, Peoria witnessed a fluctuating yet marked increase in its motor vehicle theft rates. In fact, Peoria County was one of the top five counties with the most motor vehicle theft in the state of Illinois and in 2002 Peoria County ranked seventh out of 102 counties in the state (Green, 2003). Interestingly, despite the increase in vehicle thefts from 2002 to 2003 there was actually a reduction in the number of motor vehicle theft arrests from 171 arrests in 2002 to 90 arrests in 2003 (Peoria Police Department Website, 2004).

Residents of the city of Peoria owned approximately 72,611 registered vehicles in 1990 and 75,664 vehicles in 2000. Using these numbers to create a vehicle theft rate it was determined that in 1990 there were 4.5 vehicles stolen for every 1000 registered vehicles in the city. The theft rate for 2000 tripled to 13.5 vehicles stolen for every 1000 registered vehicles in the city.

The motor vehicle theft problem in Peoria is a concern for many area neighborhoods and residents. The Peoria Police Department was eager to support a detailed research project such as this one in pursuit of a better understanding of motor vehicle theft. One of the hopeful outcomes of this project is to be able to use the findings of the study to shed some light on vehicle theft in the Peoria area so that at some point progress can be made in terms of effective prevention strategies that will help to make the city a safer place and resident's vehicles less prone to theft.

The Peoria Police Department committed their support and cooperation to the project to the extent of providing the necessary motor vehicle theft data and meeting with the researcher as necessary to discuss and clarify issues of data collection and coding.

In addition to the accessibility of official records of motor vehicle theft data and the cooperation of the police department, Peoria, Illinois was also chosen due to its familiarity to the researcher who lived in the city for approximately twenty years. The researcher has spent a considerable amount of time acquiring knowledge of the geography of the city and is well acquainted with the community landscape and community characteristics. Intimate knowledge of the study area has been highly useful in understanding and interpreting the social ecology of the city, the events, locations, demographic composition, and contexts being studied.

*Community Profile*

"Urban growth and development is incredibly complex, but not entirely random. Growth -- whether in the Tri-County area, the Midwest, or a specific neighborhood -- is a dynamic and sometimes messy process driven by demographics, economics, infrastructure and public policy" (Tri-County Regional Planning Commission, 2003). The Tri-County Area consists of Peoria County, Tazwell County, and Woodford County. Land use in this area grew 159 percent between 1960 and 1990, compared to a modest 34 percent growth in population. Many critics blame this trend for a variety of problems including but not limited to urban blight and suburban traffic congestion. The Tri-County area ranks fourth among Illinois SMSAs (standard metropolitan statistical areas) in terms of population size (behind Chicago, Eastern St. Louis, and Rockford) with approximately 350,000 residents. Peoria County comprises more than 180,000 of these residents with the city of Peoria making consisting of more than 112,000 persons (Tri-County Regional Planning Commission, 2003). While aggregate population numbers in the area have been pretty stagnant in recent decades, Peoria's landscape has changed considerably.

The city of Peoria is expanding and growing spatially and changing demographically. In recent decades the composition of the population, the work force and employment sector, housing, education, racial segregation, and crime have all changed quite dramatically. This section will discuss some of these changes in order to create a more complete understanding of the cityscape and environmental backcloth.

Over the last several decades, Peoria has earned the "All American City Award" three times. As national test marketers have found, Peoria is a microcosm of the United States population, a cross-section of Middle America. "To "Play in Peoria" is not only an old term for vaudeville, but a catch-phrase used today inside the thoughts and habits of the typical American" (Peoria Convention and Visitors Bureau web page, 2002).

Peoria, in many respects, is not unlike many other cities in the United States that are similarly situated along bodies of water, in this case, the Illinois River. Peoria has a waterfront downtown area that promotes and supports the commercial entertainment industry with numerous hotels, restaurants, bars, and both family and "adult oriented" entertainment. The city has late night entertainment with many downtown bars/restaurants staying open until 4:00 a.m. There has been a recent effort to redevelop the downtown waterfront area to make it more desirable to residents and visitors. Commercial establishments have opened up along the riverfront and both the housing stock and commercial space in the area have shown improvement via this revitalization effort.

A testament of the downtown improvement effort has been the addition of a new multi-million dollar baseball stadium in 2002 and the establishment of riverboat gambling in East Peoria, on the other side of the Illinois River, in the early 1990s. Both of these sources of entertainment draw a substantial amount of their client base from the city of Peoria and bring visitors to the surrounding area contributing to the local economy. The riverboat gambling in East Peoria has been raised as a possible crime attractor that may have an impact of surrounding community crime rates. The gambling boat certainly increases the opportunity for motor vehicle theft both at the large parking lot that contains the vehicles of visitors to the boat as well as parking lots of nearby hotels where people who intend to frequent the gambling boat stay overnight. The current study did not explore this issue.

Downtown Peoria is also home to the Peoria Civic Center, a large multifunction venue and arena used for large conferences, concerts, athletic events such as Peoria Rivermen hockey games, arena football, and Bradley Braves basketball games. Bradley University is located on the Southwest side of town, on Main Street near the downtown area. The primary police station in the city is also located downtown as is the city courthouse. Many of the community municipal services buildings are located downtown including the main branch of the public library and the gas and electric company. There are also two housing projects located in areas of the downtown.

*Employment and Industry*

One of the more salient themes in criminal justice literature is the recurring discussion of the impacts of economic conditions and employment opportunities on crime rates. The general assumption is that prosperous economic conditions and high employment rates do well at alleviating or mitigating the incidence of crime. Property crimes occur with less frequency as economic need is reduced. On the other hand, communities gripped by lackluster economic conditions often are also communities that are likely to experience cutbacks in the local labor force. In essence, one event begets the other. Prosperity creates opportunity for job growth which is a catalyst for additional growth in industry leading to additional employment opportunities. Conversely, a downturn in a community's economic condition, occasionally the result of changes in industry, leads to layoffs and downsizing which significantly limits growth opportunities and can create fertile ground for crime and criminality.

The structural changes in employment opportunities in Peoria have been particularly interesting and have had a significant impact on the local economy. The Tri-County area's economy was significantly affected during a national decline in manufacturing employment and Peoria's economic recession in the 1980s was particularly sharp due in large part to the restructuring of Caterpillar Inc. Caterpillar's worldwide headquarters are located in Peoria and the company is the largest employer in the area with several manufacturing plants and office complexes throughout. During this time of restructuring household incomes declined and fell 15 percent below the statewide household income average (Tri-County Regional Planning Commission, 2003).

National trend data suggests that cities that maintain a strong reliance on manufacturing to support the local economy have generally grown slower than cities whose economies are more reliant on service industries such as wholesale and retail trade. The Greater Peoria area economy, largely driven by manufacturing, has fallen behind the rest of the state of IL as the national economy has moved towards the service sector of employment. The Tri-County area lost over 20,000 manufacturing jobs from its peak in the late 1970s and manufacturing employment fell from 31 percent in 1970 to 14.5 percent in 2000, having a significant impact on local economies. During the 1990's cities with more than 20 percent of the work force in manufacturing grew by 5.5 percent while those with less than 10 percent of the workforce in manufacturing more than doubled growing by 12 percent (Tri-county Regional Planning Commission, 2003).

Illinois Department of Labor statistics indicate that there has been an increase in the number of non-manufacturing jobs in the area. In fact, Peoria has benefited from several growth sectors including business services and hospital/medical services which now have a strong presence in the downtown area once dominated by manufacturing (Tri-County Regional Planning Commission). Peoria with its three hospitals is well poised to benefit from the anticipated increasing demand for medical services and technologies that is anticipated as the baby-boom generation ages. This structural change in employment sectors and the development of emergent growth industries has helped to offset some of the employment and economic losses incurred by the city during the shift away from manufacturing as the primary employment sector.

*Transportation*

The following section addresses the multiple methods available to navigate the city of Peoria and surrounding area. The motor vehicle is a unique mode of transportation in that it is privately owned, often parked on the street unattended, expensive, readily available, and portable. These innate characteristics and qualities of motor vehicles make them a desirable target for some opportunistic thieves. The target suitability of the automobile is largely context specific and depends on many external factors that shape the potential theft event including get away opportunities, surveillance, guardianship, and the physical environment.

Peoria County and the associated city of Peoria is primarily an auto-oriented community with a reputation as a "15 minute area", simply put, the notion is that you can generally traverse between any two points within the city in roughly 15 minutes or less by automobile. According to the Census 2000 Supplementary Survey, more than 90 percent of households have access to at least one vehicle and the average commute to work is less than 20 minutes (Tri-county Regional Planning Commission, 2003).

Beginning in the 1970s, the Tri-County Area has experienced a sharp increase in land area. As can be expected, along with this increase in land area there has also been an increase in total road miles, leading to additional widespread mobility throughout the area. From 1991 to 1997 a clear pattern of traffic flow and migration emerged with the largest percentage increases in traffic volume occurring in the area just to the northwest in the city Peoria (Tri-county Regional Planning Commission, 2003).

The downtown area of Peoria is also the central business district and is easily accessed by a network of highways that traverse the city and numerous interstitial roadways and thoroughfares that run through the downtown and along the periphery, including the riverfront. Figure 13 shows the major roadways and access routes to the various parts of the city, including the central business district.

The city is separated from East Peoria by the Illinois River; two main bridges connect the two cities. Public transportation via bus is available throughout parts of the city with the main bus depot located downtown. The Greater Peoria Mass Transit District servicing Peoria, West Peoria, Peoria Heights, and East Peoria offers 18 bus routes with the busiest route servicing 18,000 riders per month. (Tri-County Regional Planning Commission, 2003).

Greyhound Bus Company has a depot downtown providing an option for longer distance public transportation both into and out of the city. The surrounding area is serviced by the Greater Peoria Regional Airport with several commercial airline carriers occupying terminals in the airport and offering a variety of flight options throughout the day. In addition, there is a small municipal airport, Mt. Hawley Airport, located to the North of the city that is used as a semi-private airport for smaller aircraft with no commercial airline presence at the location. In recent years, following the renovation and expansion of the main airport terminal building, the Bloomington, Illinois airport located approximately 35 miles Southeast of Peoria has emerged as a preferred option for many flyers.

*Population: Composition, Segregation, and Migration*

Despite Peoria's riverfront revitalization, overall land area growth, and commercial development, the city has experienced a decline in population over the last several decades. Peoria experienced growth from 1840 until 1930. Then in 1930, the population leveled out until the 1950s when it began to decline. The early decline has been attributed to a series of events; the interstate highway system encouraging suburbanization, more and better cars able to comfortably travel longer distances, better national economy equating to more personal income, and the desire to get out of the city for a perceived better life in the suburbs.

The population did jump during the 1970s, but this can be explained as the result of the Richwoods annexations which effectively increased the size of the city by enveloping a previously external community. Were it not for the increase via the

Richwoods annexation the population would likely have experienced a population decline from the 1950s through 2000 (Peoria, 2003).

In 1970, the most populous year for the city of Peoria, the total population was 126,963. By 1980 the city population of Peoria had dropped to 124,160. In 1990 Peoria was the third largest metropolis in the state of Illinois after Chicago and Rockford with a city population of 113,504. However, according to the 2000 decennial census survey, Peoria ranked as the fifth largest city in Illinois with a population of 112,936. Of the ten largest cities in the state, only Peoria and Decatur showed a population loss over the decade from 1990 to 2000 (Tri-County Regional Planning Commission, 2003). Table 6 shows the shifts in population from 1980 through 2000 according to the decennial census.

Many of the structural changes in population and demographics over the past decade in the city of Peoria from 1990 to 2000 can be reviewed in Table 3. The population of the city of Peoria decreased by 568 residents over the decade while the median income rose by more than $7000 dollars. The number of housing units occupied by renters decreased by 1200 while the number of single person housing units increased by 1602. The population appears to be less mobile with 5000 fewer residents indicating that they lived in a different house five years prior compared to 1990 numbers. Also, owner occupied housing units increased by 1300 from 1990 to 2000.

Interestingly, despite the overall decrease in the population, the city of Peoria added 4,130 households and 1,853 available motor vehicles indicating a trend towards smaller household sizes. Also, based on the existing ratio of households to available motor vehicles one might have expected the number of additional available vehicles from 1990 to 2000 to have outpaced the number of additional households and it did not.

Peoria is not a city known for its public transportation and most households rely on a vehicle as a primary means of transportation. The data suggests that a substantial number of the additional 4,130 households added to the population do not have an available vehicle for transportation needs if there were only an additional 1,853 vehicles added. This may suggest that the additional households were of lower socioeconomic status with limited financial resources available to afford an automobile and consequently with fewer legitimate opportunities for mobility.

A related factor contributing to the urban growth patterns in Peoria is the concentration of poverty in the urban core of the city; as it is in many communities, the area's more affluent neighborhoods tend to be in the outlying areas. Racial minorities (especially African-Americans) are concentrated in Peoria's urban core. In fact, the Tri-County Area has been ranked as the 23rd most segregated metropolitan community in the country, with a dissimilarity index score of 71.4 out of a possible 100.

*Population Segregation*

More than 50 percent of the African American population in the Tri-County area lives in a census tract where 20 percent or more of the people are classified as poor. The proportion of the white population that resides in a similarly designated census tract is 8 percent. It is worth noting that 20 percent is just a baseline and there are in fact many census tracks that have concentrations of poor residents greater than 20 percent. There are census tracts on Peoria's Southside that have poverty concentrations exceeding 40 percent (Tri-County Regional Planning Commission, 2003).

These racial and income segregation patterns can have a profound impact on how a geographic area can and will develop and the spatial distribution of crime as shown in previous discussions about heterogeneity. The African-American population in the Tri-County area increased by 6,460 during the 1990s, with nearly all of this increase occurring in the southern half of the city of Peoria. Meanwhile, whites are leaving the city of Peoria, especially the Southside. Since 1990, over 8,300 white people left the neighborhoods on the south side of the city, representing a loss of nearly 20 percent of the white population. In contrast, more than 11,000 persons of color have moved to the area over the past decade, surpassing the number of whites that left the area and nearly replacing all of the whites that left the city of Peoria during the same period of time. One reason for the dramatic migration from the Southside was in large part to escape the under funded public schools that are perceived as substandard (Tri-County Regional Planning Commission, 2003).

Profound segregation and concentrated poverty can overburden the local economy creating a disproportionate demand for services and a drain on limited community resources. "Beyond the obvious implications of blight, enclaves of poverty isolate their residents from the productive economy, rendering long-term economic improvement problematic. Such conditions can foster social instability, which discourages investment and encourages highly sought skilled workers to live elsewhere" (Tri-County Regional Planning Commission, 2003, p. 37).

Poverty and segregation are multigenerational systemic problems that tend to feed one another creating pockets in the social landscape of urban blight and disorganization often seemingly too entrenched and too overwhelming for small communities to reverse.

These deep rooted pockets of poor and disenfranchised residents can experience culture conflict, cultural transmission, reaction formation, and strain to name a few of the potential outgrowths. The criminological literature is full of research detailing the negative results of these circumstances in terms of crime and criminality.

*Population Migration*

Peoria's newer northern neighborhoods represent the only areas that had a net increase in population for the entire city. These areas added 2,621 white persons and 1,043 persons of color. People of color accounted for nearly 40 percent of the people moving into Peoria's newer northern neighborhoods. Were Peoria not to have experienced a significant increase in the number of persons of color, its population declines would have been far more dramatic (Tri-County Regional Planning Commission, 2003).

There has been a significant shift of people under the age of 18 to the area near the City of Peoria's northern boundary, particularly the areas served by the Dunlap School District. The impact of this shift has been felt by the Dunlap School District, which was required to make major new capital improvements and increases in its teaching staff to accommodate the influx of new students. Alternatively, Peoria School District 150 has lost more than 1,600 people under 18. Evaluating the implications of these continued trends will prove critical for the region and the City of Peoria (Tri-County Regional Planning Commission, 2003). The crime literature contains numerous studies linking young people, particularly males with a disproportionate amount of crimes. With regard to motor vehicle theft, in 2002 63.8 percent of arrested offenders were under the age of 25. Juveniles (those under the age of 18) accounted for 18.2 percent of those arrests. The vast majority of individuals arrested for motor vehicle theft in 2002 were males with approximately 83.5 percent of arrests (FBI, 2002).

*Housing*

The segregation of Peoria's population has had an impact on the housing market and home ownership. The denial rate of conventional owner occupied home mortgage applications is much higher on Peoria's Southside. As previously stated, this is the poorest part of the city and this finding is not particularly surprising. However, considering that it only takes a $9,000 annual income to be able to purchase the average home in certain areas, a rejection rate that exceeds 50 percent in some areas, seems to be higher than one might expect. This finding suggests that citizens are being denied loans for reasons other than insufficient annual income. "These other reasons may include, bad credit, too much debt, or a combination of other reason, with the data currently available it is impossible to say why applications are being rejected" (Tri-County Regional Planning Commission, 2003, p. 112). The significance of housing ownership to community crime is another common theme in the community crime literature. Poor housing conditions and low levels of home ownership can create opportunities conducive to high crime rates in a neighborhood. This accompanies by low household incomes, unemployment, and delinquent peers are a dubious concoction.

According to the Bureau of Justice Statistics for 1973-2003, property crime, regardless of the type, occurred more often to those living in rented property as opposed to those living in owner occupied housing. For example, in 2003 households residing in rented property experienced 206 property crimes per 1,000 households compared to owned occupied housing which experienced 140 overall property crimes per 1,000 households. Additionally, Bureau of Justice Statistics (2003) noted that households living in rented property had about twice the rate of motor vehicle theft than those in owned property.

### *Education*

The connection between schooling/education and crime is complex. Research suggests that students who experience academic failure and drop out of school are more likely to engage in juvenile delinquency, commit status offenses, and join gangs. Conversely, students who succeed in school and have stronger bonds to conventional society are less likely to commit delinquent acts and join gangs (Klein, 1995).

A shared community problem that is often poorly understood is the relationship between high home purchase loan denial rates and resulting deterioration in the quality of schools in that area. High student mobility and turnover rates are one of the greatest challenges faced by under-performing schools. The Peoria school district, District 150, contains some schools that have more than a 100 percent student mobility rate. "This means that the composition of a student body will more than completely turn over during the course of a single school year" (Tri-County Regional Planning Commission, 2003, p. 120). This turnover rate is staggering and simply unacceptable and counterproductive to the educational process. Schools with such a lack of continuity and stability also tend to have some of the lowest test scores on local and national standardized tests.

The constant movement and churning of families from rental unit to rental unit in pursuit of affordable housing and improved living conditions is the primary cause of high school mobility rates (Tri-County Regional Planning Commission, 2003). An obvious, yet evasive, means of reducing excessive student mobility rates would be to increase home ownership rates resulting in the stabilization of the student body and a more productive academic environment.

"School quality is one of the most important factors considered by young families when deciding where to live. As the tax base of inner cities has eroded, so has the quality of inner city schools. As young families have left the inner cities, their exodus fuels the cycle of tax base erosion, declining school quality, and flight to the suburbs and exurbs" (Tri-County Regional Planning Commission, 2003, p. 115). The situation described is very often the case across the United States, not just in Peoria, Illinois.

The general level of approval of our nation's public schools has been deteriorating for decades. Residents of the inner cities often perceive problems with the inner city public schools that include poor student performance on standardized tests, disparate racial composition/segregation, and basic student safety and security needs. However, suburban and other outlying schools are not perceived to have these problems. The improved conditions in the suburbs lead many families to the logical decision to relocate to the more stable, less problem impacted areas. Newly arriving families are also perceptive to these same problems with the schools and the community and will also settle elsewhere.

Much of the migration from Peoria is a classic example of "white flight" with a large number of white residents leaving the neighborhoods to the south of the city seeking better schools, improved neighborhoods, less congestion and crowding. As a result of this shift, there has been a dramatic increase in the number of people under the age of 18 in the area near the Northern boundary of the city. When families saturate the available housing in a given area, developers and local governments are typically more than willing to provide new housing that is usually more exclusive and expensive than can be found in the inner city. This process contributes to the social stratification of communities at the micro and meso levels and society as a whole at the macro level (Tri-County Regional Planning Commission, 2003).

The only area that experienced a significant increase in the number of children (persons under the age of 18) was the Dunlap School District, which increased by 953 children. The Dunlap School District has had to undergo major capital improvements and increase teaching staff to keep up with the student population growth. Between 1996 and 2000, 670 units of housing were developed in the City of Peoria's Northern growth cell, accounting for more than 80 percent of the new housing that occurred within the Dunlap school district (Tri-County Regional Planning Commission, 2003).

The Peoria School District has lost more than 1,600 students under the age of 18. The implications of a continued decline in the number of students under 18 years of age enrolled in Peoria schools and an increasing population in areas serviced by another school district equates to reduced financial support for the Peoria School District and must be reviewed by community leaders if improvements are to be made (Tri-County Regional Planning Commission).

*Crime*

Crime over the decade 1990-2000 in Peoria, Illinois had been on an upward trajectory. In 2000, Peoria County had the highest crime rate of all the state's 102 counties, and the city of Peoria was the only large city in the state that saw its crime rate rise from a decade ago. The state of Illinois crime rate dropped 4.5 percent in 2000 and was lower than it had been at any point in time since the state police began charting the statistics in 1974. According to the U.S. Census Bureau, reported crimes in the state dropped by an estimated 20 percent while the population increased by 8.5 percent. Using these figures, the states crime rate decreased by 26 percent over the decade. Cook County had had the highest crime rate in 1990, with 83 crimes reported for every 1000 people in the population. In 2000, Cook County had 58 crimes per 1000 people in the population and its rate had dropped to fourth in the state. Alternately, in 2000, Peoria County had the highest rate in the state with 71 crimes reported per 1000 people in the population, up from 68 crimes in 1990. The city of Peoria saw its crime rate rise 3.5 percent from a decade earlier, again, the only large city in the state to see an increase (Peoria Journal Star, July 15, 2001).

# CHAPTER 6

# ANALYSIS PLAN

## Types of Analyses

The current study gathered data at two points in time creating both a two-wave cross-sectional model and a lagged ecological effects model. In addition, in order to hold geographic boundaries constant, normalized Census Bureau data for the 1990 decennial census was formatted to conform to decennial census 2000 boundaries.

The analyses in this study include: 1) a discussion of the community composition and structure and the historical context of the city to provide background on the study area; 2) descriptive statistics for each study variable at both points in time, 1990 and 2000, as well as population weighted percentiles for the lagged analysis predictors; 3) collinearity diagnostics to detect conflicts among the predictors in the various models; 4) logistic regression analyses to compare the coefficients at the two points in time for the two-wave cross-sectional analysis; 6) regression tests of a lagged effects model looking at the impacts of ecological change over time on motor vehicle theft.

### *Indexing: SES and Instability*

Following established traditions of ecological research, in order to avoid issues of multicollinearity, indexes were created for socioeconomic status (SES) and instability (Instability) at the block group level. Several variables were chosen that best represented characteristics of SES. The z-scores were added up for the following correlated SES variables: percent of population in poverty, population weighted property value, and population weighted median income, to create the SES index. Similarly, several variables that represent instability were chosen for the current study.

The z-scores for the following correlated instability variables were added up to create the Instability index: percent of housing units occupied by renters, percent of single person households, percent of population that did not live in same house in 1985, and percent of multiple unit housing. While SES and Instability, as constructs, both have a long history in the community crime literature the variables chosen to create the indexes in the present study were not based on any particular existing indexes. The correlation matrices for the 1990 SES Index and Instability Index can be reviewed in tables 7 and 8 and the correlation matrices for the 2000 SES Index and Instability Index can be reviewed in tables 9 and 10.

*Population Weighting*

Population weighted percentiles allow us to place a geographic unit in an ordering based on the attribute, and have its position reflect the proportion of the total population at or below that score. Therefore, over time changes in percentiles reflect changes in a local ordering (Choldin, 1980). For example, a census block group that had no motor vehicle thefts would have a population percentile score of 0 whereas the census block group with the most motor vehicle thefts would have a population weighted percentile score close to 100. A census block group that had a population weighted percentile score of 75 for heterogeneity reflects an area that has a rate of heterogeneity that is equal to or greater than the score for 75 percent of the population across all of the block groups (Taylor, 2001; Taylor and Covington, 1988; Kurtz, 2000).

This type of analysis helps to identify shifts of a location within a larger ordering over time and space by knowing relative positions over time. These positional shifts in the percentile ordering reflect a shift in the CBG's ecological niche. (Taylor, 2001; Taylor and Covington, 1988).

### *Collinearity Diagnostics*

Ecological crime and delinquency research is susceptible to issues of multi-collinearity (Gordon, 1968). That is, predictors in a regression model may be too highly correlated to parcel out the separate effects of the independent variables.

Multi-collinearity can not be adequately diagnosed by examining the correlation matrix (Belsley, Kuh, and Welsch, 1980). Instead, in this study, the tolerance statistic is being used for diagnostic purposes. Tolerance reports the proportion of a predictor's variance not accounted for by the other predictors. A predictor with low tolerance contributes minimal information to the final model, and can inflate standard errors of b-weights and even change the signs of b-weights (Gordon, 1968). The tolerance threshold here was set at .30, but others have suggested even lower thresholds (see Hamilton, 1992).

#### *1990 Cross-sectional Analyses: Tolerance*

The 1990 cross-sectional model with all of the desired predictors in the regression equation resulted in the spatial autocorrelation predictor falling below the established tolerance threshold (.252) and the SES predictor just slightly above the threshold (.318) suggesting a possible multi-collinearity problem (see Table 11).

The analysis was run again, this time with SES remaining in the model but removing the spatial autocorrelation predictor. The output showed that no predictors fell below the tolerance cut-off of .3. The last model that was run had the SES predictor removed and kept the spatial autocorrelation predictor in the equation. The results indicated that the model was acceptable and none of the predictors were below the tolerance threshold. The 1990 tolerance values for each of the three cross-sectional regression models can be seen in Table 11.

*2000 Cross-sectional Analyses: Tolerance*

The 2000 cross-sectional model tolerance values were similar to those of the 1990 model. Inclusion of all of the desired predictors in the regression equation resulted in the SES predictor (.214) and the spatial autocorrelation predictor (.184) falling below the suggested tolerance threshold of .30 (see Table 12).

The analysis was run again, this time keeping SES in the model but removing the spatial autocorrelation predictor. The outcome was that none of the predictors fell below the tolerance cut-off of .3. The last model that was run had the SES predictor removed and kept the spatial autocorrelation predictor in the equation. The results indicated that the model was acceptable and again, none of the predictors were below the tolerance cut-off. The 2000 tolerance values for each attempted model can be seen in Table 12.

*Longitudinal Lagged Effects Analyses: Tolerance*

Below are the tolerance statistic results for the longitudinal lagged effects model that included both the lagged and unexpected change scores for the independent variables. This analysis showed somewhat similar tolerance results as the 1990 and 2000 cross-sectional models with a few noteworthy distinctions. In the first lagged model with all of the associated lagged and change variables, two predictors, lagged SES (.241) and lagged Spatial Autocorrelation (.225) fell below the suggested tolerance threshold (see Table 13).

The second model included the lagged SES variable and excluded lagged Spatial Autocorrelation and change Spatial Autocorrelation. No predictors fell below the suggested tolerance threshold of .30. In fact, tolerance scores for many of the remaining variables improved. The third and final model that was run included lagged Spatial Autocorrelation and change Spatial Autocorrelation and excluded lagged SES and change SES. None of the remaining variables fell below the tolerance cut-off but tolerance scores in general were not as robust as those in the second model that excluded the spatial autocorrelation variables. All tolerance statistics for the three lagged effects models can be found in Table 13.

*Outliers*

As previously mentioned, bivariate scatterplots were created for each predictor, in part to look for case outliers. One case repeatedly presented itself as an outlier and in fact, also exceeded recommended Leverage and Cook's D residual diagnostic thresholds for the longitudinal lagged effects analyses. The outlier case in question was case number 19. According to the 1990 normalized census data this CBG had a population of 818 residents but according to the 2000 census the population had decreased to four residents. The CBG is located on the Southside of the city and is considered part of the downtown area. The excessively low population is most certainly the factor causing complications with several of the other variables and thereby exceeding Leverage and Cook's D thresholds. Furthermore, the mean number of motor vehicle thefts for the 1990/91 period of time (Time 1) was eleven. The mean number of thefts for the 2000/01 period of time (Time 2) was two, half as many thefts as residents. As a result, the decision was made to eliminate this case and re-run the analyses.

The first model that was run when the case was eliminated was the full model with all lagged and change variables included in the analysis. This resulted in both lagged SES and unexpected change Spatial Autocorrelation falling below the suggested tolerance cut-off with scores of .247 and .220 respectively, similar to the original lagged model with case 19 included (see Table 14).

The second lagged effects model included lagged SES but excluded the lagged Spatial Autocorrelation and unexpected change Spatial Autocorrelation variables. None of the variables remaining in the analyses were below the suggested .30 threshold. The third and final model included both Spatial Autocorrelation variables and excluded both of the SES variables. None of the variables fell below the suggested tolerance cut-off. All tolerance statistics for the three lagged effects models run with the removal of one outlier case can be found in table 14.

# CHAPTER 7

# RESULTS

The analyses examined the data in two different ways to derive the results of the study. Model one is a two-wave cross-sectional design and model two is a lagged ecological effects analysis looking at the effects of lagged ecological factors and co-occurring changes. The following discussion details the steps taken, procedures employed, and the final results of these analyses.

This initial section of the research results serves to acquaint the reader with a view of the demographic composition and several relevant community characteristics at each of the two points in time, 1990 and 2000, for the study area. The intention is to show the social and structural conditions affecting city living and crime and to diagnose problems or anomalies in the data being used in the study, specifically outliers.

Descriptive statistics were generated for each predictor variable as well as the dependent variable at each of the two population points in time (1990 and 2000). Bivariate scatterplots of each variable for 1990 and 2000 were created to look for outliers and non-linearity. As previously discussed, one case - case #19 - consistently stood out in several of the bivariate scatterplots due to an extremely small population of four people in the 2000 census. Leverage and Cook's D statistics showed that this case did not exceed the standard thresholds for these diagnostic tools for either of the cross-sectional analyses. Further analyses showed virtually no impact on the outcome when removed.

The case did exceed designated thresholds for leverage and Cook's D however, for the lagged effects longitudinal analysis and removal of the case did improve the results of this analysis. Both cross-sectional and lagged analyses with and without the case in question will be discussed in the following section.

Descriptive statistics for the dependent motor vehicle theft variable for Time 1 and Time 2 can be found in Table 15. Skewness was a problem at both points in time (skewness statistics = 1.847 and 1.737 respectively). However, adding one and applying the natural log transformation to the motor vehicle theft variable reduced skewness to below one for both points in time (.227 and -.021) (see Table 15).

Motor vehicle thefts clearly went up over the decade with the un-logged mean number of thefts per block group increasing from 3.7 in 1990 to 10.9 in 2000 and the mean number of logged thefts in each block group in 1990 increasing from 1.2 to 2 in 2000 (see Table 15). The results of a two-tailed paired samples t-test support this assertion, ($t(89) = -11.20$, $p<.05$).

*Descriptive Statistics*

Descriptive statistics were generated for all of the predictor variables, both before and after indexing, for the beginning of each decade, 1990 and 2000. Table 16 shows the citywide descriptive characteristics for Time 1, before indexing. Table 17 shows the citywide descriptive characteristics for Time 2, before indexing. There are a few descriptive characteristics that are worth noting. A comparison of the two tables shows that in 1990 the minimum population was 399 compared to a minimum population of four in 2000. The case with a population of four was case #19 and was later excluded in several of the analyses. Interestingly, the mean of the CBG populations in 1990 was 1367 and in 2000 the mean was a comparable 1366. Mean median household income logged and mean median property value logged are both slightly lower in 1990 (10.06 and 10.61 respectively) than in 2000 (10.36 and 11.10 respectively).

The percent of the population with an income below the poverty level in 1990 (7 percent) is considerably smaller than the percent of the population with an income below the poverty level in 2000 (48 percent). Interestingly though, the mean percent of the population with an income below the poverty level in 1990 (20) is only slightly smaller than the mean percent in 2000 (21.53). The mean percent of housing units occupied by renters in 1990 (42) is slightly fewer than in 2000 (37). The percentage of multiple unit housing as a percent of total housing units in 1990 (28) is fewer than the percent in 2000 (26), indicating a decrease in the overall percentage of multiple unit housing over the decade. The last descriptive feature worth noting is the percent of the population living in a different house five years prior. The percent living in a different house in 1985 (51) was greater than the percent (48) living in a different house in 1995.

In conclusion, while there were shifts and changes in community level characteristics over the decade there does not appear to be any grand sign indicating dramatic deterioration in the community over the decade that might foretell the rising motor vehicle theft rates from time one to time two that were experienced.

*Descriptive Statistics for Indexes: SES and Instability*

The following discussion provides information from the 1990 and 2000 descriptive tables for the predictors after indexing - Table 18 and Table 19. There were only two indexes created, SES and Instability, so, these are the only two additions to the discussion of the citywide descriptives. In 1990 the minimum SES index score was -6.93

and in 2000 the minimum SES index score was -5.03 indicating that block groups were scoring lower in SES 1990 than in 2000. The mean SES index score for 1990 was -.00000034 and for 2000 was .00000033. The mean SES index score suggests that when all of the CBGs SES scores are averaged CBGs were slightly better off in 2000 compared to 1990.

The minimum Instability index score for 1990 was -5.69 and for 2000 was -4.87. Again, this suggests that with regard to Instability the least stable CBGs were slightly less stable in 1990 compared to 2000. The mean 1990 Instability index score was .0000010 and for 2000 it was .0000004. The mean scores for CBG Instability suggest that CBGs were slightly more stable in 2000 than in 1990. While these descriptive value shifts and differences from 1990 to 2000 may not appear dramatic, they do help to create an image and context of the study area, the city of Peoria, for the two points in time, 1990 and 2000.

In sum, the city of Peoria improved over the decade in terms of SES and Instability. The CBGs were worse off from both an SES and Instability standpoint according to 1990 Census data and made improvements over the decade. Some of the low SES and Instability present in the 1990s may have been residual effects of a downturn in the national economy in 1987 that affected the entire country. With manufacturing being a primary industry in the area the slowdown was probably particularly harmful. Furthermore, as the national economy recovered and the city of Peoria strove to become less reliant on manufacturing as the primary industry the local economy improved and lending to higher levels of SES and lower levels of Instability in the communities throughout the city.

*Cross-sectional Model Summary of Significant Predictors*

The following discussion is a brief summary of the predictors of logged motor vehicle theft in the 1990 and 2000 cross-sectional models (Table 20). Table 20 shows that the population predictor is a significant predictor in the direction expected in all cross-sectional models for 1990 and 2000. The more people present in a CBG the more motor vehicle theft there is. The SES predictor was also significant in the expected direction in the four cross-sectional models in which it was included (Models A, B, D, and E). CBGs with low SES are more likely to have motor vehicle theft than areas of higher SES. Interestingly, the Instability index was significant in the direction expected, but only in cross-sectional Model C, the model that SES was removed from. The CBGs with greater Instability experienced more motor vehicle thefts than those CBG with greater stability. That said, the SES variable is clearly moderating the effects of Instability. The contiguous boundary variable was not a significant predictor of logged motor vehicle theft in any of the cross-sectional models indicating that edge effects were not dramatically impacting the outcome. However, the straddle boundary was significant in the expected direction in four of the cross-sectional models (Models A, B, D, and E). The straddle boundary predictor measured the effects of having only partial representation of motor vehicle thefts for a CBG due to city limit parameters. The straddle boundary was not a significant predictor when SES was removed from the model, again suggestive of the significant impact that SES is having on vehicle theft. Heterogeneity was a significant predictor in the direction expected, but only in three 2000 cross-sectional models; it was not significant it any of the 1990 models. CBGs in 2000 that were more heterogeneous were also more likely to have elevated levels of motor vehicle theft. Interestingly, this was not the case for 1990. However, this could be partially explained by the dramatic shift in population that took place over the decade with many White's leaving the city and many Blacks entering the city and spreading out as the community profile describes. Only one of the male age category predictors, percent of males in the population age 14-17, was significant and in the direction expected in a single model, 1990 Model C. Finally, the spatial autocorrelation predictor was significant and in the direction expected in both sets of cross-sectional models when the SES predictor was removed. The implication being that areas in closer proximity to those with motor vehicle theft potential are more likely to themselves experience elevated levels of motor vehicle theft.

*Longitudinal Model Summary of Significant Predictors*

The following discussion provides a brief summary of the predictors of unexpected change population weighted logged motor vehicle theft in the longitudinal lagged effects models (Table 22). Further interpretation of the predictors and findings is provided in a latter section of this research.

As previously discussed the outcome variable for these analyses was changed to a population weighted measure that consisted of saving the residuals of a regression analysis that was conducted with Time 1 motor vehicle theft as the predictor and Time 2 vehicle theft as the outcome. Table 22 shows that the lagged SES predictor was significant in the direction expected in Model K, the model that excluded both spatial autocorrelation and case #19. The lagged Instability predictor was significant in Models H and K – the two models that excluded spatial autocorrelation, but interestingly, not in the direction expected. Lagged heterogeneity was significant in the direction expected in all Models G-L. Surprisingly, neither of the two lagged young male predictors (lagged percent of males in the population 14-17, lagged percent of males in the population 18-24) was significant in any of the lagged models. The lagged spatial autocorrelation predictor was only significant in Model L, the model that excluded both SES and case #19.

The unexpected change predictors showed several differences from the lagged predictors and are indicative of contemporaneous effects on the vehicle theft outcome variable. The unexpected change SES predictor was significant in the direction expected in Models K and L, the models that excluded spatial autocorrelation. The unexpected change Instability predictor was significant in all of the models except Models G and I, the lagged full model and the lagged model without SES. Interestingly, unexpected change Instability was not significant in the direction expected but rather was significant in an unexpected direction. As Instability went up the motor vehicle theft outcome variable went down. Similar to the lagged predictors, the unexpected change Heterogeneity predictor was significant in the direction expected in all models. Again, similar to the lagged models, none of the unexpected change male age category predictors (unexpected change percent of males in the population 14-17, unexpected change percent of males in the population 18-24) were significant. The unexpected change spatial autocorrelation predictor (the change in spatial autocorrelation that could not be explained by Time 1 spatial autocorrelation and could not be explained by relative change in spatial autocorrelation Time 2) was significant in all of the models in which it was present.

The contiguous boundary variable, designed to control for edge effects, was not a significant predictor of unexpected change population weighted logged motor vehicle theft in any of the longitudinal models. Interestingly, unlike the cross-sectional models, the straddle boundary predictor was not a significant predictor in any of the lagged effects longitudinal models. This predictor was significant in several of the cross-sectional models.

There are several distinctions that can be made with regard to the patterns of significance of the predictors. For example, the heterogeneity predictors are the only ones that had a dual effect across all models for lagged and unexpected change. The unexpected change spatial autocorrelation predictor was significant in every model that it was included in but the lagged predictor showed a contrasting pattern and was only significant in the model that excluded case #19, Model L. Also, the lagged and unexpected change Instability predictors showed a contrasting impact pattern when compared to the cross-sectional models. The predictor was significant in the direction expected in cross-sectional Model C (Table 22) but was significant in the opposite direction in lagged effects Models H, J, K, and L (Table 22).

*Cross-sectional Summary of 1990 Predictor Correlations*

A correlation matrix of all of the predictors and the logged motor vehicle theft outcome variable for the 1990 cross-sectional regression analyses can be viewed in table 23. As the table shows, the strongest relationship between the predictors and the outcome was the strong negative correlation (-.526) between 1990/91 logged motor vehicle thefts and SES. As the number of logged vehicle thefts increased the SES predictor tended to decrease, or conversely, as logged vehicle theft decreased the SES predictor tended to increase. Logged motor vehicle thefts showed a moderate positive correlation with the Instability index (.408). That is, areas with vehicle thefts also tended to be areas of some degree of instability and vice-versa. Next in the order of correlation size was the relationship between logged motor vehicle thefts and spatial autocorrelation (.353). CBGs that were in closer proximity to other CBGs with motor vehicle thefts were more likely themselves to also have many motor vehicle thefts.

The correlation between logged motor vehicle thefts and heterogeneity (.324) indicated that as areas became more heterogeneous they were also more likely to be areas with high motor vehicle theft incidents and vice-versa. Interestingly, there is virtually no correlation between either age group of young males in the population, percent of males in the population age 14-17 and 18-24, and logged motor vehicle theft (.144 and -.013). This calls into question the motivated offender hypothesis and suggests a need for further inquiry. Not surprisingly, there was a negative correlation between SES and Instability (-.431). As either SES or Instability increased the other decreased. The last correlation of interest was between SES and Spatial Autocorrelation (-.709). The strong negative correlation suggests that areas with high SES tended to be in proximate location to areas with low vehicle theft potential. Alternately, areas with high vehicle theft potential tended to be in closer to areas of low SES.

*Model A: Cross-sectional Model of 1990/91 Logged Motor Vehicle Thefts: Including All Predictors*

The first 1990 cross-sectional analysis had Time 1 logged motor vehicle theft counts as the outcome or dependent variable and all of the predictor variables in the equation. As Table 24, pg. 283, Model A shows, three of the predictor variables had a significant impact on logged motor vehicle theft and all of the significant impacts were in the expected direction. Higher logged motor vehicle theft (.0005194) linked to higher population, lower logged motor vehicle theft (-.174) linked to higher SES, and lower logged motor vehicle theft (-.452) linked to areas with straddled boundaries. The small observed size of the beta's was the direct result of having logged the outcome variable to control for skewness (see Table 24). Overall, the model accounted for an impressive 57.8percent of the variance in logged motor vehicle theft. As previously mentioned, tolerance for SES (.318) was very close to the threshold of .30 and Spatial Autocorrelation (.252) was below the threshold suggesting a multi-collinearity problem (see Table 11).

In conclusion, Model A indicated that population, SES, and areas with straddled boundaries were significant predictors of logged motor vehicle theft but multicollinearity might have been causing problems between some of the variables.

*Model B: Cross-sectional Model of 1990/91 Logged Motor Vehicle Thefts: Without Spatial Autocorrelation Variable*

The second 1990 cross-sectional analyses, Model B, included all of the predictor variables other than spatial autocorrelation in the equation in an effort to address the previously mentioned low tolerance levels. As Table 25, p.284, Model B shows, the exact same three predictor variables from Model A were significant with the impacts in the direction expected. Higher logged motor vehicle theft (.0005165) linked to higher population, lower logged motor vehicle theft (-.181) linked to higher SES, and lower logged motor vehicle theft (-.498) linked to areas with straddled boundaries. Again, the small size of the beta's was the direct result of having logged the outcome variable to control for skewness (see Table 26). Overall, the model accounted for an impressive 57.5percent of the variance in logged motor vehicle theft. None of the variables in model two were below the suggested tolerance threshold of .30 (see Table 11). In conclusion, the same predictors from Model A were significant with a comparable amount of the variance explained. However, in Model B there were no evident issues of multicollinearity among the predictors.

*Model C: Cross-sectional Model of 1990/91 Logged Motor Vehicle Thefts: Without SES Variable*

The third 1990/91 cross-sectional analyses can be reviewed in Table 26, p.285, Model C. The results show that there were several changes in the significant predictors of logged motor vehicle theft. Model C had four significant predictors, only one of which was significant in the earlier two models, A and B, - total population. All of the impacts were in the expected direction with higher logged motor vehicle theft (.0004165) linked to higher population, higher logged motor vehicle theft (.06528) was linked to higher Instability, higher logged motor vehicle theft (.08309) was linked to higher percent of young males age 14 to 17 in the population, and higher logged motor vehicle theft

(.00009499) was linked to areas with higher spatial autocorrelation. The observed small size of the beta's is the result of logging the outcome variable to control for skewness in the number of motor vehicle thefts (see Table 26). Overall, Model C accounted for 45.3 percent of the variance in logged motor vehicle theft, the least predictive of the three 1990 cross-sectional models tested.

None of the variables in model three were below the recommended tolerance cut-off (see Table 11). In sum, the removal of the SES predictor did result in a change in the significant predictors but the amount of variance explained was less than that in Models A and B. An analysis of the $R^2$ change revealed that the inclusion of the SES variable in this model was significant and increased the explained variance by 12 percent to 57.6 percent. However, multicollinearity would have been a problem.

*Cross-sectional Summary of 2000 Predictor Correlations*

A correlation matrix of all of the predictors in the 2000 cross-sectional regression analyses can be reviewed in Table 27. As the table shows, again the strongest relationship between the predictors and the outcome was the strong negative correlation (-.673) between 2000/01 logged motor vehicle thefts and SES. As SES decreased the number of logged vehicle thefts tended to increase, or conversely, as SES increased logged vehicle theft tended to decreased. The negative correlation was slightly larger (-.673) than in 1990/91 (-.526). Next in the order of correlation size was the relationship between 2000/01 logged motor vehicle thefts and spatial autocorrelation (.607). Census block groups (CBGs) that were in closer proximity to other CBGs with motor vehicle thefts were more likely themselves to also have motor vehicle thefts. The spatial patterning of vehicle thefts was more predictable based on the proximity of other thefts in the area than it was in 1990/91 (.353).

The next correlation of interest was between logged motor vehicle thefts and heterogeneity (.581). The most noteworthy implication is that the size of the correlation is much larger in 2000/01 than it was in 1990/91 (.324) suggesting that more heterogeneous CBGs also have more logged motor vehicle theft, especially compared to 1990/91. The correlation between logged motor vehicle thefts 2000/01 and Instability was smaller (.279) in 2000/01 suggesting that Instability had less of an impact on vehicle theft in 2000/01 than it did in 1990/91 (.408). The correlation between logged motor vehicle theft and the two young male age groups, percent of males in the population age 14-17 and 18-24, showed only slight changes from 1990/91 (.144 and -.013) to 2000/01 (.181 and .074). However, the correlations were both in the positive direction in 2000/01 compared to 1990/91. The strongest correlation in the matrix is again between SES and Spatial Autocorrelation (-.819). The same two predictors in 1990/91 had a slightly smaller but still strong negative correlation (-.709). The implication is that areas with higher SES were less likely to be in close proximity to high-risk vehicle theft areas and vice versa.

*Model D: Cross-sectional Model of 2000/01 Logged Motor Vehicle Thefts: All Predictors*

The second series of analyses that were run were the 2000 cross-sectional models. Model D included Time 2 logged motor vehicle thefts as the dependent variable and all of the predictor variables in the regression equation. As Table 28 p.287, Model D shows, four of the predictor variables had a significant impact on Time 2 logged motor vehicle thefts - total population, SES, heterogeneity, and contiguous boundary. All of the impacts were in the expected direction with higher logged motor vehicle theft (.0005188) showing a relationship with higher population, lower logged motor vehicle theft (-.194) was related to higher SES, higher logged motor vehicle theft (2.304) was related to higher heterogeneity, and lower logged motor vehicle theft (-.656) was related to areas with straddled boundaries.

Table 28, on pg. 287, Model D shows the coefficients for all of the 2000 cross-sectional predictors. The small size of the coefficients is again the result of logging the motor vehicle theft outcome variable. Overall, the model accounted for 67.3 percent of the variance in logged motor vehicle theft. Again though, it is important to note that the tolerance levels for the SES and Spatial Autocorrelation predictors were below the .30 cut-off point suggesting that multicollinearity is potentially problematic (see Table 12).

There are several observations worth noting with regard to the comparison between identical 1990 and 2000 cross-sectional models (A and D). The most obvious difference is that heterogeneity was not a significant predictor of logged motor vehicle theft in 1990, Model A, but was significant and in the direction expected in 2000, Model D. This is likely related to the shifts in population dynamics that took place over the decade with Census data showing a dramatic increase in the Black population and a decrease in the White population from 1990 to 2000. Also, the straddled boundary predictor was a stronger predictor of logged motor vehicle theft in 2000 (-.656) than it was in 1990 (-.452). Model D, with all of the same predictors as Model A, also explained more of the variance than Model A, 67.3 percent in 2000 Model D compared to 57.8 percent in 1990 Model A.

*Model E: Cross-sectional Model of 2000/01 Logged Motor Vehicle Thefts: Without Spatial Autocorrelation Variable*

The second 2000 cross-sectional model also included Time 2 logged motor vehicle thefts as the dependent variable and all of the independent variables, other than spatial autocorrelation, in the equation in an effort to address the low tolerance levels experienced in model D. As Table 29, p. 288, Model E shows, the exact same predictor variables that had a significant impact on logged motor vehicle theft in the 2000 full model, Model D, were again significant predictors of motor vehicle theft in Model E - total population, SES Index, heterogeneity, and contiguous boundary. All of the impacts were in the expected direction with the following predictors impacting logged motor vehicle thefts: population (.0005), SES (-.255), heterogeneity (2.762), and straddle boundaries (-.838) (see Table 29). Overall, the model accounted for an impressive 66.1 percent of the variance in logged motor vehicle theft. None of the predictors in Model E were below the recommended tolerance threshold of .30. (see Table 12).

There are several interesting summarizing points to be made with regard to a comparison to the 1990 cross-sectional Model B. First, the heterogeneity predictor was significant and in the direction expected in 2000 (2.762) but was not a significant predictor of logged motor vehicle theft in 1990 Model B. Also, again the straddle boundary predictor was a stronger predictor in 2000 (-.838) than in 1990 (-.498). The SES predictor was significant in both 1990 Model B and 2000 Model E but the magnitude of the b-weight changed markedly from 1990 (-.181) to 2000 (-.255). Finally, and of particular interest, is the impact that removing the spatial autocorrelation predictor had on Models B and E. A comparison of the SES standard errors for the models both pre and post removal of the spatial autocorrelation predictor in 1990 (Model A = .036 and Model B = .032) and 2000 (Model D = .050 and Model E = .035) shows that the spatial autocorrelation predictor was creating more of a problem in 2000 than in 1990. Finally, with regard to a comparison to 2000 Model D, all of the same predictors were significant with slightly more of the variance explained in Model D. However, there were no apparent issues of multicollinearity in Model E, unlike those encountered in Model D.

### *Model F: Cross-sectional Model of 2000/01 Logged Motor Vehicle Thefts: Without SES Variable*

The third and final 2000 cross-sectional model again included Time 2 logged motor vehicle thefts as the dependent variable and all of the independent variables, other than the SES, in the equation in an effort to address the afore mentioned low tolerance levels found in the first model. As Table 30 p. 289, Model F shows, there were several changes in the significant predictors of logged motor vehicle theft. Model F had three significant predictors - total population, heterogeneity, and spatial autocorrelation. Only two of the significant predictors - total population and heterogeneity - were reoccurring from the first and second 2000 cross-sectional models. All of the impacts were in the expected direction with higher logged motor vehicle theft (.0004598) related to higher population, higher logged motor vehicle theft (3.070) was related to higher heterogeneity, and higher logged motor vehicle theft (.00006023) was related to areas with higher spatial autocorrelation. Again, the outcome variable was logged to control for skewness which resulted in the small coefficients (see Table 30). Overall, the model accounted for 61.1 percent of the variance in motor vehicle theft. None of the variables in Model F were below the recommended tolerance threshold of .30 (see Table 12).

The Instability predictor in 1990 Model C was significant ($p<.01$) and in the direction expected (.065) but was not significant in the 2000 Model F. Interestingly, the betas for Instability in 1990 (-.538) and 2000 (.030) showed a dramatic shift in the magnitude of the relationship between Instability and logged motor vehicle theft. Similarly, Spatial autocorrelation was significant in both 1990 Model C and in 2000 Model F and the magnitude of the betas changed rather dramatically from Model C (.255) to Model F (.673). Lastly, the heterogeneity predictor was not significant in 1990 Model C but was significant in Model F and in the direction expected (3.070).

In sum, the most important feature of this model is the difference in magnitude between the betas for 1990 and 2000 for Instability and spatial autocorrelation. The betas suggest that the magnitude of the relationship between the predictors and the outcome were much stronger in 2000 than in 1990.

*Summary of 1990 and 2000 Cross-sectional Models*

In summary, the 1990 and 2000 cross-sectional models had many similarities and several profound distinctions for the two periods of time, Time 1 and Time 2. For example, population was consistently a significant predictor of logged motor vehicle theft and in the direction expected in every single model for both points in time, as was expected. The SES predictor, when included in a model, was consistently a significant predictor and in the expected direction for the 1990 and 2000 models. The Instability Index predictor was not as predictive as originally expected and in fact was only a significant predictor of logged motor vehicle theft in the 1990 Model C; the model that had SES removed due to low tolerance. The contiguous boundary variable was not predictive of logged motor vehicle theft at either point in time but the straddle boundary variable was consistently predictive in all models except those where SES had been removed – 1990 Model C and 2000 Model F.

Interestingly, the heterogeneity predictor was not predictive of logged motor vehicle theft in any of the 1990 models but was predictive in all of the 2000 models. The two age category predictors used to represent the percentage of young males in the population (14-17 and 18-24) were generally not predictive of logged motor vehicle theft. In fact, only 1990 Model C found percent of males in the population age 14-17 to be significant and in the direction expected. Lastly, the spatial autocorrelation predictor showed consistency in that it was significant in the exact same models for both points in time, 1990 Model C and 2000 Model F. More specifics regarding the individual coefficients, standard errors, betas, and significance levels can be reviewed in table 30. Additionally, further summation and conclusions are identified in a following section titled Summary of Findings.

### *Longitudinal Lagged Effects Analyses*

The next series of analyses are the longitudinal lagged effects models that were run to look at the impact of ecological predictors in 1990 on the motor vehicle theft outcome in 2000, as well as the contemporaneous impact of ecological predictors in 2000 on the unexpected change population weighted logged motor vehicle theft outcome in 2000. To measure the change in community structure variables the 1990 ecological predictors were regressed on the 2000 ecological predictors and both the predicted scores and the residuals were saved and used as predictors in the lagged regression analyses.

The predicted scores are the "lagged" predictors representing 1990 impacts and the residuals are the "unexpected change" predictors representing unexpected change from 1990 to 2000, also considered the contemporaneous effects in 2000. The predictors have essentially been decomposed into an effect from a prior period (1990 lagged) and an effect that can not be explained by prior vehicle theft and can not be explained based on how all CBGs have changed in motor vehicle theft relative to one another. This is referred to as unexpected change and is suggestive of a contemporaneous effect. It is important to keep in mind that the unexpected change predictors and the outcome change are not necessarily causal. In fact, the causal ordering can be reversed, for example, increasing unexpected change in population weighted logged motor vehicle thefts might depress housing values making homes more affordable and consequently increasing home ownership and community stability in an area – peculiar, but plausible.

An important point to make as part of the introduction to the lagged ecological effects models is that there were variables that were significant in the 1990 and/or 2000 cross-sectional models that were not significant in the longitudinal lagged effects models (ex. straddle boundary). Additionally, there were predictors that were not significant in the 1990 and/or 2000 cross-sectional models that were significant in several of the lagged ecological effects models (ex. heterogeneity). Finally, there were also predictors that were significant in the direction expected in the 1990 and/or 2000 cross-sectional models that were significant but not in the direction expected in the lagged ecological effects models (ex. Instability). The point is that the two analytical approaches are unique to one another and can and occasionally do render differing results. The results are provided in detail in the following section. Also, as previously discussed several of the predictors have been population weighted and converted to percentiles for further use in the regression models. A full correlation matrix of the lagged effects model predictors can be reviewed in Table 31.

*Longitudinal Lagged Effects Summary of Predictor Correlations*

A correlation matrix of all of the lagged and unexpected change predictors for the longitudinal lagged effects models can be viewed in Table 31. In brief, as previously discussed, the lagged predictors were generated by regressing the 1990 predictor on the 2000 predictor and saving the resulting predicted value scores as new variables. These scores correlate 1.0 with the 1990 predictor and represent 1990 effects. The unexpected change predictors were generated by saving the residuals from the 1990 and 2000 regressions as new variables. These unexpected change scores represent the contemporaneous effects in 2000.

As the table shows, the strongest relationship between all of the predictors was the population weighted unexpected change logged motor vehicle theft outcome variable and lagged heterogeneity (.611) suggesting that 1990 heterogeneity was strongly related to the motor vehicle theft outcome predictor. The next largest correlation between a predictor and the outcome was unexpected change spatial autocorrelation (.542) suggesting that the outcome was more spatially dependent/predictable in 2000. The next predictor, lagged SES, correlated negatively with the outcome (-.433) indicating that areas with low 1990 SES had higher 2000 vehicle theft. Similarly, there was a negative correlation between the motor vehicle theft outcome and unexpected change SES (-.347). The implication is that areas with high SES score lower on the vehicle theft outcome.

The next noteworthy predictor to correlate with the outcome was lagged spatial autocorrelation (.343), that is, areas in 1990 that were spatially predictable were also spatially predictable in 2000. Finally, unexpected change Heterogeneity was also correlated with the outcome (.238) indicating that areas with unexpected change increases in 2000 also scored higher on the vehicle theft outcome.

Also of interest are several predictors that correlated with one another. Lagged SES and lagged spatial autocorrelation were strongly negatively correlated (-.707), that is, areas in 1990 that scored high in SES tended to score lower in spatial autocorrelation indicating that they were not in close proximity to areas of high concentrations of motor vehicle theft. Lagged SES and lagged Heterogeneity were also negatively correlated (-.623) suggesting that areas in 1990 that scored high in SES scored low in Heterogeneity. Finally, lagged Heterogeneity and lagged spatial autocorrelation were positively correlated (.361). Areas in 1990 that scored high in heterogeneity also tended to score higher in spatial predictability.

*Model G: Longitudinal Lagged Effects- Population Weighted-*

*Logged Motor Vehicle Thefts: All Predictors*

All of the lagged effects models used Time 2 unexpected change population weighted logged motor vehicle thefts as the dependent or outcome variable. Model G also included all of the lagged and unexpected change variables as the independent variables or predictors. All of the control variables, other than population, were also included in the equation. Population was excluded because it had already been incorporated through the population weighting procedure that was previously discussed.

As Table 32, pg. 293, Model G shows, three of the predictor variables had a significant impact on unexpected change population weighted logged motor vehicle theft - lagged heterogeneity, unexpected change heterogeneity, and unexpected change spatial autocorrelation. All of the impacts were in the expected direction with unexpected change population weighted logged motor vehicle theft going up (.003813) as the lagged value of heterogeneity went up. Unexpected change population weighted logged motor vehicle theft went up (.003225) as the unexpected change in heterogeneity went up, and unexpected change population weighted logged motor vehicle theft went up (.00001432) as the unexpected change in spatial autocorrelation went up (see Table 32). In sum, the heterogeneity predictors were concurrently predictive of the outcome with only one additional significant predictor suggesting that racial composition and proximity to CBGs with elevated motor vehicle thefts were most predictive of unexpected change in vehicle thefts in CBGs.

Interestingly, this model found both a lagged and contemporaneous change in heterogeneity effect on unexpected change population weighted logged motor vehicle theft. Spatial autocorrelation did not have a lagged effect and only had a contemporaneous unexpected change effect. Again, it is important to note, the small size of the coefficients in all of the lagged effects models are the direct result of having logged the outcome variable to control for skewness. Overall, the model accounted for 60.1

percent of the variance in unexpected change in population weighted logged motor vehicle theft. Also, similar to the cross-sectional models, the recommended tolerance threshold of .30 was violated by the lagged SES and lagged Spatial Autocorrelation predictors indicating the possibility of a multi-collinearity problem among the predictors (see Table 13).

A further investigation comparing lagged heterogeneity and unexpected change heterogeneity revealed that the lagged beta (.438) was nearly twice the size of the unexpected change beta (.239). The magnitude of the relationship between lagged heterogeneity and unexpected change in population weighted logged motor vehicle theft suggests that Time 1 heterogeneity was a more powerful predictor of later vehicle theft than the contemporaneous unexpected change in heterogeneity predictor was. This is particularly interesting because the 1990 cross-sectional models did not show heterogeneity to be a significant predictor of 1990/91 logged motor vehicle theft and Census 2000 indicated dramatic shifts in racial composition of the city.

Also, lagged spatial autocorrelation was not a significant predictor but unexpected change in spatial autocorrelation was significant. In fact, the unexpected change beta (.296) was nearly three times the size of the lagged beta (.106). The suggestion is that the spatial patterning of vehicle theft was more predictive at Time 2 and CBGs with motor vehicle theft were more likely to be near CBGs with motor vehicle theft. Also, the contemporaneous spatial patterning and proximity of vehicle thefts was a better predictor than the lagged spatial patterning and proximity of vehicle thefts.

*Model H: Longitudinal Lagged Effects 1990/2000 - Population Weighted - Logged - Unexpected Change Motor Vehicle Thefts Without Spatial Autocorrelation*

The second 2000 lagged effects model included the Time 2 unexpected change population weighted logged motor vehicle thefts as the outcome variable and all of the lagged and unexpected change predictors as the independent variables, other than spatial autocorrelation, in the equation in an effort to address the low tolerance levels identified in the first full lagged effects model. As Table 33, p. 293, Model H shows, there were several additional significant predictors of unexpected change population weighted logged motor vehicle theft in Model H compared to Model G - lagged instability, lagged heterogeneity, unexpected change SES, unexpected change Instability, and unexpected change heterogeneity were all significant.

There were several items of interest in this model. Lagged Instability was a significant predictor of unexpected change population weighted logged motor vehicle theft. The motor vehicle theft outcome went down (-.0022) as the value of lagged Instability went up. The lagged heterogeneity variable was also a significant predictor. The vehicle theft outcome went up (.0047) as the value of lagged heterogeneity went up. Unexpected change SES was a significant predictor of the vehicle theft outcome and unexpected change population weighted logged motor vehicle theft went down (-.00698) as unexpected change SES went up. Unexpected change Instability was also significant and as unexpected change Instability went up the outcome variable, unexpected change population weighted logged motor vehicle theft, went down (-.00278). Lastly, as unexpected change heterogeneity went up unexpected change population weighted logged motor vehicle theft went up (.00355) (see Table 33).

The results showed both lagged and contemporaneous unexpected change Instability effects on unexpected change population weighted logged motor vehicle thefts. However, the impacts were not in the expected direction. The unexpected change outcome variable went down (-.00220 and -.00278 respectively) as both the lagged value of Instability and unexpected change in Instability went up. This was contrary to what was expected and does not support the associated hypotheses. The associated hypothesis states that motor vehicle theft will be elevated in CBGs that are high in instability.

In several of the proceeding regression equations the motor vehicle theft outcome variable decreased as instability increased. One would generally expect that vehicle thefts would decrease as an area of the community became more stable in terms of resident mobility, owners versus renters, multiple housing units compared to single housing units, and the like. The direction of the instability coefficient is contrary to the relationship stated by the hypothesis. One potential explanation for this finding has to do with the paradoxical relationship between gentrification, stability, and crime. According to Covington and Taylor (1989) rapid gentrification can cause such rapid instability that it increases the likelihood of robbery and larceny offenses in the gentrifying neighborhoods. Alternately, areas that have high instability scores might actually be experiencing gentrification, especially when accompanied by decreasing crime scores. The contradictory findings present in this model are addressed more thoroughly in a following chapter of this study.

Similar to the first lagged effects model, Model G, there were both lagged and contemporaneous heterogeneity effects on unexpected change population weighted logged motor vehicle theft as well. The size of the coefficients is the result of having logged the outcome variable to control skewness. Overall, the model accounted for 55.7 percent of the variance in motor vehicle theft, less that the 60.1 percent explained by Model G. However, none of the variables in Model H were below the suggested tolerance threshold of .30 (see Table 13). An analysis of the $R^2$ change shows that inclusion of the spatial autocorrelation predictor to this model would result in an increase of 5 percent additional explained variance for a total of 60.1 percent explained variance.

The primary differences between this lagged effects model - Model H - and the first lagged effects model - Model G - are that there were co-occurring effects of lagged and unexpected change Instability on the outcome. Also, unexpected change SES was a significant predictor in Model H and the beta in Model H (-.270) was nearly twice the size of the beta in Model G (-.148) suggesting that the removal of the spatial autocorrelation predictors were contributing to the predictive power of the SES variables. Both spatial autocorrelation predictors were removed from the model so they are no longer significant predictors. In fact, the only similarity between the two models is that there was still a co-occurring heterogeneity effect on the outcome variable in Model H that was also present in Model G.

*Model I: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Without SES Index*

The third 2000 lagged effects model included Time 2 unexpected change population weighted logged motor vehicle thefts as the outcome variable and all of the lagged and unexpected change variables as the predictors in the equation, other than the

SES Index, again in an effort to address the low tolerance levels identified in the first lagged effects model, Model G.

As Table 34 p. 294, Model I shows, there were three significant predictors of unexpected change population weighted logged motor vehicle theft in this model - predicted value heterogeneity, residual heterogeneity, and residual spatial autocorrelation. These were the very same significant predictors of the vehicle theft outcome variable that were found in the first lagged effects model G. All of the impacts are in the expected direction. Unexpected change population weighted logged motor vehicle theft went up (.003949) as lagged heterogeneity went up, unexpected change population weighted logged motor vehicle theft went up (.003196) as the unexpected change heterogeneity went up, motor vehicle theft went up (.00001694) as unexpected change spatial autocorrelation went up (see Table 34). Again, heterogeneity had both lagged and contemporaneous effects on unexpected change population weighted logged motor vehicle theft. Also, there appeared to be a diffusion effect on the SES predictors when the spatial autocorrelation predictors were included in the model. All of the betas were of comparable size to those in Model G. The small size of the coefficients in the model was due to logging the outcome variable to control for skewness.

Overall, the model accounted for 58.6 percent of the variance in unexplained change population weighted logged motor vehicle theft; a slight decrease in the explained variance from lagged effects Model G (60.1 percent) which had all of the same significant predictors and included both lagged and unexplained change SES. However, none of the predictors in Model I fell below the suggested tolerance threshold of .30, unlike Model G (see Table 13).

The differences between lagged effects Models H and I were very similar to the difference between lagged Models G and H. For example, there was no longer a co-occurring significant effect of lagged and unexpected change Instability on the outcome vehicle theft variable. Also, Unexpected change SES was no longer a significant predictor. However, in Model I unexpected change in spatial autocorrelation was a significant predictor suggesting that unexpected change population weighted logged motor vehicle theft was more spatially predictable at Time 2.

*Longitudinal Lagged Ecological Effects Analyses: Excluding Outlier Case #19*

The fourth series of analyses that were run were the lagged effects models without the previously identified outlier case #19 that contained a population of four. The regression models looked at the impact of ecological predictors in 1990 on the unexpected change population weighted logged motor vehicle theft outcome for 2000, as well as the contemporaneous impact of ecological predictors in 2000 on the unexpected change population weighted logged motor vehicle theft outcome in 2000. The objective was to replicate the previous series of lagged effects regression models while removing the outlier case to detect any impacts the case might have had on the original results. As previously discussed, case #19 not only presented itself as an outlier in several scatterplots but it also occasionally resulted in elevated levels of Cook's D and leverage when the lagged regression analyses were run.

*Model J: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Full Regression Model Without Case #19*

The first lagged effects model in this series was similar to the previous full lagged effects model - Model G - with the exception of removing the outlier case #19. Time 2 unexpected change population weighted logged motor vehicle theft was again used as the outcome variable and all of the lagged and unexpected change predictors were included. All control variables, other than population, were also included in the equation.

As Table 35, p. 295, Model J shows, there were four predictor variables that had a significant impact on the motor vehicle theft outcome - lagged heterogeneity, unexpected change Instability, unexpected change heterogeneity, and unexpected change spatial autocorrelation. The model - Model J - had one additional significant predictor - unexpected change Instability - than its previous counterpart Model G - which contained the excluded case. Unexpected change population weighted logged motor vehicle theft went up (.00273) as lagged heterogeneity went up. Therefore, theft risk was higher in CBGs that were more heterogeneous in 1990 and 2000; that were unexpectedly more unstable and were unexpectedly more spatially autocorrelated. Once again, not all of the impacts were in the expected direction. Contrary to the original hypothesis, unexpected change population weighted logged motor vehicle theft went down (-.00259) as unexpected change Instability went up. Population weighted logged motor vehicle theft went up (.002890) as unexpected change heterogeneity went up, and unexpected change population weighted logged motor vehicle theft went up (.00001686) as unexpected change spatial autocorrelation went up. The heterogeneity predictor had both a lagged and contemporaneous unexpected change effect on the outcome. The small size of the coefficients is due to logging the outcome variable to control for skewness (see Table 35).

Overall, the model accounted for 62 percent of the variance in motor vehicle theft compared to 60.1 percent of the explained variance in the counterpart model containing the excluded case #19 - Model G - (see Table 32). As previously mentioned, the tolerance level for lagged SES and lagged Spatial Autocorrelation were below the recommended threshold of .30 suggesting possible problems of multi-collinearity among the predictors. The multicollinearity issue was also encountered in Model G containing the excluded case (see Table 14). Despite the multicollinearity the current model is an improvement given that variance explained increased by nearly two percent with the exclusion of a single barely populated block group.

The removal of case #19 did have an impact on Model J. Most noticeably, unexpected change Instability was significant in the Model J but was not significant in the counterpart Model G that included case #19. The beta in Model G was -.145 whereas the beta in Model J was -.178, indicating a slightly greater magnitude in the relationship between the predictor and the outcome when case #19 was excluded. The remaining significant predictors in Model J were also significant predictors of unexpected change population weighted logged motor vehicle theft in Model G (Table 32).

In conclusion, Model J explained more of the variance than any of the other lagged effects models that included case #19 and contained several significant contemporaneous unexpected change effects on the outcome variable. However, multicollinearity appeared to be a problem.

*Model K: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Without Spatial Autocorrelation and Without Case #19*

The second 2000 lagged effects model of the case #19 exclusion series included Time 2 unexpected change population weighted logged motor vehicle thefts as the outcome variable. All of the lagged and unexpected change predictors, other than spatial autocorrelation, were included in the equation. The lagged and unexpected change spatial autocorrelation predictors were excluded in an effort to address the previously discussed low tolerance levels. As Table 36, p. 296, Model K shows, there were several additional unique significant predictors of unexpected change population weighted logged motor vehicle theft in the model in addition to several reoccurring significant predictors - lagged SES, lagged instability index, lagged heterogeneity, unexpected change SES, unexpected change instability, and unexpected change heterogeneity. The motor vehicle theft outcome variable went down (-.00241) as lagged SES went up. The outcome variable went up (.00345) as lagged heterogeneity went up. And the outcome variable went down (-.00186) as lagged Instability went up. Unexpected change population weighted logged motor vehicle theft went down (-.00584) as unexpected change SES went up, and the motor vehicle theft outcome variable went up (.003241) as unexpected change heterogeneity went up. Also, the outcome variable went down (-.00327) as unexpected change Instability went up (see Table 36).

The removal of case #19 clearly had an impact on Model K and resulted in several variables becoming significant predictors of the unexpected change population weighted logged motor vehicle theft that were not significant in Model J. For example, lagged SES became a significant predictor in Model K with a beta of -.307 compared to a lagged SES beta of -.195 in Model H, its counterpart model with case #19 included.

There were several co-occurring lagged and unexpected change predictors in the model. In fact, all of the significant lagged predictors – lagged SES, lagged Instability, and lagged heterogeneity - have an associated significant co-occurring contemporaneous unexpected change predictor - unexpected change SES, unexpected change Instability, and unexpected change heterogeneity.

Again, as can be seen in Table 36, p. 296, Model K, not all of the impacts were in the expected direction. Unexpected change population weighted logged motor vehicle theft went down as both the lagged instability and unexpected change instability went up (-.00186 and -.00327 respectively). This is contrary to what was expected and does not support the associated hypotheses. The small size of the coefficients was attributable to logging the outcome variable to control skewness. Overall, Model K accounted for 55.2 percent of the variance in motor vehicle theft compared to 55.7 percent of the variance explained in the counterpart Model H that included case #19. Also, while this model contained the greatest number of significant predictors, it was not the model that explained the most variance (see Model J). Importantly though, none of the variables in model K were below the recommended tolerance threshold of .30 (Table 14). An analysis of the $R^2$ change revealed that inclusion of the spatial autocorrelation predictor increased the explained variance of the model by 7 percent to 62 percent total explained variance.

Model K showed several differences from previous models and as previously noted had more significant predictors than any of the other models. Model K was the only lagged effects model to have both lagged SES and unexpected change SES as significant predictors of unexpected change population weighted logged motor vehicle theft. The primary difference between Model J and Model K, besides the removal of the spatial autocorrelation predictors, was that the lagged SES and Instability predictors are significant in Model K creating co-occurring lagged and contemporaneous unexpected change effects for both on the unexpected change population weighted logged motor vehicle theft outcome. The co-occurring effects of lagged and unexpected change heterogeneity are the same across all of the lagged effects models.

*Model L: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Without SES and Without Case #19*

The third and final 2000 lagged effects model without case #19 included Time 2 unexpected change population weighted logged motor vehicle thefts as the outcome variable and all of the lagged and unexpected change variables, other than SES, in the equation in an effort to again address the low tolerance levels.

As Table 37, p. 297, Model L shows, there were five significant predictors of the motor vehicle theft outcome variable in the model - lagged heterogeneity, lagged spatial autocorrelation, unexpected change instability, unexpected change heterogeneity, and unexpected change spatial autocorrelation - an increase in the number of predictors compared to counterpart Model I that contained the excluded case #19.

Here again, not all of the impacts are in the expected direction. Unexpected change population weighted logged motor vehicle theft went down (-.00241) as unexpected change instability went up. This is contrary to what was expected and does not support the associated hypothesis. The motor vehicle theft outcome went up (.002794) as lagged heterogeneity went up, motor vehicle theft outcome went up (.00005101) as lagged spatial autocorrelation went up, unexpected change population weighted logged motor vehicle theft went up (.002878) as unexpected change heterogeneity went up, the motor vehicle theft outcome variable went up (.0000184) as unexpected change spatial autocorrelation went up. The results show that both heterogeneity and spatial autocorrelation had a lagged effect and a contemporaneous unexpected change effect on unexpected change population weighted logged motor vehicle theft. The small size of the coefficients is due to logging the outcome variable to control for skewness (see Table 37).

Overall, the model accounted for an impressive 61.7 percent of the explained variance in motor vehicle theft compared to 58.6 percent of the explained variance in the counterpart Model I containing the excluded case #19. None of the variables in Model L were below the suggested tolerance threshold of .30 despite lagged spatial autocorrelation being somewhat close (see Table 14). This model is believed to be the single best model out of all of the longitudinal lagged effects models that were run. The amount of explained variance in the outcome variable is impressive, there are no tolerance issues and the outlier case was excluded.

A comparison of Model's L (without case #19) and its counterpart Model I (with case #19) shows that the removal of case 19 again made a difference. While lagged heterogeneity and unexpected change heterogeneity were significant in both models, that was not the case for lagged spatial autocorrelation and unexpected change Instability which were not significant predictors in Model I. The beta for lagged spatial autocorrelation in Model I was not nearly as robust (.120) as the beta in Model L (.277), which indicated a stronger relationship to the predictor when case #19 was removed. Similarly, the beta for unexpected change Instability in Model I was not as robust (-.114) as the beta in Model L (-.165) indicating that unexpected change instability was a more robust predictor of unexpected change population weighted logged motor vehicle theft when case #19 was excluded.

In conclusion, Model L, while not the lagged effects model with the greatest number of significant predictors, was the lagged effects model that explained the greatest amount of variance (61.7 percent) without having any predictors that fell below the recommended tolerance threshold of .30. Model J technically explained the greatest amount of variance among the longitudinal lagged effects models but did contain predictors that fell below the tolerance threshold. Therefore, based on the findings of Model L, it can be said that unexpected change population weighted logged motor vehicle theft was greatest in CBGs that had lagged heterogeneity, lagged spatial autocorrelation, unexpected change instability, unexpected change heterogeneity, and unexpected change spatial autocorrelation. There were concurrent lagged and unexpected change impacts for both heterogeneity and spatial autocorrelation but only unexpected change instability impacts.

# CHAPTER 8

# DISCUSSION

## *Summary of Findings*

The results of the two series of cross-sectional analyses were reviewed to determine if there were any consistently significant structural/ecological effects across the varying Time 1 and Time 2 models that explained the outcome. Additionally, the lagged effects analyses were reviewed to determine what effects structural change over time had on the outcome. The following section provides a brief summary of the findings as they relate to the individual predictors.

### *S.E.S.*

Socioeconomic status (SES) was a significant predictor of motor vehicle theft in the direction expected in all four of the cross-sectional models in which it was included for Time 1 and Time 2 - with more vehicle thefts present in areas of lower socioeconomic status. The hypothesis stated that areas of lower SES would have more motor vehicle theft. This was in fact exactly what was found in the cross-sectional analyses. For the 1990 cross-sectional analyses, model A explained the most variance (57.8 percent) in logged motor vehicle theft with SES, population, and the straddle boundary all significant. The 2000 cross-sectional model D explained the most variance (67.3 percent) of all 2000 models with SES, population, straddle boundary, and the additional predictor – heterogeneity - all significant in the model. In the lagged ecological effects models, model J explained the most variance (62 percent) and despite the fact that SES was included in this model it was not a significant predictor. (The significant predictors in model J were lagged heterogeneity, unexpected change instability, unexpected change heterogeneity, and unexpected change spatial autocorrelation. These predictors will be discussed shortly).

With regard to SES, the findings support the hypothesis in this study yet offer mixed support when compared to the existing literature. The SES predictor was not found to be a significant predictor of motor vehicle theft in the Holinger and Dabney (1999) study, nor the Miethe and McCorkle (2001) study which asserted that the "favored group" hypothesis is more predictive of motor vehicle theft than low SES. This hypothesis suggests that young males from affluent families have more exposure to motor vehicles and are therefore more likely to participate in vehicle theft. Their favored group status promotes vehicle knowledge and greater likelihood of exposure to vehicles, unlike those from impoverished homes, where vehicles are less prevalent. Copes (1999) found that the percent poor to offer the greatest contribution towards explaining the variation in vehicle theft.

The SES predictor could be linked to motor vehicle theft in a couple of related ways depending upon the theoretical orientation. It is possible that areas of low SES have more motivated offenders due to diminished economic resources creating a suitable opportunity structure whereby some residents in poor communities are more likely to steal vehicles. Additionally, the areas with the greatest concentration of motor vehicle theft tend to be in the downtown part of the city where there is also a greater concentration of vehicles due to a combination of factors including both work and entertainment. This finding lends support to the routine activities thesis and the opportunity model.

An alternate explanation may be that low SES is a predictor of logged motor vehicle as a result of poor territorial control. Residents in areas of low SES may be more withdrawn from the community and may actually relinquish external territorial control while concentrating efforts on managing the safety, security, and territorial control over the interior of their dwellings. Sparse personal and community resources do not allow for much by way of territorial markers to ward off or discourage undesirables. Also, the argument has been made that law enforcement practices tend to favor the wealthier neighborhoods or a community and that impoverished neighborhoods suffer from poor and inadequate police patrols. The explanation provided here could offer support for the human territorial control thesis.

Finally, low SES is also one of the major tenets of social disorganization. Low SES is often viewed as a precondition or antecedent factor leading to a breakdown in informal social controls within a community, similar to territorial control, creating opportunities for the infiltration of crime and criminality. It is possible that low SES in this study is indicative of a breakdown in informal control mechanisms within the community sending the signal that the neighborhood is primed for crime. Motor vehicle theft lends itself well to communities that lack mechanisms of informal social control. Thieves are more likely to pass through the community undaunted and unafraid to violate the law. A macro level predictor like low SES however, is not sufficient to specifically identify which theoretical perspective is most suitable for explaining the connection between low SES and vehicle theft.

*Instability*

Instability was rarely a significant predictor of motor vehicle theft in either series of cross-sectional models and was not significant in the two models explaining the most variance in the outcome. In fact, the only time that Instability was significant was in a 1990 Time 1 model (Model C) when SES was removed from the regression equation. This finding does not support the hypothesis and might be indicative of a diffusion process between SES and Instability. It is possible that the related dynamics between SES and Instability preclude Instability from being a significant predictor when SES is also in the model. The strength of SES as a predictor might be enveloping the effects of Instability on motor vehicle theft. The Tolerance levels in most of the models support this position and indicate that the two do not co-exist well together in the same analyses and may be telling of the diffusion that exists. In sum, it is difficult in the current study, with these data, to separate out how Instability impacts the outcome differently or uniquely from SES.

Interestingly, despite the lack of statistical significance in the cross-sectional models, Instability was a significant predictor in multiple lagged effects analyses. However, the lagged model explaining the most variance (62 percent) only found unexpected change Instability to be a significant predictor and not lagged Instability. Additionally, it was significant in the unexpected direction – as instability went down vehicle theft went up. Conjecture has been offered attempting to shed light on this unexpected finding in a following section of this dissertation but in anticipation of that discussion it is possible that gentrification is having an impact whereby positive population turnover – the relocation of more affluent individuals into previously less desirable neighborhoods - is appearing as instability when in actuality it is having a beneficial impact on vehicle thefts.

Bursik (1986) found a similar paradoxical relationship between in a study looking at delinquency data for Chicago. He found that high rates of delinquency in 1960 actually predicted increases in SES in 1970. This is contrary to what the hypothesis expected given that delinquency would be expected to lead to deterioration in neighborhood environment. The suggestion that Bursik (1986) made was that gentrification might be accounting for this paradoxical relationship between delinquency and SES (Kurtz, 2000).

Instability does not have an established presence in the motor vehicle theft literature and as a result there was no precedent in terms of findings to compare the results of this study to. Rice and Smith (2002) did study a predictor closely related to one used in the present Instability index – multiple family buildings – defined as multiple families living in the same building in the community. The related variable used in the Instability index of the present study was the percent of multiple housing units. The Instability index used in this study is a unique construct developed using variables that have been previously tested in various combinations in other community crime studies. The Rice and Smith (2002) findings suggested that multiple family buildings were significant predictors of motor vehicle theft in the direction expected. Copes (1999) studied multiple housing units as a predictor of motor vehicle theft expecting to find that multiple housing units would provide natural surveillance and mitigate the incidence of vehicle theft. This was not the case and multiple housing units were significant predictors of increased motor vehicle thefts.

Despite the lack of an Instability/Stability predictor in the motor vehicle theft literature, much of the existing communities and crime literature that has studied the impact of instability suggests that it is positively correlated with criminality rather than inversely as the present study found.

An interesting next step will be to try and determine the context of instability and its relationship to reduced motor vehicle thefts. With specific emphasis on the underpinning theoretical tenets, is the type of instability present in the study area in some way facilitating informal social controls and/or community cohesion? For example, if the increases in instability are related to gentrification, one might expect to find greater territorial control and investment in one's property both internally and especially externally. Operationalizing proxy measures for both territorial control and community disorder might help to assess the presence or absence of territorial controls. Also, Felson (1994) suggested that densely populated areas create opportunities for natural surveillance and a greater percentage of multiple housing, while suggestive of instability, might actually provide heightened natural surveillance, similar to what Copes (1999) had expected to find.

Additionally, gentrification could be pushing house prices up in the area making it difficult for all of those who desire to live in the area able to afford home ownership. As a result more individuals might be willing to rent in the improving area with more cohesion rather than purchase in the lesser area with lesser cohesion. Gentrification, which accompanies population turnover, is not the negative type of population mobility often also accompanying diminished community cohesion and rising crime rates. Rather, gentrification involves positive population turnover characterized by the displacement of lower income residents by middle or upper class residents.

Efforts will be made to clarify the role and extent of gentrification in the study area by looking at both house prices and instability change over the decade. Also, conducting field research in an effort to identify whether residents in seemingly highly gentrified areas are implementing more target hardening techniques with greater effectiveness could be useful. In relations to this additional CPTED approaches could be at work such as natural surveillance, territorial reinforcement, and natural access control. Looking more closely at ownership as compared to renters could also be insightful especially in relation to house prices (i.e. affordability) and gentrification.

*Heterogeneity*

The heterogeneity measure used in this study is a reoccurring measure that can be found in both the community crime literature and more specifically, the motor vehicle theft literature. Heterogeneity of an area was not a significant predictor in any of the 1990 cross-sectional models and therefore was not a useful predictor in model A, the model explaining the most variance in logged motor vehicle theft for Time 1. Heterogeneity was a significant predictor in all of the 2000 cross-sectional analyses, including model D, the most explanatory model. The results do not support the hypothesis for 1990 but do support it for 2000. Interestingly, both lagged heterogeneity and unexpected change heterogeneity were significant in all of the longitudinal lagged effects models, including model J, the most explanatory. The lagged results suggest that heterogeneity is having both a lagged effect on vehicle theft as well as a contemporaneous unexpected change effect.

This finding, when placed within the context of the community profile information previously provided, is not all that surprising. Parts of the city experienced profound racial population shifts with considerable out-migration of White residents and in-migration of Black residents during the 1990s. Despite a subtle general population decrease in the city, the Black population of the city actually increased and expanded throughout the city while the White population decreased. As a result, the study area generally became more heterogeneous. As previously mentioned, the Tri-County Area, of which Peoria is part of, has been ranked as the 23rd most segregated metropolitan community in the country, with a dissimilarity index score of 71.4 out of a possible 100 (Tri-County Regional Planning Commission, 2003). The greatest concentration of vehicle thefts in both 1990 and 2000 was on the racially segregated South side of the city in the downtown area.

Additionally, Whites are leaving the city of Peoria in relatively large numbers. Between 1990 and 2000, over 8,300 White people left the neighborhoods on the South side of the city, representing a loss of nearly 20 percent of the white population. In contrast, more than 11,000 persons of color have moved into the city over the past decade. In fact, people of color accounted for nearly 40 percent of the people moving into Peoria's newer northern neighborhoods and contributed to increased racial heterogeneity in parts of the city (Tri-County Regional Planning Commission, 2003).

Due to the differing results for 1990 and 2000 the findings only partially support the hypothesis in this study. Rice and Smith (2002) included both the number of Blacks in the population and a heterogeneity variable (constructed in the exact same way as the current heterogeneity variable) in their study of motor vehicle theft. They found that the number of Blacks in the population was a significant predictor of motor vehicle theft but that heterogeneity was not. Additionally, Davison (1995) also included both an African American and a heterogeneity variable in his study of vehicle theft and found that the number of African American's in the population was a significant predictor of motor vehicle theft but that heterogeneity was not. Interestingly, the findings in both of the studies with regard to heterogeneity were contrary to what was found in the current study. It is worth noting though that in preliminary analyses of the current study a Black variable was included but due to collinearity issues with both SES and Instability it was removed.

The social disorganization perspective suggests that a heterogeneity measure serves as a proxy measure predicting the likelihood and extent to which residents of an area are likely to have the same values and norms. Those heterogeneous neighborhoods with mixed racial populations are though to be less likely to share these fundamental commonalities of values, norms, and behaviors and the associated neighborhoods are therefore less likely to experience social cohesion among community members and more likely to experience culture conflict. Culture conflict results in a breakdown of informal social controls resulting in an environment where crime and criminality flourish.

Merry (1981), in her cultural diversity model, suggests that crime flourishes when poverty and anonymity coexist. Cultural differences and language barriers across ethnic lines cause neighborhood residents to interpret the apparently inexplicable behavior of their anonymous neighbors through the lens of their own culture. This often inaccurate interpretation leads to further confusion, misunderstanding, mistrust and fear.

Individuals often deal with dangerous environments by withdrawing into isolated social relationships that they are comfortable with and they avoid people who are unfamiliar and unpredictable. This response to cultural differences is fundamental to the formation of ethnic boundaries (Merry, 1981).

The cultural diversity model suggests that fear induced by cultural difference may be a contributing factor in the process leading to crime. Dissimilarities may actually serve to instigate fear of those unknown and *the* unknown creating social withdrawal.

Further exploration of the impact heterogeneity is having on micro level social processes must begin by determining the degree to which each area became more or less heterogeneous. In other words, efforts need to be made to determine the extent of heterogeneity and make sure that we don't simply have highly segregated CBGs appearing as heterogeneous CBGs. For example, it could be that the quantitative demographic counts suggest integration but that a micro level inspection actually reveals vast segregation even in a seemingly small unit of analysis. Census data query parameters prevent identification by race at micro levels of aggregation. As a result, in order to collect this information observational study and survey instrumentation might be most appropriate. Fear of crime in the community could also offer insight into community cohesion. Peoria's 90 plus neighborhood associations could be a good place to start inquiring about these issues.

*Male Age Categories: 14-17 and 18-24*

The only male age category predictor that was significant in any of the cross-sectional models was the percent of males in the population age 14 to 17. Interestingly, age 16 is generally the peak year for property crime commission. This predictor was significant in a single 1990 cross-sectional model, Model C, which excluded the SES predictor from the equation. The percent of males in the population age 18 to 24 was not a significant predictor of logged motor vehicle theft in any of the cross-sectional models for 1990 or 2000. These findings do not support the hypotheses and are quite contrary to the existing anecdotal literature detailing who the majority of offenders of motor vehicle theft are in general. The expectation was that the more young males in the population, the more motivated offenders there would be, and subsequently, the more motor vehicle thefts there would be. These findings do support research by Copes (1999) who found that young males age 15-24 did not significantly explain variation in motor vehicle theft. Young males may be more likely to be arrested for the crime of motor vehicle theft nationally but their presence in the community was not a predictor of vehicle thefts. None of the male age category predictors were significant in any of the longitudinal lagged effects models.

One possible explanation for the absence of young males as a predictor of motor vehicle theft has been discussed in more detail in a following section, but it could be that the small unit of analysis is too finite to capture the young male opportunity structure. Given that the current measure assumes that young males only commit vehicle theft in the CBG in which they reside. It could be that young males are traveling outside of their own CBG to alternate CBGs where the theft opportunity is greater. Additionally, an offender's comfort zone and activity space is not usually bounded by arbitrary spatial designations like blockgroups, or face blocks and can extend into multiple geographic units across boundaries based upon habitual paths traveled in association with home, recreation, and work (Brantingham and Brantingham, 1984).

As a following discussion will note, it is possible that a larger unit of analysis like the tract could better capture the representativeness of young males in the population in combination with vehicle thefts by more accurately accounting for activity space and mobility patterns. Further research could provide these answers whereby a larger unit of analysis is used. Also, further exploration of motor vehicle theft "hot spots" and land use could help to generate hypotheses about the offenders and the role of young males.

Copes (1999) suggests that the issue might actually have to do with vehicle availability. For example, areas with a high concentration of young people may have fewer cars due to fewer eligible drivers and as a result the opportunity to steal vehicles is reduced by not having enough suitable targets. Routine activities would explain this as follows: a lack of suitable targets, despite elevated levels of motivated offenders, can not result in elevated crime rates because the geographic area in question does not provide the suitable targets necessary. However, the motivated offenders, as previously mentioned, may travel to more fruitful locations offering an abundance of suitable targets like shopping centers, housing projects, and youth recreation facilities when it is more likely that crime will occur.

Recent work by Wilcox et. al. (2003) postulated a threefold definition of motivated offender exposure at the environmental level which may help to explain events in the study area. Motivated offender exposure applies to the number of potential offenders in a bounded space per geographic unit (concentration). Resident motivated offender exposure refers to the number of potential offenders in a bounded space per geographic unit for a more or less continuous period of time. And finally, ephemeral motivated offender exposure refers to the number of people who pas through a bounded space per geographic unit for a short period of time (Wilcox, Land, and Hunt, 2003). In light of this threefold definition it is likely that certain places/areas of the study area fall into each of the three exposure categories and the high theft areas may be more of the ephemeral exposure type, as opposed to the resident motivated offender type, with motivated offenders passing through for short periods of time (such as for recreation).

Several ways of addressing these issues might entail using a larger unit of analysis for this variable in order to expand the study area to include a wider swatch of geographic space thereby increasing the likelihood of enveloping a motivated offender's comfort zone. Also, an initial analysis might be as simple as determining a theft potential rate using the number of registered vehicles in a block group or tract and the number of young males residing in the area. Again though, it is possible that the aggregated demographics do not explain or represent the context of the actual theft locations. Land use could be useful by identifying commuter areas, residential areas, recreation areas, commercial areas, all of which provide different opportunity structures for motivated offenders.

*Contiguous and Straddle Boundary Controls*

There were two control variables developed to account for boundary related issues. The contiguous boundary control variable, indicating whether or not a CBG was abutting another CBG that was determined to be outside the city limits, was not a significant predictor of vehicle theft in any of the cross-sectional models for Time 1 or Time 2. The presence of edge effects in ecological literature is common. The concern was whether or not there were high vehicle theft areas immediately outside of the city limits that could have had an impact on vehicle theft immediately within the city limits.

The straddle boundary predictor identifying CBGs that did not share the exact same boundaries as the city limit boundaries was significant in the direction expected in all cross-sectional models other than the two when SES was excluded (Models C and F). The straddle boundary predictor was a significant predictor of motor vehicle theft in the model A and Model D, the two models explaining the most variance for both 1990 and 2000.

The findings suggest that CBGs that were segmented due to dissimilar city versus census boundaries resulted in fewer logged motor vehicle thefts. This was expected and the reason for this occurrence was relatively straight-forward. The aggregation of each individual predictor variable was at the full scale census block group level. However, only a portion of the actual motor vehicle thefts for each CBGs were available due to part of the CBG falling outside of the city boundary. As a result, the relationship between the predictors and the outcome was diluted.

The fact that the straddle boundary variable was not significant in the two models where SES was excluded lends support for the profound impact that SES had on community structure and vehicle theft. When SES was excluded structural predictors in the straddled CBG had less impact on logged motor vehicle theft. Again, SES was demonstrating a broad effect on community structure and motor vehicle theft.

*Spatial Autocorrelation*

Finally, the spatial autocorrelation control was a significant predictor of logged motor vehicle theft in two out of four cross-sectional models, both of which excluded SES from the equation. Again, it is believed that this is indicative of the impact that status had on community structure and logged motor vehicle thefts. In terms of the lagged effects models, the lagged spatial autocorrelation control was only significant in the model that excluded SES and case #19. The unexpected change spatial autocorrelation control was significant in all four models in which it was present. The finding suggests that the spatial patterning of existing motor vehicle theft was more predictive of subsequent vehicle theft later in the decade as opposed to early in the decade. Rice and Smith (2002) in their cross-sectional analysis found spatial autocorrelation to be a significant predictor of motor vehicle theft, even causing the number of Blacks to drop out of significance.

The practical application of including a spatial autocorrelation measure is that it controls for the impacts of motor vehicle theft in the surrounding city CBGs and takes account of spatially distributed vehicle thefts. Without the measure there is no way of knowing the impact of surrounding and adjacent vehicle theft and its impact on individual CBGs.

*Population*

The findings also indicated that the population control variable was a significant predictor of logged motor vehicle theft in the direction expected in all of the cross-sectional models for both Time 1 and Time 2. The findings support the stated hypothesis:

The more population in an area the greater the likelihood of motor vehicle theft. Rice and Smith (2002) and Copes (1999) both found supporting results. As population density increased so did the incidence of motor vehicle theft. Population was not included as a separate control variable in the lagged effects models because it had already been factored in during the population weighting procedure of the dependent variable.

Population as a predictor of motor vehicle theft suggests that more people in the population equates to more motivated offenders and more potential vehicle targets. However, there is also the possibility that more people in the population provide additional informal guardianship over vehicles discouraging theft.

## General Summation

In sum, what is evident from a review of the findings of the cross-sectional analyses is the significant degree to which SES in the CBG is intertwined with other aspects of community structure and resulting motor vehicle theft. There were quite clearly some deeply rooted status impacts and effects within the community structure as evidenced by the mediating/intervening effect on several other predictors when SES was included or excluded from the various regression models, both cross-sectionally and longitudinally.

While significant predictors of logged motor vehicle theft in 1990 and 2000 are what we were looking for, another useful component of the research pertains to what was not a significant predictor of logged motor vehicle theft. Surprisingly, and contradictory to the existing literature, Instability had very little apparent impact on vehicle theft. However, it was in the direction expected in the cross-sectional analyses. The general lack of significance of the Instability predictor in nearly all of the cross-sectional models does not support the hypothesis that areas of greater instability will have more motor vehicle theft.

The fact that heterogeneity was not significant in any of the Time 1 models and later was a significant predictor in all of the Time 2 models could have been testament to the profound degree of racial segregation that existed in 1990. As previously discussed, there was evident change in racial population concentrations over the decade. This change led to what initially appears to be greater amounts of racial heterogeneity and more resulting impact on 2000 community structure and motor vehicle theft, as evidenced by both cross-sectional analyses and the lagged effects analyses.

The percent of young males in the population for the two age categories (14-17 and 18-24) were not significant predictors of logged motor vehicle theft except in the Time 1 cross-sectional analyses that excluded SES. These finds were contradictory to the hypothesis stating that more young males in the population would result in more motor vehicle theft. Most motor vehicle theft studies looking at young males have suggested that these individuals commit the majority of vehicle thefts. Higher arrest rates have been used to support this conclusion. As discussed, it is plausible that young males did commit the majority of motor vehicle thefts but that they did not operate in their immediate home turf. It might be that the high vehicle theft block groups had young males from outside the block group migrating in to commit vehicle thefts. For example, one would not expect that all of the vehicle thefts from a shopping center parking lot would be perpetrated by residents of the CBG where the shopping center is located. This is one instance where it is possible that the small level of aggregation used is possibly complicating the results. For example, the larger census tract unit might have been better suited for capturing residence, work, and recreation all within the same unit of analyses and could also have possibly represented the male age structure better.

The spatial autocorrelation control variable was not significant in either of the most explanatory cross-sectional models, A and D, but was significant in both models where SES had been removed. As mentioned, SES appears to have diffused the impact of spatial autocorrelation on logged motor vehicle thefts via high multicollinearity as indicated by low tolerance levels for both of these predictors when they were simultaneously included in models (see Tables 11, 12, and 13).

The contiguous boundary predictor not being significant was actually a benefit to this study. The finding lends support to the notion that events external to the city boundary CBGs were not significantly impacting events within the city boundary CBGs. In other words, were the contiguous variable found to be significant there would be concerned about external demographic information that was impacting motor vehicle theft but was unavailable for inclusion in the analyses; this was not the case in the present study.

The lagged effects analyses rendered considerably different results from the two-waves of cross-sectional analyses. This is not the first community crime study to find divergent sets of results between cross-sectional and longitudinal analyses. Bursik (1986) in his study of deviance in Chicago found that race predicted delinquency when studied cross-sectionally. The results did not hold up during the longitudinal analyses. Similarly, Kurtz (2000) found that race predicted violence when studied cross-sectionally but these findings also did not hold up when examined longitudinally (Kurtx, 2000). In fact, because results using the same predictors can differ based on the method of inquiry, if the opportunity presents itself, it can be useful to conduct analyses using different methodologies and techniques of analyses to examine crime problems.

As previously discussed, the lagged ecological effects analyses looked at the impacts of Time 1 community structure on the unexpected change population weighted logged motor vehicle theft in 2000. The analyses were also looking at the contemporaneous impacts of community structure in Time 2 on unexpected change population weighted logged motor vehicle theft in 2000, or more specifically, the changes in community structure from 1990 to 2000.

The dependent variable for the lagged analysis required changing the dependent variable from a count variable into a population weighted percentile score for logged motor vehicle theft. The population weighted percentile scores are based on cumulative population weighting with regard to the population in the CBG and the number of associated motor vehicle thefts (Taylor, 2001). The population weighting procedure is discussed more thoroughly in the analysis plan, chapter six.

The lagged results indicated that SES was much less significant of a predictor of motor vehicle theft than in the cross-sectional analyses. Lagged SES was only significant in one model out of the four in which it was included and unexpected change SES was significant in two models out of four in which it was included. Both lagged SES and unexpected change SES, however, were simultaneously significant in one of those models suggesting both a lagged and a contemporaneous unexpected change effect on unexpected change in population weighted logged motor vehicle thefts. The model in which they were simultaneously significant predictors was model K. Model K had the spatial autocorrelation predictor removed due to low tolerance levels when both predictors were included, as well as the removal of outlier case #19. The implication is that the SES predictor acts differently depending on whether we are looking at cross-sectional effects or lagged effects and as a result. Also, spatial autocorrelation and SES do not coexist well when included in the same model. The implication is that block groups that are highly spatially autocorrelated also tend to be low SES and multicollinearity is making it difficult to determine the true impact of either predictor.

The lagged Instability predictor was only significant in the two instances when the spatial autocorrelation control was removed from the model. The unexpected change instability predictor was also significant in both models when spatial autocorrelation had been removed but was also significant in all models when case #19 had been removed. As previously mentioned, when instability was significant in the lagged models it was in the opposite direction from what was hypothesized. The expectation as suggested by the hypotheses was that community instability would be a significant predictor of more vehicle thefts. However, the findings here indicate that instability was actually a significant predictor of fewer motor vehicle thefts. There were both lagged and contemporaneous unexpected change instability effects on population weighted percentile logged vehicle theft in two of the models. The unique and unexpected findings with regard to the direction of the instability predictors are discussed below in a separate "unexpected findings" section. The following section elaborates on the impact that gentrification could be having on resulting in unexpected Instability results.

Lagged spatial autocorrelation was only significant in the model that excluded both SES and case #19. Unexpected changes in spatial autocorrelation however, were significant in all four of the lagged effects models that it was included in suggesting that the contemporaneous changes in surrounding motor vehicle theft have a greater amount of impact on vehicle theft than lagged effects of surrounding theft. In other words, the contemporaneous spatial patterning and proximity of motor vehicle thefts is more predictive of concurrent vehicle theft than the spatial patterning and proximation of previous vehicle theft. Removal of Spatial Autocorrelation due to low tolerance levels resulted in lagged Instability and contemporaneous Instability being significant predictors in a direction contrary to the hypothesis. The implications of this are discussed in the following section.

None of the young male age category predictors were significant in any of the lagged effects models. Although this is contradictory to the hypotheses and the literature it is in general concordance with the findings of the cross-sectional models for Time 1 and Time 2. The implications for this have been discussed in a preceding section.

*Summary of Cross-sectional Findings Compared to Longitudinal Findings*

The lagged effects models resulted in several differences from the cross-sectional models and exemplify the need to study ecological predictors over time looking at changes in community structure. When comparing the two cross-sectional models (Time 1 and Time 2) and the single lagged model that explains the most variance in motor vehicle theft the differences become quite evident. The primary difference between cross- sectional models A ($R^2$ = 57.8 percent) and D ($R^2$ = 67.3 percent) is the presence of heterogeneity as a significant predictor in Time 2, model D. When reviewing longitudinal lagged effects model J, which explained 62 percent of the variance in motor vehicle theft, we can see that the only lagged variable that is significant is heterogeneity. However, when looking at the unexpected change predictors, Instability, heterogeneity, and spatial autocorrelation are all significant predictors. Heterogeneity had both a lagged and contemporaneous impact on the outcome. Heterogeneity clearly had a greater impact on motor vehicle theft later in the decade than earlier for reasons already addressed.

Cross-sectionally, SES appears to be the prevailing explanation for vehicle theft while longitudinally, heterogeneity appears to be more relevant. Also, when comparing the most explanatory models, instability is not significant cross-sectionally but is significant, and in the opposite direction, as an unexpected change predictor in the longitudinal analysis. Unexpected change spatial autocorrelation is also significant in the longitudinal analyses whereas spatial autocorrelation is not significant in either of the cross-sectional models. Block groups in Time 2 in close proximity to block groups with a high incidence of vehicle thefts were more likely to also have more vehicle thefts.

*Unanticipated Findings*

The results that were found in this study were mixed in terms of what predictors were anticipated and hypothesized as impacting motor vehicle theft. It is important to note that none of the predictors was significant across all models and under all conditions. Some of the findings are in line with much of the existing ecological communities and crime research to date. For example, in several models and under varying conditions low SES, racial heterogeneity, instability, and spatial autocorrelation were significant predictors of motor vehicle theft as some of the literature suggests.

Other findings do not support the hypotheses or the existing literature. The percent of young males in the population for the two male age categories were generally not significant predictors of vehicle theft despite their overwhelming presence in the vehicle theft literature. Additionally, heterogeneity was not a significant predictor in any of the three 1990 cross-sectional models but was significant in all other models, both 2000 cross-sectional as well as the lagged effects models. Instability was only significant in one of the six cross-sectional models that it was included.

Some findings are even contradictory to the existing literature. The link between SES and vehicle theft in the literature has some research suggesting that low SES results in increased vehicle theft while other studies subscribe to the preferred group hypothesis - affluence results in more vehicle thefts due to familiarity with automobiles and driving and a greater presence of motor vehicles. The SES findings in this study suggest that when it is significant, it is that lower SES in an area, not higher, is a predictor of vehicle theft.

There is one additional particularly contradictory predictor that needs specific attention. Existing research suggests that instability in the community is related to elevated property crime rates. In fact, Sampson and Groves (1984) suggest that stability is more predictive of crime rates in places than SES, family structure, or racial composition (Robinson, 2003).

Instability is generally thought to be a necessary but not sufficient pre-condition which could result in diminished social control. It is often operationalized with some combination/variation of the following predictors: resident housing tenure, renter versus owner residential occupancy, single person households, and multiple unit housing, etc.

The social conditions listed here are generally not viewed as advantageous to the community, in fact, quite the contrary. These community characteristics are usually considered liabilities to stable structure.

Interestingly, two of the lagged effects models found that unexpected change population weighted logged motor vehicle theft went down as lagged instability increased. Unexpected change population weighted logged motor vehicle theft was down when unexpected change instability was up. This was directly the opposite of what was anticipated and pending further investigation and analysis only speculation and conjecture are available to explain the events.

One potential explanation for the phenomenon might reside in the paradoxical relationship between gentrification, stability, and crime. According to available evidence it is the rapidity of the change in the community environment that is destabilizing not the type of change (Bursik, 1986). Covington and Taylor (1986) used the rapidity of change in house values over time in a sample of Baltimore neighborhoods from 1970 to 1980 to identify rapidly gentrifying neighborhoods. Areas that had appreciated the most over the decade were areas that had previously been high crime locations at the beginning of the decade. They found that rapid gentrification increased the relative reported robbery and larceny rates in the gentrifying neighborhoods.

What might be taking place in the current study is that one or more of the variables used to create the instability index might also be indicative of the process of gentrification. In other words, not all population migration has a negative destabilizing impact on community life despite the fact that population turnover is routinely viewed as a sign of instability. It is plausible that the out-migration of undesirable residents and the in-migration of desirable residents in some CBGs registers as instability when it might also be associated with less motor vehicle theft in the area due to the new residents being more affluent, less motivated by criminal opportunities, more law abiding, and more diligent about maintaining territorial control and protecting their personal property.

The previous explanation, while plausible, does not conclusively address the issue raised by the findings. Additional research and inquiry are necessary in order to more conclusively explain the events taking place and micro level data collection might be necessary to shed more light on the role of gentrification in the study location.

Similarly contradictory results were uncovered in a study by Bursik (1986) that looked at lagged and contemporaneous effects of SES and race on delinquency changes. Bursik (1986) did not find any connection between SES and delinquency. Interestingly though, high rates of delinquency in 1960 predicted increases in SES in 1970. Generally, it would be expected that high rates of delinquency would be associated with decreasing SES and destabiliztion of the community area. A plausible explanation offered by Bursik (1986) suggests that gentrification could be the intervening factor not being accounted for. The delinquent neighborhoods in 1960 could have experienced gentrification during the decade and the in-migration of more affluent individuals capitalizing on initially low property costs.

There is also an anecdotal finding that, while not directly linked to the hypotheses proposed in the study, is interesting in that it is contrary to what would be expected given the community context, characteristics, and circumstances.

For example, as previously discussed, the city of Peoria improved over the decade in terms of SES and Instability. Some of the low SES and Instability in 1990 may have been the result of a national economic downturn in 1987. Things dramatically improved over the decade from 1990 to 2000. However, in 2000 Peoria County had the highest crime rate in the state with 71 crimes reported per 1000 people in the population. The city crime rate increased by 3.5 percent from a decade earlier.

This is quite contrary to what one would expect given the structural improvements that took place over the decade. The reason for this increase is not known at this time but it could be related to riverboat gambling, racial composition of the city, density and number of young males in the population, or other structural changes that took place around the county. Affordability could also be an issue and whether or not the improvements that were experienced as a whole for the county and city were experienced by all. Relative depravation and poverty could be having an impact, especially given the economic boom that was felt by many towards the end of the decade as the stock market climbed and employees earned more. Not surprisingly, these impacts were not felt across all echelons of the social strata. Further exploration of this phenomenon is warranted.

### *Strengths of the Study*

There are several strengths of this study that are worth mentioning. Motor vehicle theft data is unique in that the crime of motor vehicle theft is not accompanied by social stigma causing victim reluctance in reporting. In fact, quite the opposite is true and many states have laws that require victims of motor vehicle theft to report motor vehicle theft to law enforcement before they are able to file an insurance claim for damage to or loss of a stolen vehicle. As a result, the numbers of thefts and associated theft rates are more accurate than the numbers and rates for many other crimes as evidenced by a cross comparison between the Uniform Crime Report (UCR) and the National Crime Victimization Survey (NCVS). This is probably especially true given that there is an economic loss that most people seek to have recovered. The current study benefited from what is presumed to be high reporting rates of motor vehicle theft in the study area. This is likely true even despite prevalent victim blaming for careless security precautions.

This research demonstrates a methodologically unique approach to studying vehicle theft by incorporating "new" normalized Census data sources and employing several techniques of analysis never before used in studying this crime. The methods of inquiry and the types of analyses assisted in addressing several specific problems that have emerged in the ecological study of crime.

An additional strength of this study is the rich data that was available. The study benefited from a subset of eleven years of motor vehicle theft data that was provided to the researcher. The data allowed for both cross-sectional and longitudinal analyses lending to a more thorough review of the motor vehicle theft phenomenon in the study area. This study lends itself well to parallel studies of burglary and possibly even robbery. The techniques employed here are relatively easily adaptable to other crimes.

Finally, this study benefited from thorough analysis of the data utilizing multiple methods of analyses including both cross-sectional and longitudinal exploration. Particular attention was paid to diagnosing any and all emergent problems with both the data that was used for the dependent variable as well as the Census data that was used to create the predictors. Edge effects, the modifiable area unit problem, and spatial autocorrelation were all controlled for in an effort to put forth the most valuable results possible given the various circumstances that often present themselves when studying crime spatially at various levels of aggregation.

### *Limitations of the Study*

The current research was limited by several constraints that need to be addressed. First, this study relied heavily on secondary data sources, specifically police department motor vehicle theft data, and Census Bureau data for decennial survey's 1990 and 2000. As a result, there is an issue regarding the recording practices of police departments and the potential for "human error." There is no need here to detail an exhaustive list of all of the potential problems that can be encountered when using "official" records data generated by law enforcement but several of the common issues are: data entry errors, definitional problems, reporting practices, and unreliable vehicle recovery locations. In addition, census data is not immune to human error either and the potential for error, albeit slight, should not be disregarded.

The mapping portion of this study revealed a problematic issue with a unique solution. During the geocoding process - address matching crime incidents to a geographic location on a base map - several addresses did not register with the citywide base map that was acquired by GDT and could not be placed using this traditional method. In an effort to match as many vehicle theft locations as possible, a systematic "manual" matching procedure was developed whereby MapQuest and Yahoo Maps were used to cross-reference each missing address in an effort to identify the accurate location and place a corresponding point on the city base map. A minimal number of thefts were subsequently "manually" placed in their respective and corresponding block groups with as accurate of a placement as possible. This would have been more problematic if the face block were the unit of analysis but placement within the larger block group unit was done with confidence in placement accuracy.

Another issue that deserves mention is that not all of the variables that could have been useful in the study were collected and used. For example, land use data characterizing use functions into commercial, residential, mixed, municipal, and so on, has a reoccurring role in some contemporary ecological literature and its relationship to a variety of crimes has been extensively studied (see Kurtz, Koons, and Taylor, 1998). Land use has application to the theories of routine activities, territorial functioning, as well as social ecology in terms of mixed use characteristics, crime attractors and generators, creating suitable targets and concentrations of motivated offenders. Common measures of land use have been gathered from Census datafile, city zoning commissions, business directories and telephone books. Additionally, the presumably significant role of land use in the occurrence of motor vehicle theft makes it a desirable spatial construct to explore. However, due to data source constraints land use was not included in the current study.

Also, the time interval of one decade (1990-2000) may or may not have been an appropriate amount to model ecological changes over time. Some would argue that a longer interval is more suitable. Ecological change resulting in increased community crime generally requires degeneration of both informal and formal social controls. While there is no set time limit for this to occur, there are numerous factors which must overlap in time and space to create conditions conducive for community decline, including the erosion of controls, competing values, reduced community cohesion and subsequent surveillance, disorganization, etc. A decade of time may or may not be enough time. However, longitudinal analyses requires only two measurement points in time and occasionally incorporates multiple waves of data collection added sequentially. The current study takes the first step towards this objective.

Additionally, the size of the unit of analysis could be temporally related to community change. That is, a smaller unit of analysis (ex. faceblock) might experience change more rapidly and completely with potential offenders more apt to recognize these changes. A larger unit of analysis could actually diffuse the effects of decline in more mirco areas obscuring the social processes that impact motor vehicle theft. It is important to note however, that the size of the unit of analysis in this study is an improvement over what has traditionally been used in many motor vehicle theft studies.

Also, it is possible that additional or alternative predictor variables could be included in the analyses. The constructs of SES and Instability have a history in the community crime literature and it is possible that alternative measures of these constructs could be created. The inclusion of additional indexes such as family disruption/stability could also yield interesting results.

With regard to the theoretical constructs of the study, this study is modeled after the ecological inquiry of the Chicago School that views crime as an outgrowth of social processes occurring largely through group dynamics in response to environmental factors. This study does not purport to test the intervening micro level processes that come between the structural dynamics and the resulting crime but rather identifies several of the antecedent factors and associates them with various theoretical underpinnings at the meso level, prevailing approaches as well as possible alternative explanations. In this regard, the lack of inquiry into micro level community processes related to theory testing remains a deficit present in the ecological literature. A follow-up to this study intends to address issues identified here by reviewing micro-level data sources in an effort to study specific social processes.

Finally, the generalizability of the current findings are unknown given that the study was conducted as a case study analysis in a specific medium size city which may or may not be experiencing similar structural shifts as other cities in the U.S. Comparative research and follow up are necessary before generalization of the findings would be possible. This is a particularly common weakness of case study analysis. It is difficult to know whether the events and experiences of the study area are exclusive to the area or if they have broader application.

### *Theoretical Implications*

Several findings in this study support the previous contention that there is a need for theoretical refinement. First, although several of the findings are consistent with the existing literature testing a limited number of theoretical perspectives, one of the issues that has been raised here is the use of census demographic data to operationalize complex dynamic ecological processes taking place within the social structure. This is not sufficient to test the theories of social disorganization or routine activities, or most other theories contingent upon micro level social dynamics for that matter.

The findings here lend support to several of the antecedent precursors that often lead to social processes which in turn lead to diminished social control resulting in community crime. Several of the predictors of motor vehicle theft that one would expect to have been significant however, were not. So, either these predictors are not useful for studying motor vehicle theft; or other factors are mediating their impacts; or unmeasured factors such as land use, and territorial control and management are more important. It is also possible that theory refinement is necessary in combination with additional micro-level data collection. For example, instability is only significant in one cross-sectional model and that model had SES removed. Under the tenets of social disorganization one would expect that community instability and SES would be indicators of the processes leading to disorganization.

Additionally, instability, when significant in the longitudinal lagged ecological effects model, was significant in the unexpected direction. This clearly is contrary to the social disorganization model and requires micro level examination and articulation.

It is plausible that tenets of other theoretical perspectives such as territorial functioning are mediating the effects of low SES and young males (14-17 and 18-24), resulting in less criminal activity. It is also possible that these potentially mediating factors are displacing crime to surrounding less likely areas. Additionally, it is possible that the cultural diversity model better explains the effects of heterogeneity on motor vehicle theft in the community than the traditional tenets of social disorganization. For example, there may be a general fear of unfamiliar and unknown residents who are culturally different than one's self. This fear could be inhibiting and impeding resident involvement in the external community environment or when suspicious behavior is observed such as suspicious vehicle entry or removal. The result could be a general lapse in informal social control creating suitable opportunities for criminal activity within areas of the community.

In sum, the findings of this study have been informative and have offered new theoretical insights into the crime of motor vehicle theft, albeit in the form of new questions. The factors impacting the complex systemic community dynamics in the CBGs around the city of Peoria however, require further micro level exploration and further theory refinement and operationlaization.

We have established that the macro level antecedent factors studied here actually support portions of several theoretical underpinnings leading to a variety of potential alternative theoretical explanations. Additionally, we have ascertained that the fit of the theoretical model may also depend on whether or not we are looking at the crime of motor vehicle theft cross-sectionally or longitudinally as some of the significant predictors and results tend to differ based upon this distinction.

### *Policy Implications*

The potential policy implications for motor vehicle theft research are significant and broad. Both public and private insurance companies and insurance consortiums are continually assessing the models they use to calculate the insurance premiums that they charge their customers. These sophisticated actuarial algorithms often include the make, model, year, and value of the vehicle, as well as the age of the driver, the location of residence in terms of urban or rural, and several additional, often discrete, factors. This line of research and subsequent follow up studies will help address the issue of ecological risk prediction. Research that explores the phenomenon of motor vehicle theft could impact not only the models that insurance companies use to assess the risk of motor vehicle theft in unique environments in a community but they could also impact city planning efforts in the form of CPTED strategies, along with the allocation of resource decisions made by law enforcement.

The theoretical framework guiding this scientific inquiry is rooted in the ecological study of community structure and changes in community structure and its impact on crime, specifically motor vehicle theft. The literature review addresses a reoccurring theme in communities and crime research, that being the importance of community cohesion and order maintenance through informal social control. Informal social control refers to a community's ability to control deviant criminal behavior and the willingness of residents to intervene when the social order is threatened.

This study identified several antecedent factors that may lead to the breakdown or inhibition of community efforts to maintain social control such as: heterogeneity in the population, low socioeconomic status, and community instability, which all show a relationship to the crime of motor vehicle theft in one way or another.

An essential aspect of stable community living according to the communities and crime literature and the theoretical perspective of social ecology involves order maintenance through social control and cohesion among residents. While the current study did identify several antecedent predictors that may inhibit both of these objectives it is difficult to talk in specifics at this point in time.

Several of the research results that could facilitate policy decisions in the future appear to rely on several issues: the dynamic mirco level processes present and the context of those processes; and whether or not one is looking at the cross-sectional finding or the longitudinal lagged effects findings. For example, longitudinally the SES variable is not as good a predictor of motor vehicle theft as it is when reviewing the cross-sectional results.

One area that does offer promise with regard to policy implications is the role that heterogeneity plays. Given that there has been such widespread racial population shifting within the city of Peoria and that heterogeneity was a significant predictor of motor vehicle theft in all of the cross-sectional models for Time 2 and in all of the longitudinal lagged effects models for both lagged and unexpected change predictors, one might develop policies that serve to facilitate community cohesion in heterogeneous communities. For example, if Merry's (1981) cultural diversity model is correct and has application in explaining vehicle theft in the study area then we would want to facilitate a reduction in the fear of one's neighbors in an effort to build community cohesion. Efforts to strengthen community bonds among neighbors living in close proximity to one another, despite differences in race and ethnicity, could help to ward off crime. Cultural awareness workshops, neighborhood picnics, and participation in neighborhood associations could all serve to increase knowledge about one's neighbors and it turn reduce the fear of the unknown. In sum, strengthening community member ties and neighborly relationships will help to foster stronger informal controls and reduce the fear of the unknown. A continued course of both racial and economic segregation will only serve to produce additional social problems and undermine efforts at community stability. Additional support for diversity is needed to foster cohesion and reduce fear. Efforts such as those previously mentioned should be implemented.

There is great importance moving forward to develop a better understanding of the role that instability plays in the community in terms of housing tenure and gentrification and to determine if the process inhibits crime – the findings suggest that instability is generally not an issue in terms of motor vehicle theft and in fact more instability was actually related to fewer motor vehicle thefts in the lagged effects model. One would not suggest that instability somehow prevents crime but factors associated with instability, like gentrification, must be reviewed more fully and policies that promote the mediating factors should be put in place.

In terms of recommendations to the line level officer, it is difficult at this point in time to identify areas that law enforcement practices could have a direct impact on motor vehicle theft. While there are likely improvements which can be made in terms of territorial controls, CPTED, defensible space, and other control oriented outcomes as a result of limited tactical intelligence at the street level it is not prudent to speculate on the presence or absence of these strategies before more data is collected.

At this point in time it is the belief of this author that the findings are still likely to be considered to be to far removed from the micro level of the community to facilitate sound policy initiatives that would be specific enough to assist in the direct reduction of the crime of motor vehicle theft. More simply stated, there are too many degrees of separation between the antecedent predictors and the motor vehicle theft outcome to be able to suggest succinct policies that could be implemented by line level officers to change the course of events. Certainly relationships between community block group level factors and motor vehicle theft are present and policies could improve crime control efforts but specific policies for the most part are still out of reach.

*Contribution to the Knowledge Base*

The present research offers several advancements to the study of motor vehicle theft and extends the depth of knowledge and understanding regarding vehicle theft beyond its current place in the criminological literature. The void in the existing literature has already been identified and this research effort is a contribution towards filling that void.

The current study addressed the crime of motor vehicle theft from a smaller spatial unit of analysis, the census block group, rather than the commonly used census tract or city unit. The smaller unit of analysis was subsequently associated with demographic predictor variables derived from a smaller level of aggregation, the block group, as well. By reducing the size of the spatial unit of analysis and the level of aggregation we have moved one step closer to capturing the actual context of the event.

Also, it has been possible to identify vehicle theft predictors at the block group meso level that allow for honing in on community dynamics/social processes contributing to motor vehicle theft. That statement is by no means intended to suggest that we have done anywhere near all that we can do with regards to the geographic spatial unit, quite the contrary. In fact, if anything, this study helped us understand that there is much work yet to be done at the micro level of the community to identify complex social processes and micro level mechanisms of informal social control. Continued efforts to collect data that measures the micro level process associated with the maintenance or breakdown of informal social control within the community setting will be a continuing objective.

Additionally, the current study not only went beyond the usual single-wave cross-sectional analysis of motor vehicle theft, one year or less, by adding two waves of data

1990/91 (Time 1) and 2000/01 (Time 2) but also added a longitudinal lagged effects component. Until recent developments in the utility and adaptability of census data there was virtually no opportunity to study and compare large numbers of demographic predictors over time across identical spatial units of analysis. For example, the 1990 and 2000 decennial censuses could not be compared from one time to the next due to widespread spatial boundary changes – also known as the modifiable area unit problem. Redistricting and shifting population densities between during the decade resulted in changing census boundaries over time. However, newly available census data analysis products like those provided by Geolytics which normalized the census boundaries and demographics over time made it possible to look at two waves of cross-sectional data, 1990/91 and 2000/01 and draw conclusions about changes from one period of time to the next.

Additionally, besides new data products allowing for additional waves of cross-sectional data they also created an opportunity to do longitudinal analyses studying the lagged and contemporaneous unexpected change effect of several structural predictors on the motor vehicle theft outcome variable. To the best of this author's knowledge, this is the first research endeavor of this kind to study the crime of motor vehicle theft incorporating both cross-sectional and longitudinal lagged effects models. The results of the two different analytical approaches suggest that there are different dynamics impacting vehicle theft depending on which type of analysis is being conducted.

Another contribution of the current study is the identification of potential alternative theoretical explanations for the dynamic processes involved with the crime of motor vehicle theft. One of the objectives of the current study was to show that at the level of aggregation that most vehicle theft research is using there are multiple possible explanations for the relationship that has been shown to exist between several of the predictors and the outcome. The literature has traditionally approached the crime of motor vehicle theft from a limited number of theoretical orientations and has neglected alternative approaches that are also seemingly applicable, at least until more micro level relationships and explanations are examined.

Contrary to much of the existing literature (see Rice and Smith, 2002; Copes, 1999) the current study found a strong relationship between heterogeneity and motor vehicle theft. The current study also found a paradoxical relationship between Instability and motor vehicle theft that needs to be further explored. The current study supports the existing literature in that SES is a significant predictor of motor vehicle theft when studied cross-sectionally. However, SES is less significant when studied longitudinally. Spatial autocorrelation was a significant predictor in Rice and Smith's (2002) study but showed mixed results in the current study and experienced diffusion when included in models with SES. Contrary to the literature, male age categories showed virtually no significant relationship to motor vehicle theft either cross-sectionally or longitudinally. This could be due to the level of aggregation used.

The findings of the current study demonstrate the need to collect more data at the micro level of the community through observation and interview in order to better understand the social processes that take place during times of changing community structure.

*Implications for Future Research*

The next step in the research is to devise methods of data collection that measure the micro level processes within the community that more accurately operationalize the theoretical perspectives. For example, additional data sources may be gathered including: land use in terms of residential and different types of commercial activity space, lighting, disorder, sources of surveillance, community activities and outlets attracting youth. Knowing where parking lots and spaces are located could provide valuable information in terms of suitable targets and criminal opportunities. The presence of garages, as well as whether or not they are attached or unattached. Particularly insightful would be to contrast the high vehicle theft areas with the low vehicle theft areas within each decade as well as across both decades. Measures of territorial control in neighborhoods of differing theft concentration could be informative. For example, a variation on the territorial contamination experiment conducted by Worchel and Lollis (1982) whereby bags of garbage were placed in front yards, on the sidewalk, and in the street in an effort to determine how long it took residents to respond could yield interesting findings, the suggestion being that trash that was addressed sooner is probably in areas reflective of greater property maintenance and upkeep (Taylor, 1988b).

There are 96 neighborhood associations in the city of Peoria and interviews with members regarding perceptions of high risk location, community cohesion, etc. could be an informative source of information. Efforts will also be made to acquire arrest records for vehicle theft offenders in order to refine existing motor vehicle theft offender profiles.

An important aspect of vehicle theft that is not thoroughly addressed by the current study, or those before it, is the role of context - the circumstances in which the criminal event occurs; the setting. The next step of the research involves specifically identifying the breakdown in social control mechanisms as they pertain to the context of the vehicle theft utilizing several possible approaches. Several of these additional approaches have been addressed.

As previously mentioned in the study limitations discussion, one noticeably absent feature in the current study, as well as many before it, is land use. Land use is an essential part of crime setting. Land use and related zoning ordinances dictate how social space is used which has a significant impact on community development, opportunity structure, population concentration, cohesion, travel patterns, and the like. The role that land use has in terms of structuring criminal opportunity can not be overstated. Land use data can be collected from city zoning commissions, and some U.S. Census files. An example of a hypothesis taking land use into consideration would be: locations consisting of commercial entertainment establishments that cater to young people will have more vehicle thefts.

Another avenue of additional research will focus on why Peoria's theft count soared during the 1990's and was so out of step with the national vehicle theft trend. Identifying community characteristics that are accurate predictors of motor vehicle theft was the intention of the current study. Identifying the factors associated with such dramatic increases over the decade, given the overall national decline, is an important step towards controlling and managing vehicle theft in the study area and will be explored further in subsequent research.

Based on the dramatic upward trend in thefts while the national trend was downward, initial speculation is that Peoria is atypical of most places in the U.S. including those of comparable size and demographic composition. If this speculation is in fact true, that makes generalizing the findings of this study impractical. However, investigation into why the incidence of motor vehicle theft was so unique when compared to the broader country as a whole is an interesting and informative follow up study.

Another neglected avenue of inquiry is the motor vehicle thief. As previously stated the arrest rate for motor vehicle theft is surprising low. The few individuals who are arrested tend to be young males. A great deal could be learned from additional study of offenders who steal vehicles. The existing typologies that exist and are based upon arrested offender characteristics have not been updated or explored in any recent research this author is familiar with. Updating the offender typologies and validating offender characteristics with current data could be a valuable undertaking in terms of furthering the understanding of the context of motor vehicle theft with regard to who is actually doing the stealing.

In conjunction with the previously discussed updating of offender typologies, future research could try to develop accurate offender profiles based on arrest data and possibly even self reports. An important part of the offender profile could be a geographic component looking at the offender's home address. This would allow for the addition of a travel pattern dynamic to the existing offender typology. How far do motivated offenders travel when looking for a vehicle to steal and does this vary depending on the various motivations for offending? What proportion of thieves are amateur joyriders versus those that can be characterized as professional thieves?

Also, previously alluded to but not directly explored, is the role that riverboat gambling played in creating new opportunity structures over the course of the decade. The riverboat first opened up for business in the early 1990s and how it has impacted the local community both positively and negatively have not been explored in this study. It is likely and reasonable to think that is has had some impact, the extent of the impact is yet unknown. Visitors to the area tend to stay in one of the hotels in the downtown area of Peoria which provides easy access to the gambling boat as well as additional outlets for entertainment, recreation, and food. Of interest for future research would be the number of vehicles stolen that belong to residents staying in one of the areas downtown hotels. This would help to answer the question of how the riverboat gambling has changed the opportunity structure for vehicle theft in the city. Of course it would also be interesting and beneficial to study the overall impact of riverboat gambling on the incidence of crime in Peoria to see how it has impacted the lives of area residents.

Similarly related to this issue is the role that Bradley University might have played over the decade in terms of creating an opportunity structure for vehicle theft on the Southside of the city. There are several directions to go with this line of inquiry. The student body of Bradley may provide a large number of targets both on campus and in the surrounding area. Knowledge about the number of vehicles owned by students could be valuable, especially if an increase in vehicle ownership coordinates over the decade with increasing vehicle thefts. There is also the possibility that students are participating in joyriding to get around the downtown entertainment area. In addition, the question could be asked, how does the student body of Bradley University impact community stability, heterogeneity, and SES? Has the campus been expanding or contracting and has there been any change in the percentage of students living in on-campus housing as compared to off-campus housing over the decade? These are additional avenues of inquiry that have not been explored but could be could be to provide a more complete understanding of vehicle theft in the city.

Another important area of inquiry is whether or not the vehicle recovery locations would yield similar results in terms of SES, Instability, and heterogeneity to those in the present study. Vehicle recovery is an area of research that is virtually nonexistent in the literature. However, it is an important aspect of the criminal event because it provides an indication of why the vehicle was stolen. Additionally, it could yield helpful insights into the proximate location where the offender resides, works, or recreates. Geographic profiling uses serial offenses to identify likely target areas to search for suspects through sophisticated techniques of triangulation.

Vehicle theft has two related components which can provide unique insight into both the criminal event and the offender: it has a theft location and in many instances a recovery location. These two components assist in completing the criminal event. However, recording of the recovery location and associated data tends to not be as accurate as the theft data so extensive cross-checking and data cleaning are necessary.

The make, model, year, and geographic location of the vehicle when stolen could all be of interest to insurance companies. Future research could explore these aspects of the data more thoroughly.

Insurance companies attempt to set their rates in part based on actuarial prediction of the risk of theft. Areas that score highest in ecological risk prediction garner higher premiums and areas of lower risk are assessed lower premiums. The state of New Jersey has the highest auto theft rates in the country and not surprisingly, Newark, New Jersey has regularly been one of the cities leading the nation in stolen motor vehicles. The actuarial methods used to predict risk are multifaceted including both the characteristics of the vehicle (ex. alarm present, make, model, year, etc.) and the characteristics of the environment where the resident lives. Insurance companies have long been very private about their formulas for calculating risk and the associated insurance premiums that vehicle owners are charged. Further examination of the criminal event as well as the environment could possibly yield some new information by which to better predict risk.

Finally, another interesting follow up study involves looking to see if motor vehicle theft rates track with other index crime like burglary and/or robbery. Karmen (2000) found that in New York City from 1978 through 1998, the murder rate and the vehicle theft rate tended to correlate with one another. This is no longer the case in the new millennium as the murder rate has held stable while vehicle thefts have continued to plunge. However, the question is none the less interesting, are there other index crimes that correlate with motor vehicle theft in the study area and nationally? The question begets whether there are antecedent factors that predict multiple types of crime? The literature exploring this topic is rich but motor vehicle theft has not been one of the crimes looked at in connection to others. Traditional approaches have generally focused on murder and burglary and robbery. Plouffe and Sampson (2004) found that motor vehicle theft did not match overall crime rates in all areas. Some cities with high crime rates had low motor vehicle theft rates and visa-versa.

In sum, not only were several unique contributions made in terms of study design, methodology, analysis, and theoretical inquiry but there were also several findings made that offer strong potential for further research and exploration. Some of the significant findings are contrary to the existing literature on motor vehicle theft and deserve more attention. The current study results also offer promising future avenues to pursue which could have direct policy implications with regard to insurance premiums, community structure, composition, change and motor vehicle theft. While direct policy implications and coordinated tactical approaches by law enforcement are yet out of reach, future research to address these issues is an important next step in connecting community social structure and change to motor vehicle theft. Previous sections of this study have identified specific approaches for future research efforts to continue to build upon and contribute to furthering the understanding of motor vehicle theft from an ecological perspective while taking into consideration alternative theoretical underpinnings.

# APPENDIX A

# CONTROLLING FOR SPATIAL AUTOCORRELATION

As discussed previously, spatial autocorrelation is a phenomenon whereby events in one location are affecting and having an impact on events in another location within a geographic study area. Community crime researchers recognize the need to account for these extraneous impacts and effects and as a result have developed several techniques for addressing spatial autocorrelation.

The method that was used in this study to control for spatial autocorrelation involved the use of "potential variables" (see Land and Dean, 1992; and Roncek and Montgomery, 1984). The use of potential variables is considered one of the more accurate measures of spatial autocorrelation because it controls for the impact of criminal events throughout an entire geographic study area while taking into account distance from the target unit, rather than simply controlling for contiguous land units. The crime-potential variable measures the cumulative proximity of motor vehicle theft of all the areas surrounding a particular place.

The formula for calculating the current crime potential variables according to Land and Dean (1992) is as follows (with minor modification):

$CP_i = \Sigma\ (P_j/D_{ij});\ j \neq i;\ \ i = 1,\ldots,n,$

where:

$CP_i$ = the crime potential for location $i$ ($i$ = the target CBG)

$P_j$ = the number of motor vehicle thefts for CBG$j$ in the environment of CBG$i$

$D_{ij}$ = is the distance of CBG*j* from CBG*i*, and the summation is taken over all locations *j* other than *i*.

To calculate the motor vehicle theft crime potential for CBG*i* it is necessary to take the summation of vehicle thefts divided by the distance from CBG*i* for all CBGs in the city.

The step-by-step mechanics for calculating the potential variables in this study were derived from the work of Dr. Ellen Kurtz (2000). The first step of the process required locating the centroid of each census block group (N=90) in the city of Peoria using Geolytics mapping software. The centroid is the latitude and longitude centerpoint of a geographic unit. These centroids were used to calculate the distances between block groups. Next, a matrix (90 columns by 90 rows) was created in Excel to show the distance of each block group from the others in the city. Then, the number of motor vehicle thefts in each block group was divided by each column of the distance matrix, creating motor vehicle theft crime scores weighted by the inverse of the distance. Next, a summation of this division was calculated (a process repeated 90 times – once for each CBG in the city). The resulting summary number is the motor vehicle theft potential variable for the target block group. Two motor vehicle theft crime potential variables were calculated, one for the 1990/91 thefts and a second for the 2000/01 thefts (see Kurtz, 2000).

The crime potential variables must be "cleaned up" due to how they are used in the regression equations. The resulting crime potential variable can not simply be entered into the regression equation because in spatial effects models the spatial diffusion processes are determined simultaneously, producing a correlation between the potential variable and the error term, which violates an assumption of ordinary least squares regression estimation (Land and Dean, 1992). Using a two-stage process to correct this problem, instrumental variables that were good predictors of the potential variables were identified. Based on Kurtz's (2000) research, distance from the Central Business District and the interaction between a block group's latitude and longitude were selected as the requisite instrumental variables. The combination of the three resulted in high $R^2$ values of .683 for 1990/91 and .635 for 2000/01.

# BIBLIOGRAPHY

Akers, R. L. (2000). *Criminological Theories: Introduction, Evaluation, and Application.* (3rd Ed.). Los Angeles, CA: Roxbury Publishing Co.

Auto Theft Insurance Information. (n.d.). *Hot Wheels.* Retrieved December 14, 2001, from http://www.insure.com/auto/thefts/nicb01.index.html.

Belsley,D.; Kuh, E.; and Welsch, R. E. (1980). *Regression Diagnostics: Identifying Influential Observations and Sources of Collinearity.* Belmont, CA: John Wiley and Sons.

Benko, J. Peoria Police Department Personnel. Personal Correspondence from May 5, 2001 to August 2004.

Biederman, A., Johnson, L. and Weir, A. (1967). *Report on a Pilot Study in the District of Columbia on Victimization and Attitudes Towards Law Enforcement.* Presidents Commission on Law Enforcement and Administration of Justice. Washington, DC: Government Printing Office.

Biles, D. (1977). "Car stealing in Australia." *Delinquency in Australia.* St. Lucia: University of Queensland Press

Block, R. L. and Block, C. R. (1995). "Space, place and crime: Hot spot areas and hot spot places of liquor related crime." In J. Eck and D. Weisburd (Eds.), (vol.4). *Crime Prevention Studies: Crime and Place.* Monsey, NY: Criminal Justice Press.

Boggs, S. (1965). "Urban crime patterns." *American Sociological Review*, 30, 899-908.

Bottoms, a. E. and Wiles, P. (1988). "Crime and housing policy: A framework for crime prevention analysis." In T. Hope and M. Shaw (Eds). *Communities and Crime Reduction.* London: Her Majesty's Stationery Office.

Brantingham, P. J. and Brantingham, P. L. (1984). *Patterns in Crime.* NY: Macmillan Publishing Company.

Brantingham, P. J. and Brantingham, P. L. (1991). *Environmental Criminology.* Beverly Hills, CA: Sage Publications.

Brantingham, P. J. and Brantingham, P. L. (1998). "Environmental criminology: From theory to urban planning practice." *Studies on Crime and Crime Prevention*, 7, (1) 31-59.

Brantingham, P. L. and Brantingham, P. J. (1999). "A theoretical model of crime hot spot generation." *Studies on Crime and Crime Prevention* 8, (1) 7-26.

Brill, H. (1982). "Auto theft and the role of big business." *Crime and Social Justice*. 18, 62-68.

Brown, S. E., Esbensen, F. A. and Geis, G. (2001). *Criminology: Explaining crime and its context*. (4th Ed). Cincinnati, OH: Anderson Publishing Co.

Bursik, R. J. (1986). "Delinquency rates as sources of ecological change." In Byrne, J. M., and Sampson, R. J. (Eds.) *The Social Ecology of Crime*. New York, NY: Springer-Verland Inc.

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

Bursik, R. J., and Grasmick, H. G. (1993). *Neighborhoods and Crime: The Dimensions of Effective Community Control*. NY: Lexington Books.

Byrne, J. M., and Sampson, R. J. (1986). "Key issues in the social ecology of crime." In Byrne, J. M., and Sampson, R. J. (Eds.) *The Social Ecology of Crime*. New York, NY: Springer-Verland Inc.

Chakravorty, S. and Pelfrey, W. V. (2000). "Exploring data analysis of crime patterns." In Goldsmith, V., McGuire, P. G., Mollenkopf, J. H., and Ross, T. A. (Eds). *Analyzing Crime Patterns: Frontiers and Practice*. CA: Sage Publications.

Choldin, H., Hanson, C., and Bohrer, R. (1980). Suburban status instability. American Sociological Review, 45, 972-983.

Clarke, R. V. (1983). "Situational crime prevention: Its theoretical basis and practical scope." In Tonry, M. and Morris, N. (Eds) Vol. 4. *Crime and Justice: An Annual Review of Research*, Chicago: University of Chicago Press.

Clarke, R. V. (1987). "Practicalities of preventing car theft: A criminological analysis." In *Car Theft: Putting on the Brakes*, Seminar on Car Theft, National Roads and Motorist Association.

Clarke, R. V. (1991). *Preventing Vehicle Theft: A Policy-oriented Review of the Literature*. Scottish Office: Central Research Unit.

Clarke, R. V. and Harris, P. M. (1992a). "A rational choice perspective on the targets of automobile theft." *Criminal Behavior and Mental Health*. 2, 25-42.

Clarke, R. V. and Harris, P. M. (1992b). "Auto theft and its prevention." In Tonry, M. (Eds). *Crime and Justice: A Review of Research*, (vol.16). Chicago, IL: University of Chicago Press.

Clarke, R. V. and Mayhew, P. (1994). "Parking Patterns and car theft risks: Policy-relevant findings from the British crime survey." 91-107.

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

Copes, H. (1999). "Routine activities and motor vehicle theft: A crime specific approach". *Journal of Crime and Justice*, 22, (2), 125-146.

Cornish, D. B. and Clarke, R. V. (1987). *The Reasoning Criminal: Rational Choice Perspectives on Offending*. NY: Springer.

Covington, J. C., and Taylor, R. B. (1989). "Gentrification and crime: Robbery and larceny changes in appreciating Baltimore neighborhoods in the 1970's". *Urban Affairs Quarterly,* 25, 142-172.

Covington, J. C., and Taylor, R. B. (1991). "Fear of crime in urban residential neighborhoods: Implications of between- and within-neighborhood sources for current models". *The Sociological Quarterly,* 32,(2), 231-249.

Crutchfield, R., Geerken, M. and Grove, W. (1982). "Crime rate and social integration". *Criminology*, 20, 467-478.

Cullen, F.T. and Agnew, R., *Criminological Theory: Past to Present*. Los Angeles, CA: Roxbury Publishing Co.

Currie E. (1988). "Two visions of community crime prevention." In T. Hope and M. Shaw (Eds). *Communities and Crime Reduction*. London: Her Majesty's Stationery Office.

Davison, E. L. (1995). *An Ecological Analysis of Crime in a Mid-Sized Southern City: Tests of Routine Activity and Social Disorganization Approaches.* Unpublished Dissertation: North Carolina State University.

Davison, E. L. and Smith, W. R. (2000). "The relationship between crime and urban location in Raleigh, North Carolina". *Sociation, 25, 35-44.*

Faggiani, D. (1994). *Social Disorganization and Individual Choice: A multi-level causal model of the etiology of delinquency.* Unpublished Dissertation: University of Illinois at Chicago.

Felson, M. (1987). "Routine activities and crime prevention in the developing metropolis." *Criminology*, 25, 911-931.

Felson, M. (2000). "The routine activity approach as a general crime theory." In Simpson, S. (Ed.), *Of Crime and Criminality: The Use of Theory in Everyday Life*. Thousand Oaks, CA: Pine Forge Press.

Fester, L., Schachter, S. and Back, K. (1959). *Social Pressures in Informal Groups*. Stanford, CA: Stanford University Press.

Field, S., Clarke, R. V. and Harris, P. M. (1992). "The Mexican vehicle market and auto theft in border areas of the United States." *Security Journal* 2, 210-225.

Gabor, T. and Gottheil, E. (1984). "Offender characteristics and spatial mobility: An empirical study and some policy implications." *Canadian Journal of Criminology*, 26, 267-281.

Gladwell, M. (2000). *The Tipping Point: How Little Things Can Make a Big Difference*. NY: Little, Brown and Co.

Gordon, R. (1968). Issues in the ecological study of delinquency. American Sociological Review, 32, 927-944

Gottfredson, S. D. and Taylor, R. B. (1988). "Community contexts and criminal offenders." In T. Hope and M. Shaw (Eds). *Communities and Crime Reduction*. London: Her Majesty's Stationery Office.

Gould, L. C. (1969). "The changing structure of property crime in an affluent society." *Social Forces* 48, 50-59.

Green, A. (2003, July 27). Peoria cracking down on car thefts: County seventh in state for number of stolen automobiles. Peoria Journal Star, pp. C4.

Hamilton, L. (1992). *Regression With Graphics*. Belmont, CA: Wadsworth.

Henry, L. M., and Bryant, B. A. (2000). "Visualizing the spatio-temporal patterns of motor vehicle theft in Adelaide, South Australia." Retrieved http://www.aic.gov.au/conference/mapping/henry.pdf.

Hindelang, M.J. (1978). "Race and involvement in crimes." *American Sociological Review* 43, 93-109.

Hollinger, R. C. and Dabney, D. A. (1999). "Motor vehicle theft at the shopping center: An application of the routine activities approach." *Security Journal,* 63-78

Hope, T. and Hough, M. (1988). "Area, crime and incivility: A profile from the British crime survey." In T. Hope and M. Shaw (eds). *Communities and Crime Reduction*. London: Her Majesty's Stationery Office.

Hope, T. and Shaw, M. (1988). *Communities and Crime Reduction.* London: Her Majesty's Stationery Office.

Hunter, A. (1985 ). "Private, parochial and public social order: The problem of crime and incivility in urban communities." In G. Suttles, & M. Zald (Eds.), *The Challenge of Social Control.* Norwood, NJ: Ablex Publishing.

Illinois Motor Vehicle Theft Prevention Council. (2003). *Annual Report Illinois Motor Vehicle Theft Prevention Council.* Retrieved November 30, 2004, from www.icjia.state.il.us/mv

Insurance Information Institute. (2001). *Auto Theft Hot Topics and Insurance Issues.* Retrieved May 1, 2001 from http://www.iii.org/media/issues/autotheft.html.

Karmen, A. (1996). *Crime Victims: An Introduction to Victimology.* (3rd Ed.). Pacific Grove, CA: Brooks/Cole Publishing Company.

Karmen, A. (2000). *New York Murder Mystery: The True Story Behind the Crime Crash of the 1990s.* New York: New York University Press.

Kelling, G. L. and Coles, C. M. (1996). *Fixing Broken Windows.* NY: Touchstone.

Kennedy, L. W. and Forde, D. R. (1990). "Routine activities and crime: An analysis of victimization in Canada." *Criminology* 28, 137-152.

Kennedy, L. W. and Silverman, R. A. (1990). "The elderly victim of homicide: An application of the routine activities approach." *Sociological Quarterly* 31, 307-319.

Klein, M.W. (1995). *The American Street Gang.* New York: Oxford Press

Kornhauser, R.R. (1978). *Social Sources of Delinquency: An Appraisal of Analytic Models.* Chicago, IL: University of Chicago Press.

Kurtz, E. (2000). *Violent crime and community structure: Lagged and simultaneous effects in Baltimore neighborhoods from 1970 to 1990.* Unpublished doctoral dissertation, Temple University, Philadelphia.

Kurtz, E.; Koons, B.; & Taylor, R. B. (1998). "Land use, physical deterioration, resident-based control and calls for service on urban streetblocks." *Justice Quarterly*, 15, 121-149.

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

La Vigne, N. G. and Wartell, J. (1998). *Crime mapping case studies: Success in the field.* Washington, DC: Police Executive Research Forum.

Lewis, D. A. and Salem, G. (1986). *Fear of Crime: Incivility and the Production of a Social Problem.* New Brunswick, NJ: Transaction Books.

Ley, D. and Cybriwsky, R. (1974). "The spatial ecology of stripped cars." *Environment and Behavior,* 6, (1), 53-68.

Lockwood, D. (2004). Mapping violent crime in Savannah's neighborhoods, 1993-1997: Social disadvantage, land use, and violent crime reported to the police. Paper presented at the International Crime Mapping Research Conference, March 31, 2004.

Lowenthal, M. (1950). *The Federal Bureau of Investigation.* Westport, CT: Greenwood Publishing Group.

Mansfield, R., Gould, L., and Namenworth, J. (1974). "A socioeconomic model for the prediction of societal rates of property theft." *Social Forces* 52, 462-472.

Massey, J., Krohn, M. and Bonati, L. (1989). "Property crime and the routine activities of individuals." *Journal of Research in Crime and Delinquency* 26, 378-400.

Mayhew, P. (1990). "Opportunity and vehicle crime." In Gottfredson, D. M. and Clarke, R. V. (Eds), *Policy and Theory in Criminal Justice: Contributions in Honour of Leslie T Wilkins.* Aldershot, UK: Gower Publishing.

McCabe, K. A. (1996). *Structural Influences on Crime.* Unpublished Dissertation: University of South Carolina.

McCaghy, C. H., Giordano, P. C. and Henson, T. K. (1977). "Auto theft: Offense and offender characteristics." *Criminology.* 15, (3), 367-385.

McEwen, J. T. and Taxman, F. (1995). "Applications of computerized mapping to police operations." In Eck, J. E. and Weisburd, D. (Eds.), *Crime and Place.* Monsey, NY: Criminal Justice Press.

McLafferty, S., Williamson, D., and McGuire, P. (2000). "Identifying crime hot spots using Kernel Smoothing." In Goldsmith, V., McGuire, P. G., Mollenkopf, J. H., and Ross, T. A. (Eds). *Analyzing Crime Patterns: Frontiers and Practice.* CA: Sage Publications Inc.

Meithe, T.; Hughes, M. and McDowall, D. (1991). "Social change and crime rates: An evaluation of theoretical approaches." *Social Forces* 70, 165-185.

Miethe, T. and McCorkle, R. C. (2001). *Crime Profiles: The Anatomy of Dangerous Persons, Places, and Situations* (2nd Ed.). Los Angeles, CA: Roxbury Publishing Company.

Meithe, T. and Meier, R. (1990). "Opportunity, choice, and criminal victimization rates: A test of a theoretical model." *Journal of Research in Crime and Delinquency* 27, 243-266.

Merry, S. E. (1981). Urban danger: Life in a neighborhood of strangers. Philadelphia, PA: Temple University Press.

Mustaine, E. and Tewksbury, R. (1998). "Predicting risks of larceny theft victimization: A routine activity analysis using refined lifestyle measures." *Criminology* 36, 829-857.

National Insurance Crime Bureau. (n.d.). *Vehicles at risk for theft.* Retrieved February 27, 2002, from http://www.nicb.org/consumer/index.html.

Newman, O. (1996). *Creating Defensible Space.* U.S. Department of Housing and Urban Development Office of Policy Development Research.

Newman, O. (1972). *Defensible Space: Crime Prevention Through Urban Design.* NY: MacMillan Press.

Norman, J. M. (1996). *Analysis of County Crime Rates in Minnesota, Wisconsin, and Michigan: A Test of Social Disorganization Theory.* Unpublished Dissertation: South Dakota State University.

Novak, K. J. and Seiler, C. L. (2001). "Zoning practices and neighborhood physical disorder." *Criminal Justice Policy review*, 12, (2) 140-163.

Openshaw, S. (1984). "The modifiable areal unit problem." *Concepts and Techniques in Modern Geography.* 38, 41.

Peoria Convention and Visitors Bureau. (2002). *Peoria History.* Retrieved April 18, 2002, from http://www.peoria.org/history.cfm.

Peoria Police Department Crime Statistics. (2001). Retrieved Online April 4, 2001, from http://www.peoriapd.com/districts.htm.

Plouffe, N. and Sampson, R. (2004). "Auto theft and theft from autos in parking lots in Chula Vista, CA: Crime analysis for local and regional action." In Maxfield, M.G. and Clarke, R. V. Crime Prevention Studies (Vol. 17). *Understanding and Preventing Car Theft.* Monsey, NY: Criminal Justice Press.

Price, T. and Santoro, W. A. (1998). "Urban disorder and contemporary community viability: How social and physical disorder influence three quality of life outcomes." *American Sociological Association Presentation.*

Ragavan, C. and Kaplan, D. E. (1999, June). "Why auto theft is going global." U.S. News Online, Retrieved from http://www.usnews.com/usnews/usinfo/popUp3.htm.

Rainwater, L. (1966). "Fear and house-as-haven in the lower class." *Journal of the American Institute of Planners*, 32, 23-31.

Ratcliffe, J.H. and McCullagh, M.J. (1999). "Hotbeds of crime and the search for spatial Accuracy." *Journal of Geographical Systems*, 1, (4), 385-398.

Ratcliffe, J. H. (2004). "Geocoding crime and a first estimate of a minimum acceptable hit rate." *International Journal of Geographic Information Science,* 18, (1), 61-72.

Reid, S. T. (2003). *Crime and Criminology.* (10th Ed.) New York, NY: McGraw Hill.

Reiss, A. J. (1986). "Why are communities important in understanding crime?" In Reiss, A. J. and Tonry M. (Vol. 8), *Communities and Crime*. Chicago, IL: University of Chicago Press.

Rengert, G. F. (1997). "Auto theft in central Philadelphia." In Homel, R. *Crime Prevention Studies*. (Eds.). Vol. 7. Monsey, NY: Criminal Justice Press.

Rice, K. J. and Smith, W. R. (2002). "Socioecological models of automotive theft: Integrating routine activity and social disorganization approaches." *Journal of Research in Crime and Delinquency*, 39, (3), 304-336.

Robinson, M. and Robinson, C. (1997). "Environmental characteristics associated with residential burglaries of student apartment complexes." *Environment and Behavior*, 29, 657-675.

Roncek, D. and Bell, R. (1981). "Bars, blocks and crime." *Journal of Environmental Systems* 11, 35-47.

Roncek, D. and Montgomery, (1984). Spatial autocorrelation: Diagnoses and remedies for large samples. Paper presented at the 1984 annual meeting of the Midwest Sociological Society, Des Moines, IA.

Roncek, D. and Faggiani D. (1985). "High schools and crime." *Sociological Quarterly* 64, 491-505.

Roncek, D. W. and Maier, P. A. (1991). "Bars, blocks, and crime revisited: Linking theory of routine activities to the empiricism of hot spots." *Criminology* 29, 725-753.

Sampson, R. J. (1983). *The Neighborhood Context of Criminal Victimization.* Unpublished Dissertation: State University of New York at Albany

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

Sampson, R. J. and Wilson, W. J. (1995) "A theory of race, crime, and urban inequality." In Cullen, F.T. and Agnew, R., *Criminological Theory: Past to Present.* Los Angeles, CA: Roxbury Publishing Co.

Sampson, R. J., Raudenbush, S. W., and Earls, F. (1997). "Collective efficacy and crime." In Cullen, F.T. and Agnew, R., *Criminological Theory: Past to Present.* Los Angeles, CA: Roxbury Publishing Co.

Sampson, R. J. and Raudenbush, S. W. (1999). "Systematic social observation of public spaces: A new look at disorder in urban neighborhoods." *American Journal of Sociology*, 105, (3) 603-651.

Seville, G. and Murdie, R. (1988). The spatial analysis of motor vehicle theft: A case study of Peel Region, Ontario. *Journal of Police Science and Administration*, 16, (2), 126-135.

Shaw, C. R. and McKay, H. D. (1942). *Juvenile Delinquency and Urban Areas.* Chicago, IL: University of Chicago Press.

Sherman, L. W., Gartin, P. R. and Buerger, M. E. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, 27, (1), 27-55.

Sherman, L. W. (1995) "Hot spots of crime and criminal careers of places." In Eck, J. E. and Weisburd, D. (Eds.), *Crime and Place.* Monsey, NY: Criminal Justice Press.

Simcha-Fagan, O., & Schwartz, J. E. (1986). Neighborhood and delinquency: An assessment of contextual effects. *Criminology*, 24, 667-703.

Siegel, L. J. (1998). *Criminology: Theories, patterns, and typologies.* (6th Ed.) Belmont, CA: Wadsworth.

Siegel, L. J. (2001). *Criminology: Theories, patterns, and typologies.* (7th Ed.) Belmont, CA: Wadsworth.

Skogan, W. G. (1988). "Disorder, crime and community disorder." In T. Hope and M. Shaw (Eds). *Communities and Crime Reduction.* London: Her Majesty's Stationery Office.

Skogan, W. (1989). *Crime and Disorder*. New York: Free Press.

Skogan, W. (1992). *Disorder and Decline: Crime and the Spiral of Decay in American Neighborhoods*. NY: The Free Press.

Smith, W. R., Frazee, S. G. and Davison, 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.

Stark, R. (1987). "Deviant places: A theory of the ecology of crime." *Criminology* 25, (4) 893-909.

Taxman, F. and McEwen, T. (1997) "Using geographical tools with interagency work groups to develop and implement crime control strategies." In Weisburd, D. and McEwen, T. (Eds.), *Crime Mapping and Crime Prevention*. Monsey, NY: Criminal Justice Press.

Taylor, R. B. (1988a). *Human Territorial Functioning*. New York, NY: Cambridge University Press.

Taylor, R. and Covington, J. (1988b). Neighborhood changes in ecology and violence. Criminology, 26, 553-589.

Taylor, R. B. (1997). "Social order and disorder of street blocks and neighborhoods: Ecology, microecology, and the systemic model of social disorganization." *Journal of Research in Crime and Delinquency*, 34 (1), 113-155.

Taylor, R. B. (2001). *Breaking Away from Broken Windows: Baltimore Neighborhoods and the Nationwide Fight Against Crime, Grime, Fear, and Decline*. Boulder, CO: Westview Press

Thrasher, F. (1927). *The Gang*. Chicago: University of Chicago Press.

Tri-County Regional Planning Commission. (2003). *Report on the growth of Peoria*. Retrieved September 23, 2004, from http://www.ci.peoria.il.us

United States Census Bureau (n.d.). *1990 Decennial Census*. Retrieved from http://www.census.gov/.

United States Census Bureau (n.d.). *2000 Decennial Census*. Retrieved from http://www.census.gov/.

United States Department of Justice. (2003). *Bureau of Justice Statistics Annual Report*. Retrieved October 11, 2003, from http://www.ojp.usdoj.gov/bjs/cvict_c.htm#home 12-1-04

United States Department of Justice. Federal Bureau of Investigations. (2001). "Analysis of motor vehicles theft using survival model." *UCR Supplemental Report*, 283-289.

United States Department of Justice. Federal Bureau of Investigations. *Uniform Crime Reports*, 2003. Washington, D.C.

United States Department of Justice. Federal Bureau of Investigations. *Uniform Crime Reports*, 2002. Washington, D.C.

United States Department of Justice. Federal Bureau of Investigations. *Uniform Crime Reports*, 2001. Washington, D.C.

United States Department of Justice. Federal Bureau of Investigations. *Uniform Crime Reports*, 1995. Washington, D.C.

Veysey, B. M. and Messner, S. F. (1999). "Further testing of social disorganization theory: An elaboration of Sampson and Groves's 'community structure and crime." *Journal or Research in Crime and Delinquency*, 36, (2) 156-176.

Weisburd, D. and McEwen, T. (1997). *Crime Mapping and Crime Prevention*. Monsey: NY: Criminal Justice Press.

White, Matthew. Charlotte North Carolina Police Department Personnel. Personal Correspondence from December 12, 2001 to 2003.

Wilcox, P., Land, K. C., and Hunt, S. A. (2003). *Criminal Circumstance: A Dynamic Multicontextual Criminal Opportunity Theory.* Hawthorne, NY: Aldine De Gruyter.

Williams, F. P. and McShane, M. D. (1999). *Criminological Theory*. Upper Saddle River, NJ: Prentice Hall.

Wilson, J. Q. and Kelling, G. (1982). "Broken windows: The police and neighborhood safety." *The Atlantic Monthly*, (Feb.) 46-52.

Witterbrood, K. and Nieuwbeerta, P. (2000). "Criminal victimization during one's life course: The effects of previous victimization and patterns of routine activities." *Journal of Research in Crime and Delinquency*, 37, 91-122.

Worchel, S., and Lollis, M. (1982). "Reactions to territorial contamination as a function of culture." *Personality and Social Psychology Bulletin*, 8, 370-375.

Zorbaugh, H. (1929). *The Gold Coast and the Slum*. Chicago: University of Chicago Press.

Table 1. Motor Vehicle Thefts Over the Decade for Peoria, IL, 1990-2001.

| Year | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
|---|---|---|---|---|---|---|
| Thefts | 336 | 355 | 543 | 943 | 1005 | 882 |
| Change | | +19 (6%) | +188 (53%) | +400 (74%) | +62 (7%) | -123 (-2%) |

| Year | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|---|---|
| Thefts | 938 | 1093 | 1361 | 969 | 1013 | 1001 |
| Change | +56 (6%) | +155 (17%) | +289 (25%) | -392 (-9%) | 44 (5%) | -12 (-1%) |

1990 – 2001
+198 %
Vehicle Theft Increase

Table 2. Geocoding Annual Hit Rates for Peoria, IL.

| Year | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Address Match | 324 | 340 | 530 | 925 | 978 | 862 | 914 | 1061 | 1327 | 932 | 987 | 967 |
| No Match | 12 | 15 | 13 | 18 | 27 | 20 | 24 | 32 | 34 | 37 | 26 | 34 |
| Total Cases | 336 | 355 | 543 | 943 | 1005 | 882 | 938 | 1093 | 1361 | 969 | 1013 | 1001 |
| "Hit Rate" | 96% | 96% | 98% | 98% | 97% | 98% | 97% | 97% | 98% | 96% | 97% | 97% |

Notes. Address Match = all of the motor vehicle theft address locations that could be accurately matched to the base map. No Match = motor vehicle theft addresses that could not be matched due to a variety of identification problems. Total Cases = the total number of motor vehicle theft cases in a given year. "Hit Rate" = The percentage of total cases that were accurately matched to the base map.

Table 3. 1990 and 2000 Peoria Census Demographic Variables and Change Over A Decade.

| Predictor | 1990 | 2000 | Increase/Decrease |
|---|---|---|---|
| Total Population | 113,504 | 112,936 | -568 (-.005) |
| Median Household Income | $29,363 | $36,397 | $7,034 (24 %) |
| Median Property Value Owner Occupied | $51,114 | $84,000 | $32,886 (64 %) |
| Total Number of Persons Living Below Poverty Level | 20,258 (18 %) | 20,220 (19 %) | -38 (-.02 %) |
| Housing Units Occupied by Renters | 19,291 (40 %) | 18,091 (37 %) | -1,200 (-6.2 %) |
| Single Person Housing Units | 31,768 (66 %) | 33,370 (68 %) | 1,602 (5 %) |
| Population Living in Different House 5 yrs. Prior | 59,373 (52 %) | 54,373 (48 %) | -5,000 (-8.4 %) |
| Percent of Multiple Unit Housing | 15,632 (32 %) | 15,166 (31 %) | -466 (-3 %) |
| Percent of Owner Occupied Housing Units | 25,625 (53 %) | 26,996 (60 %) | 1,371 (5.4 %) |
| Percent of Population Unemployed 16 yrs. Old and Older | 3,711 (4.2 %) | 3,982 (4.6 %) | 271 (7 %) |
| Percent Black Alone in the Population | 23,469 (21 %) | 27,601 (24 %) | 4,132 (18 %) |
| Percent White Alone in the Population | 87,478 (77 %) | 78,111 (69 %) | -9,367 (-11 %) |
| Percent of Males in the Population | 53,444 (47 %) | 53,267 (47 %) | -177 (-.003 %) |
| Males Age 14 – 17 | 3,179 (6 %) | 3,226 (6 %) | 47 (1.5 %) |
| Males Age 18 – 24 | 6,828 (13 %) | 6,353 (12 %) | -475 (-7 %) |
| Vehicles Available | 66,308 | 68,161 | 1,853 (3 %) |

Table 4. 1990/91 and 2000/01 Motor Vehicle Theft Descriptives Pre-logging.

| | Min. | Max. | Mean | Std. Dev. | Variance | Skewness Stat. | Std. Error |
|---|---|---|---|---|---|---|---|
| 1990/91 Mean MVTs | 0 | 21.5 | 3.689 | 4.007 | 16.059 | 1.847 | .254 |
| 2000/01 Mean MVTs | 0 | 52.5 | 10.856 | 11.696 | 136.794 | 1.737 | .254 |

Notes. N = 90 CBGs

Table 5. 1990/91 and 2000/01 Motor Vehicle Theft Descriptives Post-logging.

| | Min. | Max. | Mean | Std. Dev. | Variance | Skewness Stat. | Std. Error |
|---|---|---|---|---|---|---|---|
| 1990/91 Mean MVTs | 0 | 3.11 | 1.234 | .787 | .620 | .227 | .254 |
| 2000/01 Mean MVTs | 0 | 3.98 | 2.029 | .976 | .952 | -.021 | .254 |

Notes. N = 90 CBGs

Table 6. Peoria, Illinois City Population Change 1980-1990-2000.

| PIA City Population 1980 | PIA City Population 1990 | PIA City Population 2000 |
|---|---|---|
| 124,160 | 113,504 | 112,936 |
| Change | -10,652 (-8.5%) | -572 (-.05%) |

Table 7. Correlation Matrix of 1990 SES Index.

| | PINPOV9B | POPWPROP | POPWMINC |
|---|---|---|---|
| PINPOV9B | 1.0000 | | |
| POPWPROP | .7146 | 1.0000 | |
| POPWMINC | .8112 | .8614 | 1.0000 |

Notes. N=90 CBGs; PINPOV9B = percent of the population with income below poverty level 1990; POPWPROP = population weighted median property value 1990; POPWMINC = population weighted median household income 1990.
The 1990 Cronbach's alpha for SES was $\alpha = .9113$

Table 8. Correlation Matrix of 1990 Instability Index.

| | OCCRNT90 | HH1PERS9 | MULHSP90 | NOSHSE85 |
|---|---|---|---|---|
| OCCRNT90 | 1.0000 | | | |
| HH1PERS9 | .5476 | 1.0000 | | |
| MULHSP90 | .8956 | .5634 | 1.0000 | |
| NOSHSE85 | .5708 | .3065 | .5300 | 1.0000 |

Notes. N=90 CBGs; OCCRNT90 = percent of housing units occupied by renters 1990; HH1PERS9 = percent of single person occupied housing units 1990; MULHSP90 = percent of multiple unit housing as a percentage of total housing units 1990; NOSHSE85 = percent of the population having resided in a different house in 1985.
The 1990 Cronbach's alpha for Instability was $\alpha = .8301$

Table 9. Correlation Matrix of 2000 SES Index.

| | POPWMINC | POPWPROP | PINPOV0B |
|---|---|---|---|
| POPWMINC | 1.0000 | | |
| POPWPROP | .7685 | 1.0000 | |
| PINPOV0B | .8013 | .6059 | 1.0000 |

Notes. N=90 CBGs; PINPOV0B = percent of the population with income below poverty level 2000; POPWPROP = population weighted median property value 2000; POPWMINC = population weighted median household income 2000.
The 2000 Cronbach's alpha for SES was $\alpha = .8708$

Table 10. Correlation Matrix of 2000 Instability Index.

| | OCCRNT00 | HH1PERS0 | MLTHPCT | DHSE95 |
|---|---|---|---|---|
| OCCRNT00 | 1.0000 | | | |
| HH1PERS0 | .3123 | 1.0000 | | |
| MLTHPCT | .8217 | .4276 | 1.0000 | |
| DHSE95 | .4590 | .2695 | .3786 | 1.0000 |

Notes. N=90 CBGs; OCCRNT00 = percent of housing units occupied by renters 2000; HH1PERS0 = percent of single person occupied housing units 2000; MLTHPCT = percent of multiple unit housing as a percentage of total housing units 2000; NOSHSE95 = percent of the population having resided in a different house in 1995.
The 2000 Cronbach's alpha for Instability was $\alpha = .7626$

Table 11. Tolerance Values For All 1990 Cross-sectional Models.

| Predictor | Tolerance With All Variables in Model -A- | Tolerance With S.E.S. w/o Spatial Autocorrelation -B- | Tolerance With Spatial Autocorrelation w/o S.E.S. -C- |
|---|---|---|---|
| Population | .674 | .695 | .722 |
| S.E.S. | .318 | .411 | N/A |
| Instability | .651 | .658 | .749 |
| Contiguous Boundary | .887 | .902 | .887 |
| Straddle Boundary | .527 | .766 | .549 |
| Heterogeneity | .571 | .617 | .635 |
| Percent of Males in the Population Age 14-17 | .824 | .837 | .899 |
| Percent of Males in the Population Age 18-24 | .755 | .810 | .782 |
| Spatial Autocorrelation | .252 | N/A | .328 |

Notes. N = 90 CBGs; DV = 1990/91 Logged Motor Vehicle Thefts.

Table 12. Tolerance Values For All 2000 Cross-sectional Models.

| Predictor | Tolerance With All Variables in Model -D- | Tolerance With S.E.S. w/o Spatial Autocorrelation -E- | Tolerance With Spatial Autocorrelation w/o S.E.S. -F- |
|---|---|---|---|
| Population | .560 | .570 | .579 |
| S.E.S. | .214 | .445 | N/A |
| Instability | .653 | .659 | .717 |
| Contiguous Boundary | .886 | .891 | .901 |
| Straddle Boundary | .529 | .654 | .604 |
| Heterogeneity | .537 | .569 | .554 |
| Males Age 14-17 | .724 | .750 | .772 |
| Males Age 18-24 | .763 | .855 | .793 |
| Spatial Autocorrelation | .184 | N/A | .382 |

Notes. N = 90 CBGs; DV = 2000/01 Logged Motor Vehicle Thefts.

Table 13. Tolerance Values For All Lagged Regression Models And All Cases Included.

| Predictors | Full Lagged Model w/ All Predictors -G- | Lagged Model w/ S.E.S. and w/o Spatial Autocorrelation -H- | Lagged Model w/ Spatial Autocorrelation and w/o S.E.S. -I- |
|---|---|---|---|
| Lagged S.E.S. | .241 | .491 | N/A |
| Lagged Instability | .622 | .737 | .703 |
| Lagged Heterogeneity | .456 | .472 | .505 |
| Lagged Percent of Males in the Population Age 14-17 | .710 | .812 | .806 |
| Lagged Percent of Males in the Population Age 18-24 | .764 | .806 | .791 |
| Lagged Spatial Autocorrelation | .225 | N/A | .398 |
| Unexpected Change S.E.S. | .584 | .771 | N/A |
| Unexpected Change Instability | .759 | .789 | .813 |
| Unexpected Change Heterogeneity | .925 | .947 | .928 |
| Unexpected Change Percent of Males in the Population Age 14-17 | .801 | .845 | .812 |

*Continued* - Table 13. Tolerance Values For All Lagged Regression Models And All Cases Included.

| | | | |
|---|---|---|---|
| Unexpected Change Percent of Males in the Population Age 18-24 | .858 | .858 | .862 |
| Unexpected Change Spatial Autocorrelation | .491 | N/A | .703 |
| Contiguous Boundary | .694 | .812 | .705 |
| Straddle Boundary | .558 | .798 | .565 |

Notes. N = 90 CBGs; DV = Unexpected Change Population Weighted Logged Motor Vehicle Thefts.

Table 14. Tolerance Values For Lagged Regression Models Without Outlier Case #19.

| Predictors | Full Lagged Model w/ All Predictors -J- | Lagged Model w/ S.E.S. and w/o Spatial Autocorrelation -K- | Lagged Model w/ Spatial Autocorrelation and w/o S.E.S. -L- |
|---|---|---|---|
| Lagged S.E.S. | .247 | .463 | N/A |
| Lagged Instability | .619 | .746 | .695 |
| Lagged Heterogeneity | .427 | .451 | .471 |
| Lagged Percent of Males in the Population Age 14-17 | .708 | .811 | .805 |
| Lagged Percent of Males in the Population Age 18-24 | .763 | .810 | .775 |
| Lagged Spatial Autocorrelation | .220 | N/A | .371 |
| Unexpected Change S.E.S. | .611 | .834 | N/A |
| Unexpected Change Instability | .800 | .824 | .846 |
| Unexpected Change Heterogeneity | .921 | .942 | .926 |
| Unexpected Change Percent of Males in the Population Age 14-17 | .819 | .858 | .832 |

*Continued* - Table 14. Tolerance Values For Lagged Regression Models Without Outlier Case #19.

| | | | |
|---|---|---|---|
| Unexpected Change Percent of Males in the Population Age 18-24 | .853 | .854 | .859 |
| Unexpected Change Spatial Autocorrelation | .484 | N/A | .702 |
| Contiguous Boundary | .691 | .802 | .706 |
| Straddle Boundary | .551 | .799 | .558 |

Notes. N = 90 CBGs; DV = Unexpected Change Population Weighted Logged Motor Vehicle Thefts.

Table 15. Descriptive Statistics for Block Group Motor Vehicle Theft Counts: 1990 and 2000.

| | Min. | Max. | Mean | sd. | Skewness |
|---|---|---|---|---|---|
| 1990/91 Mean MVTs | 0 | 21.500 | 3.689 | 4.007 | 1.847 |
| 2000/01 Mean MVTs | 0 | 52.500 | 10.856 | 11.696 | 1.737 |
| 1990/91 Mean MVTs Logged | 0 | 3.110 | 1.235 | .787 | .227 |
| 2000/01 Mean MVTs Logged | 0 | 3.980 | 2.029 | .976 | -.021 |

Notes. N = 90 CBGs

Table 16. 1990 Descriptives of All Census Predictors Before Indexing SES and Instablity.

| | N | Min. | Max. | Mean | s.d. |
|---|---|---|---|---|---|
| Total Population 1990 | 90 | 399 | 5551 | 1367.97 | 882.64 |
| Median Household Income logged | 90 | 8.52 | 11.36 | 10.06 | .55 |
| Median Property Value logged | 88 | 9.36 | 12.02 | 10.61 | .55 |
| Percent of the Population w/ Income Below Poverty Level (*-1) | 90 | 93 | 0 | 20 | 19 |
| Percent of Housing Units Occupied by Renters | 90 | 4 | 100 | 42 | 21 |
| Percent of 1Person Housing Units | 90 | 1 | 71 | 30 | 12 |
| Multiple Unit Housing as a Percent of Total Housing Units | 90 | 0 | 98 | 28 | 24 |
| Percent of Population Living in a Different House 5 yrs. Prior | 90 | 21 | 84 | 51 | 11 |
| Percent of Males in the Population Age 14-17 | 90 | 0 | 8 | 2.76 | 1.8 |
| Percent of Males in the Population Age 18-24 | 90 | 1 | 43 | 5.92 | 6.89 |
| Heterogeneity | 90 | 0 | .25 | .11 | .08 |
| Spatial Autocorrelation | 90 | -1454.95 | 15068.91 | 10394.65 | 3180.65 |

Table 17. 2000 Descriptives of All Census Predictors Before Indexing SES and Instability.

| | N | Min. | Max. | Mean | s.d. |
|---|---|---|---|---|---|
| Total Population | 90 | 4 | 6164 | 1366.66 | 1006.73 |
| Median Household Income logged | 90 | 8.81 | 11.56 | 10.36 | .52 |
| Median Property Value logged | 88 | 9.84 | 12.26 | 11.10 | .56 |
| Percent of the Population w/ Income Below Poverty Level (*-1) | 90 | 62 | 0 | 21.53 | 18 |
| Percent of Housing Units Occupied by Renters | 90 | 2 | 100 | 37 | 20 |
| Percent of 1 Person Housing Units | 90 | 0 | 72 | 31 | 11 |
| Multiple Unit Housing as a Percent of Total Housing Units | 90 | 0 | 100 | 26 | 25 |
| Percent of Population Living in a Different House 5 yrs. Prior | 90 | 0 | 85 | 48 | 14 |
| Percent of Males in the Population Age 14-17 | 90 | 0 | 8 | 3 | 2 |
| Percent of Males in the Population Age 18-24 | 90 | 0 | 39 | 5 | 6 |
| Heterogeneity | 90 | 0 | .25 | .12 | .08 |
| Spatial Autocorrelation | 90 | 7471.70 | 53871.42 | 31449.30 | 12279.25 |

Table 18. Descriptive Statistics for Year 1990 Predictors After Population Weighting and Adding Up the z-scores and Indexing.

| | Valid N | Min. | Max. | Mean | Std. Dev. |
|---|---|---|---|---|---|
| Population | 90 | 399 | 5551 | 1367.97 | 882.64 |
| S.E.S. | 90 | -6.93 | 5.070 | -.00000034 | 2.79 |
| Instability | 90 | -5.69 | 9.99 | .0000010 | 3.29 |
| Contiguous Boundary | 90 | 0 | 1 | .120 | .33 |
| Straddle Boundary | 90 | 0 | 1 | .140 | .36 |
| Spatial Autocorrelation | 90 | -1454.95 | 15068.91 | 10394.65 | 3180.65 |
| Heterogeneity | 90 | 0 | .250 | .113 | .08 |
| Percent of Males in the Population Age 14-17 | 90 | 0 | 8 | 2.7 | 1.8 |
| Percent of Males in the Population Age 18-24 | 90 | 1 | 43 | 5.9 | 6.89 |

Table 19. Descriptive Statistics for Year 2000 Predictors After Population Weighting and Adding Up the z-scores and Indexing.

| | N Valid | Min. | Max. | Mean | St. Dev. |
|---|---|---|---|---|---|
| Population | 90 | 4 | 6164 | 1366.656 | 1006.731 |
| S.E.S. | 90 | -5.033 | 5.034 | .00000033 | 2.710 |
| Instability | 90 | -4.874 | 10.247 | .0000004 | 3.056 |
| Contiguous Boundary | 90 | 0 | 1 | .120 | .329 |
| Straddle Boundary | 90 | 0 | 1 | .140 | .354 |
| Spatial Autocorrelation | 90 | -5799.41 | 43738.79 | 31449.30 | 10897.94 |
| Heterogeneity | 90 | 0 | .250 | .124 | .076 |
| Percent of Males in the Population Age 14-17 | 90 | 0 | .080 | .029 | .018 |
| Percent of Males in the Population Age 18-24 | 90 | 0 | .390 | .054 | .056 |

Table 20. Summary Table of Cross-sectional Models 1990 and 2000 and Significant Predictors.

| Predictors | Cross-sectional 1990 Full Model -A- | Cross-sectional 1990 w/o Spatial Auto. -B- | Cross-sectional 1990 w/o S.E.S. -C- | Cross-sectional 2000 Full Model -D- | Cross-sectional 2000 w/o Spatial Auto. -E- | Cross-sectional 2000 w/o S.E.S. -F- |
|---|---|---|---|---|---|---|
| Population | + | + | + | + | + | + |
| S.E.S. | - | - | N/A | - | - | N/A |
| Instability | NS | NS | + | NS | NS | NS |
| Contiguous Boundary | NS | NS | NS | NS | NS | NS |
| Straddle Boundary | - | - | NS | - | - | NS |
| Heterogeneity | NS | NS | NS | + | + | + |
| Percentage of Males in the Population Age 14-17 | NS | NS | + | NS | NS | NS |
| Percentage of Males in the Population Age 18-24 | NS | NS | NS | NS | NS | NS |
| Spatial Autocorrelation | NS | N/A | + | NS | N/A | + |

Notes. + = significant predictor in positive direction; - = significant predictor in negative direction; NS = not significant; N/A = not applicable due to removal from model; A, B, C, D, E, F = letter corresponding to specific model for cross referencing in later discussion.

Table 21. Percentiles for Longitudinal Lagged Model Predictors: 2000 Predicted Score Based on 1990 Score.

| | 10% | 25% | 50% | 75% | 90% |
|---|---|---|---|---|---|
| Lagged Predictors: 2000 Predicted Score Based on 1990 Score | | | | | |
| Lagged S.E.S. | 7.351 | 17.755 | 37.835 | 62.043 | 78.075 |
| Lagged Instability | 16.477 | 27.411 | 49.117 | 69.756 | 86.097 |
| Lagged Heterogeneity | 16.853 | 32.927 | 55.316 | 77.455 | 88.754 |
| Lagged Percent of Males in the Population Age 14-17 | 41.492 | 43.433 | 48.072 | 52.252 | 54.834 |
| Lagged Percent of Males in the Population Age 18-24 | 33.991 | 39.509 | 49.888 | 60.356 | 64.756 |
| Lagged Spatial Autocorrelation | 14965.760 | 21951.260 | 31650.860 | 40700.130 | 47220.510 |
| Change Predictors: 2000 Unexpected (Unpredicted) Change | | | | | |
| Unexpected Change S.E.S. | -9.651 | -5.311 | -.488 | 5.369 | 9.888 |
| Unexpected Change Instability | -18.929 | -11.130 | 1.675 | 9.305 | 18.715 |
| Unexpected Change Heterogeneity | -21.436 | -11.094 | 2.987 | 9.476 | 18.176 |
| Unexpected Change Percent of Males in the Population Age 14-17 | -39.456 | -27.655 | -5.103 | 31.405 | 43.313 |

*Continued* - Table 21. Percentiles for Longitudinal Lagged Model Predictors: 2000 Predicted Score Based on 1990 Score.

| | | | | | |
|---|---|---|---|---|---|
| Unexpected Change Percent of Males in the Population Age 18-24 | -45.592 | -27.880 | 1.338 | 29.588 | 40.476 |
| Unexpected Change Spatial Autocorrelation | -3778.410 | -2444.160 | -918.942 | 744.010 | 7473.326 |

Table 22. Summary Table of Longitudinal Lagged Effects Models and Significant Predictors.

| | Lagged Full Model<br>-G- | Lagged Full Model w/o Spatial Auto.<br>-H- | Lagged Full Model w/o S.E.S.<br>-I- | Lagged Full Model w/o Case #19<br>-J- | Lagged Full Model w/o Spatial Autocor. and w/o Case #19<br>-K- | Lagged Full Model w/o S.E.S. and w/o Case #19<br>-L- |
|---|---|---|---|---|---|---|
| Lagged Predictors | | | | | | |
| S.E.S. | NS | NS | N/A | NS | - | N/A |
| Instability | NS | - | NS | NS | - | NS |
| Heterogeneity | + | + | + | + | + | + |
| Percent of Males in the Population Age 14-17 | NS | NS | NS | NS | NS | NS |
| Percent of Males in the Population Age18-24 | NS | NS | NS | NS | NS | NS |
| Spatial Autocorrelation | NS | N/A | NS | NS | N/A | + |
| Unexpected Change Predictors | | | | | | |
| S.E.S. | NS | - | N/A | NS | - | N/A |
| Instability | NS | - | NS | - | - | - |
| Heterogeneity | + | + | + | + | + | + |
| Percent of Males in the Population Age 14-17 | NS | NS | NS | NS | NS | NS |

*Continued* - Table 22. Summary Table of Longitudinal Lagged Effects Models and Significant Predictors.

| | | | | | | |
|---|---|---|---|---|---|---|
| Percent of Males in the Population Age 18-24 | NS | NS | NS | NS | NS | NS |
| Spatial Autocorrelation | + | N/A | + | + | N/A | + |
| Contiguous Boundary | NS | NS | NS | NS | NS | NS |
| Straddle Boundary | NS | NS | NS | NS | NS | NS |

Notes. + = significant predictor in positive direction; - = significant predictor in negative direction; NS = not significant; N/A = not applicable due to removal from model; G, H, I, J, K, L = letter corresponding to specific model for cross referencing in later discussion.

Table 23. Correlation Matrix of 1990 Predictors of Logged Motor Vehicle Theft Time 1.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | .261* | -.526** | .408** | -.126 | -.154 | .324** | .144 | -.013 | .353** |
| 2 | | 1 | .376 | .011 | -.034 | .405** | -.143 | .036 | -.047 | -.454** |
| 3 | | | 1 | -.431** | .139 | .272** | -.596** | -.132 | .008 | -.709** |
| 4 | | | | 1 | -.094 | -.141 | .217** | -.174 | .278** | .397** |
| 5 | | | | | 1 | -.153 | -.141 | .013 | -.149 | -.123 |
| 6 | | | | | | 1 | -.147 | .109 | -.111 | -.592** |
| 7 | | | | | | | 1 | .037 | -.086 | .520** |
| 8 | | | | | | | | 1 | -.290** | -.099 |
| 9 | | | | | | | | | 1 | .225* |
| 10 | | | | | | | | | | 1 |

Notes. * Correlation is significant at the .05 level; ** Correlation is significant at the .01 Level; 1 = 1990/91 logged Motor Vehicle Thefts (Outcome); 2 = Population; 3 = SES Index; 4 = Instability Index; 5 = Contiguous Boundary; 6 = Straddle Boundary; 7 = Heterogeneity; 8 = Percent of Males in the Population Age 14-17; 9 = Percent of the Males in the Population Age 18-24; 10 = Spatial Autocorrelation.

Table 24. Model A: Cross-Sectional Model of 1990/91 Logged Motor Vehicle Thefts: All Predictors.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | .442 | .426 | | 1.039 | Ns |
| Population | .00052 | .0789e-4 | .582 | 6.582 | p<.001 |
| S.E.S. | -.174 | .036 | -.616 | -4.780 | p<.001 |
| Instability | .029 | .022 | .120 | 1.335 | ns |
| Contiguous Boundary | -.120 | .184 | -.050 | -.649 | ns |
| Straddle Boundary | -.452 | .223 | -.203 | -2.030 | p<.05 |
| Heterogeneity | -.588 | .962 | -.059 | -.610 | ns |
| Percent of Males in the Population Age 14-17 | 4.411 | 3.668 | .096 | 1.202 | ns |
| Percent of Males in the Population Age 18-24 | -.349 | .954 | -.031 | -.366 | ns |
| Spatial Autocorrelation | .000012 | .0358e-4 | .050 | .348 | Ns |

Notes. N = 90 CBGs; $R^2 = .578$

Table 25. Model B: Cross-Sectional Model of 1990/91 Logged Motor Vehicle Thefts: Without Spatial Autocorrelation Variable.

| | B Weights | Std. Error | Beta | T | Sig. |
|---|---|---|---|---|---|
| (Constant) | .596 | .198 | | 3.007 | p<.05 |
| Population | .00052 | .0774e-4 | .579 | 6.666 | p<.001 |
| S.E.S. | -.181 | .032 | -.643 | -5.693 | p<.001 |
| Instability | .029 | .021 | .120 | 1.342 | Ns |
| Contiguous Boundary | -.125 | .182 | -.052 | -.686 | Ns |
| Straddle Boundary | -.498 | .184 | -.223 | -2.701 | p<.05 |
| Heterogeneity | -.486 | .923 | -.049 | -.527 | Ns |
| Percent of Males in the Population Age 14-17 | .034 | .035 | .078 | .984 | Ns |
| Percent of Males in the Population Age 18-24 | -.003 | .009 | -.029 | -.354 | Ns |

Notes. N = 90 CBGs ; $R^2 = .575$

Table 26. Model C: Cross-Sectional Model of 1990/91 Logged Motor Vehicle Thefts: Without SES Variable.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | .536 | .421 | | -1.275 | ns |
| Population | .000423 | .0862e-4 | .475 | 4.917 | p<.001 |
| Instability | .065 | .023 | .273 | 2.874 | p<.05 |
| Contiguous Boundary | -.143 | .208 | -.060 | -.685 | ns |
| Straddle Boundary | -.243 | .247 | -.109 | -.983 | ns |
| Heterogeneity | -.919 | 1.032 | .092 | .891 | ns |
| Percent of Males in the Population Age 14-17 | .083 | .038 | .189 | 2.186 | p<.05 |
| Percent of Males in the Population Age 18-24 | -.013 | .011 | -.111 | -1.200 | ns |
| Spatial Autocorrelation | .000095 | .0355e-5 | .384 | 2.674 | p<.05 |

Notes. N = 90 CBGs; $R^2 = .453$

Table 27. Correlation Matrix of 2000 Predictors of Logged Motor Vehicle Theft Time 2.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | .021 | -.673** | .279** | -.124 | -.226* | .581** | .181 | .074 | .607** |
| 2 | | 1 | .416 | -.038 | -.071 | .531** | -.195 | .045 | .018 | -.521** |
| 3 | | | 1 | -.376** | .169 | .242* | -.626** | -.125 | -.054 | -.819** |
| 4 | | | | 1 | -.063 | -.165 | .265* | -.307** | .239* | .356** |
| 5 | | | | | 1 | -.153 | -.165 | -.093 | -.134 | -.062 |
| 6 | | | | | | 1 | -.148 | .020 | -.132 | -.502** |
| 7 | | | | | | | 1 | .214* | -.056 | .558** |
| 8 | | | | | | | | 1 | -.236* | -.035 |
| 9 | | | | | | | | | 1 | .232* |
| 10 | | | | | | | | | | 1 |

Notes. * Correlation is significant at the .05 level; ** Correlation is significant at the .01 Level; 1 = 2000/01 Logged Motor Vehicle Thefts; 2 = Population; 3 = SES Index; 4 = Instability Index; 5 = Contiguous Boundary; 6 = Straddle Boundary; 7 = Heterogeneity; 8 = Percent of Males in the Population Age 14-17; 9 = Percent of the Males in the Population Age 18-24; 10 = Spatial Autocorrelation.

Table 28. Model D: Cross-Sectional Model of 2000/01 Logged Motor Vehicle Thefts: All Predictors.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | .359 | .469 | | .764 | Ns |
| Population | .00052 | .08274e-4 | .535 | 6.270 | p<.001 |
| S.E.S. | -.194 | .050 | -.538 | -3.902 | p<.001 |
| Instability | .029 | .022 | .120 | 1.335 | Ns |
| Contiguous Boundary | .034 | .201 | .011 | .167 | Ns |
| Straddle Boundary | -.656 | .243 | -.238 | -2.705 | p<.01 |
| Heterogeneity | 2.304 | 1.124 | .179 | 2.050 | p<.05 |
| Percent of Males in the Population Age 14-17 | 2.320 | 4.112 | .043 | .564 | Ns |
| Percent of Males in the Population Age 18-24 | -.313 | 1.199 | -.019 | -.261 | Ns |
| Spatial Autocorrelation | .000023 | .01332e-4 | .255 | 1.712 | Ns |

Notes. N = 90 CBGs; $R^2 = .673$

Table 29. Model E: Cross-Sectional Model of 2000/01 Logged Motor Vehicle Thefts: Without Spatial Autocorrelation Variable.

| | B Weights | Std. Error | Beta | T | Sig. |
|---|---|---|---|---|---|
| (Constant) | 1.077 | .213 | | 5.053 | p<.001 |
| Population | .00050 | .08298e-4 | .516 | 6.025 | p<.001 |
| S.E.S. | -.255 | .035 | -.708 | -7.309 | p<.001 |
| Instability | -.024 | .025 | -.074 | -.931 | ns |
| Contiguous Boundary | .0614 | .203 | .021 | .303 | ns |
| Straddle Boundary | -.838 | .221 | -.304 | -3.797 | p<.001 |
| Heterogeneity | 2.762 | 1.105 | .214 | 2.500 | p<.05 |
| Percent of Males in the Population Age 14-17 | .762 | 4.058 | .014 | .188 | ns |
| Percent of Males in the Population Age 18-24 | .359 | 1.146 | .022 | .313 | ns |

Notes. N = 90 CBGs; $R^2 = .661$

Table 30. Model F: Cross-Sectional Model of 2000/01 Logged Motor Vehicle Thefts: Without SES.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | -.947 | .357 | | -2.653 | p<.05 |
| Population | .00046 | .08820e-4 | .475 | 4.917 | p<.001 |
| Instability | .0095 | .026 | .030 | .364 | Ns |
| Contiguous Boundary | -.071 | .216 | -.024 | -.326 | Ns |
| Straddle Boundary | -.321 | .246 | -.116 | -1.304 | Ns |
| Heterogeneity | 3.070 | 1.200 | .238 | .2558 | p<.05 |
| Percent of Males in the Population Age 14-17 | 6.729 | 4.287 | .124 | 1.570 | Ns |
| Percent of Males in the Population Age 18-24 | -1.211 | 1.276 | -.074 | -.949 | Ns |
| Spatial Autocorrelation | .000060 | .01002e-4 | .673 | 6.005 | p<.001 |

Notes. N = 90 CBGs; $R^2 = .611$

Table 31. Correlation Matrix of Longitudinal Lagged Effects and Unexpected Change Predictors.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | -.433 | -.347 | .002 | .058 | .611 | .238 | -.097 | .085 | -.031 | .178 | .343 | .542 |
| 2 | | 1 | .045e-15 | -.332 | -.122 | -.623 | -.068 | .062 | .055 | -.015 | -.082 | -.707 | -.304 |
| 3 | | | 1 | .036 | -.275 | -.281 | -.052 | -.096 | -.022 | -.191 | .020 | -.116 | -.347 |
| 4 | | | | 1 | -.095e-15 | .245 | .047 | -.196 | -.292 | .067 | .211 | .292 | -.210 |
| 5 | | | | | 1 | .231 | .093 | -.092 | -.094 | .242 | -.030 | .115 | .062 |
| 6 | | | | | | 1 | .051e-15 | -.073 | .055 | .010 | .213 | .476 | .361 |
| 7 | | | | | | | 1 | .019 | .056 | .040 | -.124 | .002 | .091 |
| 8 | | | | | | | | 1 | .012e-17 | -.174 | -.219 | -.298 | .055 |
| 9 | | | | | | | | | 1 | -.005 | .025 | -.162 | .144 |
| 10 | | | | | | | | | | 1 | -.015e-15 | .208 | -.154 |
| 11 | | | | | | | | | | | 1 | .112 | -.014 |
| 12 | | | | | | | | | | | | 1 | -.017e-14 |
| 13 | | | | | | | | | | | | | 1 |
| 14 | | | | | | | | | | | | | |
| 15 | | | | | | | | | | | | | |

*Continued* - Table 31. Correlation Matrix of Longitudinal Lagged Effects and Unexpected Change Predictors.

| | 14 | 15 |
|---|---|---|
| 1 | -.089 | -.147 |
| 2 | .141 | .299 |
| 3 | .138 | -.053 |
| 4 | -.079 | -.116 |
| 5 | .083 | -.090 |
| 6 | -.170 | -.131 |
| 7 | -.069 | -.040 |
| 8 | -.011 | .267 |
| 9 | -.123 | .116 |
| 10 | -.258 | .002 |
| 11 | -.073 | -.054 |
| 12 | -.258 | -.546 |
| 13 | .112 | .072 |
| 14 | 1 | -.153 |
| 15 | | 1 |

Notes. 1 = Population Weighted Unexpected Change Logged Motor Vehicle Theft; 2 = Lagged SES; 3 = Unexpected Change SES; 4 = Lagged Instability; 5 = Unexpected Change Instability; 6 = Lagged Heterogeneity; 7 = Unexpected Change Heterogeneity; 8 = Lagged Percent of Males in the Population Age 14-17; 9 = Unexpected Change Percent of Males in the Population Age 14-17; 10 = Lagged Percent of Males in the Population Age 18-24; 11 = Unexpected Change Percent of Males in the Population Age 18-24; 12 = Lagged Spatial Autocorrelation; 13 = Unexpected Change Spatial Autocorrelation; 14 = Contiguous Boundary; 15 = Straddle Boundary.

Table 32. Model G: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts: All Predictors.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | -.030 | .305 | | -.098 | ns |
| Lagged S.E.S. | -.000124 | .001 | -.015 | -.100 | ns |
| Lagged Instability | -.00125 | .001 | -.135 | -1.459 | ns |
| Lagged Heterogeneity | .00381 | .001 | .438 | 4.051 | p<.001 |
| Lagged Percent of Males in the Population Age 14-17 | -.00330 | .004 | -.072 | -.835 | ns |
| Lagged Percent of Males In the Population Age 18-24 | -.000295 | .002 | -.015 | -.179 | ns |
| Lagged Spatial Autocorrelation | .00000205 | .02981e-5 | .106 | .689 | ns |
| Unexpected Change S.E.S. | -.00383 | .002 | -.148 | -1.551 | ns |
| Unexpected Change Instability | -.0022 | .001 | -.145 | -1.736 | ns |
| Unexpected Change Heterogeneity | .00323 | .001 | .239 | 3.150 | p<.01 |
| Unexpected Change Percent of Males in the Population Age 14-17 | -.000213 | .001 | -.030 | -.369 | ns |
| Unexpected Change Percent of Males in the Population Age 18-24 | .000826 | .001 | .116 | 1.473 | ns |
| Unexpected Change Spatial Autocorrelation | .0000143 | .05036e-5 | .296 | 2.844 | p<.01 |
| Contiguous Boundary | .00898 | .059 | .013 | .153 | ns |
| Straddle Boundary | -.0270 | .061 | -.043 | -.442 | ns |

Notes. N = 90 CBGs; $R^2 = .601$

Table 33. Model H: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Without Spatial Autocorrelation.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | .244 | .245 | | .997 | ns |
| Lagged S.E.S. | -.00162 | .001 | -.195 | -1.806 | ns |
| Lagged Instability | -.00220 | .001 | -.237 | -2.686 | p<.01 |
| Lagged Heterogeneity | .00427 | .001 | .490 | 4.443 | p<.001 |
| Lagged Percent of Males in the Population Age 14-17 | -.00544 | .004 | -.119 | -1.416 | ns |
| Lagged Percent of Males In the Population Age 18-24 | -.00090 | .002 | -.045 | -.538 | ns |
| Unexpected Change S.E.S. | -.00698 | .002 | -.270 | -3.127 | p<.01 |
| Unexpected Change Instability | -.00278 | .001 | -.184 | -2.151 | p<.05 |
| Unexpected Change Heterogeneity | .00355 | .001 | .263 | 3.377 | p<.001 |
| Unexpected Change Percent of Males in the Population Age 14-17 | -.000228 | .001 | -.032 | -.390 | ns |
| Unexpected Change Percent of Males in the Population Age 18-24 | .000841 | .001 | .118 | 1.443 | ns |
| Contiguous Boundary | .04193 | .056 | .063 | .7433 | ns |
| Straddle Boundary | -.0118 | .053 | -.019 | -.224 | ns |

Notes. N = 90 CBGs; $R^2 = .557$

Table 34. Model I: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Without SES Index.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | -.125 | .227 | | -.553 | ns |
| Lagged Instability | -.00121 | .001 | -.130 | -1.487 | ns |
| Lagged Heterogeneity | .00395 | .001 | .453 | 4.391 | p<.001 |
| Lagged Percent of Males in the Population Age 14-17 | -.00228 | .004 | -.050 | -.612 | ns |
| Lagged Percent of Males In the Population Age 18-24 | -.000203 | .002 | -.010 | .123 | ns |
| Lagged Spatial Autocorrelation | .00000233 | .02253e-5 | .120 | 1.033 | ns |
| Unexpected Change Instability | -.00172 | .001 | -.114 | -1.397 | ns |
| Unexpected Change Heterogeneity | .003196 | .001 | .237 | 3.109 | p<.01 |
| Unexpected Change Percent of Males in the Population Age 14-17 | -.000226 | .001 | -.032 | -.393 | ns |
| Unexpected Change Percent of Males Age 18-24 | .000809 | .001 | .114 | 1.437 | ns |
| Unexpected Change Spatial Autocorrelation | .0000169 | .04231e-5 | .350 | 4.004 | p<.ool |
| Contiguous Boundary | -.00298 | .059 | -.004 | -.051 | ns |
| Straddle Boundary | -.0245 | .061 | -.039 | -.402 | ns |

Notes. N = 90 CBGs; $R^2 = .586$

Table 35. Model J: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts With All Predictors but Without Case #19.

| | B Weights | Std. Error | Beta | T | Sig. |
|---|---|---|---|---|---|
| (Constant) | -.0542 | .282 | | -.193 | ns |
| Lagged S.E.S. | -.000322 | .001 | -.041 | -.284 | ns |
| Lagged Instability | -.000665 | .001 | -.075 | -.826 | ns |
| Lagged Heterogeneity | .00273 | .001 | .329 | 2.997 | p<.01 |
| Lagged Percent of Males in the Population Age 14-17 | -.00247 | .004 | -.057 | -.672 | ns |
| Lagged Percent of Males in the Population Age 18-24 | -.00124 | .002 | -.066 | -.804 | ns |
| Lagged Spatial Autocorrelation | .00000444 | .02811e-5 | .241 | 1.579 | ns |
| Unexpected Change S.E.S. | -.00163 | .002 | -.064 | -.694 | ns |
| Unexpected Change Instability | -.00259 | .001 | -.178 | -2.215 | p<.05 |
| Unexpected Change Heterogeneity | .00289 | .001 | .228 | 3.055 | p<.01 |
| Unexpected Change Percent of Males in the Population Age 14-17 | -.000334 | .001 | -.050 | -.629 | ns |
| Unexpected Change Percent of Males in the Population Age 18-24 | .000556 | .001 | .083 | 1.068 | ns |
| Unexpected Change Spatial Autocorrelation | .0000169 | .04679e-5 | .371 | 3.603 | p<.001 |
| Contiguous Boundary | .00539 | .054 | -.009 | -.099 | ns |
| Straddle Boundary | -.00136 | .057 | -.002 | -.024 | ns |

Notes. N = 89 CBGs; $R^2 = .620$

Table 36. Model K: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Without Spatial Autocorrelation and Without Case #19.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | .362 | .236 | | 1.532 | ns |
| Lagged S.E.S. | -.00241 | .001 | -.307 | -2.721 | p<.01 |
| Lagged Instability | -.00186 | .001 | -.211 | 2-.378 | p<.05 |
| Lagged Heterogeneity | .00345 | .001 | .415 | 3.636 | p<.001 |
| Lagged Males Age 14-17 | -.00574 | .004 | -.133 | -1.565 | Ns |
| Lagged Males Age 18-24 | -.00159 | .002 | -.085 | -.993 | Ns |
| Unexpected Change S.E.S. | -.00584 | .002 | -.228 | -2.718 | p<.01 |
| Unexpected Change Instability | -.00327 | .001 | -.224 | -2.651 | p<.01 |
| Unexpected Change Heterogeneity | .00324 | .001 | .256 | 3.237 | p<.01 |
| Unexpected Change Percent of Males in the Population Age 14-17 | -.000412 | .001 | -.061 | -.740 | Ns |
| Unexpected Change Percent Males in the Population Age 18-24 | .000607 | .001 | .091 | 1.089 | Ns |
| Contiguous Boundary | .02248 | .054 | .036 | .417 | Ns |
| Straddle Boundary | -.00820 | .050 | -.014 | -.163 | Ns |

Notes. N = 89 CBGs; $R^2$ = .552

Table 37. Model L: Longitudinal Lagged Effects 1990/2000 Population Weighted Logged Unexpected Change Motor Vehicle Thefts Without SES and Without Case #19.

| | B Weights | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | -.134 | .206 | | -.651 | ns |
| Lagged Instability | -.000555 | .001 | -.063 | -.739 | ns |
| Lagged Heterogeneity | .00279 | .001 | .336 | 3.252 | p<.01 |
| Lagged Percent of Males in the Population Age 14-17 | -.00179 | .003 | -.042 | -.526 | ns |
| Lagged Percent of Males in the Population Age 18-24 | -.00113 | .002 | -.060 | -.748 | ns |
| Lagged Spatial Autocorrelation | .00000510 | .02143e-5 | .277 | 2.380 | p<.05 |
| Unexpected Change Instability | -.00241 | .001 | -.165 | -2.138 | p<.05 |
| Unexpected Change Heterogeneity | .00288 | .001 | .227 | 3.082 | p<.01 |
| Unexpected Change Percent of Males in the Population Age 14-17 | -.000328 | .001 | -.049 | -.628 | ns |
| Unexpected Change Percent of Males in the Population Age 18-24 | .000529 | .001 | .079 | 1.030 | ns |
| Unexpected Change Spatial Autocorrelation | .0000184 | .03848e-5 | .405 | 4.781 | p<.001 |
| Contiguous Boundary | -.00952 | .053 | -.015 | -.179 | ns |
| Straddle Boundary | .00214 | .056 | .004 | .038 | ns |

Notes. N = 89 CBGs; $R^2 = .617$

Figure 1. Integrated Theoretical Model of Car Thefts in Peoria.

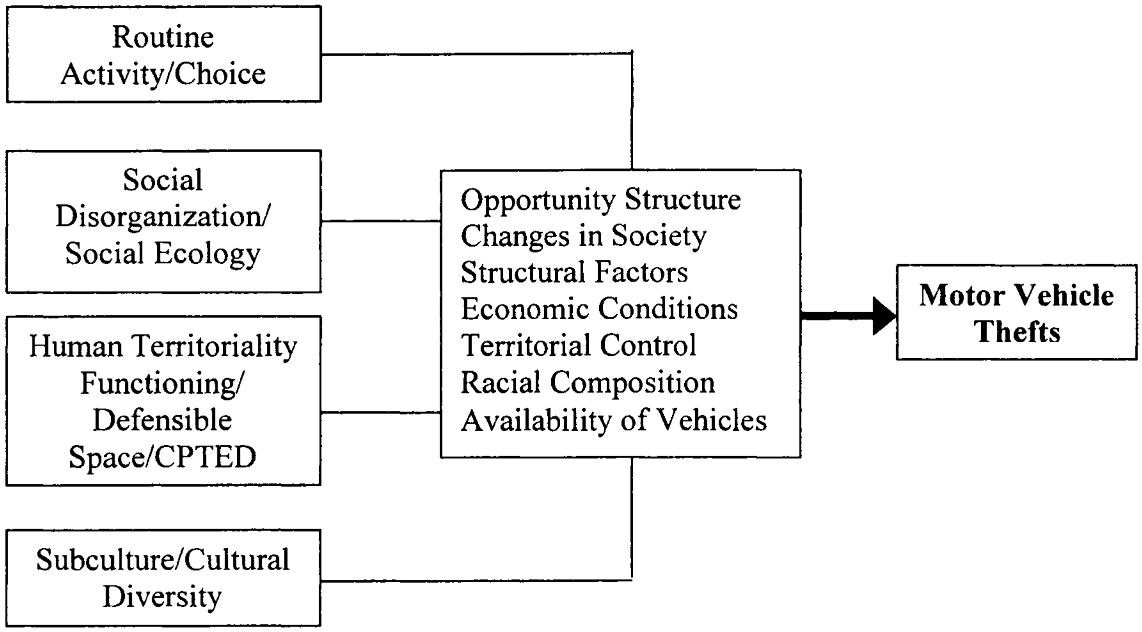


Figure 2. Cross-sectional 1990 and 2000 Conceptual Model.

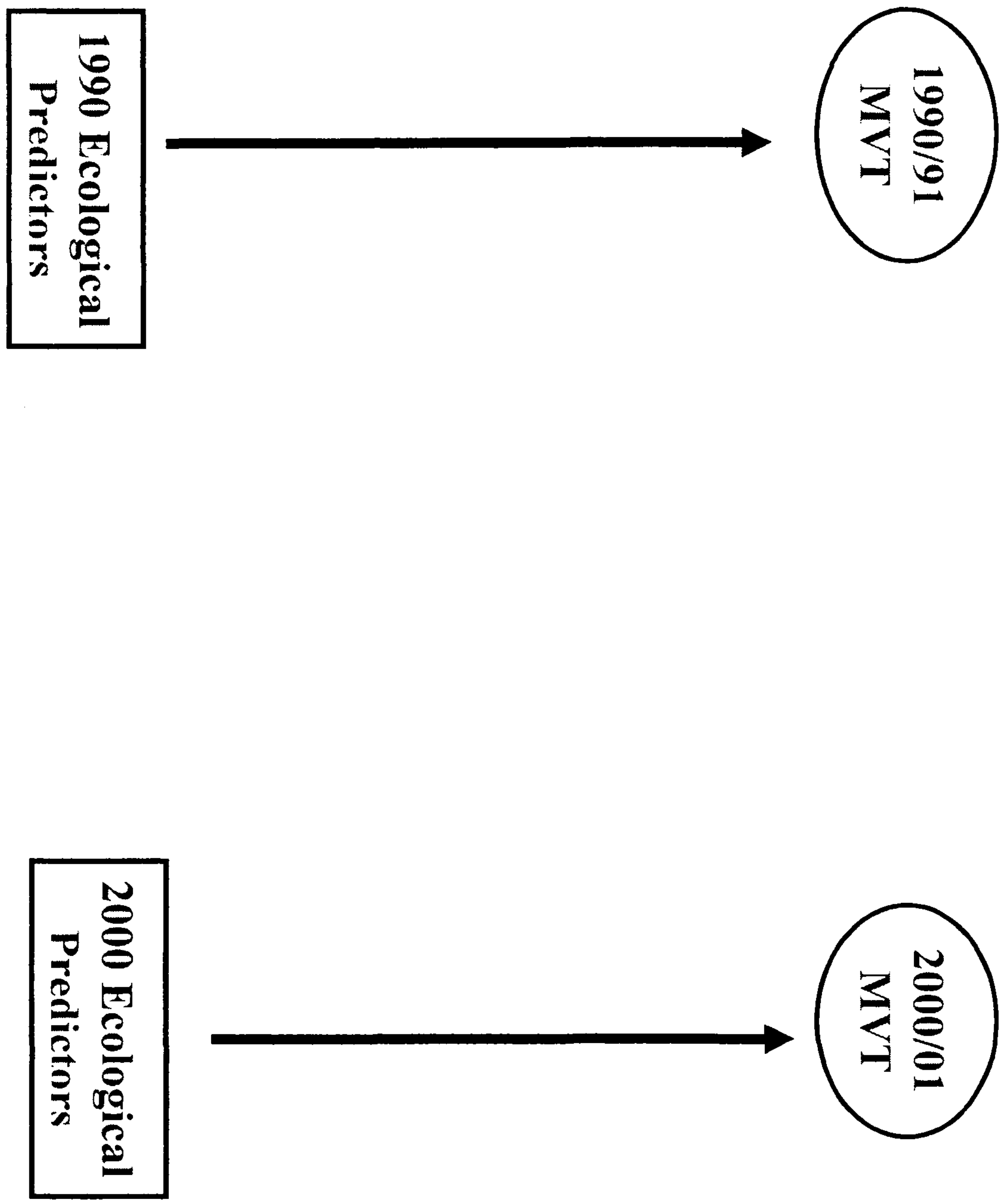


Figure 3. Longitudinal Lagged Ecological Effects Conceptual Model.

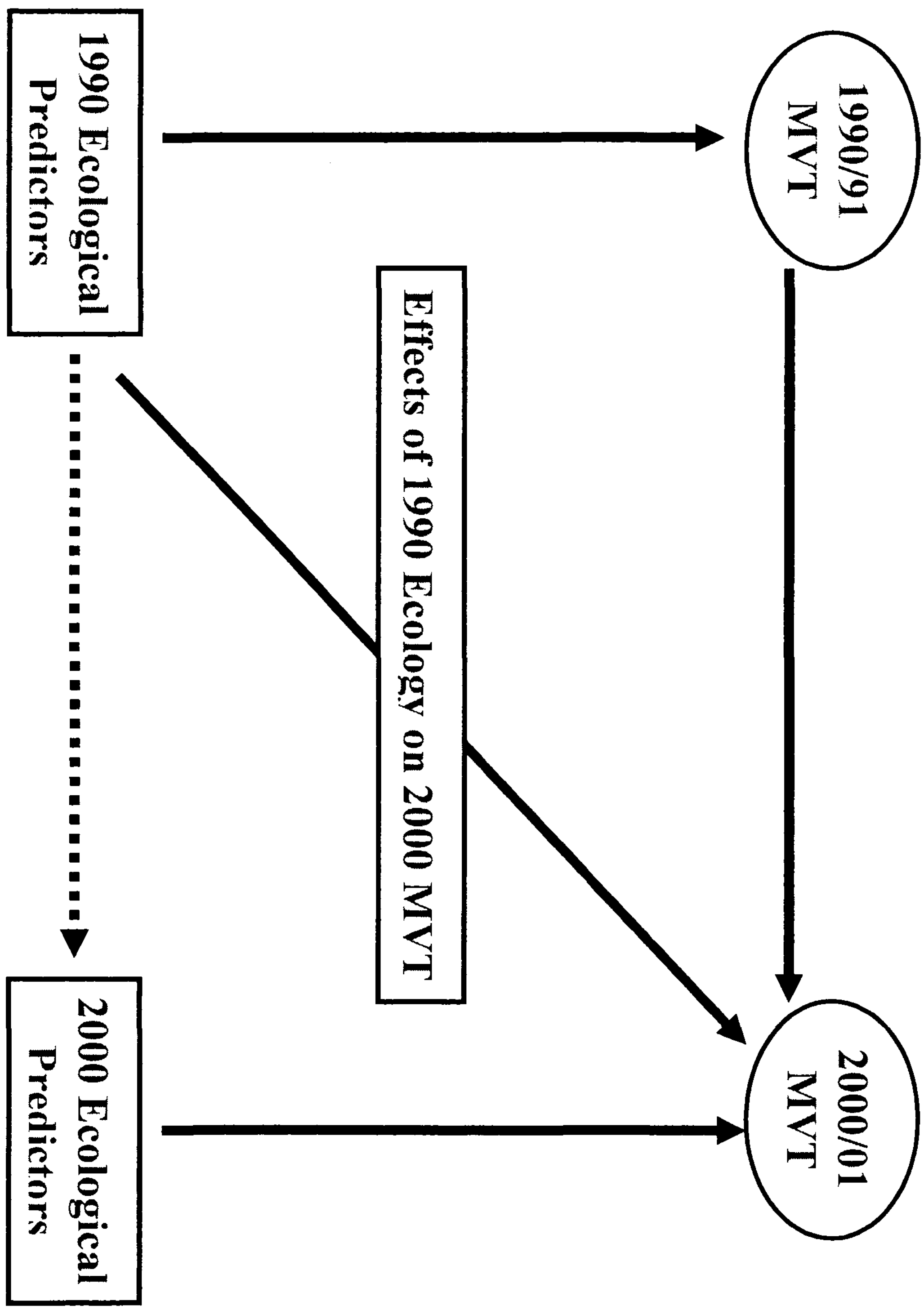


Figure 4. City of Peoria Boundary and Adjacent Municipalities 1990 and 2000.

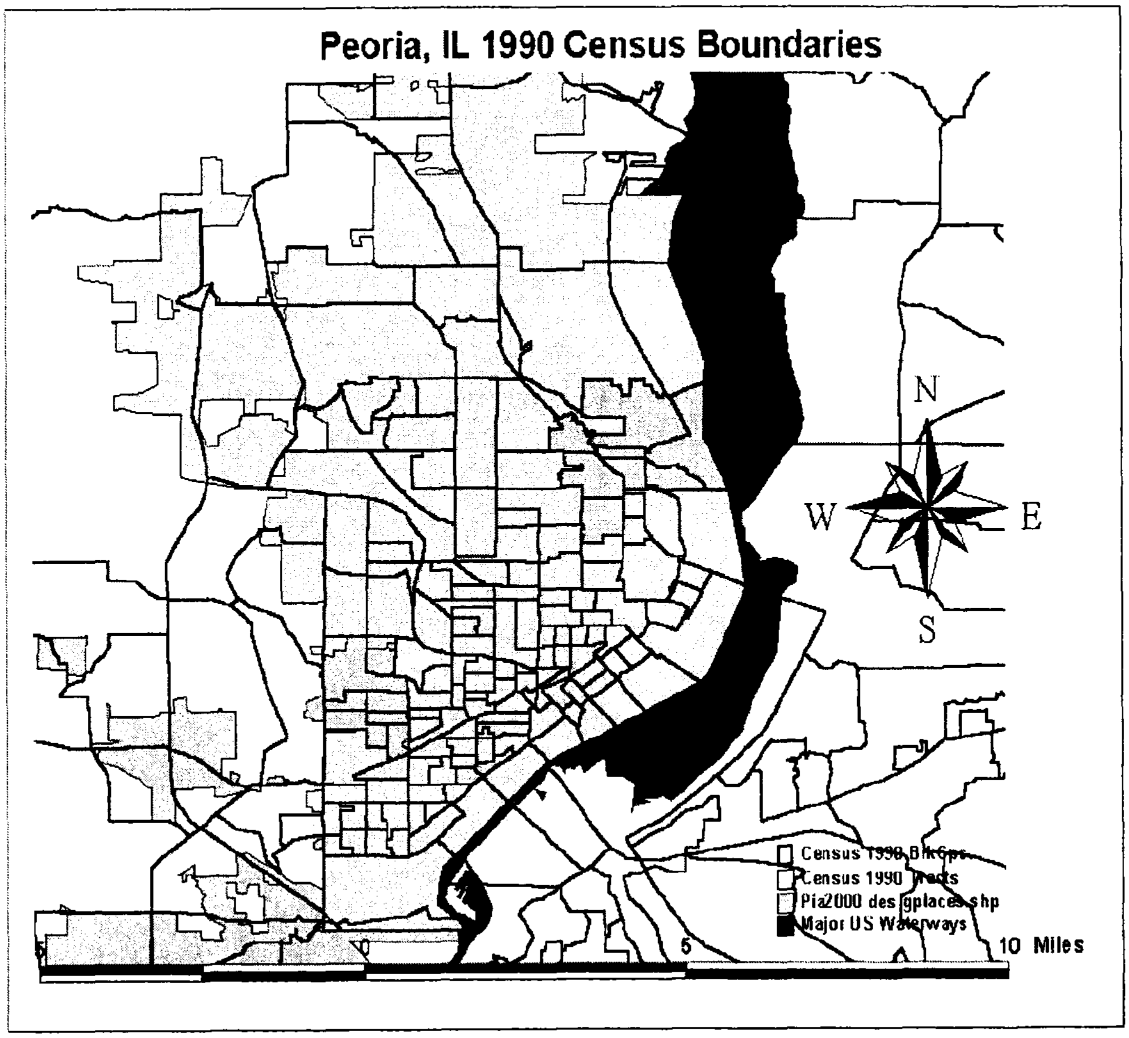


Figure 5. City of Peoria and Contiguous Area Showing 1990 Census Tract and Block Group Boundaries.

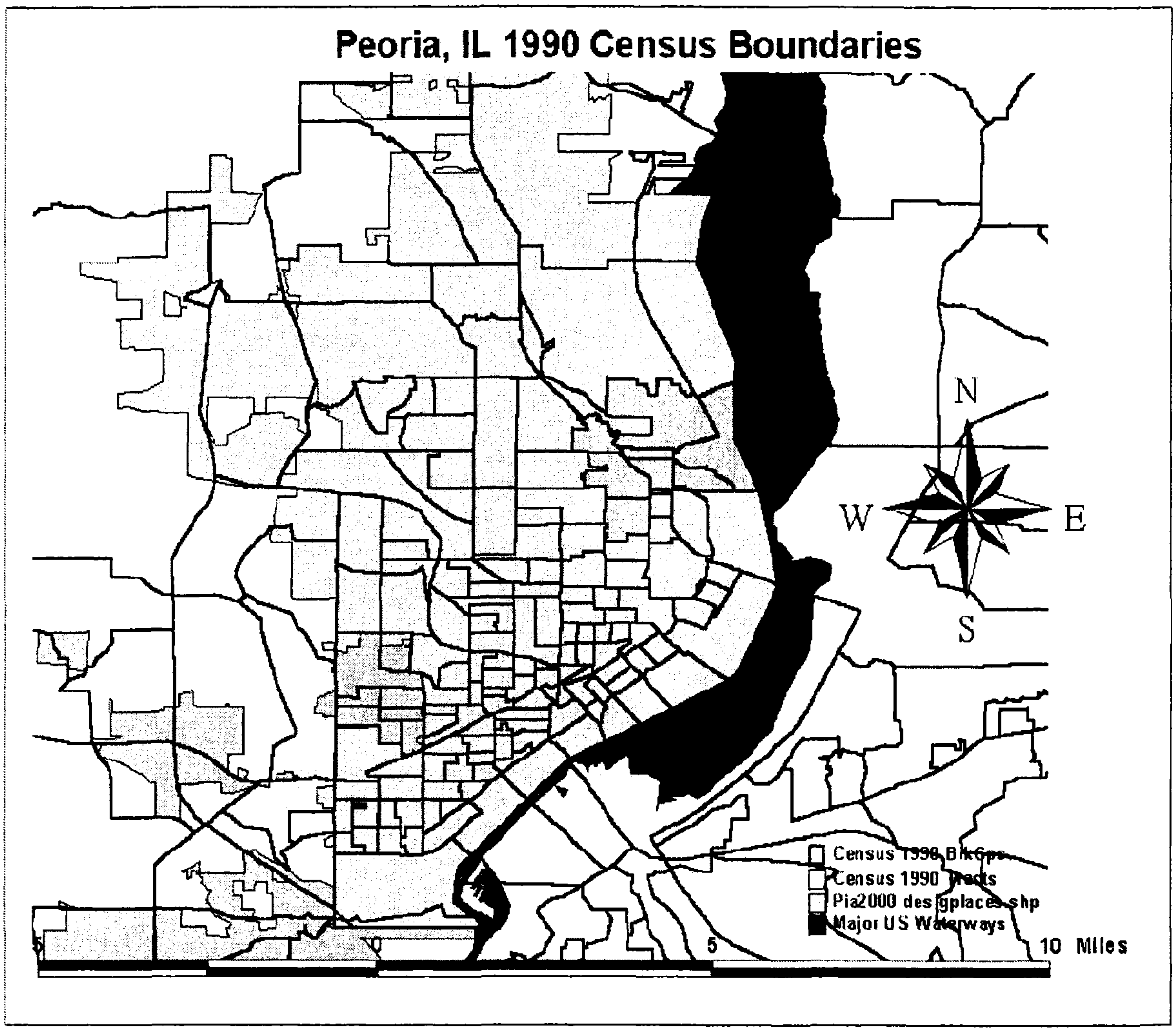


Figure 6. City of Peoria and Contiguous Area Showing 2000 Census Tract and Block Group Boundaries.

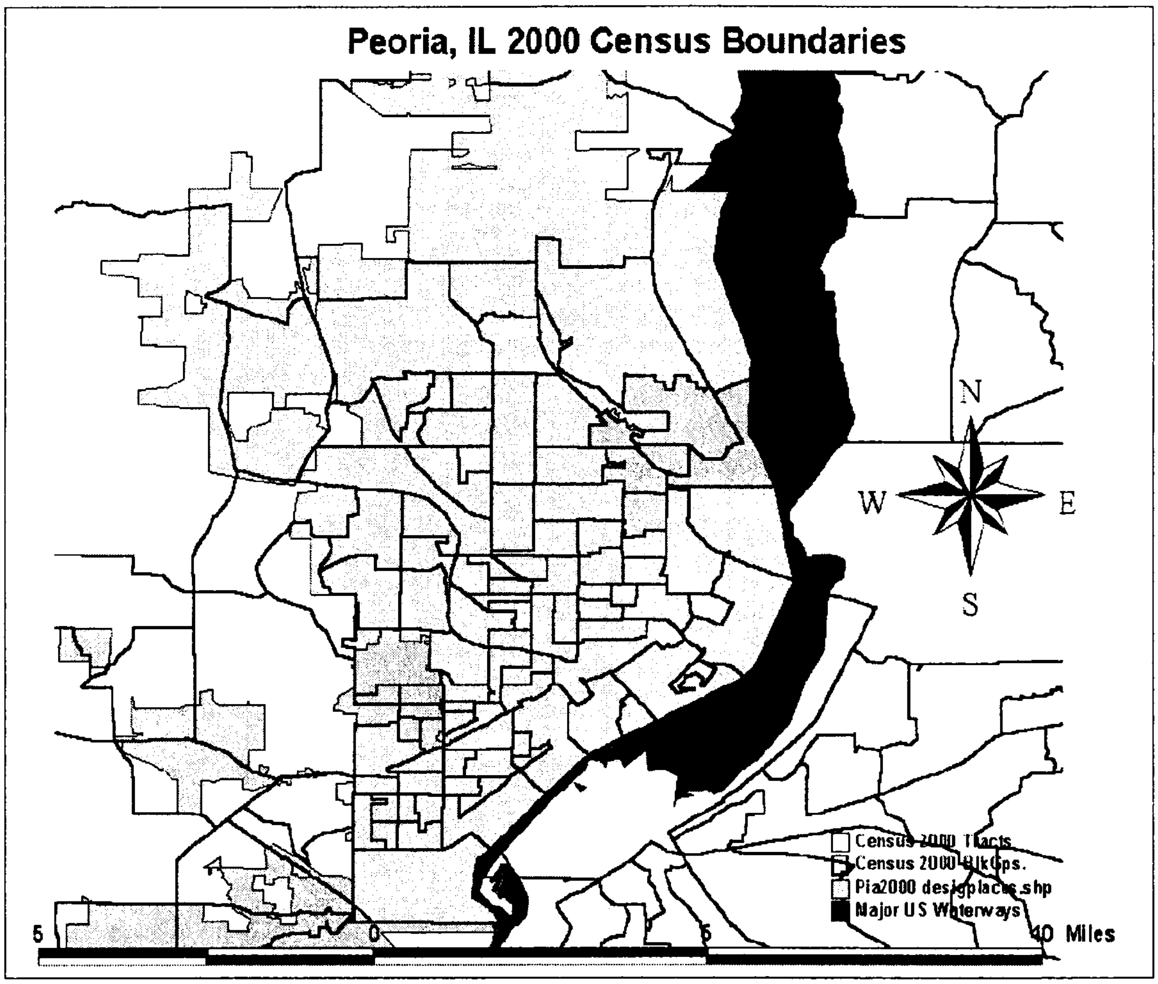
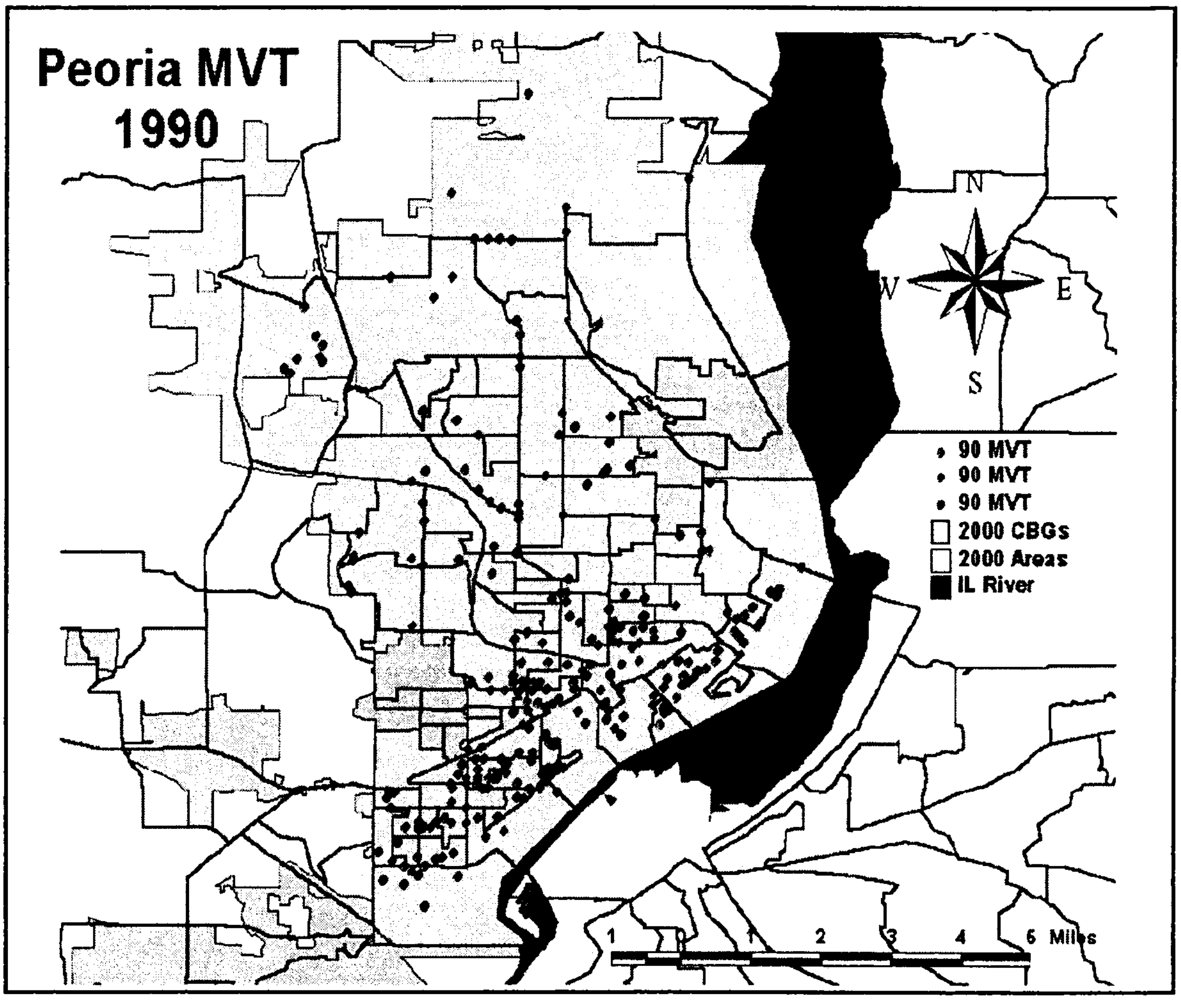
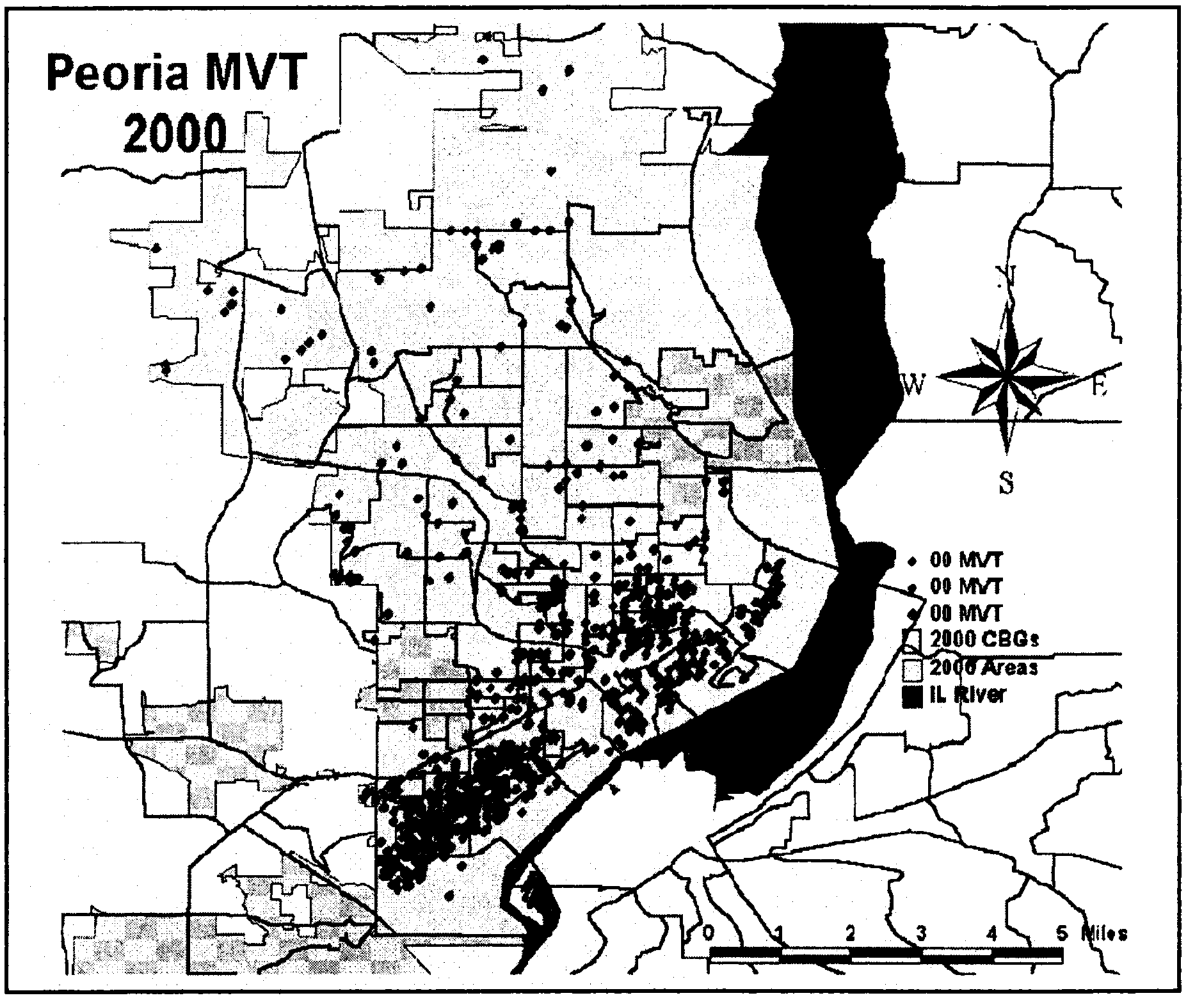


Figure 7. Spatial Distribution of 1990 Motor Vehicle Theft Point Locations in Peoria.



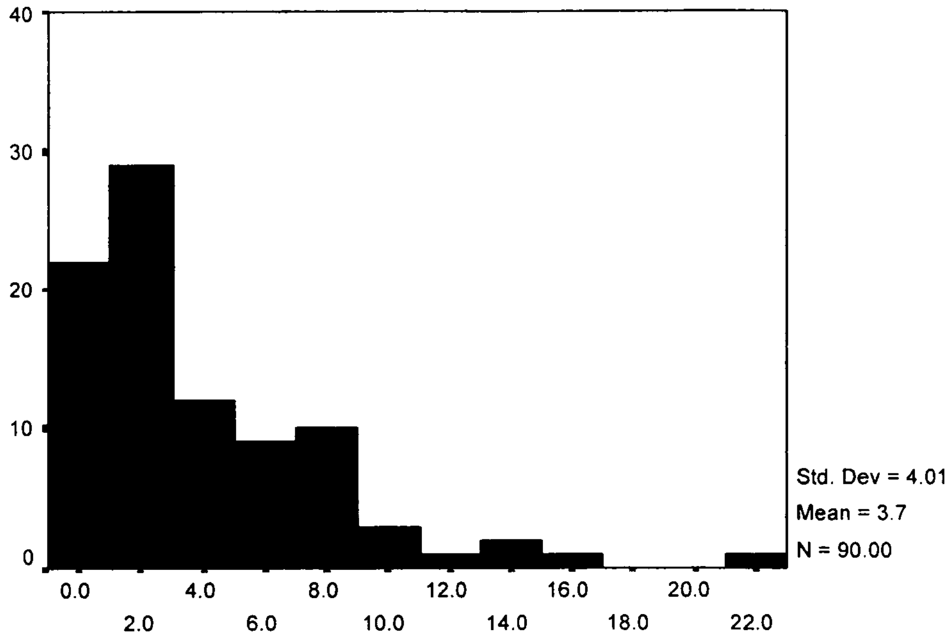

Notes. The three 1990 MVT features in the legend represent mapped point locations utilizing three methods of geocoding that were necessary to yield the greatest hit rate.

Figure 8. Spatial Distribution of 2000 Motor Vehicle Theft Point Locations in Peoria.



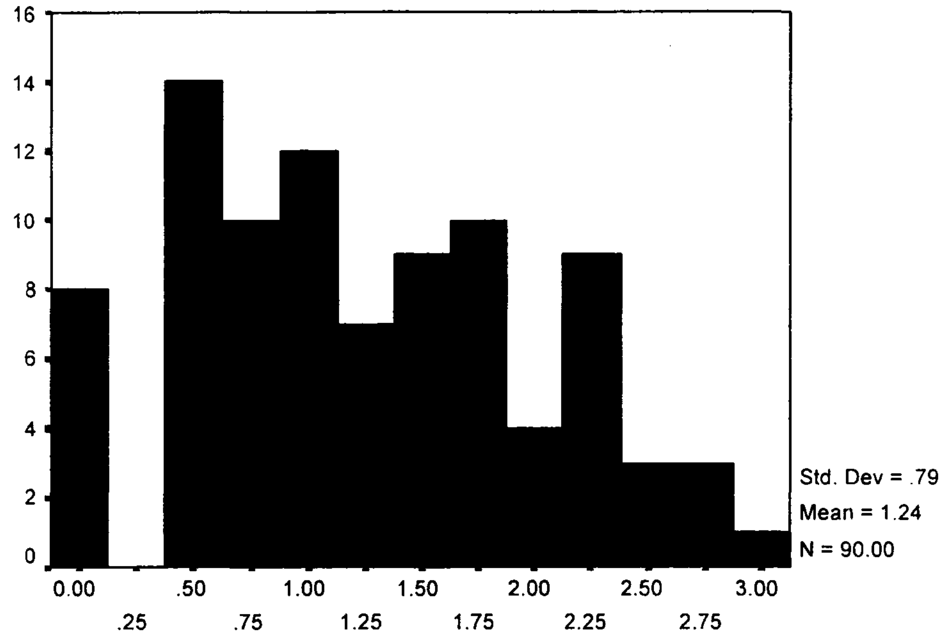

Notes. The three 2000 MVT features in the legend represent mapped point locations utilizing three methods of geocoding that were necessary to yield the greatest hit rate.

Figure 9. 1990 and 1991 Motor Vehicle Thefts Averaged Together.



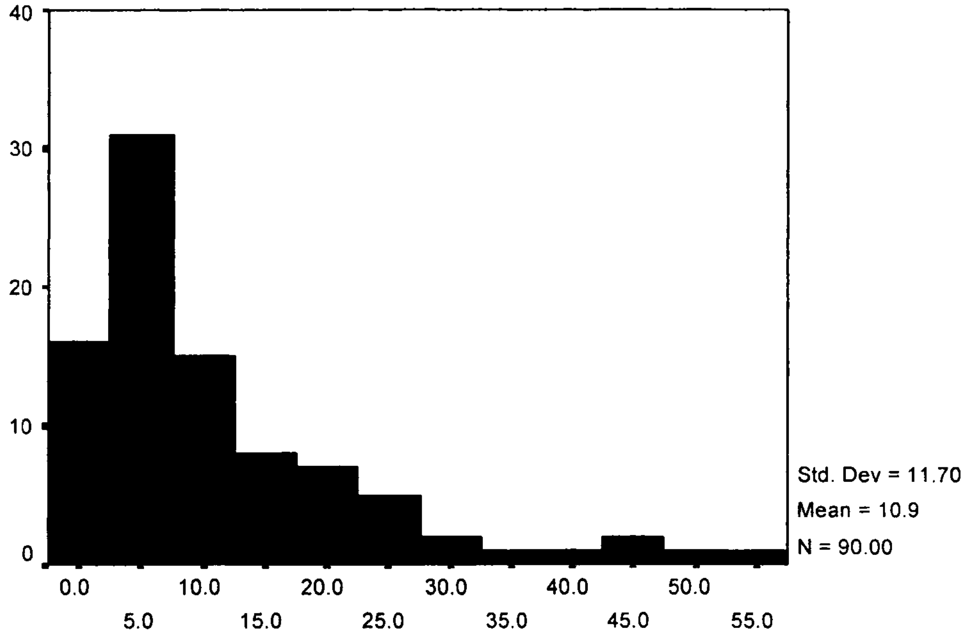

Notes. Y axis = number of census block groups; X axis = mean number of motor vehicle thefts for 1990 and 1991

Figure 10. 1990 and 1991 Motor Vehicle Thefts Averaged Together and Logged.



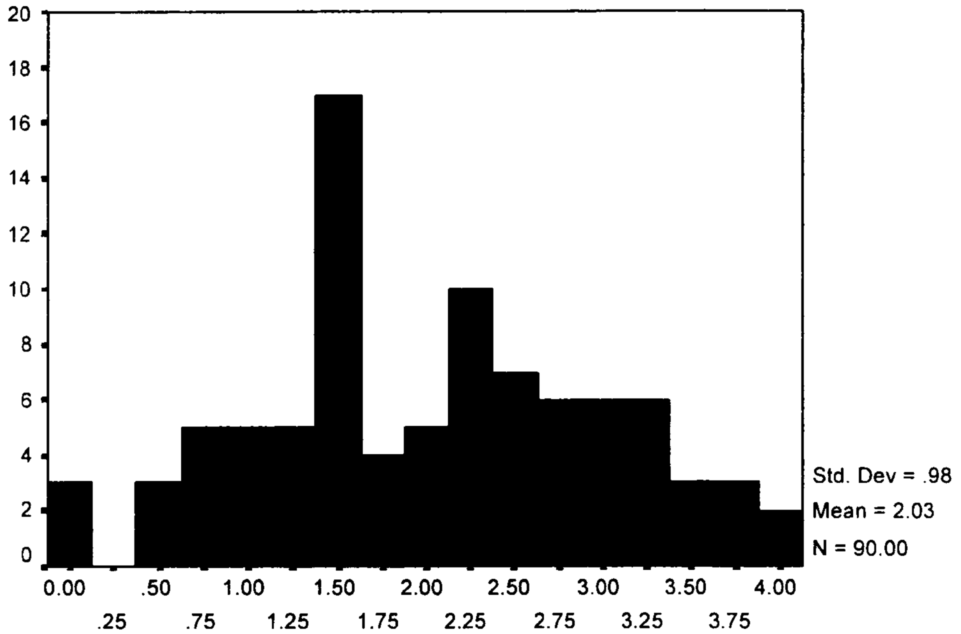

Notes. Y axis = number of census block groups; X axis = mean number of motor vehicle thefts for 1990 and 1991 logged

Figure 11. 2000 and 2001 Motor Vehicle Thefts Averaged Together.




Notes. Y axis = number of census block groups; X axis = mean number of motor vehicle thefts for 2000 and 2001

Figure 12. 2000 and 2001 Motor Vehicle Thefts Averaged Together and Logged.




Notes. Y axis = number of census block groups; X axis = mean number of motor vehicle thefts for 2000 and 2001 logged

Figure 13. Peoria Area Major Roads and Thoroughfares.

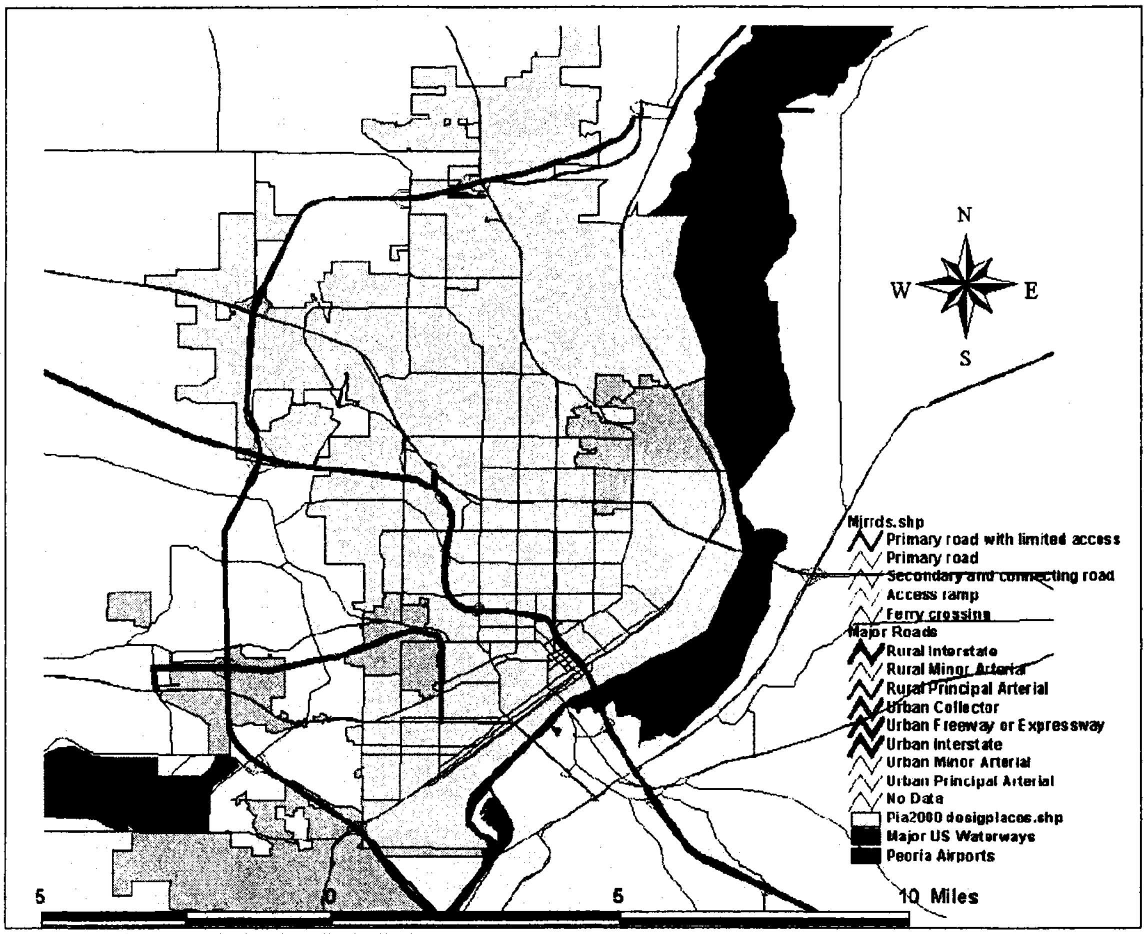


Figure 14. Motor Vehicle Theft Trends Over the Decade: Local and National.