ISOLATING OPPORTUNITY FROM DEMOGRAPHICS: A CASE STUDY OF MOTOR VEHICLE THEFT IN PHILADELPHIA

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ABSTRACT

Title: Isolating Opportunity from Demographics:
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Considering the extent of the motor vehicle theft (MVT) problem, it is surprising that there is such a dearth of studies on these crimes at the neighborhood level. In 2008, nearly one million vehicles, valued at 6.4 billion dollars, were reported stolen in the United States. Additionally, only half of these stolen vehicles were ever recovered. The purpose of this study is to increase the limited knowledge base on the characteristics of neighborhoods that predict MVT levels. Its focus is on the identification of specific types of land use that increase MVT levels, net the impact of sociodemographics, as posited by the opportunity theories of rational choice, routine activities, and crime pattern theory.

The study site is Philadelphia, Pennsylvania with its 1816 census block groups serving as the unit of analysis. The percentage of total land area for each block group utilized by various theorized criminogenic land uses is determined by Geographic Information System (GIS). Evaluated land uses include shopping centers, bars, high schools, colleges, parking lots, youth hangouts, and single family homes. A ‘proximity space’ variable is also computed consisting of the percentage of block group area that is located within one street block of the combined criminogenic land uses. Its usefulness is in determining whether the impact of crime-producing land uses spreads into the surrounding neighborhood. Negative binomial regression models test various hypotheses around the general research question “After controlling for socio-structural correlates, is the presence of certain land uses predictive of MVT levels found at the neighborhood level?”

Results demonstrate that land use, both independently and through neighborhood demographic structure, promotes or suppresses MVT levels, a finding consistent with opportunity theories. Specifically, the percentage of land use in block groups utilized by shopping centers, bars, and commercial parking lots is related to higher MVT counts, but that utilized by colleges and single family homes predicts lower MVT counts, net the impact of neighborhood sociodemographics. Interaction models demonstrate that SES, racial heterogeneity, single-parent families, and percentage 15-24 year olds moderate the impact of land use on MVT. Findings are relevant to urban planners, crime practitioners, and crime theorists.

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CHAPTER 1

INTRODUCTION

Considering the extent of the motor vehicle theft (MVT) problem in the United States, it is surprising that there is such a dearth of studies on these crimes at the neighborhood level (Maxfield, 2004; Walsh & Taylor, 2007a). In 2008, nearly one million vehicles, valued at almost 6.4 billion dollars, were reported stolen in the United States (Federal Bureau of Investigation [FBI], 2009). Additionally, only slightly more than half of stolen vehicles were recovered (FBI, 2001). Although losses to insurance companies in reimbursing owners for damaged and never-recovered vehicles are no doubt a daunting sum, many Americans, especially those of lower socio-economic status, own older cars and do not pay, or cannot afford, theft insurance. This is an especially poignant point because the majority of stolen vehicles are older models (Clarke & Harris, 1992a; National Insurance Crime Bureau [NICB], 2007; Weisel, Smith, Garson, Pavlichev, & Wartell, 2006).

The purpose of this study is to increase the limited knowledge base on the characteristics of neighborhoods that promote higher levels of MVT. Of special interest, are increases in MVT counts related to high levels of crime opportunity inherent in the daily activities and physical characteristics of certain types of land use and facilities.

Not only are there few neighborhood studies examining MVT, but most completed to date have failed to examine more than a narrow range of potential correlates. Some examine only the relationship between MVT and community sociodemographics, failing to control for varying levels of opportunity found within the physical environment of neighborhoods (Copes, 1999; Miethe & Meier, 1994; Saville & Murdy, 1988; Walsh & Taylor, 2007a, 2007b). Other studies focus only on opportunity variables, such as the criminogenic impact of parking lots, high schools, and nightclub districts shown to be related to MVT, and fail to control for community sociodemographics (Henry & Bryan, 2000; Plouffe & Sampson, 2004; Rengert, 1997). Findings from studies that separately evaluate these two sets of predictors (sociodemographics and land use) are incomplete and may be suspect because MVT is likely a product of both sets of predictors interacting with each other. Some crime-producing land uses tend to be located in neighborhoods of lower socioeconomic status due to economic or political reasons. Without considering both the presence of the land use and sociodemographic composition of the neighborhoods, there is no way to be sure which factors are impacting MVT levels due to confounding between variables. For example, high levels of MVT have been associated with neighborhoods of high transience (Miethe & Meier, 1994), but is this due to the short tenure of residents or the presence of apartment complexes with poorly-secured community parking lots that provide ample opportunities for MVT to occur (Plouffe & Sampson, 2004)? Additionally, might the high levels of MVT found in studies of low socio-economic status (SES) neighborhoods (Walsh & Taylor, 2007a) be the result of mixed land use, a common situation found in inner-city, low income areas that also may increase the number of vehicles in the neighborhood that can be stolen? Theory development, especially opportunity theory, which is the focus of this research study, may lack explanatory strength as a result of incomplete models.

The failure to use predictive models that include both opportunity and sociodemographic variables can result in misunderstandings of not only the problem, but also potential solutions. This is an especially important point for crime prevention efforts, for while there may be limited opportunities to alter the sociodemographic status of residents, say, as in the percentage of renters in an area, reducing opportunity (such as through increasing security in apartment parking lots) is far more feasible and has been shown to be successful (Clarke & Harris, 1992b; Plouffe & Sampson, 2004).

A handful of neighborhood studies on MVT do combine opportunity and sociodemographic factors (Rice & Smith, 2002; Roncek & Faggiani, 1985; Roncek & Lobosco, 1983; Roncek & Maier, 1991; Weisel et al., 2006). The majority of these studies however suffer important methodological or analytical limitations. Some include only a single opportunity factor, such as the presence of high schools or bars, and most fail to include a spatial lag to control for the impact of surrounding neighborhoods. A spatial lag is often necessary to control for spatial autocorrelation in the dependent variable which has been shown to inflate error terms in regression models (Chainey & Ratcliffe, 2005; Walsh & Taylor, 2007). Still others studies use inappropriate statistical analysis methods to handle the highly skewed data common in crime research.

In summary, missing from the limited neighborhood research to date on MVT is the establishment of an analytically appropriate approach to identify specific characteristics of ecological units that explain the impact of opportunity while controlling for sociodemographic factors. Such a model would include demographic variables suggested by the communities and crime literature, combined with variables from the opportunity literature that are operationalized at the areal level. Additionally, because it is an ecological model, a test for spatial autocorrelation in the dependent variable should be performed and a spatial lag included if necessary. Finally, the analysis must be performed by a statistical method that can handle the highly skewed data common in spatial crime research. It is the goal of this research to take all of these issues into consideration to create analytically appropriate models for examining MVT in Philadelphia, Pennsylvania. This study also seeks to identify opportunity factors, specifically, land uses and facilities types that increase MVT levels, net the effects of neighborhood sociodemographics.

Research Question

The primary research question asked in this study is "After controlling for socio-structural correlates, is the presence of certain land uses predictive of MVT levels found at the neighborhood level?" Although definitions of neighborhoods vary, it is operationalized here as the census block group, consistent with other neighborhood studies (Bursik & Grasmick, 1993; Oberwittler & Wikstrom, 2009; McNulty & Holloway, 2000), including those of MVT (Walsh & Taylor, 2007a, 2007b). Subsequent aims are to test for interactions between opportunity and sociodemographic factors to develop a better understanding of how opportunity for MVT is moderated by, or may work entirely separately from, neighborhood sociodemographics.

This Study

This study attempts to answer the research questions by investigating MVT levels across the 1,816 census block groups in the city of Philadelphia, Pennsylvania. The dependent variable is the count of motor vehicle thefts reported to the Philadelphia Police Department aggregated for the years 2006, 2007, and 2008. Predictor variables include both opportunity and sociodemographic factors operationalized at the block group level.

Opportunity factors evaluated by the study are consistent with explanations posited by the opportunity models of rational choice (Clarke & Cornish, 1985), routine activity (Cohen & Felson, 1979), and crime pattern theories (Brantingham & Brantingham, 1991). Together these theories explain the how, when, and where of high crime opportunity. Opportunity is defined as the settings or physical requirements necessary to commit a crime (Felson & Clarke, 1998). Opportunity predictor variables consist of a number of specified land use and facility types theorized as criminogenic for MVT by these opportunity theories, and the limited available empirical research. The opportunity variables include shopping centers, bars, high schools and colleges, commercial parking lots, youth hangouts, and single family detached homes and are operationalized as the total percentage of land area of each census block group utilized by each land use type. For example, the percentage of total land area utilized by shopping centers in block groups is expected to be related to the number of vehicle thefts because large parking lots provide greater opportunity for MVT due to more vehicles being present. Additionally, some land uses such as high schools have been shown to increase crime not only within their own property borders, but also in their immediate surroundings due to an increase in the awareness of crime opportunities by offenders that visit these high activity nodes (Brantingham & Brantingham, 1993a). For example, students who travel through neighborhoods to get to school become aware of opportunities for committing crimes in the neighborhood near the school. To measure these 'proximity' effects, the total land area that falls within a prescribed distance surrounding theorized criminogenic land uses is evaluated for its impact on neighborhood MVT levels.

Sociodemographic factors serve primarily as control variables in this study, although findings may add to the current knowledge base of these factors in explaining MVT. Demographic data, provided by the 2000 U. S. Census, include variables for the concepts of SES, race composition, neighborhood disruption, family disruption, and age composition. Specific demographic factors were chosen for the analysis due to their predictive power in the communities and crime literature and from the limited neighborhood research on MVT.

A Geographic Information System (GIS) is used to aggregate individual MVT incidents to provide a count for each block group covering the years 2006-2008 and to determine the percentage of total land area utilized by each opportunity variable. GeoDa software is used to produce a spatial lag variable due to spatial dependence in the MVT block group counts. As explained in Chapter 3, negative binomial regression is used to perform the multivariate analyses because the dependent variable is counts of

MVT per block group, data which are highly skewed and show evidence of overdispersion.

The analysis involves a series of models. The first examines only the influence of sociodemographic control variables on MVT, the second examines the impact of opportunity factors only, and the third model combines both sociodemographic and opportunity factors. Tests for interaction effects are evaluated in additional analyses.

The following chapters explain the study and results in detail. Chapter 2 – Literature Review- is a comprehensive examination of the extant research on opportunity and sociodemographic factors related to MVT. A critique of this work provides the rationale for the current study. This chapter also presents the hypotheses to be tested. Chapter 3 – Methodology - describes in detail how the study was conducted. It identifies in detail the data used, operationalization of opportunity factors, and analytical methods. Chapter 4 – Results - presents descriptive data for the study area and the results of the hypotheses testing. Chapter 5 - Discussion – summarizes the findings of the analyses and discusses their implication to theory, policy, and future research.

CHAPTER 2

LITERATURE REVIEW

This chapter begins by examining the extent of the MVT problem and discusses the lack of robust empirical studies examining this crime at the neighborhood level. Next, it identifies sociodemographic and opportunity variables that have been shown, or are likely to explain variations in MVT counts across neighborhoods. The chapter ends with the specific hypotheses that the study examines.

The Motor Vehicle Theft Problem

Motor vehicle theft is defined by the Uniform Crime Reporting Handbook as the theft or attempted theft of a motor vehicle. Motor vehicles are self-propelled vehicles that run on land surfaces and include automobiles, trucks, sport utility vehicles, buses, motorcycles, motor scooters, and all-terrain vehicles, but exclude farm and construction machinery, aircraft, and watercraft (FBI, 2004).

Thefts of motor vehicles in the United States peaked in 1991, and like most major crimes, decreased significantly during the 1990's. However, these relatively recent decreases had followed substantial and steady increases during the 1960s, 70s and 80s resulting in a level (in 1991) equal to nearly four times that of the 1960 rate (Figure 1). This rate of increase was significantly higher than any other UCR Part 1 index crime, save robbery. After decreasing significantly between 1992 and the end of the decade, MVT rates again rose noticeably over the years 2001, 2002, and 2003, and slowly decreased, but not reaching the lower 2000 level until 2006 (Bureau of Justice

Statistics, 2008). No other index crime displayed a similar pattern of multi-year increase and reduction during this time period. Thefts continued to decrease after 2006.

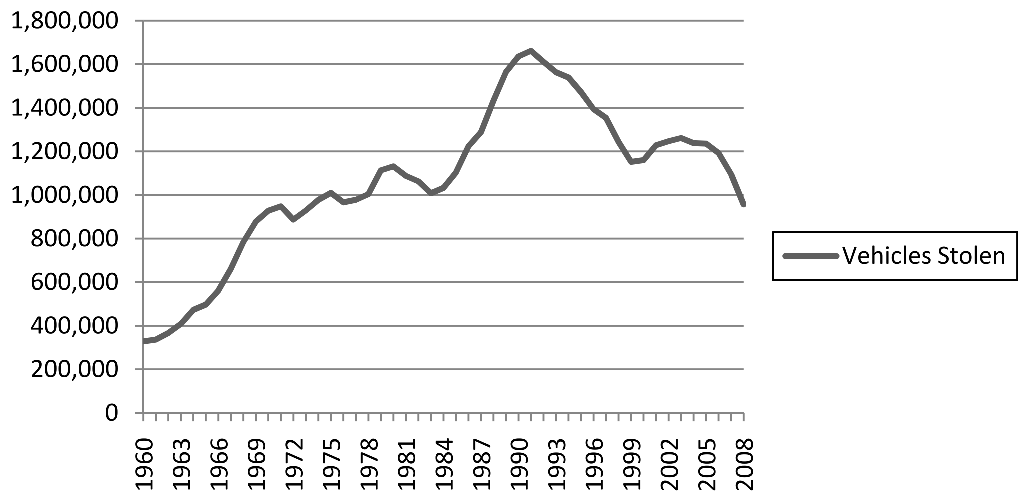

Figure 1. Reported Number of Vehicle Thefts in the U.S., 1960-2008

Law enforcement has found it particularly difficult to combat MVT as shown by historically low clearance rates (Walsh & Taylor, 2007a). In 2008, only 12% of motor vehicle thefts were cleared by arrest or exceptional means. This rate, below even burglary at 12.5%, was the lowest for all UCR Part 1 index crimes. With an average-vehicle-loss value of $6,751 in 2008, vehicle thefts are far more costly than the average burglary loss of $2,079 (FBI, 2009).

Besides the direct monetary loss, MVT also results in inconvenience and loss of work time for its victims, injuries that occur while joy riding and trying to evade the police, increased facilitation of other crimes committed when stolen vehicles are used, and expenses incurred when investigating crimes or attempting to prevent thefts (e.g., insurance and antitheft devices) (Harlow, 1988; Hough & Mayhew, 1985; Rice & Smith, 2002). Although the emotional response to being the victim of vehicle theft is not comparable to violent crime, it is, however, more than trivial. For example, the 2000 British Crime Survey found that 72% of respondents in MVT victimized households reported being either “quite a lot” or “very much “ emotionally affected by having a vehicle stolen (Kershaw et al., 2000).

The above review demonstrates that MVT is an important and expensive crime; one criminologists should understand in detail so effective prevention techniques can be applied. However, the following review shows this has not been realized in the relatively small number of empirical studies of MVT. Neighborhood-level studies on MVT are limited in number and most fail to include both sociodemographic and opportunity variables to help enable a more thorough understanding of the situational context of MVT. Additionally, much of this research also suffers key methodological limitations.

Limited Neighborhood Studies on MVT

Most of the previous research on MVT has been centered on the characteristics of offenders, their decision-making regarding target selection, and security features of high theft locations, especially parking lots. Only a limited number of neighborhood-level studies on MVT have been completed to date. These studies will be reviewed here but specific findings will be discussed later in this paper. For now, the focus is on highlighting key problems in their methodological approach, thus showing the need for the current study and subsequent neighborhood-level research on MVT. For clarity, the neighborhood studies are grouped in the following manner; national crime victimization survey studies, demographic-only studies, opportunity-only studies, and sociodemographic-opportunity studies.

The first group of studies utilizes national crime victimization survey data (U.S. and British) aggregated to neighborhood levels in an attempt to identify factors that correlate with MVT. However, they all suffer from a significant data limitation; respondents are only queried concerning their own household victimization and frequently only on thefts that occurred in their home neighborhoods (Hope & Hough, 1988; Kennedy & Forde, 1990; Kershaw et al., 2000; Miethe & Meier, 1994; Sampson & Groves, 1989). Missing from these studies are vehicle thefts suffered by visitors and workers outside their home neighborhoods, as well as all thefts from businesses. Prior research suggests that a substantial percentage, from 17 to 34% of thefts occur away from victims' homes (BJS, 2004; Plouffe & Sampson, 2004). Thus, failure to include these additional crimes may have introduced spatial bias into the findings of this type of studies regarding areal crime patterns and correlates of MVT.

The second group of extant neighborhood studies on MVT focuses only on sociodemographic correlates (Copes, 1999; Miethe & Meier, 1994; Saville & Murdy, 1988; Walsh & Taylor, 2007a, 2007b). These examinations use police data which may more accurately reflect the number of MVT thefts in an area (the 2003 National Crime Victimization Survey (NCVS) found a 95% reporting rate for MVT), but these studies only include demographic predictor variables, neither identifying nor controlling for opportunity factors found in neighborhoods. This line of research helps identify relationships between community demographic structure and MVT, but by excluding opportunity factors, it is missing important variables that could explain theoretically contradictory findings across studies. For example, some studies show that neighborhoods of higher socio-economic status, a variable usually associated with low crime areas, are found to experience high rates of MVT (for an example, see Rengert, 1997).

An additional concern with demographic-only studies is that some variables may be confounded with opportunity variables, such as may be the case with the percentage of renters (versus homeowners) in a population. A high percentage of renters may relate to a lack of commitment by residents that can reduce social control and increase crime (Schuerman & Korbin, 1986; White, 2001), or it may indicate the presence of apartment complexes with their often poorly secured, lighted, and surveilled off-street lots that are associated with higher MVT levels (Clarke & Mayhew, 1994; Mayhew & Braun, 2004; Plouffe & Sampson, 2004; Rice & Smith, 2002).

The next group of studies at the neighborhood level is opportunity-only studies, which consider only opportunity factors found within the built environment as predictors of MVT (Henry & Bryan, 2000; Plouffe & Sampson, 2004; Rengert, 1997). These examinations typically use Geographical Information Systems (GIS) software to identify *hot spots*, or clusters of MVT (Sherman, Gartin, & Buerger, 1989). Researchers then identify the characteristics of the places in which the crime clusters are found, and applying opportunity theories, explain how particular land uses provide extra opportunity for MVT resulting in the hot spots. Researchers may refer to demographic variables in these studies, such that a cluster of crimes is observed in a low-income neighborhood, but the emphasis is on identifying opportunity factors alone.

While useful, opportunity-only studies lack the ability to isolate the importance of opportunity factors from demographic structure. For example, in a streetblock-level study that included sociodemographic factors and numerous land uses, Rice and Smith (2002) found that a high number of empty lots, commonly found in low income areas suffering from economic disinvestment, were associated with higher numbers of MVT. Only through the inclusion of the neighborhood socio-economic status variables in their model were they able to suggest the relationship between the number of vacant lots and MVT was a positive one. It could have been a spurious one, resulting not from the presence of the many vacant lots but rather from the processes of low SES neighborhoods on crime that are so often described in the literature.

Only by including both sociodemographic and opportunity variables in multivariate analyses is it likely that the true correlates of high neighborhood MVT levels can be identified. This is especially important to crime prevention efforts. For example, there may be limited opportunities to alter the sociodemographic status of residents, say, as in the percentage of renters in an area, but reducing opportunity (such as through the increasing of security at parking lots) is far more feasible and has already been shown to be successful against MVT (Clarke & Harris, 1992b; Plouffe & Sampson, 2004).

A final but limited group of neighborhood studies combines opportunity and sociodemographic factors, as done in the current study. However, although each of these has added important information to the understanding of MVT, most suffer potentially serious methodological limitations. For example, Roncek and colleagues (Roncek & Faggiani, 1985; Roncek & Lobosco, 1983; Roncek & Maier, 1991) completed a series of studies of San Diego and Cleveland examining the influence of both demographic and opportunity factors (present in select land uses) on crime. They found that close proximity (within one block) of both high schools and bars predicted higher counts of MVT in census blocks, while controlling for sociodemographic differences. Unfortunately, their two studies examining the impact of high schools on crime (Roncek & Faggiani, 1985; Roncek & Lobosco, 1983) did not address spatial autocorrelation or include spatial lag terms. Failure to include a spatial lag to account for spatial autocorrelation in ecological data, a statistical necessity that has only been appreciated in recent years, has been shown to inflate error terms in regression models (Chainey & Ratcliffe, 2005; Walsh & Taylor, 2007). Thus, the results from these two models are suspect because some of the predictor coefficients may have been statistically significant in error, a byproduct of inflated error terms in multiple regression models. All three of the Roncek studies also included only one theorized opportunity-producing land use, either high schools or bars, and thus were limited in their ability to examine the relationship between several neighborhood opportunity variables, sociodemographics, and MVT.

In another study, Weisel et al. (2006) examined MVT in four contiguous non-urban counties in North Carolina. This study included both demographic and opportunity variables, but also failed to consider spatial autocorrelation. Opportunity factors included the amount of residential, commercial, industrial, and office parcels in each of the block groups analyzed. The results presented were informative, but using general categories of land use limited the study's usefulness in understanding the opportunity-enhancing effect of specific land uses, which is the goal of the present study.

Rice and Smith (2002) completed a streetblock-level study in an unidentified southeastern U.S. city that included both demographics and opportunity-related land uses and facilities. Their opportunity variables included the number of vacant lots, parking lots, restaurants, gas stations, bars, youth hangouts (schools, arcades, and public pools), apartment buildings, retail stores, non-retail commercial places, and hotels and motels. The inclusion of the many specific land uses and demographics in the study was informative, but the study suffered from two important limitations. First, the dependent variable, which consisted of the count of vehicle thefts per block, was highly skewed, even after the statistical transformations were applied (skewness statistic of 3.68 and 88% of blocks had no thefts), indicating that the OLS regression analysis used was not entirely appropriate. Secondly, the spatial lag included was poorly designed because it did not control for the influence of MVT counts on streetblocks encircling each unit of analysis, but rather was bi-directional only. Thus, the implications of this study, which showed that nearly all variables (including the interaction terms in every model) were statistically significant, are arguable.

The above review has revealed the weaknesses and limitation in the extant neighborhood-level studies on MVT. Specific findings, with the caveat of the aforementioned statistical issues, will be discussed later in this paper. It is clear from the review that scientific knowledge concerning MVT at ecological levels is in need of further development and testing. Future studies should test for the existence of interactions between opportunity and sociodemographic variables, include spatial lag variables when necessary, and use an appropriate analytical technique that addresses the highly skewed nature of MVT data.

The present research overcomes the aforementioned limitations. It includes both opportunity and sociodemographic variables, controls for spatial autocorrelation, and use analytical methods appropriate for the dependent variable. In order to proceed, it is necessary to understand the role opportunity plays in crime, and particularly in MVT. To do so, the following section outlines three opportunity theories and relates specific constructs within each as possible explanations for MVT.

Theoretical Foundations of Opportunity and Crime

Without opportunity, there can be no crime. No matter how motivated a potential offender may be (say to steal a vehicle) there can be no crime if the situational context that provides the opportunity to commit the crime does not exist. The more obvious example of opportunity in MVT consists of a vehicle in a setting where the theft is unlikely to be hampered by the vehicle’s owner, neighbors, passers-by, or a police officer. However, ethnographic research identifies other important opportunities that also need to be present. Especially important is the availability of particular types or models of vehicles that the offender already possesses skills needed for entering, starting the engine, and driving off in the vehicle (Clarke & Harris, 1992a; Light, Nee,

& Ingham, 1993; Fleming, Brantingham & Brantingham,1994). Additionally, the available vehicle must fit within the offender's particular motivations for the crime. This may include; having valuable after-market parts that can be resold, being the make and model that meets a "chopshop" or other buyer's preference, looking "cool" enough to impress the offender's friends, or being a model that won't stand out to the police when being used for temporary transportation (Cherbonneau & Copes, 2006; Copes & Cherbonneau, 2006; Copes, 2003).

Opportunity for crime, including MVT, is not found uniformly across the urban landscape (Brantingham & Brantingham, 2008). Studies show that crime tends to cluster in areas of high opportunity, where characteristics of the environment make it easier to commit offenses in general, or crimes of particular types (Sherman, Gartin, & Buerger, 1989). The clustering of street robberies around subway stations (Block & Block, 2000; Block & Davis, 1996; McCord & Ratcliffe, 2009), assaults around bars (Block & Block, 1995; Roncek & Maier, 1991), and property and violent crime around high schools (Brantingham & Brantingham, 1995a, Roncek & Faggiani, 1985; Roncek & Lobosco, 1983), are all explained by the increase in crime opportunity provided by these specific categories of land uses (subway stations, bars, and high schools).

Three opportunity theories (Felson & Clarke, 1998) explain how and why these crime opportunities exist and where they can be found in the urban landscape. These theories are the rational choice perspective (Clarke & Cornish, 1985; Cornish & Clarke, 1986), routine activities (Cohen & Felson, 1979: Eck, 1994), and crime pattern theory

(Brantingham & Brantingham, 1991; 2008). To understand how opportunity factors in MVT may play out across the urban environment, each theory is examined below.

Rational Choice Perspective

The rational choice perspective is based on the proposition that offenders use some level of rational thinking in their decision making concerning crime (Clarke & Cornish, 1985; Cornish & Clark, 1986). Its main assumption is that offending is purposeful behavior designed to benefit the offender in some way (Felson & Clark, 1998). Decisions for becoming involved in criminal acts, which type of crime, and the when, where, and how these crimes will be committed, have all been shown to involve some level of rational thinking on the part of offenders (Cornish & Clarke, 2008). Evidence of this rationality is revealed not only in interviews with offenders, but also through the study of criminal events and target selection (Clarke, 1997; Cornish & Clarke, 2008).

Criminal decision-making, as explained by rational choice theory, is characterized by a rudimentary, or *bounded*, cost-benefit analysis, not the complete utilitarian analysis suggested by neoclassical economists such as Becker (1968). Constraints and benefits of criminal behavior are expressly viewed and weighed from the subjective standpoint of the offender, and when viewed this way, rationality is found in most criminal acts (Cornish & Clarke, 2008). For example, the benefit of most property crime is financial gain, however, violent crime also can be viewed as being a rational choice as well. This occurs when a juvenile commits a violent act to further the reputation of a gang or when an assault is committed to regain or ensure respect (Anderson, 1999; Opp, 1997). As explained by rational choice theory, the more latent benefits of feeling of belonging to the gang or increased respect, are alone, enough motivation to commit these acts. Joyriding (the act of stealing a car, driving it around for a short while and then leaving it parked somewhere) may not appear to be a rational act considering the legal consequences of arrest and possible imprisonment; however, to a juvenile offender, the reward for taking and driving the car often includes a heightened feeling of masculinity, excitement, dangerousness, and pride in displaying the technical mastery of skills needed to steal and drive another person's automobile (Fleming, Brantingham, & Brantingham, 1994; O'Connor & Kelly, 2006).

In their seminal book on rational choice, Cornish and Clarke (1986) present a two-phase model explaining the decision-making process of potential offenders. The first phase of the model is described as the *initial involvement* phase and relates to motivation. It includes decisions made up to the point the offender decides to commit a particular crime (Cornish & Clark, 1986; Lersch, 2004). The second phase of the model is the *event decision* and relates directly to opportunity. It is here that the offender selects a specific crime target based upon situational circumstances found within the immediate environment. Event decisions are based upon subjective assessments of the best, or at least acceptable, opportunities available, as defined by the amount of effort, risk, and reward inherent in committing the act (Cornish & Clark, 1986; Lersch, 2004). It is in this second phase where the presence of available "good" opportunities (as perceived by the offender) determines where and when the crime will be committed. Places and neighborhoods of high opportunity, as determined by many like-minded offenders, will result in many offenses being committed there (Sherman, Gartin, & Buerger, 1989).

The criminal is seen as a rational human being in the rational choice perspective. He/she seeks opportunities within the environment to help ensure the success of his/her crime, reduce the amount of effort necessary to commit the act, and ensure the highest reward. "Good" opportunities for crime are specific situational factors resulting from the everyday activities of people and places, as explained by the next theory of routine activities.

Routine Activity Theory

The second opportunity theory examined is routine activity. This theory explains the occurrence of crime as the convergence in time and place of a *motivated offender* with a *suitable target*, in a place absent a *capable guardian* (Cohen & Felson, 1979). A capable guardian is any person who by his or her mere presence prevents a crime from occurring. The theory posits that the interactions of these three conditions (motivated offender, suitable target, lack of capable guardian) provide opportunity for crime, and that opportunity is brought about by the daily, normal activities of victims and offenders in society (Cohen & Felson, 1979).

Felson (1986) added to the theory by incorporating ideas from Hirschi's (1969) social control theory resulting in the concept of the *handler*. This person prevents crime through the supervision of likely offenders brought about by a socially identified bond, such as shared by parents, teachers, relatives, or friends. Felson (2008) however clarifies that routine activity remains a theory of crime, not criminality. In referring to control by handlers, he states, "rather than viewing control as something internalized, it [theory] emphasized the presences or absences of others who might supervise a person. Thus, parents can influence their children to be good, but not so effectively when the parents are away" (Felson, 2008, p. 74).

Upon completing a comparative study between apartment complexes where drug sales occurred and others where they did not, Eck (1994) added to routine activity theory with the addition of a *place manager* concept. Place managers are persons who monitor or control places and include homeowners, door and parking lot attendants, private security officers, motel clerks, and apartment managers. Crime opportunity reduction can result from place managers either through their presence (i.e., access controlled to a building or parking lot by an attendant), or through everyday decisions and rule setting that purposely, or inadvertently, reduces crime opportunities.

Routine activity theory thus identifies three objects of supervision, a target, an offender, and a place. A guardian supervises the target, a handler supervises the offender, and a manager supervises a place. Crime opportunity is explained under the theory as occurring when an offender away from the supervision of a handler, comes into contact with a suitable target, in a place that lacks effective guardianship. Lacking any one of these conditions decreases opportunity for the offender and reduces the likelihood of a crime occurring.

Crime Pattern Theory

Crime pattern theory, developed by Brantingham and Brantingham (1993a; 2008) is particularly useful in explaining where crime opportunities will be found across the urban landscape. It combines routine activity and rational choice theories while considering how people and objects involved in crime move about in space and time

(Felson & Clarke, 1998). The location and movement of offenders, targets, handlers, guardians, and managers across spatial and temporal patterns all relate to where and when crime opportunities will be located.

An important concept in crime pattern theory is *awareness space*; an idea related to the cognitive map people form concerning geographical relationships in the world around them (Brantingham & Brantingham, 1993a). As people move about during the day attending to their regular activities (i.e., working, going to school, shopping) they develop an awareness of places they experience. For the criminally inclined, this awareness includes information on locations where they perceive crime opportunity. The motivated offender may take advantage of opportunities presented immediately, or wait until a later time and return to the location.

Awareness spaces change as offenders age, alter friendship networks, shift jobs and schools, or move residences. Studies in commute distances to crime reveal that many offenses are spatially centered on offenders' homes because of familiarity with these areas (see review in Rossmo, 2000). In one such study of 2100 arrested adult offenders, the median distance from home to robbery sites was 1.62 miles, to burglary sites 1.2 miles, and to rape sites .73 miles (Rhodes & Conley, 1991).

Nodes and *paths* are terms used in crime pattern theory to define the parameters of awareness space (Brantingham & Brantingham, 1993b). Nodes are central and frequently visited places in a person's life. They can be individual in nature, including one's home address, school, or worksite, or more public, as in a frequented park or shopping center. Paths are streets, walkways, or pathways on which people travel between nodes.

High activity nodes and paths contribute to the awareness space of many people. This can lead to more crime in these areas because of the increased awareness of crime opportunities by the many potential offenders utilizing them. For example, neighborhoods containing or located near high activity nodes such as high schools (LaGrange, 1999; Roncek & Faggiani, 1985; Roncek & LoBosco, 1983) and shopping centers (Andresen, 2007; Miethe & McDowall, 1993; Wilcox, Quisenberry, Cabrera, & Jones, 2004) have been shown to have higher levels of crime than neighborhoods farther away. Neighborhoods adjacent to heavier trafficked streets (paths) and neighborhoods whose design makes them more accessible to the public (more entrance/exit streets, gridiron designed roadways) are also found to have higher crime rates (Beavon, Brantingham, & Brantingham, 1994; White, 1990; Wright & Decker, 1997). Convenience stores located on busier streets are at higher risk for robbery (Duffala, 1976) and homes located near busy highways have increased risk of burglary (Rengert & Wasilchick, 2000). However, houses located on much less-trafficked cul-de-sacs experience far less burglary victimizations (Hakim, Rengert, & Shachamurove, 2000). In each of these situations, crime opportunities falling in the awareness space of many offenders result in higher crime levels than if the locations were more secluded and known to fewer offenders.

Edges refers to the boundaries of areas where people live, work, shop, or seek entertainment and are easily distinguished via differences in buildings, land use, physical features, and sometime sociodemographics. Edges include the land at a river's edge, the border where residential and business properties meet, and the interstitial areas that may separate a predominately white from black, or middle-income from lower-income neighborhoods. Crime often occurs on edges of neighborhoods where strangers are ignored because they are part of everyday legitimate activities, such as on a residential street that borders a commercial center. Farther inside the neighborhood, a stranger would be more closely watched by residents or challenged concerning his reason for being in the area. Additionally, edges often contain concentrated criminal opportunities due to the mixed land use frequently found on borders such as those formed by major roadways (Brantingham & Brantingham, 1993b; Lersch, 2004).

Crime *generator* and crime *attractor* are terms used by Brantingham and Brantingham (1995b; 2008) to label specific nodes or land uses that become crime hotspots. The reason for this clustering of crime differs between the two but is closely related to the specific daily routine activities associated with each group. Crime generators produce crime because they attract many people for non-criminal reasons, but some of these individuals are motivated enough to take advantage of opportunities for criminal behavior present. Generators include shopping centers, high schools, sport stadiums, and entertainment districts. Crime attractors are places, areas, or districts where a high proportion of offenders are specifically attracted due to a high level of criminal opportunities available there. Crime attractors include street drug markets, bar districts, prostitution strolls and "red-light" districts, and large shopping malls or unsecured parking lots that offer many well-known crime opportunities (Brantingham & Brantingham, 1995b).

Eck (1995) adds the term *facilities* to crime pattern theory as environments that are designed and operated for specific functions. Schools involve teaching and studying, transport centers collect and move people around, retail stores display products and involve monetary transactions, and industrial sites produce products from raw material (Clarke & Eck, 2003). Some facility types are criminogenic in nature due to the specific activities occurring there (Eck, 1995). Shopping centers, bars and other liquor outlets, subway stops, and high schools all have been shown to produce high levels of crime (Block & Davis, 1996; Gorman, Speer, Gruenewald, & Labouvie, 2001; Roncek & Faggiani, 1985; Schweitzer, Kim, & Mackin, 1999). *Risky facilities* are those facilities within a defined category that are the most crime prone, often due to poor place management and an excess of crime opportunities (Clarke & Eck, 2003).

Together, rational choice, routine activity, and crime pattern theory explain the why, where, and when crime opportunities will locate and cluster across the varying structures, pathways, and public areas that make up the urban mosaic. I now turn to opportunity dealing specifically with the crime of MVT.

Opportunity and MVT

In recent years, there has been a considerable amount of research focused on preventing MVT via *situational crime prevention*, techniques specifically designed to reduce opportunities for crime to occur (see Clarke, 1997; Clarke & Harris, 1992b; Weisel et al, 2006). With this crime prevention research has come a more thorough understanding of MVT and the types of opportunities necessary to commit the crime. Although these studies focus on specific situational factors and are not evaluated across neighborhoods, they do assist in providing a better understanding of how opportunity might play out across the urban environment. This is especially true when evaluated in concert with the three opportunity theories previously discussed and applied specifically to MVT.

One important opportunity-related finding from these studies concerns the selectiveness of offenders in the type and model of vehicles they steal. Both ethnographic and quantitative studies of vehicle model theft rates provide strong evidence of a systematic selection process by offenders (Clarke & Harris, 1992a; Copes, 2003; Fleming, Brantingham, & Brantingham, 1994; O'Connor & Kelly, 2006; Weisel et al., 2006). For example, studies show that older models are specifically targeted and stolen at higher rates primarily due to lower levels of security on the vehicles (Clarke & Harris, 1992a; Newman, 2004; NICB, 2007; Weisel, et al., 2006). Electronic immobilizers and other sophisticated security devices introduced in recent years have made it difficult for all but the most advanced thieves to target newer vehicles. As a result, Copes and Cherbonneau (2006) find that inexperienced juvenile offenders often search for vehicles left with keys in the ignition because they do not have the skills necessarily to defeat many new car security systems.

Vehicle selectiveness is also present in the literature concerning MVT motivation. Researchers have identified three types of MVT based upon the offender's motivation for the crime; stealing a vehicle for temporary transportation purposes, stealing for vehicle parts, and stealing for permanent use (Clarke & Harris, 1992a; Weisel et al., 2006). Stealing a vehicle for temporary use, either for transportation or to commit another crime, includes the many vehicles stolen for joyriding by juveniles. Common everyday models that are easy to steal and drive, and those popular with youth, are more likely to be stolen when the motivation involves temporary use (Clarke & Harris, 1992a; Copes & Cherbonneau, 2006). The second type of MVT involves stealing a vehicle for its parts, especially expensive after-market wheels and stereo systems. Vehicles with expensive and flashy add-ons are particularly sought after with the stolen parts resold or placed on the offender's own vehicle (Clarke & Harris, 1992a; Copes, 2003; Keister, 2007). The third motivation concerns the stealing of vehicles for permanent use. These are generally newer, high-dollar sporty or foreign vehicles that have their vehicle identification numbers (V.I.N.) switched with that of a salvaged vehicle to hide their stolen identity or are exported to other countries for resale (Brown & Clarke, 2004).

The strong evidence of selection in MVT indicates that thieves do not merely steal the first vehicle they come across but rather shop around for preferred makes and models. This suggests that locations where large numbers of vehicles are parked should experience higher rates of MVT due to wider selection being available. A review of the literature supports this hypothesis. Parking lots, whether designed specifically for commuters using public transportation, or private lots for the use of customers and employees of shopping centers, motels, colleges, office complexes, and industrial facilities have all been identified as locations where large numbers of MVT occur

(Clarke, 2002; Plouffe & Sampson, 2004; Rice & Smith, 2002). Larger lots, those with over 100 stalls, offering a larger selection appear to be targeted specifically (Fleming, Brantingham, & Brantingham, 1994). Parking lots of “big box” retail stores such as Target, Home Depot, and Wal-Mart also facilitate high levels of MVT due to their high density of parking stalls (Plouffe & Sampson, 2004).

A large concentration of vehicles alone, however, is not sufficient opportunity for MVT. Offenders also must be able to commit these crimes in places where they will not be hindered by others or thwarted by on-site security measures. Research examining theft levels across parking lots find those with security features including perimeter fencing, exit bars, CCTV cameras, and good lighting, have significantly lower theft rates than those without these features (Clarke & Goldstein, 2003; Mayhew & Braun, 2004; Plouffe & Sampson, 2004). Multi-level parking structures which commonly have on-site attendants who exercise extra surveillance through their job as fee collectors, and whose design generally restricts pedestrian and vehicle movement through only one entrance, also experience many fewer thefts (Clarke, 2002). For example, Clarke & Goldstein (2003) found that thefts from single, ground–level parking lots in Charlotte, North Carolina were six times higher than multi-level deck parking because of the lower level of security they provide.

The decreased level of surveillance provided by darkness is also sought out by MVT offenders. Estimates for nighttime thefts as a percentage of all vehicle thefts range from 56% to 70% across studies (FBI, 2001; Fleming, Brantingham, & Brantingham, 1994; Sallybanks & Brown, 1999). In addition, many offenders themselves report they prefer to commit these crimes during hours of darkness to avoid being seen (Light, Nee, & Ingham, 1993), again showing a degree of rational choice.

The combination of opportunity provided by darkness and greater selection of vehicles and models explains the clustering of MVT found around many nighttime entertainment venues. Movie theatres, restaurants, and bars and nightclubs, especially where they are found grouped together in busy late-night districts, provide strong attraction for vehicle thieves resulting in higher levels of thefts in these areas (Henry & Brian, 2000; Plouffe & Sampson, 2004; Rengert, 1996; Rice & Smith, 2002).

Residential areas have their own opportunity structure that plays into available opportunity and offender decision making. Reduced outside activity during nighttime hours in residential neighborhoods provides concealment for offenders, but housing design can also add opportunity for theft. Research in residential areas shows that the risk for MVT is about three times higher for vehicles parked on streets than driveways, and is about twenty times higher than for vehicles parked in the owner's garage (Clark & Mayhew, 1998). Additionally, theft levels from single family residences, which frequently have garages or private driveways, are at least half that of multi-family dwellings where vehicles are more often parked in semi-public lots or on nearby streets (Weisel et al., 2006).

Demographic Covariates and MVT

The current study also includes neighborhood-level sociodemographic variables to evaluate the impact of opportunity factors net the effect of the characteristics of the people who live in the neighborhoods. The selection of demographic variables is based upon the communities and crime literature and the few available neighborhood level studies on MVT.

Socio-economic status (SES) has emerged as one of the strongest correlates of delinquency, victimization, crime, and offending rates (Bursik & Grasmick, 1993). As early as the mid 1800s, researchers including Andre-Michel Guerry and Adolphe Quetelet (as cited in Vold, Bernard, & Snipes, 1998) noted the importance of socio-economic status in their studies of social conditions and crime in France. This relationship, usually shown as a negative one where lower SES is correlated with higher crime and delinquency rates, is found to exist across varying units of analysis (cities, census tracts, block groups) in macro-level studies (Pratt, 2001). This is the case even though research on individual-level socio-economic status often fails to show a strong link with criminality (see Title & Meier, 1990).

SES has been operationalized a number of ways, including median household income, percentage population below the poverty level, unemployment rate, median rent, median property value, and in indices that combine these variables. Regardless of how it is measured, research generally supports the idea that neighborhoods of lower SES tend to have higher violent and property crime rates (Pratt, 2001; Sampson & Lauritsen, 1994).

Neighborhood-level studies on MVT also find it has a negative relationship with SES. In a cross-sectional study of a Midwestern city, Walsh & Taylor (2007b) found that their SES index (composed of median owner-occupied property value, median household income, and percent population below poverty line) related negatively to

MVT rates aggregated at the block group level, while controlling for other primary demographics and including a spatial lag. However, the same authors, using nearly identical variables in a 10 year longitudinal study of the same city found SES was not a significant predictor of MVT rate changes across time (Walsh & Taylor, 2007a).

Miethe and Meier (1994) reported a negative relationship between median household income and MVT across the 114 Seattle census tracts that controlled for other primary demographics. Their study, however, did not include a spatial lag or opportunity factors.

Rice and Smith (2002), using percent below median property value as an SES variable, also found a significant and negative relationship with MVT in their study of streetblocks. Their study also controlled for numerous opportunities factors, other primary demographics, and spatial autocorrelation of the dependent variable (MVT counts).

Weisel et al. (2006) examined MVT at the block group level in a rural four-county area of North Carolina, a study which included general categories of land use opportunity factors, a spatial lag, and a long list of sociodemographic indicators. Using forward-entry OLS regression, SES indicators of percent population below the poverty level, percent population 1.5 times below the poverty level, and median household income were all dropped automatically from the model.

In Roncek and Maier's (1991) study that included bars as an opportunity variable, a spatial lag, and other primary demographics, SES was measured as the median owner-occupied property value and was found to be positive and significant;

that is, block groups with higher median property values had higher counts of MVT. The authors did not comment on this finding but it is interesting to note that in their reported results (Table 2, p. 740) only MVT of the seven index crimes examined revealed this relationship.

The remaining neighborhood studies on MVT were not useful in evaluating SES. Roncek and Faggiani (1985) and Roncek and Lobosco (1983) both included SES variables but did not report on them or any other demographic results. Saville and Murdy (1988) did not include a SES variable, and Copes (1999) combined percentage residents living below the poverty line with the percentage males 15-24 yrs old, confounding any interpretation of SES.

In summary, SES variables were evaluated (and reported) in six neighborhood studies. Of these six studies, three showed a negative relationship between MVT levels and SES measured as median income, median owner-occupied property value, and Walsh and Taylor's SES index composed of median income, median property value, and percentage population living below the poverty line. Of the remaining three studies, SES was found insignificant in two, and positive and significant in the third.

Race composition and *racial heterogeneity* have been associated with various crime types and victimization rates. Race composition is frequently operationalized as the percentage of African Americans or Hispanics in a population. Racial heterogeneity is a product term quantifying the level of racial mix in a population. It most often consists of the proportion of whites multiplied by the proportion of African Americans, although additional race/ethnicity proportions also may be included (see Blau, 1977).

Neighborhoods of higher minority population or mix are generally related to higher crime levels (Bursik & Grasmick, 1993; Sampson & Groves, 1989; Warner & Pierce, 1993). Pratt (2001) found that these variables were strong and stable predictors across various units of analysis, many crime types, and in both cross-sectional and longitudinal studies in a meta-analysis of 214 studies.

Given the past work in the communities and crime literature one would expect to find that race composition is related to MVT, but this does not appear to be the case. Rice and Smith (2002) found that the number of African Americans per streetblock was positively related to MVT, but their racial heterogeneity index was non-significant, in an analysis that included numerous opportunity variables and spatial lag. Although, Walsh & Taylor (2007a) found higher racial heterogeneity (percentage white/percentage black) was related to increased MVT rates in their longitudinal study that included demographics and a spatial lag, none of the other three available neighborhood studies that included and reported results for race composition found these variables were significantly related to MVT (Miethe & Maier, 199; Walsh & Taylor, 2007b; Weisel et al., 2006).

In summary, in contrast to that of other crime types, the relationship between neighborhood race composition and MVT appears to be a weak, if non-existent one. Of the five neighborhood studies that included race variables, only two studies found a significant relationship with MVT.

Neighborhood stability is typically operationalized as the proportion of residents in a neighborhood living in the same dwelling for the previous five years. However, other variables, including percentage residents that are homeowners or renters also have been used as appropriate definitions of this concept (Heitgerd & Bursik, 1987; Sampson, 1986; Sampson, Raudenbush, and Earls, 1997). Neighborhood stability has been shown to be associated with crime, beginning at least as far back as Shaw and McKay's 1942 original thesis on social disorganization (Bursik & Grasmick, 1993). Pratt's (2001) meta-analysis found neighborhood stability levels impacted both violent and property crime rates, although it was more influential for the latter. It was found to be an important predictor in both cross-sectional and longitudinal studies.

Neighborhood-level studies examining the effects of neighborhood stability on MVT are too few to provide any general conclusion on how these variables are related. Miethe and Meier (1994) found that higher levels of neighborhood instability (percent in same house less than 5 years) predicted higher MVT rates, but, as noted before, this study included other primary demographics and no opportunity factors or spatial lag. In contrast, neither of the studies by Walsh and Taylor (2007a; 2007b) that included demographics and spatial lags but no opportunity factors, found stability influenced the outcome. Their neighborhood stability variable in both studies, however, was an index combining the percentage of renters, population in same house less than 5 years, one person households, and multi-housing units. It is unclear whether the inclusion of these additional variables measured some additional construct and thus impacted their results. None of the other neighborhood studies included in this paper either incorporated a neighborhood stability variable or reported on their results.

In summary, the criminogenic effect of neighborhood stability found significant for other crimes has not been researched sufficiently to indicate if it has an impact on MVT rates. Only three MVT studies that included neighborhood stability were identified; one reported a positive relationship and the remaining two reported no relationship.

Family disruption levels have been associated with crime and victimization at the neighborhood level (Miethe & Meier, 1994; Sampson, 1986; Sampson & Groves, 1989; Smith, Frazee, & Davison, 2000). In Pratt's (2001) meta-analysis, family disruption was found to have both a high level of impact and stability of effects across property and violent crimes, varying macro-sized levels of analysis, and in both cross-sectional and longitudinal studies.

Family disruption is commonly operationalized as the percentage of single-parent families, female-headed households, divorced, or primary (single)-headed households. The impact of family disruption on neighborhood MVT rates has reached a consensus, albeit through only a few studies. In three of four studies that included the variable and reported on it, higher levels of family disruption predicted higher MVT rates (Miethe & Meier, 1994; Rice & Smith, 2002; Weisel et al., 2006). The fact that two of these three studies also controlled for numerous opportunity factors further suggests the importance of this variable for predicting MVT levels. The fourth neighborhood study that included a family disruption variable was Roncek and Maier (1991). They report a non-significant finding using the percentage female-headed households, however, the three other studies used the percentage of single-parent families.

In summarizing the impact of family disruption on MVT, this variable appears to have a positive and significant effect on the outcome. Three of the four available neighborhood-level studies that operationalized family disruption as either the number or percentage of single-parent households found a positive relationship. The fourth study used percentage female-headed households, perhaps overly restricting the evaluation to only a partial group of single-parent households in an age of high divorce rates where children are often split between parents of both sexes. This variable may also be confounded with other socio-economic indicators especially race and SES.

Age composition concerns the proportion of a population thought to be in their crime-prone years, and there is a general consensus in criminology that crime in general is perpetuated by the young. In 2006, 15-19 year olds consisted of 7.1% of the estimated U.S. population, but accounted for over 20.4% of all arrests. Conversely, those 65 yrs and older were 12.4% of the population but accounted for less than 1% of all arrests (Pastore & Maguire, n.d.). However, age may not be as important for explaining crime rates at the ecological level as arrest statistics may suggest. Meta-analyses of studies on the impact of age composition show it has a low mean effect size and only moderate stability across crime types, levels of analysis, and time dimension (cross-sectional versus longitudinal) (Marvell & Moody, 1991; Pratt, 2001).

Arrest statistics also suggest that MVT is a crime perpetuated by the young. The 15-19 year olds that made up the estimated 7.1% of the nation’s population in 2006 were responsible for over 31.5% of the MVT arrests reported to the FBI, while 20-24 year olds made up another 7.1% of the population and accounted for an additional 19.6% of MVT arrests (Pastore & Maguire, n.d.). These data, however, may be biased towards youth because they are based only on those who are arrested, and it could be that juvenile offenders are more easily caught, thus accounting for their unusually high prevalence in the data (Marvell & Moody, 1991). Similar to crime in general, age composition may not be a good predictor of MVT at the ecological level. In a review of the available neighborhood research, six studies included and reported on an age composition indicator. Only Saville and Murdy (1988) found their variable (the number of 20-24 year olds in police patrol beats) was significantly and positively related to MVT levels. Their research included limited demographic data, no opportunity factors or spatial lag, and found other age composition variables (the number of 15-19 and 25-29 year olds) insignificant. Conversely, Copes (1999) found that the percentage of males 15-24 years old was negatively related to MVT rates in his census tract-level study that included only demographics and no spatial lag. The remaining four neighborhood studies found no relationship between age composition and MVT. However, each of these four studies standardized for population differences between units of analysis by examining percentage, rather than count, of members in the targeted age categories. It is unclear whether this may have affected the outcome, especially as Saville and Murdy used thefts-per-capita as the dependent variable, thus some population standardization was built into the model. The age categories used in the remaining studies that showed non-significant findings included percentage 14-17 and

18-24 year olds (Walsh & Taylor, 2007a; 2007b), below 18 years and over 60 years (Roncek & Maier, 1991), 15-19 and 20-35 years (Weisel et al., 2006), and males only, 15-24 (Copes, 1999).

In summary, the effects of age composition on MVT may be a weak one as found with other crimes in ecological studies. Of the six available studies that evaluated this factor, and 11 different age variables, only one study showed findings in the theorized direction.

To summarize findings on demographic factors, past work on the relationship between MVT and community structure is limited and has been reported to be in need of further research (Copes, 1999; Walsh &Taylor, 2007a; 2007b). As reported above and considering the limited neighborhood level research available, only SES and family disruption have shown any consistency in their relationship with MVT. Race and age composition shows little relationship and neighborhood stability has been included in too few studies to reach a conclusion regarding their impact.

Testing for Interactions

Many researchers do not check for interaction effects although doing so may lead to significant theoretical and practical knowledge. This may be because it would be a daunting task to check for every possible interaction between variables in most studies. For example, a model with 10 variables would eventually involve over 1,000 degrees of freedom. Researchers, therefore, have to assume the absence of some interactions and design tests based upon the specific questions asked by the investigation (Darlington, 1990). The present study includes an exploratory examination of interactions. It asks whether the impact of land use on MVT is moderated by sociodemographics or other opportunity land uses in the neighborhood. Answers to these questions can add much to the current knowledge base on the relationship between opportunity, land use, and MVT.

Previous research examining interactions between land use, community structure, and crime is limited. Wilcox, Quisenberry, Cabrera and Jones (2004) examined the influence of land use, disorder, and neighboring relationships on burglary and violence in Seattle census tracts. Although they tested numerous interactions, only two proved significant; playgrounds had a negative effect on violence but only in highly unstable neighborhoods, and the criminogenic effect of businesses on burglary was tempered by neighborhood instability, contrary to theory. In another study, Smith, Frazee, and Davison (2000) examined the impact of social disorganization and opportunity variables on street robbery in a southern U.S. city. They found several significant interactions including one between the percentage of single-parent families and their commercial land variable (combined motels/hotels, bars, restaurants, and gas stations) which further increased the impact of these land uses on streetblock robbery levels. Additionally, greater distance from the center city area reduced the impact of this commercial land use variable on robbery levels.

In the available literature on MVT, only two studies have evaluated interactions between community structure, opportunity variables, and MVT. Rice and Smith (2002) found that higher percentages of single-parent families on streetblocks increased the (positive) relationship between stores, hotels/motels, and restaurants, gas stations and bars (combined) on MVT. Their SES variable (percentage below median building value) also was found to increase the already positive impact of commercial places (business offices, industrial buildings, and warehouses) on MVT. Additionally, longer distances from the center city area were found to reduce the criminogenic impact of commercial places, motels/hotels, youth hangouts, apartments, and vacant/parking lots on the number of vehicle thefts. One final extant study, by Weisel et al. (2006), examined census block groups in rural areas testing for interaction effects between the number of residential, commercial, and industrial properties and sociodemographic variables (excluding SES). Contrary to the prior study, no significant interactions were found.

Research is sparse, but it suggests that the effects of land use on crime, including MVT, can be moderated by area sociodemographics. This study therefore, tests for interactions between each of the eight opportunity and five socio-economic variables, while also testing the main effects related to opportunity factors themselves. The goal is to determine whether the impact of land use on MVT is moderated by neighborhood sociodemographics or other opportunity land uses in the area. Higher scores on the SES index, as suggested by the communities and crime literature, are expected to suppress the effect of the opportunity land uses on MVT in neighborhoods. Higher levels of racial heterogeneity, tenure less than 5 years, single-parents, and percent 15-24 year olds are expected to increase the impact of the opportunity land uses on MVT.

Interaction effects among land use categories themselves also are expected to be found, based upon the nature of crime opportunity each land use category provides as suggested by the literature. For example, shopping centers are expected to increase theft levels because they provide large mostly unsupervised parking lots giving offenders a wide selection of targets, and because they attract many outsiders to neighborhoods, some who are criminally-minded. These are the expected main effects. The presence of shopping centers in neighborhoods is also expected to increase the impact of other opportunity land uses on MVT. These are due to the increase in potential offenders attracted to the area because of the shopping center but who also learn about and take additional advantage of other high-opportunity land uses nearby. This is the expected interaction effects. The presence of youth hangouts, colleges, and high schools may also amplify the effect of nearby opportunity land uses because they specifically attract more crime-prone young people into the neighborhoods where other criminogenic land uses are located.

This research is focused on evaluating opportunity variables related to MVT, therefore, the analysis of interactions is limited to those that include opportunity factors (opportunity X demographics, opportunity X opportunity). Interactions among sociodemographic variables alone are not evaluated.

Hypotheses

Using the theoretical base of crime opportunity, this research intends to isolate the effects of specific land uses on MVT from neighborhood sociodemographic structure. In light of the literature review, the following hypotheses are proposed:

H_1 Neighborhoods with a larger proportion of their land area utilized by shopping centers and "big box" retail will have higher MVT levels, net the effects of sociodemographic composition.

H_2 Neighborhoods with a larger proportion of their land area utilized by bars and nightclubs will have higher MVT levels, net the effects of sociodemographic composition.

H_3 Neighborhoods with a larger proportion of their land area utilized by high schools and colleges will have higher MVT levels, net the effects of sociodemographic composition.

H_4 Neighborhoods with a larger proportion of their land area utilized by commercial parking lots will have higher MVT levels, net the effects of sociodemographic composition.

H_5 Neighborhoods with a larger proportion of their land area utilized by youth hangouts (parks and recreation centers, public pools, movie theatres) will have higher MVT levels, net the effects of sociodemographic composition.

H_6 Neighborhoods with a larger proportion of their land area falling within the proximity space of shopping centers, bars and nightclubs, high schools and colleges, and youth hangouts will have higher MVT levels, net the effects of sociodemographic composition.

H_7 Neighborhoods with a larger proportion of their land use being detached single family residences will have lower MVT levels, net the effects of sociodemographic composition.

H_8 Interaction effects will exist between the opportunity factors listed in H_1 to H_7 and sociodemographic factors, as well as among opportunity factors themselves.

The next chapter will present the methodology used in the research that tests these hypotheses. It describes in detail the sample, data collection, and operationalization of the variables.

CHAPTER 3

METHODOLOGY

This chapter describes in detail the data sources and variables that are used in the analysis. It also details how opportunity and sociodemographic variables are operationalized at the neighborhood level and the statistical methods used to analyze the relationship of the independent variables and the selected interactions to MVT.

Data Sources

This study uses data from numerous government and private sources. MVT data were provided by the Philadelphia Police Department. Parcel data from 2007 were provided by the City of Philadelphia. Land use zoning data for the City of Philadelphia for the year 2008 were obtained via the Pennsylvania Spatial Data Access on-line clearinghouse (www.pasda.psu.edu). Census data, derived from the 2000 United States Census, were provided in CD form by GeoLytics, Inc. (2001). The addresses of some land uses were identified through on-line and hard copy telephone books. They were confirmed via orthographic fly-over photographs of the city provided by the Pennsylvania Spatial Data Access on-line clearinghouse, and street view and satellite photographs provided on-line by Google (http://maps.google.com).

Study Site and Unit of Analysis

The study site includes all of the incorporated city of Philadelphia, Pennsylvania. According to the 2000 U.S. Census Bureau, Philadelphia has a population of slightly over 1.5 million residents. The city consists of four major racial/ethnic groups: whites (45%), blacks or African-Americans (43.2%), Asians

(4.5%), and those reporting Hispanic ethnicity (8.5%). Approximately one-fourth (23%) of Philadelphia's population reported living in poverty at the time of the 2000 Census, and the city's median household income was estimated at $30,746. Compared to the U.S. and Pennsylvania, Philadelphia's population contains approximately four times the percentage of Blacks, twice as many people living below the poverty level, and a median income approximately 25% less than the two larger entities. Philadelphia is much like other large East Coast cities struggling to recover from the blight-inducing impacts of de-industrialization and de-population beginning in the 1960's (McGovern, 2006). One bright spot is the city's large downtown district, which in recent years has once again become a thriving retail and nighttime entertainment area through a process of gentrification and business reinvestment.

The unit of analysis is all 1816 census block groups in the city. Block groups are chosen because of their alignment with many community-level dynamics (Bursik & Grasmick, 1993) and because they are the smallest unit at which the various census variables are available. Additionally, block groups are small enough to reduce internal heterogeneity as found in larger units such as census tracts, while increasing the number of units available for analysis and thus improving the overall robustness of the investigation (Oberwittler & Wikstrom, 2009). Smaller units of analysis, including streetblocks or blockfaces have been recommended by some researchers (see for example, Groff, Weisburd, & Morris, 2009), but these smaller units may add additional error to the analysis due to potential lack of accuracy with the geocoded crime incidents (Ratcliffe, 2004). The crime data were provided in already geocoded X, Y coordinates and could not be verified for spatial accuracy.[1] Finally, because the necessary census data are available at the block group level, there is no need to interpolate variables to smaller units such as streetblocks, which would add an additional source of error. Block groups have been used in a large number of empirical studies examining crime, including MVT (Bursik & Grasmick, 1993; Walsh & Taylor, 2007a; 2007b; Weisel et al., 2006).

Boundaries for the Philadelphia block groups were provided by the U.S. Census Bureau, via the Pennsylvania Spatial Data Access on-line clearinghouse (www.pasda.psu.edu) in a GIS shapefile (mapping) format. Selected 2000 U.S. Census data variables were matched with the appropriate block group in GIS by the author.

Dependent Variable

The dependent variable is the combined count of reported vehicle thefts per block group over the three-year study period (2006-2008). The Philadelphia Police Department provided this information in X, Y (mapping) coordinates. Of the 31,400 total reported thefts, only 351 (1.1%) had no X, Y coordinates, likely the result of incorrect or missing addresses. This 98.9% (100%- 1.1%) geocoding hit rate exceeds both the conventionally accepted hit rate of 90% for accurate mapping suggested by Bichler and Balchak (2007), and the empirically derived minimum of 85% recommended by Ratcliffe (2004). The location of MVT incidents were aggregated to block group via a GIS point-in-polygon operation (Chainey & Ratcliffe, 2005) resulting

[1] J. H. Ratcliffe (personal communication, February 1, 2010) reports he has worked with this data for seven years and has found no identified patterns of spatial error when compared to non-geocoded data.

in a total count per block group. The three-year count is used to minimize the impact of annual and seasonal fluctuations, and to increase the likelihood of having sufficient incidents across the block groups for analysis.

Independent Variables

Independent variables consist of opportunity factors operationalized at the block group level, demographics data from the 2000 U.S. Census, and statistical controls for block group size and population. A spatial lag to control for the effects of spatial autocorrelation is also added to all models.

Opportunity variables

The opportunity variables evaluated are drawn from the aforementioned literature examining individual opportunity factors related to MVT, and the few studies that have examined opportunity structure at the neighborhood level.

In the prior neighborhood studies, summarized in the literature review, the impact of opportunity-related land uses was evaluated either through dummy variables indicating the presence of an opportunity land use, or the count of like land uses present in the unit of analysis. For example, Roncek's series of studies (Roncek & Faggiani, 1985; Roncek & Lobosco, 1983; Roncek & Maier, 1991) identified census blocks as either containing or not containing a bar or high school, while Rice & Smith (2002) and Weisel et al. (2006) used the count of theorized opportunity land uses in their analysis. In these studies no consideration was given to the size of these places, yet size is likely related to the amount of MVT opportunity present. Parking lots, high schools, and shopping centers all vary considerably in size and in the number of MVT opportunities available, suggesting that the spatial dimensions of these locations are relevant to a study of their impact on MVT. The current study avoided this limitation through a methodology that identified the size in land area, of each examined land use.

Using GIS software, the current study determined the proportion of total land area per block group utilized by each of the opportunity land uses (shopping centers, bars, commercial parking lots, high schools, colleges, youth hangouts, and single family homes). The percentages for each land use category serves as predictor variables in regression models that also include the total area of each block group as control variables. It is hypothesized that the percentage of opportunity land uses (save single family residences) will be positively related to the count of MVT in each block group; net the impact of the other variables. Single family residences are hypothesized to be related to lower MVT counts.

Basing the analysis on the land area of the theorized land uses has two limitations. First, some locations within their land use type may be under or over utilized for their size, resulting in a weaker proxy for the theorized amount of MVT opportunity present. Secondly, a location may be a multi-level building that includes more actual area than its parcel foot print suggests. Both of these limitations are important ones. Still, this method of measurement is expected to be an improvement over the mere counts or dichotomous dummy variables (present-not present) used in prior research that did not include consideration for variance in size and use, and thus no quantification of relative *potential* for MVT opportunity.

Digitized city parcel data, zoning maps, and high-resolution aerial photographs were used to establish the area per block group utilized by each land use. Addresses obtained from on-line and hard copy telephone books augmented the data. The parcel data provided by the City of Philadelphia included parcel addresses, boundaries, and building uses. The file is missing building uses on a number of parcels but this information was obtained from other resources when necessary. For example, the location and boundaries of high schools and colleges can be identified through their addresses, building codes ("schools"), zoning code ("IDO"), and aerial photographs to ensure accuracy.

Data on shopping centers was collected primarily via zoning data. Two types of shopping centers are identified by Philadelphia's zoning code; "*neighborhood shopping centers*" (NSC) and "*area shopping centers*" (ASC). These categories of land use consist of multiple retail outlets and required off-street parking lots. The existence and size of each was verified via aerial photographs and were added to the data. Several parcels of land were found to be zoned as shopping centers but were not yet built, and were excluded from the data.

The zoning code also identified C-7 as commercial retail zones that required off-street parking. Many of these were found to be small parcels with few parking spaces, often a small store or two, and were excluded from the analysis. A minimum of 100 parking stalls (identified via aerial photographs) was set as the minimum requirement by the researcher for C-7 zoning areas to be defined as shopping centers and included in the study. This number was based upon the definitions of shopping centers as used in the literature (Fleming, Brantingham, & Brantingham, 1994). Many of the C-7 zoning areas were found to be big-box retail stores including Best Buy, Home Depot, Ikea, Target, K-mart, and Wal-Mart stores that had their own large (over 100 stalls) off-street parking lots. These land uses were also added to this category. A total 121 shopping centers made up this variable.

The category "bars" consists of nightclubs, taverns, private clubs, and restaurants with full bars; all uses that sell alcoholic beverage for on-site consumption and that are generally open late at night. These land uses were identified by parcel data and addresses listed in the 2008 database of Philadelphia alcohol sales licenses provided by the Pennsylvania State Police. On-line resources and telephone calls were used to separate corner markets that sold beer in cans for off-site use from restaurants and taverns that sold beer for on-site consumption, thus meeting the requirements for this study.[2] Additionally, a few (less than 15) taverns and restaurants with bars were located in shopping centers and were not included in this category because their land area could not be determined separate from that of the shopping center. A total 1,321 locations made up this variable.

High school and college land use were identified separately by a GIS shapefile provided by the Philadelphia Police Department, addresses provided by on-line sources, zoning, and parcel data, and verified via aerial photography. These two categories were originally planned to be analyzed together under the assumption that their impact on neighborhood MVT would result from their large parking lots as well as from the many

[2] The author thanks Brian Lockwood for his assistance in cleaning the alcohol license data.

young people of crime-prone ages they draw into neighborhoods. However, during data collection, aerial photographs showed that most high schools in the city did not have parking lots, therefore, the impact of these two opportunity variables were tested separately.

The high school shapefile contained data on the size of the student population and type of high school (traditional, technical, alternative, etc.). These data, which were verified via the Philadelphia School District website (www.phila.k12.pa.us), indicated that the district provides many alternative high schools that have small student populations and are located in noncampus-like settings such as office buildings. Only traditional, public high schools are included in the analysis because of their larger size, design, and student population (minimum 400, a natural break in the data). Private high schools were excluded from this study because they generally have smaller student populations and their presence was found not to be related to MVT in prior studies (Roncek & Faggiani, 1985; Roncek & Lobosco, 1983). The high school variable in this study contains a total of 49 locations.

Philadelphia has a large number of public and private colleges. Many of these colleges have small student populations and are located in office buildings. The study intended to evaluate the impact of traditional college campuses on MVT, therefore, only those universities that had larger populations, dorms, and multi-building campuses were included. Zoning and parcel data were confirmed via aerial photographs and augmented by on-line resources, including individual college websites that provide student population estimates. This variable consisted of 157 parcels for 13 different colleges.

Commercial parking lots were identified via parcel data enhanced by on-line parking information (yellow pages, Philadelphia Parking Authority, Southeastern Pennsylvania Transportation Authority) and aerial photographs. The lots included in the study are stand alone lots (not connected to any business or shopping center), street-level, open to the public, and publicly or privately owned. Many had on-site attendants that collected fees while others (predominantly government owned) were provided free, and with little security, to the public. Multi-level parking structures are excluded from the analysis due to their higher levels of security (controlled access, attendants, and exit arms) that result in very few thefts as shown, and also resulting in their exclusion in prior studies (Clarke, 2002; Clarke & Goldstein, 2003). A total of 194 lots were identified and included in the analyses.

Youth hangouts include neighborhood parks and recreation centers, public pools, and movie theatres, places previously identified in the literature (Rice & Smith, 2002). They were identified via on-line and hard copy telephone books, parcel data, aerial photographs, and a shapefile of Philadelphia parks provided by the Philadelphia Police Department. This variable consists of a total 188 youth hang outs.

The amount of single family detached homes in block groups is expected to be inversely related to the number of vehicle thefts. This is due to requirements in the Philadelphia zoning laws that these structures must have off-street parking (driveways & garages) which has been shown to reduce the risk of MVT victimization (Clark &

Mayhew, 1998; Weisel et al., 2006). This variable was operationalized as the percentage of all residential land use in a block group identified as R-1/R-1A (detached homes, no other land uses allowed) in the zoning data. A total of 303 areas containing only single family homes were identified.

Operationalizing proximity space

A goal of the proposed study is to test for the existence of higher than normal concentrations of MVT in close proximity to the theorized criminogenic land uses as further evidence of their criminogenic potential. This “proximity effect” is expected because crime pattern theory suggests these areas will fall into the awareness space of the many potential offenders who use and are drawn to the evaluated land uses. The analyses cannot specifically test awareness space because this concept is individual in nature and includes not only the area around frequently visited nodes, but also along the pathways travelled by potential offenders. Therefore, it is argued that evidence of MVT clustering in areas surrounding the evaluated criminogenic land uses (proximity space) results from the accumulated knowledge of observed opportunities by the many potential offenders travelling through these areas. The question then is how far out from the theorized criminogenic land uses should we expect to find (and test for) these proximity effects?

Research on the spatial extent of the criminogenic effects of certain land uses suggests they are measurable out to a distance of one to two city blocks. Studies find this phenomena and common distance across crime types, and in examinations that compare crime counts in zones or buffers of varying distance around suspected land uses, as well as studies that use multivariate techniques of areal units that include neighborhood sociodemographics. For example, Brantingham and Brantingham (1982) found that commercial burglaries were likely to cluster within one block of bars and fast-food restaurants. Violent crime was found to be significantly higher in 300-foot diameter zones immediately surrounding public housing projects, and then decrease substantially in adjacent 300 foot (concentric) zones (Fagan & Davies, 2000). In a multivariate analysis controlling for many sociodemographic factors, Schweitzer, Kim, and Mackin (1999) found that the total count of combined violent and property crimes, including MVT, were higher on streetblocks within two blocks of convenience stores. The density of combined violent and property crimes (including MVT) was substantially higher within .1 mile (528 feet) of bars in Minneapolis, and then dropped to significantly lower levels in three concentric zones of the same width (Frisbie, Fishbine, Hintz, Joelson & Nutter, 1978). In studies examining drug sales arrests across two cities, incidents were found to cluster within one block (400 feet) of liquor stores and bars, check cashing stores, and subway stations (McCord & Ratcliffe, 2007; Rengert, Ratcliffe, & Chakravorty, 2005) in multivariate analyses. And finally, Roncek and his colleagues report that MVT individually, as well as other Part 1 crimes, all concentrate within the equivalent of two blocks surrounding high schools and bars in multivariate analyses (Roncek, 2000; Roncek & Faggiani, 1985; Roncek & Lobosco, 1983).

Each of the above findings can be attributed to the area around criminogenic opportunity land uses falling within the awareness spaces of many potential offenders. Some land uses, however, may attract specific types of crime to their proximity not only due to awareness space, but also because of other enhanced opportunities they provide. For example, research has shown that street robbery tends to concentrate within the area between one and two blocks away from subway stops, especially in late evenings (Block & Block, 2000; McCord & Ratcliffe, 2009). This finding is not explained through awareness space, although it may also be a factor. Rather, due to the additional opportunity for robbery presented when late night subway riders, often intoxicated and easy marks for muggers, leave well-lighted stations for dimly lit parking lots or walk to nearby homes through dark and quiet streets (Wright & Decker, 1997). Additional research, especially qualitative and survey studies are no doubt needed to uncover other latent crime opportunities resulting from the presence of particular types of land uses in neighborhoods.

Based upon the above research findings, the proximity space evaluated here consists of the land area that falls within a 400 foot wide zone (approximately one average block length in Philadelphia) immediately surrounding the identified shopping centers, bars, high schools, colleges, and youth hangouts. There is no theoretical reason for why the distance around the different types of land uses should vary, so the 400 foot zone is used for all. GIS was used to identify these areas, merge them into a single layer, and to calculate the percentage of each block group's total land area. Proximity spaces that overlap into adjoining block groups were included in the total proximity land area of the overlapped block group and were identified through the join function of GIS. This methodology adds to the analytical robustness of the model by reducing the impact of the Modifiable Areal Unit Problem (MAUP). The MAUP is a situation "where the results of any geographic process, such as the count of crimes within a set of geographic boundaries, may be as much a function of the size, shape and orientation of the geographic areas as it is of the spatial distribution of the crime data" (Chainey & Ratcliffe, 2005 p. 151-152). The MAUP is thus reduced because proximity space overlapping into another block group is not ignored but rather assigned and analyzed with the other ecological factors associated with the over-lapped block group.

Control Variables

Sociodemographic variables

Based upon their predictive power in the communities and crime literature, and from the limited neighborhood-level research available on MVT, specific demographic variables from the 2000 census were selected for the analysis as control variables. These factors include neighborhood disruption (percent same house less than 5 yrs), family disruption (percent single-parent families with children), and age composition (percent 15-24 year olds). SES and racial heterogeneity indices also were created and included in the analyses.

The SES index follows Walsh and Taylor's (2007a; 2007b) index and consists of the summed *z*-scores of median income logged, median owner-occupied property value logged, and the percent of people living below the poverty line (inverted and logged). These three variables were found to be predictive of MVT levels in the literature review as both indices and individual predictors.

The racial heterogeneity index follows Blau's (1977) assessment of diversity model. It is derived from the proportion of Whites, Blacks, Hispanics, and Asians in each block group. These four groups are used because they comprise the primary racial groups in Philadelphia. Blau's index is estimated as $1- \sum Pi^2$, where Pi is the proportion of the group in the *i*th category. For example, a block group of residents 70% Black, 20% White, 4% Hispanic, and 6% Asian would have an index score of .46 as estimated by Blau's index $(1- (.70^2 + .20^2 + .04^2 + .06^2) = 1- (.49 + .04 + .0016 + .0036) = 1-.54 = .46)$. Blau index values with four categories range from 0.0 to 0.75 with larger values indicating greater diversity.

The census data used is from 2000 and the MVT data are for 2006-2008. Updated census data are not available at the block group level, thus there may be some changes in local area sociodemographics that are not accounted for in the analysis. However, there is no easy way to determine these changes and this is recognized to be a limitation of the study.

Thirty-one block groups in the city have zero population. Visual examination of aerial photographs from 2004 indicates there are no residential structures in these block groups, with most being industrial, institutional, or utilized primarily by major highways. Zoning and parcel data also indicate no residences in these areas. These 31 block groups make up less than two percent of the total count of all block groups. All but two have reported vehicle thefts falling within their boundaries, with the highest containing 125 incidents. Rather than dropping these block groups from the analysis and possibly losing important information, grand mean replacement values are used for demographic data (mean income, heterogeneity score, percentage single-parents, 15-24 year olds, and same house less than 5 years) while zero remains as the population count.

Using the mean replacement value for this small percentage of cases (<2%) does not affect the mean of the distribution for the affected variables and should have little effect on the findings across the large number (1816) of block groups (Tabachnick & Fidell, 2001).

Statistical control variables

It is necessary to include three statistical control variables in the multivariate analyses. The first is the size or total land area for each block group. This variable is necessary because larger block groups are expected to contain more area where MVT can occur. It has been found significant in prior neighborhood studies of MVT (Rice & Smith, 2002; Smith, Frazee, & Davison, 2000). The addition of this variable adds a standardizing function so that block groups of varying size are not biased in the assessment of their counts of MVT.

The second statistical control variable is the total population of each block group. This variable is necessary because areas that contain a higher number of residents are likely to contain more vehicles, and thus more opportunity for theft, especially at night when the vehicles are left unattended. Population counts were obtained from the census data. The two known studies of MVT that include population count as a variable report conflicting results. Weisel et al. (2006) report their population count was positively related to MVT in block groups, but Rice and Smith (2002) find the opposite with higher numbers of residents per streetblocks predicting lower MVT counts.

The population count and total land area of block groups are seen as two separate predictors in this analysis. As stated, block groups with higher populations are expected to have more MVT due to the presence of more vehicles available to be stolen, especially at night when vehicles are left parked on streets or driveways. Total land area, however, includes not only residential, but also non-residential land uses and facilities where vehicles can be stolen, including the shopping centers, bars and others being examined in this research. The larger the block group, the more land available for vehicles to be parked and stolen, therefore, the analysis must also contain a statistical control for total land area. The bivariate correlation between population and land area(ln) is a weak one ($r = .32$, $p < .001$). An analysis of tolerance and variance inflation factors for population (VIF = 1.20, tolerance = .834) and area(ln) (VIF = 1.76, tolerance = .568) confirmed a lack of multicollinearity.

The third statistical control variable included in the multivariate models is a spatial lag. Spatial lags are necessary in regression models where substantial evidence of spatial autocorrelation exists, that is, the clustering of like dependent variable values among neighboring units of analysis. Failure to include a spatial lag when necessary can result in biased parameter estimates, false indications of significance, and misleading suggestions of model fit (Chainey & Ratcliffe, 2005; Messner et al., 1999). A global spatial autocorrelation analysis of the count of MVT per block group utilizing Moran's I revealed a score of .29 ($m = -0.0008$, $SD = .0133$, $p = .001$, 999 permutations, first-order queen contiguity), indicating positive spatial autocorrelation exists in the dependent variable. To reduce this problem a spatial lag variable was computed by Geoda and added to the regression models. Geoda is free software provided by the Spatial Analysis Laboratory at the University of Illinois and supported by the U.S.

National Science Foundation. The software produces a spatial lag value for each block group based upon the weighted average of the MVT count value of neighboring locations (Anselin, 2003).

Interaction Variables

The present study tests for interaction effects between each of the eight opportunity and five socio-economic variables as well as between the opportunity factors themselves. The goal is to determine if the impact of an opportunity land use on MVT is moderated by neighborhood sociodemographics or other opportunity land uses in the area.

The interaction terms utilized are two-way product terms calculated from the aforementioned variables (e.g., percentage land area shopping centers x SES index). Tests for multicollinearity between the components and interaction terms were performed and found within acceptable limits per Jaccard (2001) (see also Jaccard and Turrisi, 2003; Jaccard, Turrisi, & Wan, 1990). These authors argue that even high correlations are acceptable (up to 0.98) among components and interaction terms when the emphasis is in understanding the strength of moderating effects, as emphasized in this study. They also warn that mean centering, which is frequently done in interaction models and usually has no effect other than to aid in interpretation, can in rare cases increase correlation. This, they point out, is especially true when component variables are not normally distributed as are the opportunity variables in this research. Mean centering of component variables are also not performed in the current study because they are not needed to assist in interpretation.

Following the analysis technique suggested by Darlington (1990), a group test of interaction variables is first performed. Interaction terms for each component variable are grouped into one model so their impact can be analyzed across the opportunity variables as a group. Individual interactions are then examined. This results in two tests for interaction effects. First, a postestimation likelihood ratio (lr) test determines whether the inclusion of the group of like interaction terms (e.g., SES and all land uses) significantly increases the fit of the model over that of the non-interaction hierarchical model. Secondly, the *p* value for each individual interaction term coefficient is examined in turn.

Analysis

The tests of the hypotheses are accomplished through a series of negative binomial regression models. Negative binomial regression is the preferred method because the dependent variable, count of MVT per block group, is skewed (skewness statistic = 2.57, 9 zero values) and shows evidence of overdispersion (variance of 144.29 substantially larger than the mean of 17.10). These models can be viewed as an extension of Poisson regression that relaxes the assumptions that the variance is equal to the mean. To account for overdispersion, the negative binomial model introduces an additional parameter that estimates the extent of the overdispersion in the data (Long & Freese, 2006). Although ordinary linear regression models have been applied to count outcomes, they can result in inefficient, inconsistent, and biased estimates (Long & Freese, 2006).

Hypothesis testing is accomplished via a series of hierarchical models. The first model includes only sociodemographic variables and the statistical control variables of population, total area of the block group, and the spatial lag. This model provides preliminary indications of the impact of the control variables on neighborhood MVT levels and their agreement with findings in previous research.

The second model includes only the opportunity and statistical control variables. The purpose of this analysis is to provide preliminary indications of the importance of opportunity factors on MVT at the neighborhood level.

The third model combines all opportunity, sociodemographic, and statistical control variables. This combined model identifies the importance of the opportunity variables to MVT, net the influence of socio-economic structure.

Interactions are tested next. A series of models that include interaction terms computed from each of the opportunity variables and sociodemographic variables, as well as between each opportunity variable and every other opportunity variable are tested and evaluated. Results are shown only for those models whose postestimation likelihood ratio (lr) test determined a significantly better model fit than the combined model without the interaction terms.

Prior to model testing, predictor variables were examined for multicollinearity using statistical tests of variance inflation factor (VIF) and tolerance. All were found to be within acceptable limits with no variance inflation factor over 2.7 or tolerance value below .38. Multicollinearity in the interaction models was evaluated per Jaccard (2001) as explained above. Predictor variables are naturally logged when necessary to reduce skewness.

Residuals from the combined model (opportunity, sociodemographic, and statistical controls) were examined which identified six outlier block groups. The model was rerun without these outliers resulting in no significant changes in coefficient values or direction; therefore, these block groups were retained in all models.

This chapter has presented the specific variables used in the analysis and explained how they were operationalized at the neighborhood level. The next chapter explains the results of the analyses.

CHAPTER 4

RESULTS

This chapter presents the results of the analysis. It begins with descriptive statistics of predictors, controls and the dependent variable, then presents bivariate correlations, and ends with the negative binomial models that specifically examine the stated hypotheses.

Descriptive Statistics

Table 1 reports the descriptive statistics for the dependent variable and each of the opportunity and sociodemographic variables, as well as the statistical control variables. As shown, the count of MVT per block groups varies significantly with some block groups having no thefts (9), and the highest having 146. Values for predictor variables also range significantly, and many have been naturally logged to reduce the effects of skewness and have been identified as such.

To add to the descriptive analysis, a thematic map is included which displays the density for each block group in location quotient values (Figure 1). Location quotients are ratio values used extensively in the regional sciences (Miller, Gibson, & Wright, 1991) to compare characteristics of smaller sub-areas to the larger, surrounding area. They were introduced to criminology in the mid 1990's by Paul and Patricia Brantingham (1995a). A location quotient value of two indicates that the density of crime in a sub-area (block group) is twice that of the overall study area (City of Philadelphia), while a value of 0.75 indicates the density is 25% less than the city average.

Table 1. Descriptives for Outcome and Predictor Variables in Philadelphia Block Groups (N = 1816)

	Mean	**SD**	**Min.**	**Max.**
MVT count	17.10	12.01	0.00	146.00
Opportunity Variables				
% Shopping centers(ln)	0.14	0.59	0.00	4.00
% Bars(ln)	0.15	0.31	0.00	2.47
% High schools(ln)	0.67	0.44	0.00	4.34
% Colleges(ln)	0.10	0.55	0.00	4.43
% Parking lots(ln)	0.07	0.33	0.00	3.95
% Youth hangouts(ln)	0.21	0.70	0.00	3.82
% Proximity space	36.68	28.36	0.00	99.77
% Single family homes(ln)	0.09	0.53	0.00	4.41
Demographic Variables				
SES index	0.00	2.49	-6.78	26.83
Racial heterogeneity index	0.29	0.22	0.00	1.00
% Residents < 5 Years	37.38	16.58	0.00	100.00
% Single-parent families	25.21	17.07	0.00	100.00
% 15-24 yr olds(ln)	2.60	0.56	0.00	4.62
Control Variables				
Population	835.66	519.31	0.00	4012.00
Area(ln)	14.02	0.82	12.03	18.16
Spatial lag	17.95	8.43	1.33	65.83

Note. Predictor variables are naturally logged (ln) where indicated due to skewness.

As shown on the map, overall MVT density is highest in the center, near-north, and south-west (West Philadelphia) parts of the city. These areas tend to be neighborhoods of high minority and population density, and low median income. Row homes with on-street parking are the typical type of housing structures found in these areas. The north-west and north-eastern parts of the city with location quotient values below 1.0 are more suburban-like areas. These neighborhoods typically have lower population densities and percentages of minorities, and higher median income. More single family residences with their off-street parking are located in these areas. The extreme south of the city with its low density of MVT includes the Philadelphia International Airport, areas of industrial and warehouse use, commercial and naval shipping yards, and large swaths of undeveloped marsh land including the approximate 1200 acres of the John Heinz National Wildlife Refuge.

As displayed on the map (and supported by the earlier mentioned Global Morian's I analysis value of .29), block groups of like MVT density in Philadelphia tend to be near those of similar levels, that is, high density near high density and low density near low density. However, many block groups of below average density are also observed among areas of higher values.

Bivariate and Multivariate Analysis Results

Having examined the descriptive nature of the data I now turn to the results of bivariate and multivariate analyses used to test the study's hypotheses.

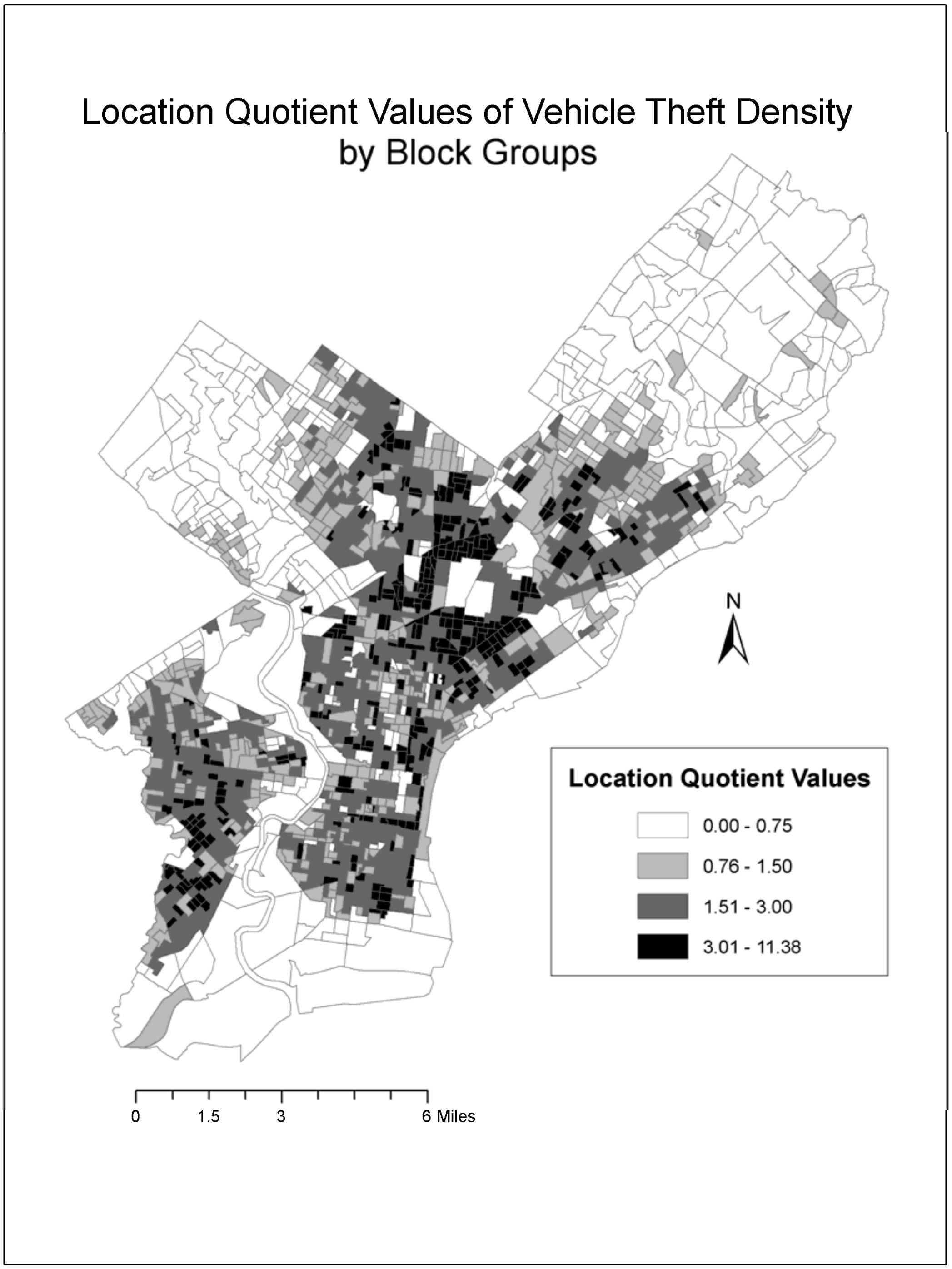

Figure 2. Location Quotient Values of Vehicle Theft Density in Philadelphia by Block Groups (N = 1816)

Bivariate analysis

Table 2 displays Pearson correlations between all variables. Significant correlations (in bold) provide information on correlates of MVT as well as information on the neighborhood context of block groups. The count of MVT is shown to be positively and significantly correlated with higher percentages of land use utilized by shopping centers and bars, and neighborhoods of greater racial heterogeneity, less time at current residence (percent less than 5 yrs), and single-parent families. MVT is negatively and significantly correlated with the percentage of land use utilized by single family residences, higher levels of SES, percentage of the population 15-24 year olds, and the total population count. Because these correlations do not control for other factors, they are of limited use in understanding the impact of neighborhood land use and sociodemographic factors on MVT. These correlations, however, are useful for providing information about the types of opportunity land uses and sociodemographics found together in Philadelphia neighborhoods. They do not necessarily identify cause and effect, but the story they tell is still useful when examining land use impacts on crime. Next I examine the Pearson correlations between each specific land use category and the demographic and control variables. As before I only discuss significant findings.

As displayed in Table 2, higher percentages of land utilized by shopping centers tends to be located in neighborhoods characterized by higher SES and population, and lower percentages of single-parent families. This finding suggests developers of shopping centers are “building where the money is.”

Higher levels of bar and nightclub land use tend to be located near colleges and commercial parking lots, and in neighborhoods of higher racial mix, less time at current residence (less than 5 yrs), and fewer single-parent families. This finding suggests bars in Philadelphia tend to be located around colleges and in neighborhoods of lower stability.

High schools have few significant correlates with either opportunity land uses or sociodemographics, save a positive one with block groups of higher percentage of 15-24 year olds. Colleges, however, have many such significant relationships. In Philadelphia, colleges tend to share neighborhoods where more land use is dedicated to bars and commercial parking lots, as well as areas of higher racial mix, less tenure, and more 15-24 year olds in the population. Most of these correlations appear to be related to the large student population attracted to these neighborhoods, and all are in the direction of hypothesized criminogenic relationships with MVT suggesting that college neighborhoods have many factors likely to promote MVT. However, the bivariate relationship between colleges and MVT is a negative one. If this negative relationship survives in the multivariate analyses, it suggests that some characteristic of colleges reduce the expected crime-producing impact of these other characteristics of college neighborhoods in Philadelphia (i.e., more bars and commercial parking lots, high racial mix, less time at current residence, and more 15-24 year olds in the population).

Youth hangouts showed only one significant correlation with either group land use or demographics variables. The percentage of 15-24 year olds in the population is found significant and this is a negative one, contrary to expectations that these land uses would be located in neighborhoods of higher proportions of young people.

The percentage of land utilized by single family residences in a neighborhood has the highest value correlation (-.15) with MVT of all land use variables. This may not be entirely unexpected considering the characteristics of the neighborhoods in which this land use tends to be found. Single family residences do not have a significant correlation with any of the other opportunity-producing land uses, with 5 of these 7 non-significant correlations being negative, and the remaining 2 with coefficient values of .00. Additionally, the proximity space variable is significantly and negatively related to the amount of single family homes. Higher levels of single family residences also are found in neighborhoods of higher SES (highest coefficient in Table 2 at .39), lower single-parent families, and fewer young people (15-24 yrs old) in the population. These findings all suggest single family residences tend to be located in neighborhoods characterized by low crime-producing factors, in reference to both land use and sociodemographics. If the negative relationship between MVT and single family homes persists once these other variables are statistically controlled in multivariate models, this may suggest that the design of single family homes is also related to crime opportunity (i.e., the inclusion of driveways and garages required by the zoning code). The argument that housing design can reduce crime has been made by Crime Prevention through Environmental Design (CPTED) practitioners (Crowe, 2000), and multiple regression results in this research may help clarify the relationship.

Table 2. Pearson Bivariate Correlations between Outcome and Predictor Variables in Philadelphia Block Groups (N = 1816)

Variables	MVT	Shopping	Bars	High schl	Colleges	Park lots	Youth hng	Prox space	SF homes	SES index	Race index	Res < 5 yrs	Sing-prnt	15-24 yrs	Population	Area
1. MVT																
2. Shopping	**.17**															
3. Bars	**.07**	-.03														
4. High schools	.02	.00	-.04													
5. Colleges	-.08	-.02	**.09**	.04												
6. Parking lots	.03	-.01	**.24**	.03	**.07**											
7. Youth hang	-.01	-.03	-.01	.02	-.02	-.02										
8. Prox space	.03	**.05**	**.46**	**.08**	**.07**	**.15**	**.22**									
9. SF homes	**-.15**	-.01	-.05	-.03	.00	.00	-.02	**-.17**								
10. SES index	**-.14**	**.07**	.04	-.01	-.03	.03	-.03	**-.16**	**.39**							
11. Race index	**.25**	.02	**.06**	.01	**.10**	**.09**	-.01	**.06**	-.02	-.01						
12. Resid < 5 yrs	**.08**	.01	**.25**	.02	**.26**	**.25**	-.03	**.18**	-.03	.02	**.38**					
13. Sngl-parent	**.11**	**-.10**	**-.12**	.03	-.04	**-.09**	.05	.01	**-.17**	-.56	.00	.03				
14. 15-24 yrs	**-.07**	-.04	.01	**.05**	**.24**	.00	**-.07**	.03	**-.11**	-.22	**.15**	**.14**	**.18**			
15. Population	**-.06**	**.08**	-.00	-.03	**.07**	**-.07**	**-.06**	**-.09**	**.07**	**.13**	.11	**.06**	**-.14**	**.14**		
16. Area	.01	**.24**	**-.08**	**.07**	**.06**	.04	.01	**-.38**	**.29**	**.37**	**.06**	.04	**-.23**	**-.10**	.32	
17. Spatial lag	-.01	.04	.03	.01	**-.12**	**-.05**	-.01	.00	**-.19**	**-.15**	**.32**	**.06**	**.13**	**.08**	**.10**	**.10**

Note. Bold coefficient values indicate $p < .05$

Proximity space (as defined earlier in this paper) includes the total area of a block group that falls within 400 feet of all opportunity land uses excluding single family residences. It is found to have a negative correlation with SES, and a positive one with racial heterogeneity and residents in same house less than five years. As expected, it has a positive correlation with its component land uses. Proximity space also has a negative relationship with percentage single family homes. Taken together, these findings suggest that neighborhoods of high proximity space tend to be less residential in nature with higher racial mixes and fewer long-term residents.

Multivariate models

The analysis now turns to the results of the hierarchical series of multivariate models that were used to test the study's hypotheses. Negative binomial regression models by default produce coefficients that are the log of the expected count and are not amenable to straightforward interpretation. To assist in the interpretation of estimates, two statistical transformations are reported in the tables. The first is incidence rate ratios (IRR) that indicate the factor by which the expected count of MVT will change given a one unit increase in the predictor variables. The second transformation indicates the expected percent change in count of MVT for a one standard deviation increase in the predictor variables. For example, an IRR value of 1.16 for block group area would indicate an increase in the expected count of MVT by a factor of 1.16, for each one percentage increases in area size. Additionally, a 12.8% value for block group area in the expected change in count per standard deviation would indicate an expected increase of 12.8% in the number of vehicle thefts in a block group for each standard deviation increase in area size. Because percentages are the unit of measurement for predictors, with small percentage differences providing little intuitive meaning, findings will be discussed via the expected percent change in the count of MVT per standard deviation increase of the predictor variables.

Each regression model shows the results of a likelihood ratio chi-square test of the model fit. These tests are calculated as negative two times the difference of the likelihood for the null model and the fitted model. A significant value indicates the fitted model is a substantially better fit than the constant-only model.

Each model is also compared for model fit to the combined model which consists of the opportunity, sociodemographic, and controls variables. A likelihood ratio (LR) test of the nested model is used for this analysis with significant results indicating the more complex model is a better fit of the data. The more complex model is the combined model when evaluated against the sociodemographic-only and opportunity-only models, and is the interaction model (with the included interaction terms) when these models are evaluated.

Count models are non-parametric and do not generate true R-squared values such as would be found with linear regression. Therefore, Bayesian Information Criterion (BIC) scores are used as model-to-model comparative measures of model fit (Long & Freeze, 2006). BIC analysis is based upon the difference of log likelihoods between compared models but is more conservative than a simple LR test due to a considerable penalty added for each new parameter. Raftery (1996) provides guidelines for the strength of evidence favoring one model over another with an absolute difference between BIC scores of 0-2 as being weak, 2-6 as positive, 6-10 as strong, and greater than 10 as very strong.

The first model of the analysis includes only sociodemographic variables and the statistical controls of population, total area of the block group, and the spatial lag (Table 3). As shown, the SES index is significant and has, by far, the largest impact of any other demographic variable. The results shows that a one standard deviation increase in the SES index decreases the expected block group count of MVT by 13.5%. This finding is consistent with the literature that shows a strong negative impact of SES on crime, including MVT. Tenure, or percentage of residents living in the same house less than 5 years, is positive and significant, and is also consistent with the literature on MVT. The analysis shows that a one standard deviation increase in tenure is expected to increase the expected count of MVT by nearly 3%. The Blau racial heterogeneity index, percent single-parent, and percent 15-24 year olds in the population did not rise to the level of statistical significance. Of these, the prior limited research suggests race and percent younger people in the population are not usually found to be related to MVT levels. The percentage of single-parent families however is shown by the literature to be a fairly strong predictor of MVT. This contrasts with the results found in this initial analysis of the relationship between sociodemographics and MVT counts.

All three of the statistical control variables (block group area, population, and spatial lag) are positive and significant with high levels of expected change in the count of MVT for one standard deviation increases in their values.

Table 3. Sociodemographic Factors Predicting MVT Count in Philadelphia Block Groups (N = 1816)

Variables	**IRR**	**SE**	***Z***	***P*** **<**	**Change in Count Per One SD Increase**
SES index	0.94	.006	-8.93	.001	-13.5%
Racial heterogeneity	1.11	.065	1.75	*ns*	2.3%
Residents < 5 years	1.00	.001	2.04	.05	2.7%
Single-parent families	1.00	.001	0.80	*ns*	1.2%
15-24 yr olds(ln)	0.98	.023	-1.02	*ns*	-1.3%
Control Variables					
Area(ln)	1.16	.018	9.41	.001	12.8%
Population	1.00	.000	14.13	.001	19.2%
Spatial lag	1.04	.002	23.42	.001	35.9%
Model Fit Statistics					
-2 Log likelihood ratio				-6150.63	
Model fit chi-square				1089.98***	
BIC				-1251.67	
LR test nested model				180.80***	

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

The second model includes only the opportunity land use variables and the statistical controls of area, population, and spatial lag (Table 4). As shown, 5 of the 8 land uses attained levels of significance, with all but one of these in the expected direction. The percentage shopping centers, commercial lots, and proximity space in block groups are all related to higher counts of MVT. Single family residence and, unexpectedly, the percentage of land use utilized by colleges in block groups are related to lower MVT counts. The percentage of single family residences is the strongest of all predictors with a one standard increase in its value predicting a 15.3% decrease in MVT. The statistical control variables of area, population and spatial lag remain strong predictors of MVT with values nearly identical to the sociodemographics-only model (Model 1).

Table 4. Opportunity Land Uses Predicting MVT Counts in Philadelphia Block Groups (N = 1816)

Variables	**IRR**	**SE**	***Z***	***P* <**	**Change in Count Per One SD Increase**
Shopping centers(ln)	1.06	.020	3.27	.001	3.8%
Bars(ln)	1.06	.047	1.38	*ns*	1.9%
High schools(ln)	1.02	.027	0.69	*ns*	0.8%
Colleges(ln)	.91	.020	-4.20	.001	-5.1%
Commercial lots(ln)	1.08	.039	2.06	.05	2.5%
Youth hangouts(ln)	.99	.017	-0.74	*ns*	-0.8%
Single family homes(ln)	.73	.021	-10.82	.001	-15.3%
Proximity space	1.00	.001	4.20	.001	6.5%
Control Variables					
Area(ln)	1.16	.021	8.41	.001	12.9%
Population	1.00	.000	14.35	.001	19.1%
Spatial lag	1.04	.002	25.19	.001	36.0%
Model Fit Statistics					
-2 Log likelihood ratio				-6115.72	
Model fit chi-square				1159.80***	
BIC				-1298.98	
LR test nested model				110.98***	

*$p<.05$, **$p<.01$, ***$p<.001$

Of particular note is the BIC score for this model showing it to be 47.31 points lower than the demographics-only model. This finding indicates that the opportunity land use variables as a group are better predictors of MVT then the group of sociodemographic variables, and that the observed difference is "very strong" per the Rafferty (1996) guidelines.

The third model combines the opportunity and sociodemographic predictors, and statistical controls into a single model (Table 5). This combined model is compared to all other models because its findings are critical in answering the primary research question, that is; Is the presence of certain land uses predictive of MVT levels in neighborhoods, net the socio-economic impact of the people living there?

The results of this combined model show that the percentage of single family residences is the strongest predictor of either opportunity or sociodemographic variables with a one standard deviation increase reducing the expected MVT count by nearly 13%. However, the amount of impact of single family residences exhibits a substantial decrease from the prior opportunity-only model (-15.3% to -12.8), which did not control for sociodemographic variables. This suggests a considerable amount of the explanation for lower MVT levels in single family residential neighborhoods in Philadelphia is related to the socio-economic characteristics of the people living there, but in no way can these factors be seen as the only explanation.

The amount of land use utilized by colleges in block groups remains an important crime suppressor in the combined model that controls for sociodemographics. The impact increased from -5.1% to -6.4% per one standard deviation further suggesting there is something about college neighborhoods, net the effect of the sociodemographics of residents, that has a restraining effect on MVT levels. This finding is contrary to the hypotheses and what is expected from a reading of the opportunity and crime literature, which suggests the large number of young people and student parking lots at colleges should increase, not decrease, MVT levels.

On the crime-promoting side, shopping centers remained significant predictors of MVT in the combined model, increasing their expected impact on MVT counts per standard deviation from 3.8% to 4.4%, once neighborhood sociodemographics were

Table 5. Combined Model of Opportunity and Sociodemographic Factors Predicting MVT Counts in Philadelphia Block Groups (N = 1816)

Variables	IRR	SE	*Z*	*P* <	Change in Count Per One SD Increase
Opportunity Variables					
Shopping centers(ln)	1.08	.020	3.95	.001	4.4%
Bars(ln)	1.14	.050	2.92	.01	4.0%
High schools(ln)	1.01	.026	0.46	*ns*	0.5%
Colleges(ln)	.89	.020	-5.21	.001	-6.4%
Commercial lots(ln)	1.07	.039	1.95	.05	2.3%
Youth hangouts(ln)	.99	.017	-0.92	*ns*	-1.1%
Single family homes(ln)	.77	.023	-8.76	.001	-12.8%
Proximity space	1.00	.001	3.70	.001	5.6%
Demographic Variables					
SES index	0.95	.006	-7.16	.001	-11.0%
Racial heterogeneity	1.15	.065	2.54	.01	3.2%
Residents < 5 years	1.00	.001	0.26	*ns*	0.4%
Single-parent families	1.00	.001	2.44	.05	3.5%
15-24 yr olds(ln)	1.00	.023	0.00	*ns*	0.0%
Control Variables					
Area(ln)	1.20	.021	10.51	.001	16.5%
Population	1.00	.000	14.96	.001	19.8%
Spatial lag	1.03	.002	21.49	.001	31.4%
Model Fit Statistics					
-2 Log likelihood ratio				-6060.23	
Model fit chi-square				1270.78***	
BIC				-1372.44	
LR test nested model				n/a	

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

Commercial lots remained significant predictors but with a minor difference in the expected count increase (from 2.5% to 2.3%) in the combined model. These findings support the related hypotheses and opportunity theory.

The percentage of land use utilized by bars and night clubs rose to the level of statistical significance (from p greater than .05 to less than .01) in the combined model. As shown, a standard deviation increase in this variable is expected to increase the MVT count by 4%. This percentage is nearly equivalent to that of shopping centers (4.4%) and is considerably higher than commercial lots (2.3%). This finding supports both the hypothesis and opportunity theory.

The percentage land utilized by high schools and youth hangouts remain insignificant as they were in the opportunity-only model. This is contrary to the hypotheses and opportunity theory.

Proximity space, the percentage of land in a block group located within one block of the opportunity land uses excluding single family residences, remained a significant and positive predictor of MVT in the combined model. However, net the sociodemographic controls in this model, the percentage increase in expected count for one standard deviation decreased from 6.5% in the opportunity-only model, to 5.6% in this model (14%). Still, overall findings for this variable support the hypotheses and opportunity theory that areas immediately surrounding specific criminogenic land uses are also at higher risk for MVT.

The BIC values for the combined model dropped considerably from both the opportunity-only land use model (down 73 points) and sociodemographic-only model (down 121 points). These large BIC differences suggest the combined model is a much better fit to the data than the other two models alone. This is further confirmed by the likelihood ratio chi-square tests of the nested models as shown in the appropriate table for each model. The LR chi-square value of 180.80 ($p < .001$) for the sociodemographics-only model, indicates that the combined model is a significantly better fit with the inclusion of the opportunity variables. The LR chi-square value of 110.98 ($p < .001$) for the opportunity land use-only model indicates that the combined model is a significantly better fit with the inclusion of the sociodemographic variables. Clearly, these two groups of variables together better explain MVT levels in neighborhoods than either does separately.

The statistical control variables of block group area, population, and spatial lag continue to be positive and significant, net the influence of the sociodemographic variables. The positive spatial lag indicates that block groups of like MVT values tend to be located near one another, high near high and low near low, even when controlling for opportunity and sociodemographic factors.

The analyses to this point has answered the main research question by identifying the importance of opportunity land uses in explaining MVT count in block groups, net the impact of sociodemographic factors. The analyses have also shown that sociodemographics are important predictors of MVT, although their overall combined impact is less than that of the combined opportunity variables. The next series of analyses evaluate interaction effects among the variables for a better understanding of the relationship between opportunity producing land uses, neighborhood demographics, and MVT.

Interaction Analysis Results

A series of grouped interaction models were run testing for group-level interaction effects among the opportunity land use variables and the opportunity and sociodemographic variables. Results are shown only for those models whose postestimation likelihood ratio (LR) test determined a significantly better model fit than the combined model (opportunity, sociodemographics, and statistical controls only).

The tests of the grouped opportunity land use interaction models (land use x land use) produced surprising results with none of the models providing significantly better fit than the combined model per the LR test. This finding of a lack of interaction between land use categories may be feasible, but the problem also may be a mathematical one. Examination of the data showed that many of the multiplicative interaction terms resulted in values that were, in the majority, zero. For example, interactions between shopping center and high schools, shopping centers and youth hangouts, youth hangouts and bars, youth hangouts and colleges, and high schools and colleges, to name a few, resulted in less that 10 block groups each having an interaction value greater than zero. These models are likely not robust enough to uncover interaction effects, even if present.

Tests of the grouped sociodemographic interaction models proved more fruitful with all but the percentage residents-less-than-five-years model providing better model fit of the data than the combined model only (see Tables 5-9). This suggests the importance of people-place interactions in understanding MVT levels in neighborhoods. Although the models overall were statistically significant, only one or two of the individual sociodemographic-opportunity interactions were significant in each model.

The first significant model of sociodemographic interactions contains terms composed of the SES index and the opportunity land use variables (Table 6). Two interaction terms were found to be significant. The first identified is a negative interaction between SES and the impact of high schools on MVT. According to the combined model absent any interaction terms as shown in Table 5, a one standard deviation increase in high schools increases the expected count of MVT in a block group by (non-significant) 0.5%, controlling for all other factors. However, as shown in this model in Table 6, a similar increase in high schools in a high SES block group (one standard deviation above the mean), decreased the expected count by 2.4%. This finding identifies a moderating effect of SES on the impact of high schools on MVT.

The other significant interaction identified in this model is a positive one between SES and the impact of proximity space on MVT. A one standard deviation increase in proximity space was found to increases the expected count of MVT by 5.6% (cf. Table 5), but a similar increase in a high SES (one standard deviation) block group <u>increases</u> the expected count by 9.3%. This finding appears to run contrary to what a reading of the literature suggests being that higher levels of SES are usually associated with lower crime levels. However, because multiplicative interaction terms are bi-directional mathematically, they also can be interpreted bi-directionally. In this case, the term can also be interpreted as a one standard deviation increase in SES usually

Table 6. SES Interaction Model Predicting MVT Counts in Philadelphia Block Groups (N = 1816)

Variables	**IRR**	**SE**	***Z***	***P <***	**Change in Count Per One SD Increase**
Opportunity Variables					
Shopping centers(ln)	1.07	.021	3.27	.001	3.9%
Bars(ln)	1.08	.047	1.74	*ns*	2.4%
High schools(ln)	1.00	.026	0.00	*ns*	0.0%
Colleges(ln)	.88	.021	-5.41	.001	-7.0%
Commercial lots(ln)	1.07	.038	1.89	*ns*	2.2%
Youth hangouts(ln)	.98	.017	-1.21	*ns*	-1.4%
Single family homes(ln)	.77	.036	-5.59	.001	-13.0%
Proximity space	1.00	.001	4.45	.001	6.8%
Demographic Variables					
SES index	0.92	.010	-8.39	.001	-19.4%
Racial heterogeneity	1.19	.067	3.12	.01	4.0%
Residents < 5 years	1.00	.001	-0.30	*ns*	0.0%
Single-parent families	1.00	.001	2.13	.05	3.1%
15-24 yr olds(ln)	1.00	.022	0.11	*ns*	0.1%
Interaction Variables					
SES X Shopping centers(ln)	1.01	.010	0.82	*ns*	0.9%
SES X Bars(ln)	1.02	.016	0.96	*ns*	1.5%
SES X High schools(ln)	.97	.013	-2.15	.05	-2.4%
SES X Colleges(ln)	.99	.009	-1.58	*ns*	-2.3%
SES X Commercial lots(ln)	1.01	.012	1.17	*ns*	1.5%
SES X Youth hangouts(ln)	1.00	.008	0.06	*ns*	0.8%
SES X SF homes(ln)	1.01	.008	1.14	*ns*	3.4%
SES X Proximity space	1.00	.000	3.76	.001	9.3%
Control Variables					
Area(ln)	1.22	.022	11.19	.001	17.8%
Population	1.00	.000	14.95	.001	19.9%
Spatial lag	1.03	.002	21.03	.001	30.5%
Model Fit Statistics					
-2 Log likelihood ratio				-6039.54	
Model fit chi-square				1312.16***	
BIC				-1353.78	
LR test nested model				41.38***	

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

decreases the expected count of MVT in a block group by 11.0% (Table 5), but a similar increase in a high proximity space (one standard deviation) block group, increases the expected count by 9.3%. This explanation concurs with the literature and shows a moderating relationship exists between SES and proximity space in neighborhoods.

The next model includes interaction terms for the Blau racial heterogeneity index and all opportunity land uses (Table 7). Only one interaction in the model was statistically significant (race x colleges). The results of the analysis shows that although a one standard deviation increase in space assigned to colleges usually decreases the expected count of MVT by 6.4% (Table 5), a similar increase in a high racially mixed (one standard deviation) block group decreases the count by 7.3%. This result also can be interpreted as a one standard deviation increase in racial heterogeneity usually increases the expected count by 3.2% (Table 5), but a similar increase in a high college (one standard deviation) block group decreases the expected count by 7.3%. This latter interpretation supports the earlier finding of the combined model that the presence of colleges has a suppressing effect on MVT in block groups.

The next model examines the percentage of single-parent families and opportunity land use interactions (Table 8). Again, only 1 of the 8 interactions included was found to be statistically significant. According to the analysis, a one standard deviation increase in land use utilized by colleges usually decreases the expected count by 6.4% (Table 5), but when combined with a high single-parent (one standard deviation) block group, the expected count increases by 6.2%. This finding indicates

Table 7. Racial heterogeneity Interaction Model Predicting MVT Counts in Philadelphia Block Groups (N = 1816)

Variables	IRR	SE	*Z*	*P* <	Change in Count Per One SD Increase
Opportunity Variables					
Shopping centers(ln)	1.10	.035	2.93	.01	5.7%
Bars(ln)	1.24	.102	2.59	.01	6.8%
High schools(ln)	.98	.038	-0.41	*ns*	-0.7%
Colleges(ln)	.99	.043	-0.21	*ns*	-0.5%
Commercial lots(ln)	1.12	.072	1.69	*ns*	3.6%
Youth hangouts(ln)	1.02	.027	0.83	*ns*	1.5%
Single family homes(ln)	.78	.042	-4.63	.001	-12.5%
Proximity space	1.00	.001	1.81	*ns*	4.3%
Demographic Variables					
SES index	0.95	.006	-7.38	.001	-11.3%
Racial heterogeneity	1.21	.107	2.20	.05	4.4%
Residents < 5 years	1.00	.001	0.61	*ns*	0.8%
Single-parent families	1.00	.001	1.97	.05	2.9%
15-24 yr olds(ln)	1.01	.023	0.57	*ns*	0.7%
Interaction Variables					
Race X Shopping centers(ln)	.94	.078	-0.72	*ns*	-1.3%
Race X Bars(ln)	.78	.163	-1.18	*ns*	-3.0%
Race X High schools(ln)	1.09	.110	0.86	*ns*	1.5%
Race X Colleges(ln)	.75	.072	-3.00	.01	-7.3%
Race X Commercial lots(ln)	.91	.125	-0.67	*ns*	-1.4%
Race X Youth hangouts(ln)	.88	.062	-1.79	*ns*	-3.2%
Race X SF homes(ln)	.98	.167	-0.12	*ns*	-0.3%
Race X Proximity space	1.00	.002	0.46	*ns*	1.3%
Control Variables					
Area(ln)	1.20	.021	10.29	.001	16.1%
Population	1.00	.000	15.10	.001	19.9%
Spatial lag	1.03	.002	21.18	.001	30.9%
Model Fit Statistics					
-2 Log likelihood ratio				-6052.19	
Model fit chi-square				1286.87***	
BIC				-1328.49	
LR test nested model				16.09*	

$^*p<.05$, $^{**}p<.01$, $^{***}p<.001$

a higher relative strength in the impact of single-parent families on MVT than the suppressive nature of colleges on MVT in Philadelphia.

The next interaction model examines the influence of the percentage of 15-24 year olds on the relationship between the opportunity variables and MVT (Table 9). Two interaction terms were significant. The first shows that for percentage of area assigned to bars, a one standard deviation increase usually increases the expected MVT count by 4% (Table 5). However, with a similar increase in a high percentage 15-24 year old (one standard deviation) block group, the expected count decreases by 13.2%. The interaction between colleges and 15-24 year olds also was negative. For colleges, a one standard deviation usually decreases the expected count by 6.4% (Table 5). However, with a similar increase in a high 15-24 year old (one standard deviation) block group, the expected count decreases further to 12.3%.

The two findings above suggest that although the percentage of 15-24 year olds has little overall impact on MVT in the combined model, it does have a strong moderating effect on the relationship between colleges, bars, and MVT. In each case, high levels of 15-24 year olds in the population interact with colleges and bars resulting in substantially <u>lower</u> MVT counts. Age composition has been shown in the literature review to be a poor predictor of either crime in general or MVT in particular. These findings suggest that any impact of age may only be a moderating, and not a direct one, found only in specific interactions between opportunity factors and crime.

The final interaction model (Table 10) is a full model including the opportunity land uses, sociodemographics, statistical controls, and all six significant individual

Table 8. Single-parent Interaction Model Predicting MVT Counts in Philadelphia Block Groups (N = 1816)

Variables	**IRR**	**SE**	***Z***	***P* <**	**Change in Count Per One SD Increase**
Opportunity Variables					
Shopping centers(ln)	1.08	.032	2.71	.01	4.8%
Bars(ln)	1.16	.071	2.37	.05	4.5%
High schools(ln)	.99	.047	-0.30	*ns*	-0.6%
Colleges(ln)	.81	.029	-5.92	.001	-10.9%
Commercial lots(ln)	1.02	.050	0.37	*ns*	0.6%
Youth hangouts(ln)	1.03	.032	0.79	*ns*	1.8%
Single family homes(ln)	.74	.035	-6.35	.001	-14.6%
Proximity space	1.00	.001	3.24	.001	8.4%
Demographic Variables					
SES index	.95	.006	-7.39	.001	-11.3%
Racial heterogeneity	1.17	.066	2.75	.01	3.5%
Residents < 5 years	1.00	.001	0.54	*ns*	0.7%
Single-parent families	1.00	.001	2.35	.05	5.4%
15-24 yr olds(ln)	1.01	.023	0.44	*ns*	0.6%
Interaction Variables					
Sngl Pnt X Shop centers(ln)	1.00	.001	-0.28	*ns*	-0.5%
Sngl Pnt X Bars(ln)	1.00	.002	-0.36	*ns*	-0.6%
Sngl Pnt X High schools(ln)	1.00	.001	0.69	*ns*	1.4%
Sngl Pnt X Colleges(ln)	1.00	.001	3.35	.001	6.2%
Sngl Pnt X Comm lots(ln)	1.00	.002	1.57	*ns*	2.3%
Sngl Pnt X Youth hang(ln)	1.00	.001	-1.52	*ns*	-3.3%
Sngl Pnt X SF homes(ln)	1.01	.004	1.28	*ns*	2.8%
Sngl Pnt X Proximity space	1.00	.000	-1.38	*ns*	3.9%
Control Variables					
Area(ln)	1.21	.022	10.53	.001	16.6%
Population	1.00	.000	15.02	.001	19.9%
Spatial lag	1.03	.002	21.33	.001	31.1%
Model Fit Statistics					
-2 Log likelihood ratio				-6049.70	
Model fit chi-square				1291.84***	
BIC				-1333.46	
LR test nested model				21.05**	

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

Table 9. Percentage of 15-24 Year Olds Interaction Model Predicting MVT Counts in Philadelphia Block Groups (N = 1816)

Variables	**IRR**	**SE**	***Z***	***P* <**	**Change in Count Per One SD Increase**
Opportunity Variables					
Shopping centers(ln)	1.23	.096	2.60	.01	12.8%
Bars(ln)	1.77	.324	3.12	.01	19.1%
High schools(ln)	1.10	.162	0.63	*ns*	4.1%
Colleges(ln)	1.11	.102	1.16	*ns*	6.1%
Commercial lots(ln)	.89	.103	-0.97	*ns*	-3.6%
Youth hangouts(ln)	1.00	.068	-0.01	*ns*	0.0%
Single family homes(ln)	.85	.084	-1.66	*ns*	-8.3%
Proximity space	1.00	.002	0.31	*ns*	2.1%
Demographic Variables					
SES index	.95	.006	-7.61	.001	-11.7%
Racial heterogeneity	1.15	.065	2.53	.01	3.2%
Residence < 5 years	1.00	.001	0.72	*ns*	1.0%
Single-parent families	1.00	.001	1.70	*ns*	2.5%
15-24 yr olds(ln)	1.04	.042	0.94	*ns*	2.1%
Interaction Variables					
15/24 yr X Shop centers(ln)	.95	.029	-1.70	*ns*	-7.5%
15/24 yr X Bars(ln)	.85	.057	-2.50	.01	-13.2%
15/24 yr X High schools(ln)	.97	.051	-0.55	*ns*	-3.5%
15/24 yr X Colleges(ln)	.94	.025	-2.47	.01	-12.3%
15/24 yr X Comm lots(ln)	1.07	.045	1.67	*ns*	6.7%
15/24 yr X Youth hang(ln)	1.00	.026	-0.17	*ns*	-0.8%
15/24 yr X SF Homes (ln)	.96	.040	-0.94	*ns*	-4.7%
15/24 yr X Proximity space	1.00	.001	0.45	*ns*	3.1%
Control Variables					
Area(ln)	1.20	.021	10.30	.001	16.1%
Population	1.00	.000	15.34	.001	20.4%
Spatial lag	1.03	.002	21.39	.001	31.1%
Model Fit Statistics					
-2 Log likelihood ratio				-6050.55	
Model fit chi-square				1290.14***	
BIC				-1331.76	
LR test nested model				19.36*	

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

interactions identified in the previous interaction models (cf. Tables 6-9). This model proved to be a significantly better fit to the data than the combined model alone (Table 5) as indicated by the LR test of the nested model. As shown, only two of the six interaction terms remained significant, net the effect of all other variables. Both of these interaction terms contained the SES index, one with high schools, and the other with proximity space.

As displayed in Table 10, the analysis shows that although a one standard deviation increase in high schools usually increases the expected count of MVT in a block group by a (non-significant) 0.5% (Table 5), a similar increase in high schools in a high SES block group decreases the expected count by 2.5%. This finding identifies a moderating effect of SES on the criminogenic effect of high schools on MVT and is in the direction expected by a read of the literature.

The other significant interaction term in the final interaction model is SES and proximity space. The analysis showed that a one standard deviation increase in proximity space usually increases the expected count of MVT by 5.6% (Table 5), but a similar increase in a high SES (one standard deviation) block group, increases the expected count by 10.7%. The term can also be interpreted as a one standard deviation increase in SES usually decreases the expected count of MVT in a block group 11.0% (Table 5), but a similar increase in a high proximity space (one standard deviation) block group, increases the expected count by 10.7%. This second explanation concurs with the literature concerning the criminogenic nature of proximity space (Brantingham & Brantingham, 1993a).

Table 10. Full Model of All Variables and Significant Interactions Predicting MVT Counts in Philadelphia Block Groups (N = 1816)

Variables	**IRR**	**SE**	***Z***	***P* <**	**Change in Count Per One SD Increase**
Opportunity Variables					
Shopping centers(ln)	1.07	.020	3.87	.001	4.3%
Bars(ln)	1.40	.219	2.16	.05	10.8%
High schools(ln)	1.00	.025	-0.04	*ns*	-0.01%
Colleges(ln)	.96	.115	-0.32	*ns*	-2.1%
Commercial lots(ln)	1.08	.038	2.11	.05	2.5%
Youth hangouts(ln)	.98	.016	-1.07	*ns*	-1.2%
Single family homes(ln)	.81	.024	-7.19	.001	-10.9%
Proximity space	1.00	.001	4.11	.001	6.3%
Demographic Variables					
SES index	.92	.009	-8.79	.001	-19.4%
Racial heterogeneity	1.20	.068	3.29	.001	4.2%
Residents < 5 years	1.00	.001	0.18	*ns*	0.2%
Single-parent families	1.00	.001	1.53	*ns*	2.2%
15-24 yr olds(ln)	1.04	.026	1.36	*ns*	2.0%
Interaction Variables					
SES X High school(ln)	.97	.013	-2.19	.05	-2.5%
SES X Proximity space	1.00	.000	5.28	.001	10.7%
Race X Colleges(ln)	.90	.112	-0.87	*ns*	-2.8%
Sngl Prt X Colleges(ln)	1.00	.001	1.58	*ns*	3.6%
15/24 yr X Bars(ln)	.91	.052	-1.59	*ns*	-7.3%
15/24 yr X Colleges(ln)	.97	.030	-0.86	*ns*	-5.1%
Control Variables					
Area(ln)	1.22	.022	11.08	.001	17.4%
Population	1.00	.000	15.36	.001	20.2%
Spatial lag	1.03	.002	20.93	.001	30.1%
Model Fit Statistics					
-2 Log likelihood ratio				-6035.60	
Model fit chi-square				1320.05***	
BIC				-1376.68	
LR test nested model				49.26***	

*$p<.05$, **$p<.01$, ***$p<.001$

This section on interactions has added to the understanding of the impact of opportunity land uses and sociodemographics on MVT. It has shown that interactions between types of people and opportunity provided by certain land uses do exist and that they tend to be in the direction suggested by the literature. Interaction effects between opportunity land uses themselves however either are very weak or do not exist, and/or the methods used in this analyses are not robust enough to identify them.

This chapter has described the analysis results in detail and how they relate to the main research question and the hypotheses. The next chapter identifies the implications of this research.

CHAPTER 5

DISCUSSION

Does the presence of certain land uses in neighborhoods predict higher MVT levels? Will these land uses likely produce crime even in higher SES neighborhoods? Do neighborhood sociodemographics interact with these criminogenic land uses to amplify or diminish their impact on MVT levels? This research has provided answers to these questions and the answers have important implications for crime theory, public policy, and future research.

The research has identified the following findings:

- The combined model, which includes both land use and sociodemographic variables, produces substantially better model fit (explanatory power) than either group of variables did alone (combined model BIC = -1372.44, land use model BIC = -1298.98, sociodemographic model BIC = -1251.67).
- The explanatory power of the land use variables alone was greater than that of the sociodemographic variables alone (land use BIC = -1298.98, sociodemographic BIC = -1251.67).
- A one standard deviation increase in the percentage of land utilized by shopping centers in a block group is expected to increase the MVT count by 4.4%; for bars the MVT count is expected to increase 4.0%; for commercial lots the MVT count is expected to increase 2.3%; and for proximity space the MVT count is expected to increase 5.6%, net the impact of the sociodemographic factors.

- A one standard deviation increase in the percentage of land utilized by colleges in a block group is expected to decrease the MVT count by 6.4%; for single family homes the MVT count is expected to decrease 12.8% - the largest impact of any land use or sociodemographic variable, net the impact of the sociodemographic factors.
- Concerning demographic factors, a one standard deviation increase in the SES index in a block group is expected to decrease the expected MVT by 11.0%. A one standard deviation increase in the racial heterogeneity index of a block group is expected to increase the MVT count by 3.2%; and for single-parent families the MVT count is expected to increase 3.5%, net the impact of the land use factors.
- The percentage of land utilized by high schools and youth hangouts, along with neighborhood stability (in same home less than five years) and15-24 year olds in the population, were not related to MVT levels.
- Race heterogeneity and percent single-parent families only became statistically significant predictors of MVT in the combined model that controlled for land use, while neighborhood stability lost significance in the combined model. Bars, the only land use variable to change statistical significance across models, became a statistically significant predictor of MVT in the combined model.
- SES, racial heterogeneity, and the percentage of single-parent families and 15-24 year olds in the population interacted with some land uses increasing their impact on MVT counts in neighborhood.

Implications for Crime Theory

Results of the present analysis indicate that MVT levels are related to specific land use types, regardless of the characteristics of the people living in the neighborhood. While controlling for SES, racial heterogeneity, percentage residents in same house less than five years, and percentage of single-parent families and young people in the population (15-24 year olds), shopping centers, bars, and commercial lots were predictive of higher MVT counts, and colleges and single family homes predicted lower MVT counts in Philadelphia neighborhoods. These land use categories were chosen due to expectations that they would produce high levels of opportunity for MVT as posited by the three opportunity theories of rational choice, routine activity and crime pattern theory, findings from a limited number of prior empirical neighborhood-level studies, information garnered from survey studies of offenders and victims, and descriptive studies of MVT "hot spots." Findings were generally consistent with predictions based on opportunity theories, and they provide important information about the opportunity-land use-crime relationship. It is useful to further explore and recapitulate these findings for each land use category (i.e., shopping centers, bars, colleges, etc.) so their relationship to theory as well as their potential for application to MVT crime prevention schemes can be specifically addressed.

Shopping centers

The amount of land use dedicated to shopping centers in neighborhoods was found to have a positive relationship with MVT (4.4% increase in expected count per standard deviation) in agreement with theory and prior studies. This relationship is argued to be the product of several opportunity-enhancing factors. The first is the high number of vehicles available to steal and the importance of choice in offender selection criteria. Second, the easy access to vehicles in shopping center lots due to a lack of surveillance and access controls also increases opportunity. Third, concerns the large number of potential offenders drawn to shopping centers who gain awareness of crime opportunities at these locations. The results suggest that had the shopping centers not been in these neighborhoods, MVT counts would have been significantly lower.

The impact of shopping centers on MVT in Philadelphia is exemplified by the Franklin Mills Mall. This large retail mall and its acres of parking spaces are located in the north-eastern part of the city. Although the mall is situated in a high SES neighborhood, the block groups in which it is located has the third largest number of reported vehicle thefts (128) of all 1816 block groups in the city. Thus, some land uses predict increased levels of MVT even in the affluent areas of the city.

Bars and nightclubs

The presence of bars and nightclubs were also related to increased MVT levels (4.0% increase in expected count per standard deviation) in Philadelphia neighborhoods. This finding is consistent with other opportunity research, including two comprehensive neighborhood studies (Rice & Smith, 2002; Roncek & Maier, 1991). Opportunity theory suggests this relationship with MVT is due to the "loose" atmosphere frequently found in bars that may attract motivated offenders, and the numerous unattended vehicles of customers that are left, predictably, parked near bars late into the night when natural surveillance is minimized. These explanations are especially salient because only a handful of the bars in the present study had parking lots, thus requiring patrons to park on the street in nearby neighborhoods, rather than in supervised parking areas.

Interestingly, bars were not significantly related to MVT in the opportunity-only regression model (Table 4). An examination of the correlation table (Table 2) suggests this may be the case because it shows that bars tend to be located in neighborhoods of low population stability (residents in same house less than five years) and higher racial heterogeneity. It is only after these sociodemographics are controlled for in the combined model that the criminogenic effect of bars on MVT was apparent. If the current research had not controlled for neighborhood socioeconomic structure (an omission in some studies), the finding of the criminogenic relationship between bars and MVT would not have been exposed.

The impact of bars is exemplified in the high MVT counts in the block groups that line South Street and in the area of Second and Front streets in the Center City area of Philadelphia. Both of these areas are well-known nighttime entertainment districts drawing people in from throughout the region to the many bars and late night restaurants with full-service bars located there.

High schools

High schools located in Philadelphia block groups appear to have little overall effect on MVT, and this finding runs contrary to those of the earlier neighborhood studies completed by Roncek and associates (Roncek & Faggiani, 1989; Roncek & Lobosco, 1983). Why this is the case is not clear. Although only a few high schools in Philadelphia have parking lots for either students or staff (as observed in aerial photographs), opportunity theory suggests higher MVT counts are still expected due to students' familiarity with opportunities in the surrounding neighborhoods they transverse through enroute to school.

Youth hangouts

Youth hangouts (parks and recreation centers, public pools, and movie theatres) also had no impact on MVT levels. This finding, like high schools, is again surprising considering both groups of land use attract large numbers of young people in their crime-prone years into the neighborhoods in which they are located. Additionally, the one prior neighborhood study available found youth hangouts were related to higher MVT levels (Rice & Smith, 2002). A supplemental model was analyzed (not shown) that combined youth hang outs and high schools, but the variable remained statistically insignificant.

The finding of a lack of impact on MVT for the two youth-related land uses (youth hangouts and high schools) in Philadelphia is interesting. Perhaps Philadelphia youth are not into motor vehicle theft because they do not yet possess the necessary skills to steal and drive cars. Philadelphia is a high poverty city and has an extensive public transportation system that is utilized by many of its students to commute to school. It seems likely that many of these younger residents do not have access to cars and have not yet learned to drive, a required skill of automobile thieves. Therefore, their frequently visited nodes and hang outs (high schools, parks) are less likely to be centers of MVT activity. A survey study of MVT offenders in Philadelphia would be necessary to support such an inference. Additionally, studies in other cities that do not have equally high poverty levels or comprehensive public transportation, thus likely increasing the driving skills of teens, may produce different results.

Colleges

Colleges were found to have a strong negative relationship with MVT (6.4% decrease in expected count per standard deviation) in Philadelphia, which is surprising because this result seems to run contrary to opportunity theory. The now disproved hypothesis (at least within this study) of an expected positive relationship was based upon the presence of large campus parking lots that are utilized during day and nighttime hours, the belief that many students park in nearby neighborhoods to avoid expensive on-campus parking fees, and that college campuses are utilized by many students who are in their crime-prone years. However, something about campus neighborhoods not only holds these opportunities in check, but also has a strong safety impact that significantly reduces MVT levels.

No neighborhood-level studies examining the relationship between MVT and colleges were identified by the literature review, but studies comparing college crime rates to those of the cities in which they are located are consistent with the inverse relationship found in this research. According to these studies, college campuses tend to have significantly lower crime-per-student rates than the surrounding cities have crimes per population, including MVT (Bromley, 1992; Fernandez & Lizotte, 1995). Although it can be argued that these two rates are not completely comparable, evidence of low crime on campuses is also observed in the statistics colleges provide as required by federal law. For example, the University of Pennsylvania, a large campus spread across several blocks in west Philadelphia with over 24,000 students, reported only 31 auto thefts during the three-year study period in its jurisdiction (University of Pennsylvania, 2009). Temple University, also a large multi-block campus with over

27,000 students located in northern Philadelphia, reported only 42 MVT in its jurisdiction (Temple University, 2009). Both of these campuses are located in urban areas of Philadelphia and are adjacent to high crime neighborhoods. Chestnut Hill College, a much smaller college of just over 2,600 students located in a high income, almost rural-like area of north-west Philadelphia, reported no vehicle thefts for the entire three year study period (Chestnut Hill College, 2009).

It is likely that a good part of the explanation for these low MVT counts is found in the attention to crime prevention exhibited by colleges through the employment of high numbers of police and security officers and the use of other crime prevention techniques. These efforts may also filter out into the surrounding community providing safety to adjacent neighborhoods in what is referred to as "diffusion of benefits" (Clarke & Weisburd, 1994). For example, the University of Pennsylvania Police, a department of 116 police officer and 500 security officers, patrol an area of responsibility that includes 500 yards from all campus facilities (University of Pennsylvania, 2009). The Temple University Police, a department of 118 officer and 289 security officers, also patrol many adjacent off-campus neighborhoods in their jurisdiction (Temple University, 2009). Chestnut Hill College utilizes the services of the Philadelphia Police Department but also maintains its own 40 person security department (Chestnut Hill College, 2009). These colleges also use highly visible crime prevention techniques including security kiosks that are frequently placed in public places along college-neighborhood borders, high levels of lighting, outside emergency telephones, CCTV, and territorial markers of signs and banners on campus perimeters. Many of these situational crime prevention techniques have been evaluated and proven to be quite effective (see for example Clarke, 1997). It is likely the presence of all this extra security and other crime prevention techniques increases overall neighborhood safety. It is also possible that the presence of students during the nighttime hours (all colleges evaluated had student dorms except one) added to the level of "eyes on the street" or informal surveillance of the surrounding neighborhoods (Jacobs, 1961). Additionally, college students are not a cross section of young people in the population, rather, they are highly selected achievers and their presence in great numbers in these neighborhoods may not be highly criminogenic (Rengert, Mattson, & Henderson, 2001). When evaluated in respect to the opportunity-reducing aspects of the aforementioned high levels of police/security, crime prevention techniques, and increased nighttime informal surveillance, the finding that neighborhoods with college campuses have lower MVT levels is seen as concurring with opportunity theory, and not in conflict with it.

Commercial parking lots

As hypothesized, the percentage of land use utilized by commercial parking lots in neighborhoods was found to have a positive relationship with MVT (2.3% increase in expected count per standard deviation), and this finding concurs with the prior research (Clarke, 2002; Plouffe & Sampson, 2004; Rice & Smith, 2002), including the lone neighborhood study that includes this variable (Rice & Smith, 2002). Although not specifically answered by the current study, it is likely that a lack of surveillance and access control, as well as a large selection of targets define opportunities for MVT, but lots are also important centers of other crimes probably due to the first two factors.

According to the 2006 National Crime Victimization Survey, 14% of purse snatches, 13% of robberies, 6% of assaults and 5% of all sexual assaults occur in parking lots and garages (Bureau of Justice Statistics, 2008). Unfortunately, the national data does not differentiate between lots and multi-level garages so it is unclear if victimization levels in lots are significantly higher, as they are with MVT. In matters of neighborhood safety and crime, parking lots should be recognized for their criminogenic nature.

Single family homes

The percentage of single family homes in neighborhoods was negatively related to MVT (12.8% decrease in expected count per standard deviation) and had the highest effect size of all opportunity and sociodemographic variables. Opportunity theory suggests this is due to the garages and driveways associated with these structures where owners can better secure and watch over their vehicles. This explanation seems especially plausible because the sociodemographic variables in the models likely already control for such crime suppressing factors as found on costlier newer model vehicles with their better security devices and the high levels of social efficacy found in higher income neighborhoods (Sampson, Raudenbush, & Earls, 1997). It also is likely that offenders in Philadelphia recognize there is much less risk to stealing vehicles in the many row home neighborhoods of the city where few houses have garages or driveways, and residents have to park their vehicles on the public streets, often out of view and away from their homes.

Proximity space

Proximity space, a term developed and used in this dissertation to describe the percentage of land use in a neighborhood falling within one block of the combined opportunity land uses, is a positive and significant predictor of MVT levels in Philadelphia (5.6% increase in expected count per standard deviation). By including proximity space in the models, the analyses showed that the impact of criminogenic land uses extends beyond property lines and into the surrounding neighborhoods for a distance of least one block (400 feet) in Philadelphia. This finding concurs with a number of analyses examining other crime types, as well as three available studies on MVT (Roncek, 2000; Roncek & Faggiani, 1985: Roncek & Lobosco, 1983). Per opportunity theory, these areas were expected to have elevated levels of MVT due to the awareness of crime opportunities gained by potential offenders that pass through them enroute to the nearby opportunity land uses. Results from the present analyses are particularly robust because the GIS methodology also evaluated proximity space that overlaps into bordering block groups. This methodology prevents the effect of overlapping proximity space from being truncated in the analyses, or ignored, either statistically or theoretically.

Sociodemographic factors

This study, although focused on opportunity and land use, adds to the limited literature concerning the importance of neighborhood social structure on MVT. SES, racial heterogeneity, and single-parent families were significant predictors of MVT, net the impact of neighborhood land use. The impact of SES (11.0% decrease in expected count per standard deviation) and single-parent families (3.5% increase in expected count per standard deviation) on MVT is in agreement with previous neighborhood studies in both importance and direction, as is the non-significant finding of the percentage of 15-24 year olds in the population. But more to the point of this study and its hypotheses, results reveal that the impact of racial heterogeneity and population stability (residents in the same house less than five years) on MVT are confounded with those of land use in Philadelphia. Recall that in the demographic-only model (Table 3), racial heterogeneity was non-significant, and population stability was positive and significant. The more likely overall impact of these two variables on MVT was only revealed in the combined model (Table 5) where racial heterogeneity became a statistically significant predictor (3.2% increase in expected count per standard deviation) and percentage population at the same residence for less than five years while population stability was no longer significantly related to MVT. Had the opportunity land use variables not been included in the multiple regression analyses in this study, the interpretation of the impact of these two sociodemographic variables would be erroneous. This calls into question findings in prior research on MVT and other crimes that evaluate only sociodemographics and fails to consider opportunity structure in neighborhoods.

Of the eight land uses evaluated in this study, only the impact of bars changed (from non-significant to significant) once sociodemographic factors were controlled. This shows that, at least in the land use categories evaluated, land use has its own direct effect on crime and does not work solely through neighborhood sociodemographics. This finding supports opportunity theories because certain land uses are posited to attract offenders into neighborhoods increasing crime levels, regardless of the number (also controlled in the models) or types of people living in the area.

Interactions

Interaction testing in the present analyses added further to the theoretical understanding of the relationship between opportunity, land use, sociodemographics, and MVT in neighborhoods. Exploratory testing for interaction among land use types, not found in previous neighborhood-level studies, was unsuccessful with no group models (per LR tests) proving significantly better predictors of MVT than the combined model without the interaction terms. This may indicate a lack of land use interactions but is also likely due to the utilized data and methodology. Many of the interaction terms tested contained too many cases of zero value, due to a lack of presence of either variable in a high number of block groups. Therefore, the analysis was not robust enough to uncover interactions, if present. Applying the present methodology to larger units of analysis, such as census tracts, might provide the robustness needed to answer the question concerning interactions between land uses. Findings concerning interaction between land use and demographics, however, were very fruitful and helpful in advancing crime theory. Although it was shown that land use has a direct impact on MVT, neighborhood sociodemographic structure can moderate the level of this impact.

The interaction analyses showed that increased levels of SES and the percentage of 15-24 year olds in neighborhoods reduced the impact of criminogenic land uses, and higher levels of racial heterogeneity and single-parents further exasperated the already present crime-producing impacts of the land uses. These findings are generalized from the results of the group analyses, as well as the six significant individual interaction terms. In the final model that included all six interactions, only two remained significant net the effect of all other variables. These remaining two were both SES component terms, supporting prior ecological studies on the importance of neighborhood SES levels.

The analyses have shown that land use, both independently and through the characteristics of the people living in the surrounding neighborhood, can promote or deter MVT levels. Based upon these findings and those of the few neighborhood studies available, a strong MVT opportunity-land use relationship exists as posited by the opportunity theories of rational choice, routine activities, and crime pattern theory.

This study suggests that a truly comprehensive crime theory must recognize that the built environment may be as important a predictor of crime as the characteristics of the people living in the area. Neither offers a sufficient explanation of ecological crime levels without the other. Criminologists and criminological theory has long dwelled on the characteristics of people to explain crime. To move forward, these two areas must be better integrated into one comprehensive model.

Implications for Policy

The results of the present research have important implications for crime prevention policy as applied to both communities and individual places. First, a stated goal of urban planning and land use regulation by government entities is to promote the health, safety, and general welfare of the public (Cullingworth & Caves, 2003). Through land use zoning power, business license regulation, and city ordinances, local governments have the legal authority to control both the placement and utilization of land use in ways that can reduce the impact of crime and disorder. Courts only require that local governments prove a reasonable link between regulatory action, nuisance land use, and the undesirable “secondary effects” of crime and disorder (Nolan & Salkin, 2006). Study findings, such as the present one, make the showing of these links possible. Equipped with this information, city officials would be in a position to improve overall community safety by requiring “secondary effect studies” for all new development of land use categories identified as particularly criminogenic. These studies are now frequently completed on adult entertainment businesses (Nolan & Salkin, 2006). Such reviews could include information concerning potential crime and disorder impacts both on and off the property, and based upon the use, design, and location of the proposed development. Mitigating procedures can then be required and include such things as denying or relocating the project, applying specific crime prevention and place management techniques, or the collection of extra fees for supplemental policing and other public safety expenditures, such as improved street lightening. This type of review would require the input of external or local police crime prevention experts, a facet of government review that it is currently completed for all new developments in reference to traffic and environmental impacts (Cullingworth & Caves, 2003; Nolan & Salkin, 2006).

Related to land use regulation are the issues of social justice and geographic inequality. In communities across the country, city leaders, public health specialists, and grass-root community groups are already voicing concerns about crime and health issues related to high concentrations of alcohol outlets found in poor, minority neighborhoods (Alaniz, Cartmill, & Parker, 1998; LaVeist & Wallace, 2000; Roman, Reid, Bhati, & Tereshchenko, 2008). Some argue that race and income discrimination are ultimately responsible for the concentration of alcohol outlets and other *locally undesired land uses* (LULUs) in these neighborhoods, while others state an economic element alone is responsible (Nolan & Salkin, 2006; Pacione, 2005). Either way, neighborhoods that are least likely to be able to handle the negative side effects are frequently the home to problem land uses. In the present study, vehicle theft counts are found to be especially high in neighborhoods that contain bars and commercial parking lots, and both of these land uses are found at higher levels in racially mixed neighborhoods. Interaction analyses also shows that the crime-producing impact of some land uses are intensified by increased levels of racial heterogeneity and single-parent families frequently found in high crime neighborhoods. These findings suggest questions concerning social justice, geographic inequality, and crime and community safety. Are land use location decisions by developers and city leaders partially responsible for the high crime rates found in low income, minority neighborhoods? Do these officials have the moral responsibility to avoid further jeopardizing the safety of people that don't have the resources to protect themselves? If land use is partially responsible for the high crime in these areas, can better land use regulation improve safety while reducing the reliance on heavy policing in these areas that results in disproportionally high arrest rates for minority Americans?

The present study also has implications for crime prevention policy as applied to criminogenic land uses by owners (private and governmental), developers, police and security, and concerned community members. Much of the prior MVT research examined characteristics of high-theft places to better inform applications of situational crime prevention (Clarke, 1997). These crime prevention responses are intended to reduce crime opportunities at locations, resulting in fewer vehicle thefts. Frequently missing from these studies, however, is adequate consideration given to the fact that characteristics of the surrounding neighborhood also can impact crime levels at these places. For example, the present study has shown that lower SES levels, and higher levels of racial heterogeneity and single-parent families, can amplify the criminogenic impact of certain land uses on MVT. These findings suggest that the level of crime prevention applied at locations can be increased or decreased based upon the surrounding neighborhood socio-economic characteristics. Thus, crime prevention policy at places should be more global in its interpretation of risk, considering both situational factors (on the property) and those found in the immediate neighborhood. Crime prevention through environmental design (Cozens, 2008; Crowe, 2000), a popular on-site focused crime prevention program used by architects, developers, and required by some local governments in the U.S., is likely to be more effective with a more holistic view.

Lessons learned from this study and others that identify specific criminogenic land uses are especially useful to police departments. Modern policing techniques include problem-oriented policing which emphasizes the identification of hot spots of crime, attempts to understand the underlying issues, and responds with focused crime reduction efforts in order to reduce overall neighborhood crime levels (Clarke & Eck, 2003). Although police officers and crime analysts may easily identify hot spots through repeated response and crime mapping, understanding their context and causal factors is more difficult, frequently resulting in unsuccessful responses (Clarke & Eck, 2003). Possessing a working knowledge of the three crime opportunity theories, as well as a glossary of crime-producing land uses developed through empirical studies like the present one, may help to improve police department problem solving and hot spot policing.

Implication for Future Research

Results of the current study suggest a standardized methodology is necessary to more fully understand crime in neighborhoods; statistical models must include both land use and sociodemographics, and controls for spatial autocorrelation when necessary. Recall that the influence of bars on MVT was not identified until sociodemographic factors were controlled for in the combined model, and the influence of racial heterogeneity on MVT was not observed until after land use was controlled. The spatial lag control variable also was strong and statistically significant in every model. The combined model was rerun minus the spatial lag (Appendix A) resulting in a loss of statistical significance for commercial lots, highly inflated effect sizes for most land use and sociodemographic variables, and a BIC score increase of 427.59 points, indicating far less model fit.

The present study also promotes the use of appropriate statistical analysis method in ecological research. Here, negative binomial models were the preferred method because the dependent variables are positive integers, highly skewed, and show evidence of overdispersion, a condition typical of ecological crime data. Some researchers still use OLS regression for these analyses which has been shown to result in inefficient, inconsistent, and biased estimates, making their findings suspect (Long & Freese, 2006).

Lastly, much more research is needed to identify specific types of criminogenic land uses. The methodology used in this analysis can be easily applied to other crime and land use types. Hot spot studies and survey data can be used, as in this study, to suggest the types of land use that should be examined. An eventual goal of this line of research would be the development of an encyclopedia of crime-producing land use and facility types that can be shared with crime prevention specialists and city planners. Such research may also further support present criminological theory, or even uncover presently unknown relationships that may suggest new theories.

Limitations

As with all research, the present study has a number of limitations. The first is in its cross-sectional design, thus causality cannot be confirmed. It is reasonable to assume that some land uses produce MVT due to the opportunities they provide, but it is also possible, even likely considering economic and social considerations, that the presence of some crime-producing land uses are only tolerated in neighborhoods that already experience high MVT levels. The inclusion of the sociodemographic variables in the models helps control for high levels of social disorganization that are frequently found in high crime neighborhoods and are related to a lack of organization and political power to fight the location of nuisance land uses (Sampson & Groves, 1989), but it will take longitudinal studies to firmly establish directions of causality between land use and crime.

A second potential limitation concerns the use of total land area as a proxy for the amount of opportunity utilized for each land use category in block groups. Some locations may be under or over utilized for their size while others may be multi-level buildings that include more actual area than their parcel "foot print" suggests. Both these limitations are important ones. Still, this method includes consideration for variance in size offering a quantification of the relative *potential* for MVT opportunity missing from prior studies that quantify land use by mere counts or dichotomous dummy variables (e.g., present-not present).

A third limitation is that this is a case study of one city, albeit a large one with neighborhoods of varying land uses, sociodemographics, and population density. It could be that the results are specific only to large, post-industrial cities and not to suburban areas with distinctly separated land uses. External validity is not a limitation per se, but is an empirical question answered only by future research (Taylor, 1994).

A fourth limitation concerns the operational definitions of some land use types utilized in the study resulting in some places being excluded. Due to a lack of detailed definitions in the available criminological literature, and because the intent was to include only readily recognized and understood land uses, some coding decisions were made somewhat arbitrarily. For example, only traditional campus high schools and colleges were included in the analysis, while less traditional, non-campus high schools and colleges were excluded. It is unknown how these exclusions may have altered the findings.

A final limitation concerns excluded physical attributes of neighborhoods that were not available for this study, but may be related to MVT. These physical attributes may include such features as level of street lighting, openness of sight lines related to building placement, and the presence of highly-trafficked intersections and sidewalks, that theories suggest may also be related to crime opportunity. Roman et al. (2008) state that including such measures in land use studies "will enable a more nuanced understanding of how crime opportunity is created by different land use characteristics in conjunction with neighborhood factors such as disadvantage, poverty, or racial heterogeneity" (p. 103).

The study has several strengths which should allay some of the concerns about limitations. First, the methodology utilized includes both sociodemographic factors and a spatial lag variable which allows the impact of land uses to be evaluated, net the impact of these confounding variables. Second, negative binomial regression models were appropriately used to model MVT count data. Third, the choice of evaluated land uses was based on a comprehensive review of the MVT literature including theory, offender/victim surveys, and hot spot research. This review prompted the examination, and consequential identification of new land use types found to be significant predictors of MVT (commercial lots, colleges, and single family homes) not tested in prior neighborhood levels studies. Fourth, much of the prior research on land use and crime improperly assumes the impact of criminogenic land uses end at the offending land use's property line. By setting the unit of analysis as the neighborhood, and developing the predictor variable of proximity space, the present study was able to demonstrate that neighborhoods, not just individual places, suffer increased MVT levels due to the presence of certain criminogenic land uses.

It should also be remembered that the present study examined only one category of crime (MVT). It is an unanswered empirical question as to whether or not the identified relationships between the selected land uses and MVT will hold across other closely related crimes such as thefts from vehicles, or unrelated crimes such as assaults and robberies. This study argues that the present relationships exist because of high levels of particular types of crime opportunity for MVT that the selected land uses provide. Shopping centers and commercial parking lots provide large selections of vehicles in low security environments which this study shows are related to higher MVT levels in neighborhoods. However, the limited studies available also suggest these opportunities are important to thefts from vehicles (Clarke, 2002; Clarke & Goldstein, 2003), with high or 'good' selection relating to vehicles with valuables (cell phones, CD radios, expensive chrome wheels, etc.) in plain view and accessible. Shopping centers and commercial lots are also likely related to other non-vehicle related crimes and thefts (e.g., shoplifting and robbery) because of these same factors; high numbers of suitable targets in low security environments. The presence of bars in this study was shown to elevate MVT levels as opportunity theory would suggest due to vehicles being left parked in low security environments during late nighttime hours at locations these locations that attract motivated offenders. Studies have also shown bars to be related to higher levels of both violent and other property crimes in neighborhoods due in part to similar opportunity variables, along with the impact of alcoholic beverages consumed on premise (Roman et al., 2008; Roncek & Maier, 1991). The important question for both theory and policy is which land uses are related to specific crime types, and which land uses may be criminogenic across different types of crime categories. These questions can only be answered by further land use studies which, like the present analysis, are based on opportunity theory and use analytical techniques appropriate to the data.

Conclusion

The current research posed the following question: After controlling for socio-structural correlates, is the presence of certain land uses predictive of MVT levels found at the neighborhood level? The primary findings were that shopping centers, bars, colleges, commercial parking lots, and single family homes had significant influence on the number of vehicle thefts, both independent of, and in concert, with neighborhood social structure. Contrary to the hypotheses, youth hangouts and high schools were found to have no impact while colleges had negative effects on neighborhood MVT levels. These findings support the importance of understanding crime in neighborhoods as a product of land use, and the people that live there. They also have important implications for theory, public policy, and crime prevention efforts.

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APPENDIX A

Combined Model Minus Spatial Lag Variable Predicting MVT Count

Variables	**IRR**	**SE**	***Z***	***P*** **<**	**Change in Count Per One SD Increase**
Opportunity Variables					
Shopping centers(ln)	1.06	.022	2.86	.01	1.0%
Bars(ln)	1.22	.060	4.04	.001	1.1%
High schools(ln)	1.01	.029	0.35	*ns*	1.0%
Colleges(ln)	.81	.020	-8.22	.001	-10.8%
Commercial lots(ln)	1.00	.040	0.02	*ns*	1.0%
Youth hangouts(ln)	.97	.018	-1.40	*ns*	-2.0%
Single family homes(ln)	.70	.022	-11.19	.001	-17.5%
Proximity space	1.00	.001	3.91	.001	6.7%
Demographic Variables					
SES index	0.94	.006	-8.16	.001	-13.8%
Racial heterogeneity	1.76	.104	9.53	.001	13.4%
Residents < 5 years	1.00	.001	-0.88	*ns*	-1.3%
Single-parent families	1.00	.001	3.49	.001	5.7%
15-24 yr olds(ln)	1.03	.026	1.02	*ns*	1.5%
Control Variables					
Area(ln)	1.31	.025	13.98	.001	24.7%
Population	1.00	.000	13.66	.001	20.5%
Model Fit Statistics					
Log likelihood				-6277.76	
Model fit chi-square				835.73***	
BIC				-944.89	
LR test nested model				n/a	

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