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ABSTRACT

Opportunity theories of crime emphasize the importance of crime specificity, the tendency for crime to spatially cluster, and the influence that certain types of places have on the micro-level spatial distribution of crime events. Research using this theoretical framework overwhelmingly supports these assertions. However, much of this research falls short due in part to the choice of dependent variable. For instance, some research ignores the importance of crime specificity by using crime indices, which fail to account for the intricacies of criminal opportunity among crime types. Research focusing on individual crime types, such as robbery, also fail to account for within-crime type heterogeneity. Some newer research accounts for this by using disaggregated crime types, such as street, commercial, or residential robberies. That being said, how researchers define their dependent variable may influence their results and conclusions about the link between crime and place. The current study examines how sensitive spatial patterns of robberies are to different operationalizations of robbery.

This study used Cincinnati Police Department robbery data from 2014 through 2016 (N = 4,066) which were then coded by Haberman et al. (forthcoming) to account for differences in victim-offender interaction and spatial environment. Using three different operationalizations of robbery, the following research questions were answered: (1) How, if at all, do different types of robbery spatially cluster? (2) Is the spatial clustering of robbery sensitive to its operationalization? (3) Is the relationship between potentially criminogenic places and robbery sensitive to its operationalization?

The results suggest (1) all measures cluster spatially at small units of analysis; (2) while located in spatially proximate areas, differences were seen among the robbery measures and their clusters in terms of their makeup, where they were located, and how many clusters were formed; and (3) all measures were predicted by similar types of potentially criminogenic places. These results have implications for both theory and practice. Theoretically, the results conformed to expectations based on the law of crime concentration (Weisburd, 2015) as well as research linking facilities and crime (e.g. Bernasco & Block, 2011). Generally speaking, operationalization did not influence either of these findings. However, an examination of robbery measure-specific hot spots and spatial clusters suggest practical implications. Differences in these measures, coupled with the importance of crime specificity in environmental criminology (which is the framework of much crime and place research as well as prevention measures) imply that future research, when possible, should use dependent variables that are narrowly defined to support this framework.

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CHAPTER 1: INTRODUCTION

Environmental criminology states that the spatio-temporal distribution of crime events is a function of the interactions among potential offenders, potential victims, and the physical environment (e.g. Cohen & Felson, 1979; Brantingham & Brantingham, 1993; 1995). This is especially so for what Cohen and Felson (1979, p. 589) labeled "direct-contact predatory violations. These interactions tend to concentrate in space, particularly at the micro-level (Sherman, Gartin, & Buerger, 1989). Places play an important role in shaping this distribution. Certain types of businesses and non-residential land uses tend to attract a disproportionate amount of crime. Commonly studied examples include bars, parks, bus stops, and illicit markets to name a few (see Bernasco & Block, 2011; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015).

Inherent in theories that make up environmental criminology is that the opportunity structure (Eck & Madensen, 2009) for crime varies greatly by crime type. That is, the decisions made before, during, and after crime commission differ based on what crime is being committed (Clarke & Cornish, 1985). For example, Wright and Decker's (1994; 1997) interviews of active residential burglars and street robbers illustrated that different decisions are made regarding, among other things, area selection, target selection, and escape.

While crime specificity is generally regarded as a key requirement of understanding crime patterns and developing prevention strategies, differences within crime types may be just as important. In other words, not all robberies, burglaries, or homicides are the same. Evidence suggesting within-crime type variation is not a novel concept. Wolfgang (1958) and Normandeau (1968) highlighted differences in offender, victim, and event characteristics for Philadelphia homicides and robberies, respectively. Haberman et al. (forthcoming) have extended this line in inquiry to examine variation within robberies, specifically among different robbery environments and offender-victim interactions.

While Haberman et al. (forthcoming) and other scholars have identified important trends within robbery incidents, much of the crime and place research has ignored this and other important variation in their dependent variable. Commonly used dependent variables include multi-crime indices (e.g. Part I violent crime), aggregated crime types (e.g. total robberies), or poorly identified disaggregated crime types (e.g. public location robberies). The current study uses Haberman et al.'s (forthcoming) robbery typology and Cincinnati, Ohio robbery data to explore the sensitivity of robbery operationalization when analyzing their spatial patterns. Specifically, three robbery dependent variables (total robberies, police-designated street robberies, and qualitatively coded opportunistic robberies) were examined to answer the following research questions. First, do the different types of robbery concentrate in space? Second, is this spatial clustering sensitive to how robbery is operationalized? Third, is the relationship among potentially criminogenic places and robbery sensitive to how robberies are operationalized?

The remainder of this dissertation is broken down into chapters as follows. Chapter Two discusses the literature on criminal opportunity, crime concentration, the impact of facilities on the spatial distribution of crime, and robbery disaggregation. Chapter Three reviews the methods of the study, including a review of the research questions, study site, data, and analysis plan. Chapter Four provides results from said analyses, detailing how robbery operationalization influences crime and place research. Finally, Chapter Five discusses these findings and their implications as well as the limitations of the study.

CHAPTER 2: THEORY AND LITERATURE REVIEW

The spatial patterning and linkage between robbery incidents and different types of facilities is based on a number of theoretical foundations and subsequent research exploring those foundations. This chapter is broken down into three parts. First, criminal opportunity and the theories that encompass it are outlined. Second, research on crime concentration and the influence of facilities and land use is discussed. Third, the heterogeneity of robbery incidents and robbery typologies found in the literature are considered, including a discussion of the Haberman et al. (forthcoming) typology and its use in the current study.

Criminal Opportunity

Two theoretical foundations underlie much of the research in the field of crime opportunity: (1) offenders are rational and (2) crime is not randomly distributed. These axioms are inherent in what researchers have termed "opportunity theories" or "environmental criminology". These theories emphasize the notion that even the most motivated would-be criminals cannot offend without the opportunity to do so. Rather than focusing solely on offenders or victims, researchers instead examine the circumstances that lead to the formation of opportunities for crime. Overall, crime and place research has shown crime is geographically concentrated and specific types of places can explain spatial crime patterns.

<u>Routine Activity Theory</u>

Cohen and Felson (1979) developed their routine activity theory (RAT) as a way to explain why crime rates were increasing despite improvement in socio-economic conditions. Drawing from Hawley's (1950) work on rhythm, tempo, and timing, Cohen and Felson attempted to explain crime events, specifically direct-contact predatory violations, as a function of the daily, patterned activities of both offenders and non-offenders alike. Routine activities were defined as “any recurrent and prevalent activities which provide for basic population and individual needs” (Cohen & Felson, 1979, pg. 593). Included in common routine activities are work, school, dining, and leisurely activities.

What made Cohen and Felson’s work different was that they had very little to say about offender motivation, the crux of sociological and criminological theories. Rather, they were interested in crime opportunities. As illustrated in Figure 2.1, crime opportunities require (1) a motivated offender to converge in space and time with (2) a suitable target (3) lacking capable guardianship (Cohen & Felson, 1979, pp. 589). The confluence of these three elements is all that is needed for a crime event to occur. Conversely, the lack of any one of these elements is enough for the prevention of a crime event. For example, a motivated offender, even in the absence of a capable guardian, cannot commit a crime if there is not a suitable target present.

Figure 2.1: Routine Activity Theory

Since the development of RAT, other researchers have elaborated and built upon its core principles. Sherman et al. (1989) suggested that place played a vital role in the routine activities of people, similar to the integral roles that motivated offenders and suitable targets played. Additional developments of the theory by Felson (1986) and Eck (1994) led to each essential aspect of a crime event (offenders, targets, and places) having their own controller: (1) guardians, those of supervise suitable targets; (2) handlers, those who supervise motivated offenders; and (3) place managers, those who supervise places (see Felson, 1995). Eck (2003) merged these concepts into the familiar crime triangle (see Figure 2.2) as a police-training tool. While the inner triangle details the necessary elements of a crime opportunity, the outer triangle conceptualizes the varying aspect of social controllers.

Figure 2.2: Crime Triangle

Adapted from popcenter.org

Rational Choice Perspective

Opportunity theories take into account the importance of offender decision-making (Felson & Clarke, 1998). This is a stark contrast to many criminological theories which suggest that criminal involvement is primarily based some underlying factor, such as psychological and structural influences. Using a framework based on sociology, criminology, economics, and cognitive psychology, Clarke and Cornish (1985) developed a perspective on criminal decision making. Their work detailed two types of decision-making processes that offenders go through: involvement decisions and event decisions. Involvement decisions include the initial choice to commit a crime, future choices to continue committing crime, and, eventually, the choice to cease criminal activity. Event decisions differ from involvement decisions, as the offender must "ready" his or herself before they decide how to commit their crime of choice. Event decisions may include where to offend, target selection, and planning an escape route. As criminals commit more and more crimes, these choices become second nature to them, thus reducing the amount of time it takes them to make these decisions.

Borrowing again from cognitive psychology, Cornish (1994) advocated for the use of crime scripts in order to better understand the criminal decision-making process. Scripting is the process by which one can procedurally analyze the numerous processes and sequences that go into an event, whether it be a crime or any number of everyday behaviors. Script analysis "offers a useful analytic tool for looking at behavioral routines in the service of rational, purposive, goal-oriented action" (Cornish, 1994). While acknowledging that individual decisions of specific crime events may vary based on situational variables, the use of universal scripts allows for a better understanding of decision-making in general (see Ekblom, 1991 for an example of a universal script of subway mugging) and allows for further refinement of what Cornish and others called "decision-tracks" (i.e. situationally-specific circumstances).

Cornish (1994) and others argued that the importance of crime scripts lies in their ability to develop richer situational preventative actions. Situational Crime Prevention (Clarke, 1992; Cornish & Clarke, 2003) attempts to alter opportunity structures in order to thwart criminal acts. According to Cornish (1994), understanding the systematic nature of criminal decision-making could help in the creation of situationally specific prevention measures that directly alter certain processes in a crime event (or what he called crime-commission failures). Another benefit of crime scripts involves the exploration of lesser-studied crimes. For example, certain white-collar crimes have been studied using a crime script approach (Tompson & Chainey, 2011; Kennedy, Haberman, & Wilson, 2017). Finally, the creation of metascripts (i.e. those for broad crime categories, such as robbery) and more specific tracks (i.e. those for sub-types of a broad crime type, such as commercial robbery) may allow for a better understanding of how crimes of the same general type differ based on the decisions made throughout their commission (Cornish, 1994; Borrion, 2013).

Perhaps the best evidence supporting rational choice theory comes from interviews made with active offenders. In separate works, Wright and Decker (1994; 1997) interviewed active burglars and armed robbers in order to better understand the decision-making process undergone by offenders. In both works, active offenders detailed the extensive decision-making processes that went on before, during, and after the commission of a crime. For instance, many of the interviewed robbery offenders preferred to hold up drug dealers, as they often had tangible goods (e.g. money or drugs) and would not call the police. Other instances of clear decision-making processes at work included the decision to offend in the first place, the choice of robbery over other crime types, target area selection, and whether to use violence during the commission of the robbery (Wright & Decker, 1997). Like the crime script literature, Wright and Decker's (1994; 1997) interviews with active offenders illustrated the importance of understanding the different decisions that offenders can make for different crime types (i.e., robbery vs. burglary) and crime sub-types (i.e., drug-dealer robbery vs. commercial robbery), and how each decision may be effected by different contexts and circumstances.

Of primary importance to the rational choice perspective of criminal offending is the concept of crime specificity (Clarke & Cornish, 1985, pp. 165). Decisions made during the commission of different types of crime vary greatly from one another. That is, the involvement and event decisions put forth by Clarke and Cornish (1985) will not be the same for all types of crime. While some similarities may exist (e.g. the motivation of needing money), other aspects of decision-making will vary greatly based on the type of crime. While this may seem intuitive, it runs contrary to many criminological theories that attempt to explain all types of crime (e.g.

Gottfredson & Hirschi, 1990). The importance of crime specificity is of primary concern in crime prevention measures, as evident in the Situational Crime Prevention literature (Clarke, 1992). For instance, prevention measures attempting to alter burglary opportunities (e.g. alarm systems) would have little effect on the opportunity structure of armed street robbery.

The need for specificity exists even within crime types. While considered later in this chapter (see Crime Specific Outcomes section), a discussion on within-crime differences is warranted. Robbery is a broad category of crime encompassing criminal acts whereby a theft occurs during which the offender has a deadly weapon, uses force, or threatens to use force against the victim (29 O.R.C. § 2911.02). Would-be robbers could choose to offend at a local convenience store (commonly referred to as commercial robbery) or they could choose to rob bar patrons walking back to their cars at night (commonly referred to as street robbery). While both of these events are technically robberies according to basic legal definitions, the decisions that make up these crimes and the techniques needed to prevent them differ enough that require individual examination (also see Eck & Clarke, 2003).

Crime Pattern/Offender Search Theory

While routine activities theory was originally conceptualized as a way to explain criminal opportunity structures, crime pattern theory/offender search theory (CPT), as put forth by Patricia and Paul Brantingham (1981; 1984), attempts to explain spatio-temporal crime patterns. However, offender search theory draws on routine activities theory in many ways, especially regarding the importance of potential offender/victim interaction. In effect, offender search theory is a spatialized version of routine activities theory that highlights the importance of places in the spatial patterning of crime events.

As the emphasis of CPT is on the spatial patterning of criminal opportunity, Brantingham and Brantingham (1993) focus on what they call the environmental backcloth. This is described as "uncountable elements that surround and are part of an individual and that may be influenced by or influence his or her criminal behavior" (Brantingham & Brantingham, 1993, p. 6). Inherent in the environmental backcloth is the physical setting where potential offenders and victims interact with one another. Brantingham and Brantingham dubbed this the "urban mosaic", which consists of different places, land uses, street layouts, and naturally occurring geographic boundaries. Crime patterns can be understood as a function of this physical layout and how offenders and victims perceive and interact with it.

Specific elements of the physical environment that influence spatio-temporal crime patterns include nodes, pathways, and edges (Brantingham & Brantingham, 1993; 1995). Nodes are the places where everyday activities occur, including home, work, school, and entertainment sites. High activity nodes have the ability to generate crime opportunities or attract those looking for criminal opportunities. The types of crime and people involved with them vary by the type of node involved. Traveling from node to node requires the use of pathways. Pathways include street, interstate, and other transportation networks. Highly trafficked pathways not only lead to activity nodes where crime occurs, but can also be crime sites themselves. For instance, would-be robbers may target bar patrons walking from one node (the bar) to another node (their home or parking lot). Finally, the physical environment includes perceptual and physical edges where the urban mosaic changes from one kind of use to another. Edges range from extreme physical barriers such as rivers to less nuanced changes such as the border between a university and the surrounding area. Due to the makeup of edges and the potential that they lie outside of one's traditional awareness space, edges also experience higher levels of criminal opportunity (Brantingham & Brantingham, 1993; 1995).

CPT plays an important role in the understanding of crime patterns. While RAT and its extensions conceptualized the formation of crime opportunities, CPT created a theoretical framework for discussing how and why crime opportunities concentrate in space and time. The merger of RAT, CPT, and the rational choice perspective led to a large body of research detailing, among other things, how crime concentrates within different units of analysis and around specific types of places. Overall, this literature is referred to as "crime and place research".

Past Crime and Place Research

Overview

Crime and place research deals specifically with the concentration of crime at small units of analysis as well as how and why crime patterns cluster near certain types of places. The research supporting the link between crime and place is extensive, thus justifying the notion that crime and its prevention extend beyond offender-based criminological explanations.

Before examining the role of place in crime patterns, a definition of place is needed. Eck and Guerette (2012) list five characteristics of places: location, boundaries, function, control, and size. First, places must be located in physical space. Second, places must have boundaries, whether set or perceived, in order to identify events that occur inside and outside of said place. Third, places must have a certain utility. For instance, the function of a bar is to serve alcohol to patrons. Fourth, a person, persons, or other entities must manage a place. Fifth, places must be relatively small in nature, which effectively means places should be traversable over a short period of time and distance. Although these are not hard and fast rules, they are generally the needed criteria in order to discuss places and crime. Importantly, while no specific unit of analysis has been chosen by crime and place researchers as the "best" or "correct" unit, commonly used places include addresses (e.g. Sherman et al., 1989), street segments or street blocks (Taylor, 1997), street corners (Taniguchi, Ratcliffe, & Taylor, 2011), and census blocks (Bernasco & Block, 2011).

Eck and Guerette (2012) further discuss why it is important to study crime at places. One of their main points harkens back to one of the two premises that underpin the study of crime events, that crime is concentrated in space and time. This concept holds for crime and place – very few places contain a very large proportion of all crime events (Weisburd, 2015). The following section details two areas of focus within the criminology of place: crime hot spots and the influence of the characteristics of places on crime patterns. While discussed separately, it is important to understand that through the development and discovery of crime hot spots, researchers began to realize the importance of specific places on the spatial patterning of crime events. Thus, these two bodies of literature are intrinsically linked.

Crime Hot Spots

As previously stated, one of the core concepts in the realm of criminal opportunity is the non-random distribution of crime across space and time. This phenomenon is critical to the understanding of criminal opportunity, as it emphasizes the concept that there is something about certain countries, states, neighborhoods, streets, or places that make them more crime prone than others.

Many researchers have noted French scholars were among the first to show the crime concentration phenomenon were in the 1820s (e.g. Cohen & Felson, 1979; Brantingham & Brantingham, 1981; Weisburd, Groff, & Yang, 2012). These scholars examined the variation of crime across large regions in France, noticing that certain regions experienced more crime than other regions (see Guerry, 1833; Quetelet, 1831; 1842). Similarly, researchers at the University of Chicago noticed a concentration of crime and delinquents in certain communities within the city of Chicago (Shaw & McKay, 1942). Following in the Chicago School tradition, scholars in the late 1900s reemphasized the role that communities played on crime. These researchers attempted to explain community-level variation in crime and disorder by examining the structural and societal deficits faced by many crime-prone neighborhoods (e.g. Reiss, 1986; Bursik & Grasmick, 1993; Sampson, Raudenbush, & Earls, 1997).

These approaches to studying crime concentration occurred at the macro-level. That is, these researchers examined crime clusters at larger units of analysis, ranging from countries to communities. However, opportunity theorists began to move down the cone of resolution in their study of crime and place towards smaller units of analyses (Brantingham, Dyerson, & Brantingham, 1976). Among the first to capture micro-level crime concentration patterns were Sherman et al. (1989) in their work on police calls for service in Minneapolis, Minnesota. Premising their study on routine activities theory, Sherman et al. (1989) measured the number of police calls for service at each of the over 115,000 addresses and intersections in Minneapolis over a calendar year. Over half (50.4%) of all calls for service were dispatched to only 3.3% of potential places in the city, supporting the concept of crime concentration.

Weisburd and colleagues (2004; 2012) extended crime concentration research by examining the stability of crime concentration over time. Using group-based trajectories, Weisburd et al. (2004; 2012) grouped street blocks into categories based on their year-to-year trends. Their initial analysis indicated that for each of the 14 years in the study period, around 50% of all reported crime incidents occurred at 4-5% of all street blocks. While some street blocks saw an increase or decrease in reported crime incidents over time, the overwhelming majority of street blocks remained stable over time, thus providing further support for the concentration of crime at place over both space and time (Weisburd et al., 2012). Similar findings of stability using different methods and a more crime-specific focus further support this notion (e.g., see. Braga et al.,2010; 2011).

Subsequent work on the stability of crime at place came to similar conclusions. Groff, Weisburd, and Yang (2010) and Weisburd et al. (2012) tested whether high-crime street blocks tended to cluster near other high-crime street blocks. If so, the researchers explained, then there would be little need to study crime at *micro*-places, as the concentration of crime would be better explained at larger units of analyses, such as neighborhoods or communities. While they found some evidence of high-crime street block clustering, the researchers also discovered that low-crime street blocks surrounded many high-crime street blocks. In sum, this area of research emphasizes the importance of studying crime at small units of analysis, and more specifically at places.

An important emerging research question regarding crime concentrations is whether or not researchers should examine crime-general or crime-specific spatial crime patterns (Weisburd et al., 1993; Andresen & Linning, 2012). Crime-general studies attempt to explain the spatial patterning of aggregated crime types, including all crime types or violent/property crime indices. Crime-specific studies examine incidents within crime types, such as all robberies, or even within disaggregated crime types, such as all street robberies. For example, newer research on crime concentration has examined crime-specific hot spots and the extent to which they overlap with one another. This is an important research question because theories differ on whether or not spatial patterns of different crime types should overlap, thus empirically addressing that research question has import for testing criminological theory as well as crime prevention policy (see Haberman, 2017). Citing previous research that was limited in its ability to answer the question of overlapping hot spots (see Weisburd et al., 1993; Weisburd & Mazzerolle, 2000; Lum, 2008; and Andresen and colleagues 2009; 2011; 2012), Haberman (2017) used multiple hot spot identification techniques to examine how hot spots of 11 crime types overlapped. While some crime-specific hot spots overlapped, not all did. His results emphasize the need to move beyond homogenous crime hot spots and instead focus on how specific types of crime concentrate.

That being said, it may also be important to examine whether or not crime concentrates within specific crime types. That is, do sub-types of crimes spatially cluster together, or are there distinct patterns? Haberman et al. (forthcoming) examine this issue as it pertains to disaggregated robberies in Cincinnati. Their work seeks to explore the spatial distribution of robbery incidents that have been categorized using a typology based on event characteristics. This work and typology is further discussed later on in this chapter.

Facilities and Crime

Nonetheless, another focus of crime and place research is the impact that certain types of places have on the spatial patterning of crime incidents. While Brantingham and Brantingham (1993; 1995) called these places activity nodes, the current study uses the term facilities as suggested by Eck and colleagues (Eck & Weisburd, 1995; Eck, Clarke, & Guerette, 2007; Eck and Guerette, 2012). Facilities are homogeneous sets of places that have a single function. Examples of facilities include bars, high schools, and convenience stores. While the distinction in many types of facilities depends on the level of precision, most places fit neatly into a certain type of facility.

The following section highlights a number of facility types and their link to spatial crime trends. While not every potential facility type has been studied, they all operate similarly when viewed through the lens of opportunity theory. That is, these places bring people together, creating the potential for criminal opportunity. This review breaks down facility types into sections. It should be noted that while some studies discussed below examine only one type of facility (e.g. bars), others take into account the heterogeneity of the urban mosaic and include multiple types of facilities (e.g., bars while controlling for subways, schools, etc.).

Bars

Bars are one of the most studied facility types in crime and place research. Bars are a unique potentially criminogenic place for two reasons. First, their usage primarily occurs at night and early morning hours (Haberman & Ratcliffe, 2015), whereas usage at most other facilities transpires during the day or evening. Second, inebriated clientele make for attractive targets to potential offenders (see Mustaine & Tewksbury, 1998). Therefore, bars have long been hypothesized to link to spatial crime patterns.

Roncek and colleagues were among the first to study liquor selling establishments and crime. Roncek and Bell (1981) found that Cleveland, Ohio census blocks with bars had more crime (defined as all index crimes or only violent index crimes) than those without. Each additional bar on a city block increased the number of index crimes per year by four and violent index crimes per year by 1.2. These effects remained even when controlling for neighborhood sociodemographic characteristics, indicating that the bars themselves, not the areas where they were located, influenced the level of crime. Additional research replicated and expanded the original Cleveland study with similar results in San Diego (Roncek & Pravatiner, 1989) and a larger study period with more controls in Cleveland (Roncek & Maier, 1991).

Bars have remained a focus in recent research. Bernasco and colleagues (2011; 2013; 2017) have consistently found a significant positive relationship between the presence of bars and street robbery counts or site selections in Chicago, IL census blocks. Alternatively, Haberman and Ratcliffe (2015) found no relationship between bars and street robberies in Philadelphia, PA census blocks; however, they did find evidence that bars in census blocks spatially adjacent to a census block linked to higher street robbery counts during daytime and nighttime hours.

Additional studies have examined the spatial extent of bars' impact on crime. Groff (2011) discovered that total crime counts are higher within 800 feet and 1,200 feet of a bar (depending on the distance measure used). Groff (2014) explored how distance from bars influences violent crime on street blocks. Using two measures of distance, she found that bars influence the level of violent crime up to 2,000 feet (Euclidean distance) and 2,800 feet (inverse weighted distance). Ratcliffe (2011; 2012) found that violent crime concentrated within 325 feet of Camden, NJ bars and with 85 feet of Philadelphia, PA bars. Kumar and Waylor (2003) saw similar results when testing the relationship between the distance from bars and densities of a number of crime categories, including assaults, property crimes, and vehicle-based crimes.

Finally, "risk maps" created using risk terrain modeling (RTM), which uses potentially criminogenic places and other factors that influence crime as risk factors, have suggested that bars influence robbery (Barnum et al., 2017b) and aggravated assault (Kennedy et al., 2016), but not drug sale arrests (Barnum et al., 2017a).

Alcohol Outlets

Similar to the literature on the bars-crime link, others have looked more broadly at how alcohol-selling places influence crime. This line of research often uses the term "alcohol outlets" to describe a number of facilities, including bars, restaurants, and taverns (commonly referred to as on-premise alcohol outlets) as well as liquor stores and convenience stores (commonly referred to as off-premise alcohol outlets). While some researchers test on- and off-premise separately (e.g. Scribner, MacKinnon, & Dwyer, 1995), others combine to create a total alcohol outlet measure (e.g. Speer et al., 1998).

In sum, the research linking alcohol outlets and crime mirrors that of bars. Even at different units of analysis and for different types of crime, alcohol outlets tend to have a positive influence on spatial crime patterns (e.g. Speer et al., 1998; Gyimah-Brempong, 2001; Grubesic & Pridemore, 2011; Snowden & Pridemore, 2014). That being said, much of this research focuses on units of analysis larger than the preferred micro-units of crime and place literature. Scribner et al. (1995) found a relationship between on-premise, off-premise, and total outlet density on Part I violent crimes in Los Angeles County municipalities; however, Gorman et al. (1998) could not replicate these findings in New Jersey municipalities. Other large-area research has focused on the density of alcohol outlets at the census tract level. Gyimah-Brempong (2001) found a significant positive relationship between alcohol outlet density (combined on- and off-premise) and four crime categories: Part I total, Part I violent, Part I property, and homicide. A later study from Gyimah-Brempong and Racine (2006) indicated that the linear models used in Gyimah-Brempong (2001) downplayed the impact that density has on crime, thus furthering the link between outlets and serious crime. Nielsen and Martinez (2003) came to similar conclusions regarding the alcohol outlet density-crime link when looking at aggravated assaults, robberies, and a combined rate in Miami, FL. When looking at ethnicity-specific rates, however, they found that alcohol outlet density was related to Latino violence only (Nielsen, Martinez Jr., & Lee, 2005).

There is additional evidence linking alcohol outlets and crime at the micro-level (e.g. see Bernasco & Block, 2011; Bernasco et al., 2013; Barnum et al., 2017a; Kennedy et al., 2016; Barnum et al., 2017b; Bernasco et al., 2017 which were previously reviewed). Additionally, at the census block level, Costanza, Bankston, and Shihadeh (2001) found a link between package-only outlets and both robbers and assaults while Grubesic and Pridemore (2011) found evidence of a link between total alcohol outlet density and assaults. Finally, Xu and Griffiths (2016) and Day et al. (2012) found that distance from outlets had a significant effect on gun violence and serious violent crime, respectively. However, Haberman and Ratcliffe (2015) found no link between alcohol stores and street robberies, citing that alcohol stores in Philadelphia are much different from other cities due to local laws.

Cash Businesses

A number of other economically-driven facilities have been linked (or potentially linked) to increased criminal opportunity. Convenience/corner stores, gas stations, restaurants, retail stores, barbershops, and laundromats are types of facilities where customers go to purchase items or services. These types of places can increase crime opportunities as they generate more human activity amongst persons carrying cash (and other goods). Previous ethnographic studies have suggested that would-be offenders tend to look for targets that may be carrying cash (St. Jean, 2007; Wright & Decker, 1997).

First, it is important to note that research linking alcohol outlet density to crime often includes convenience stores, corner stores, gas stations, and restaurants as many of them have a license to sell alcohol (e.g. Grubesic & Pridemore, 2011; Snowden & Pridemore, 2014). Additional research has linked different types of business to crime. In an early test of the spatial influence of places on crime, Brantingham and Brantingham (1981) found higher rates of burglary in residential blocks with fast food and regular restaurants. LaGrange (1999) found higher levels of property damage in enumeration areas (the Canadian equivalent of census block groups) that contained shopping malls. Street robberies in Chicago census blocks were influenced by a number of cash-oriented businesses, including restaurants, barbershops and salons, grocery stores, general merchandise stores, gas stations, and laundromats (Bernasco & Block, 2011; Bernasco et al., 2013; 2017). Similarly, Philadelphia census blocks with corner stores and fast food restaurants experienced higher levels of street robbery (Haberman & Ratcliffe, 2015). Studies using RTM have also shown links between gas stations, restaurants, grocery stores, and variety stores and drug arrests (Barnum et al., 2017a), between grocery stores and aggravated assaults (Kennedy et al., 2016), and between gas stations, grocery stores, variety stores, and laundromats and robbery incidents (Barnum et al., 2017b). Again, at least one study did not find a link between fast food stores, gas stations, or laundromats and gun violence at the facility-level; however, grocery stores were significantly related to gun violence (Xu and Griffiths, 2016).

Entertainment Places

Other activity nodes that draw potential offenders and victims together include entertainment places such as casinos, arenas, and hotels, which often serve as a "home base" for those frequenting entertainment places. Casinos are a commonly studied facility due to the negative connotations surrounding gambling and the gambling industry (Miller & Schwartz, 1998). While the theoretical connection between casinos and crime is sound (i.e. vice industry influenced by money and alcohol), little evidence exists linking the two. Most of the research examining the casino-crime link has been conducted at the macro-level, looking for patterns at the city or county level. These studies looked at specific cities, such as Atlantic City (Hakim & Buck, 1989; Buck, Hakim, & Speigel, 1991), and found that violent crime dissipated as one moved further away from the city and its casinos. Giacopassi and Stitt (1993) and Chang (1996) observed that some, but not all, crime categories increased in Biloxi, MS after the opening of its first casino. Stitt et al. (2000; 2003) also found mixed results when comparing new casino cities with comparison non-casino cities. Overall, while some studies saw higher crime post-casino implementation, others saw no change or even decreases in crime rates.

Some studies have attempted to examine the link between casinos and crime in smaller units of analysis. For example, Barthe and Stitt (2007; 2009a; 2009b) compared casino zones (casinos with a small buffer zone) and non-casino zones, and found that hot spots and temporal crime patterns were not drastically different between casino and non-casino zones. Johnson and Ratcliffe (2016) found no evidence suggesting that a new casino in Philadelphia influenced crime in or around the area. One explanation for the null relationship between casinos and crime is that casinos attract a large number of customers, thus increasing the population (and perhaps guardianship) and decreasing crime rates (e.g. Albanese, 1985).

Sports stadiums are another entertainment place studied in the crime and place literature. Stadiums, like casinos, attract a large number of people at specific times and days. Additionally, live sporting events often go hand-in-hand with drinking and other problem behaviors (Breetzke & Cohn, 2013), thus increasing the potential for deviant behaviors. Research suggests that citywide crime patterns are higher on game days when compared to non-game days (Sivarajasingam, Moore, & Shepherd, 2005; Rees & Schnepel, 2009; Kalist & Lee, 2016). Next, Kirk (2008) examined neighborhood-level crime patterns in downtown Vancouver, British Columbia, and found assaults and vehicle theft were higher during and after home NHL games. Billings and Depkin (2011) found that crime patterns around Charlotte, North Carolina's NFL stadium and NBA arena changed depending on whether or not a game took place on that day. Total crime, total violent crime, and total property crime were higher within a half-mile buffer of the stadium and arena. Additionally, they found that violent crime was higher near the stadium but not the arena, potentially due to the influence of tailgating. Breetzke and Cohn (2013) found similar results for assaults and drunk and disorderly incidents around the rugby/soccer stadium in Tshwane, South Africa. Finally, Kurland, Johnson, and Tilley (2014) found that spatial patterns of violent crime and theft around Wembley Stadium in London, England differed based on whether a there was a match or an event occurring at the stadium.

Hotels also potentially influence crime patterns as they serve as anchor points for people who may be visiting a new city and unaware of their surroundings. While few studies have controlled for their presence, those that have indicate that they may be important places in the distribution of crime. Smith, Frazee, and Davison (2000) found that the presence of a hotel or motel on a street block increased street block robbery by 9%. However, this effect was found primarily in areas with a high level of single-parent households. Drawve and Barnum (2017) linked aggravated assaults to the density of hotels and motels, suggesting that stand-alone hotels or motels have less of an influence than do hotels and motels that are spatially concentrated. Finally, de Montigny et al. (2011) found that single-room occupancy hotels were a significant predictor of discarded needles, an indication of nearby drug use. It should be noted that not all entertainment nodes have been assessed for their criminogenic impact. For instance, museums, amusement parks, and movie theaters have yet to be controlled for in the crime and place literature (to this author's knowledge), yet they may influence crime as they bring potential offenders and victims together in space.

Fringe Banking

Fringe-banking facilities have also been linked to spatial crime patterns. According to Kubrin et al. (2011), fringe-banking facilities include payday lenders, pawn shops, and check-cashing stores. These facilities are primarily found and used by those living in lower-income neighborhoods. Kubrin et al. (2011) found a significant positive relationship between payday lenders and crime, both violent and property, at the census tract level. A later study by Kubrin and Hipp (2016) expanded on the role that fringe banking plays in crime patterns. They found that certain Part I crime types, especially robbery, concentrated near fringe banks at the census-block level. However, further specification of this relationship revealed that check-cashing stores and payday lenders, but not pawn shops, were linked to higher crime. Additionally, this relationship was moderated by a number of socio-demographic variables, suggesting that fringe banks in disorganized neighborhoods generate more criminal opportunity than those located in organized neighborhoods (Kubrin & Hipp, 2016).

Additional information on fringe banks' relationship with crime can be found in studies controlling for multiple types of facilities and land use types simultaneously. Pawnshops (Bernasco & Block, 2011; Bernasco et al., 2013) and currency exchanges (Bernasco et al., 2017) were found to be significant predictors of block-level street robberies in Chicago. Both check-cashing and pawn shops were linked to block-level street robberies in Philadelphia, although not at all times of the day (Haberman & Ratcliffe, 2015). Finally, some studies have found less support for fringe banks' impact on crime. Results from a study on payday lenders and Part I crime in Norfolk, Virginia were inconsistent with those of Kubrin et al. (2011) in that property crimes were related to fringe banking in 2010 but not 2005, and violent crimes were only marginally related in 2010 (Lee, Gainey, & Triplett, 2014). Additionally, Barnum and colleagues found no evidence of a link between pawn shops and drug crime (Barnum et al., 2017a), and only found a link between pawn shops and robberies in Chicago, but not Kansas City or Newark (Barnum et al., 2017b).

Schools

While the facilities discussed above are linked to crime primarily through the human activity they generate due to their economic function, other facilities may increase crime opportunities by increasing human activity. Educational institutions are one such facility. Research has examined the link among different types of educational institutions, ranging from elementary schools to colleges and universities, and crime.

Research by Roncek and colleagues was among the first to study the spatial link between educational institutions and crime. Looking at the differences in public and private high schools in San Diego (Roncek & LoBosco, 1983) and Cleveland (Roncek & Faggiani, 1985), they found that residential blocks near public high schools experienced significantly more crimes, while blocks near private high schools failed to correlate with increased crime. In a later study, Kautt and Roncek (2007) also found public high schools link to burglary.

Other studies have included additional educational institutions, such as elementary and middle schools. LaGrange (1999) found an association between minor property damage complaints and public junior and senior high schools, but not Catholic junior and senior high schools. Willits, Broidy, and Denman found in two separate studies that the presence of a middle school or high school in a census block group was positively related to aggravated assaults (2013) and drug crimes (2015). Additionally, they found that robberies were only linked to the presence of high schools (2013) while elementary schools had no positive effect on any type of crime. Murray and Swatt (2013) found that variation in the types of schools at the block level led to variation in their relationship with crime. For instance, burglaries were lower in blocks with any public school, but this effect was due primarily to the influence of elementary schools. Unlike Roncek and colleagues, they found a positive relationship between private schools and both burglaries and motor vehicle thefts; however, only public schools were linked to nearby robberies.

Like other types of facilities, the effect of schools on crime exists even after controlling for other types of places. Chicago (Bernasco et al., 2013; 2017) and Philadelphia (Haberman & Ratcliffe, 2015) high schools were linked to variation in street robbery across census blocks net of other facility types. Groff and Lockwood (2014) linked street block disorder crimes (but not violent or property) to non-elementary schools. Other studies have found mixed support for the school-crime link. Results from studies using RTM found no link between schools and aggravated assaults (Kennedy et al., 2016), although they did find a link between schools and drug crimes (Barnum et al., 2017a) and robberies in Chicago and Newark (but not Kansas City) (Barnum et al., 2017b). Xu and Griffiths (2016) did not find any correlation between gun violence and distance to the nearest non-elementary school. Lastly, Stucky and Ottensmann (2009) found a negative correlation between schools and two crime types, homicide and rape, in Indianapolis.

Finally, researchers have examined the spatial crime patterns around colleges and universities. While campuses themselves are generally safe places (Volkwein, Szelest, & Lizotte, 1995), research has shown that campus estimates of crime may be misleading. Nobles et al. (2012) estimated that nearly half of the crimes that occurred near (within 500 feet) their campus of study were not reported by the university police department, suggesting that crimes may concentrate on the outskirts of campus where students tend to live and recreate. Other evidence supports this claim. LaRue (2013) and LaRue and Andresen (2015) found that dissemination area-level burglaries and motor vehicle theft were predicted by the presence of universities in Ottawa. Lastly, McGrath, Perumean-Chaney, and Sloan (2014) measured the amount of property crime located near different parts of a college campus, finding that crime was higher near the side of campus that housed a large medical center as opposed to the side that housed the rest of the university.

Parks

The presence of parks and other open spaces also have been linked with deviant behavior and crime. While some have suggested that parks serve as a deterrent to criminal activity (e.g. Jacobs, 1961), others have noted the potential impact they have on crime and fear of crime

(Schroeder & Anderson, 1984; Knutsson, 1997). Evidence linking parks and open spaces to crime patterns is sparse, with much parks-crime research focusing on perceptions of crime (e.g. Westover, 1985) or prevention efforts (e.g. McCormick & Holland, 2015; Payne & Reinhard, 2016).

In an early study on the potential impact of parks on crime, Crewe (2001) compared calls for service coming from houses near a five-mile liner park in Boston to calls for service coming from houses near busy streets as well as the city average. Houses nearby the park generated more calls for service than houses farther away, even when compared to houses near busy commercial streets. In a more direct test of their spatial influence, Groff and McCord (2012) and later McCord and Houser (2017) measured crime density in neighborhood parks compared to both nearby areas and randomly drawn street intersections in Philadelphia (Groff & McCord, 2012; McCord & Houser, 2017) and Louisville (McCord & Houser, 2017). Both studies came to similar conclusions regarding the parks-crime link. They found that violent crime, property crime, and disorder events clustered around parks more so than it did in the city as whole, in nearby buffer areas, and in random street intersections. Philadelphia parks were also found to be significant predictors of street robberies at the census block level when controlling for numerous other facilities (Haberman & Ratcliffe, 2015). Kimpton, Corcoran, and Wickes (2017) saw similar patterns of clustering near greenspaces (which include parks, gardens, greened thoroughfares, sporting fields, and ovals) in Brisbane, Australia.

On the other hand, Stucky and Ottensmann (2009) found that the percent of area made up of parks in 1000x1000 foot grids in Indianapolis had a significant negative relationship with both homicides and aggravated assaults. Barnum and colleagues (2017a; 2017b) also found mixed evidence supporting the link. Among patterns of marijuana, heroin, crack, and powder cocaine arrests, only heroin arrests were spatially concentrated near parks (Barnum et al., 2017a). For robbery incidents, parks were a significant predictor only in Kansas City, not in Chicago or Newark (Barnum et al., 2017b).

Public Transportation

Public transportation, which includes bus stops, subway stations, and light rail stations, present a number of challenges related to the spatio-temporal patterning of crime. Public transportation stops are a unique activity node due to the nature of the facility. While they generate relatively predictable patterns of behavior (i.e. scheduled stops and transfers) like other places, some of the opportunities generated by them are 'non-static' (Newton, 2004). That is, some crimes occur while in route from stop to stop, thus creating difficulties in studying them as potentially criminogenic facilities (see Newton, 2004). However, research examining the static nature of public transportation stops indicates they are influential in the spatial patterning of criminal opportunity. While some studies test multiple types of public transportation stops (e.g. van Wilsem, 2009), most consider only one type, be it bus stops, subway stations, or light rail stations.

Evidence supporting the link between bus stops and crime varies by study methodology. Qualitative evidence suggests that bus stops generate criminal opportunities due to situational characteristics within the environmental backcloth (Levine, Wachs, & Shirazi, 1986; Loukaitou-Sideris, 1999; Kooi, 2015). Other evidence suggests that crime near bus stops is dependent upon crime levels in nearby areas (Pearlstein & Wachs, 1982; Newton, 2008). Evidence linking bus stops and crime at micro-units of analysis are also generally supportive. Kooi (2004; 2013) found that bus stop density within census block groups was tied to the level of outdoor crimes, which included robberies, drug crimes, and disorder events. Using 500x500 foot grids in Indianapolis, Stucky and Smith (2014) found that the presence of bus stops, while positively related to all Part

I crimes except homicide and motor vehicle theft (which was not used in their analysis), was conditional upon nearby commercial, industrial, and high-residential areas. Specifically, the effect of bus stops was greater in commercial and industrial areas, but reduced in high-residential areas. Additional studies using RTM modeling discovered that narcotics, aggravated assaults, and robberies all clustered around bus stops (Barnum et al., 2017a; 2017; Kennedy et al., 2016). Finally, using conjunctive analysis of case configurations, Hart and Miethe (2014) found that bus stops were included in high-crime profiles more often than other activity nodes and that the risk for robbery within the proximate environment of bus stops (within 1000ft) depended on the presence of bus stops along with other nodes.

Like bus stops, subway and rail stations have been extensively reviewed for their ties to micro-level crime patterns. Subway stations in Philadelphia have been linked to Type I and II crimes at the street block level (Groff & Lockwood, 2014) as well as street robberies at both the station level (McCord & Ratcliffe, 2009) and census block level (Haberman & Ratcliffe, 2015). Rail stations, which are typically located above ground, also experience increased levels of crime. Chicago El stations were linked to street robberies in a number of studies (Block & Davis, 1996; Bernasco & Block, 2011; Bernasco et al., 2013; 2017). Type I crime incidents near stations on the Los Angeles Green Line were shown to be influenced by nearby levels of disadvantage (Loukaitou-Sideris, Liggett, & Iseki, 2002), even though implementation of the same line and stations did not affect neighborhood level crimes (Liggett, Loukaitou-Sideris, & Iseki, 2002). Additional research supports evidence suggesting the implementation of rail transit lines do not increase crime (e.g. Poister, 1996; Billings, Leland, & Swindell, 2011; Ridgeway & MacDonald, 2017), thus limiting the overall support linking public transportation stops and crime.

Public Housing

Evidence linking the presence of public housing communities and crime suggests at best a tenuous relationship. While some studies show that crime is higher in or near public housing communities and crime (e.g. Dunworth & Saiger, 1994), others did not (e.g. Farley, 1982). Weatherburn, Lind, and Simon (1999) were among those who found a very weak correlation between public housing communities and crime. They hypothesized that the public housing-crime relationship was due to the concentration of disadvantaged populations in these communities rather than due to the design of the communities themselves.

Still, many other studies provide evidence suggesting that crime concentrates in and around public housing communities. One way researchers have identified this link was by examining crime before and after redevelopment or demolition of public housing communities and subsequent relocation of residents. Aliprantis and Hartley (2015) and Sandler (2017) measured the impact of the demolition of Chicago public housing communities in the 1990s. Testing the relationship at the census block level, both studies uncovered significant reductions in crime post-demolition. Aliprantis and Hartley (2015) found a reduction in homicides and calls for service in blocks previously occupied by high-rise public housing communities. While they also found increases in crime in the blocks where residents were displaced, their results suggested that the benefits of demolition outweighed the costs of moving crime to a new area. Sandler (2017), looking at Part I crimes and drug arrests, found that block-level homicides, robberies, assaults, burglaries, and thefts all decreased within a quarter mile of blocks with demolished public housing communities. Similarly, Suresh and Vito (2009) found that homicide patterns in Louisville tended to follow residents as public housing was redeveloped over a 19-year period. Finally, Cahill (2011) found mixed support for violent and property crime displacement and diffusion of benefits around redeveloped public housing sites in Milwaukee and Washington D.C. While some displacement was found around redeveloped Milwaukee communities, results in Washington D.C. indicated a consistent diffusion effect.

Other studies have used more traditional methods by examining the presence of active public housing communities on aggregate geographic crime levels. Roncek, Bell, and Francik (1981) examined block-level Part I crimes in Cleveland. Their results mirrored similar studies by Roncek and colleagues in Cleveland that examined bars and schools (see above) in that they found evidence suggesting blocks near public housing had higher violent crime than blocks not adjacent to public housing. Using slightly larger block groups, McNulty and Holloway (2000) and Holloway and McNulty (2013) found varying support for certain aspects of the public housing-crime link in Atlanta. In their first study, they found evidence supporting their hypothesis that much of the race-crime link was tied to the concentration of public housing, especially for homicide, rape, assault, and public order crimes. Specifically, they suggest, like Weatherburn et al. (1999), that public housing "spatially anchor(s) poverty and other sources of social disorganization in neighborhoods" (McNulty & Holloway, 2000, p. 720). However, their other work suggests that certain types of public housing communities, specifically those with more units and high-rise communities, influenced violent crime more than others (Holloway & McNulty, 2003).

Using smaller units of analysis, researchers have confirmed a general, albeit variable, public housing link with crime. Studies using public housing communities as the unit of analysis have measured their effect on crime both within and near the sites. Fagan and Davis (2000) discovered that violent crime concentrated in buffer zones between 0 and 100 yards outside of public housing communities relative to buffer zones 100 to 200 yards out and the communities themselves. Their results suggested that crime had a diffusion effect stemming out from public housing communities. Holzman, Hyatt, and Kudrick (2005) discovered varying levels of crime by type. Specifically, their results suggested that only assaults were clustered within the communities themselves, while robbery and property crimes were higher in 300-meter buffer zones around the communities. Haberman, Groff, and Taylor (2013) found that public housing communities varied in their impact on street robberies. That being said, certain elements were tied to increased expected street robbery counts, including the clustering of public housing communities as well as highly populated communities. Finally, using an innovative technique called mobility triangles, which group incidents into a typology based in the locations of the event, victim home, and offender home, Griffiths and Tita (2009) found that homicides in public housing communities are typically committed by and on residents, suggesting that public housing communities are not a homicide generator.

Drug Treatment and Halfway Houses

Drug treatment centers and halfway houses have the potential to influence crime patterns as they concentrate known offenders or drug users in specific areas. Some municipalities cite this point (often without evidence), which limits where these facilities can be opened (Boyd et al., 2012; Furr-Holden et al., 2016). Support for this link is mixed. When examining the distribution of drug arrests, McCord and Ratcliffe (2007) and Taniguchi, Rengert, and McCord (2009) found that Philadelphia drug arrests tended to cluster around halfway houses and drug treatment facilities at multiple bands around the facilities. However, both studies failed to find evidence that drug arrests diffused from these facilities. That is, they did not come to the conclusion that halfway houses and drug treatment centers were generating drug arrests in a meaningful way. Additionally, McCord and Ratcliffe (2007) found that the presence of halfway houses and drug treatment centers constrained an area's ability to sustain a drug market, and both variables were negatively associated with the size of drug markets.

Additional studies from Philadelphia confirm this variable connection between drug treatment centers, halfway houses, and crime. Groff and Lockwood (2014) found that drug treatment centers had no influence on violent crime patterns and a varying positive impact on property and disorder crime. Halfway houses, on the other hand, only influenced violent, property, and disorder crime in buffer areas located 400 feet or beyond away from the facilities. Haberman and Ratcliffe (2015) found that drug treatment facilities in Philadelphia only influenced street robberies during daytime and evening hours, but not during morning or late night hours.

Boyd et al. (2012) and Furr-Holden et al., (2016) tested the link between drug treatment locations and crime directly. Boyd et al. (2012) measured the level of Part I crimes around methadone maintenance treatment facilities as well as three types of control areas: convenience stores, residential locations, and general hospitals. The found no evidence that Part I crimes clustered near methadone treatment facilities or hospitals, whereas clustering did exist at convenience stores during the day. Similarly, Furr-Holden et al. (2016) compared the distribution of violent crime around drug treatment centers as well as comparison facilities, including liquor stores, corner stores, and convenience stores. After matching these facilities based on neighborhood disadvantage, their results suggested that while each tended to attract violent crime, drug treatment centers did not differ greatly when compared to the other facility types. In sum, Boyd et al. (2012) and Furr-Holden et al. (2016) come to the conclusion that the negative stigma surrounding these types of facilities in unwarranted, even though they may attract some level of crime.

Gang Territory

While they do not technically fall under the term facilities, gang territories have been considered a crime attractor, as they are locations where gang members congregate and conduct illicit business. Gang-controlled territory tends to increase the level of violence in nearby areas, and researchers have attributed this to a number of factors. Gang members tend to be more violent than non-gang members (Ebensen, Huizanga, & Weiher, 1993; Huff, 2004; Thornberry et al., 1993) and expose community members to increased levels of violence (Klein & Maxson, 2006).

Beyond individual elements of the gang-crime link, certain ecological factors of gang territory create criminal opportunity. Many gangs, as a way to raise money, participate in drug markets, thus linking the violence to drug markets to violence of gang territories (Ratcliffe & Taniguchi, 2008; Taniguchi et al., 2011). Tita, Cohen, & Engberg (2005) examined ecological correlates to what they called gang "set space". These are places and areas where gang members tend to "hang out" with one another. They found that certain aspects of gang set spaces in Pittsburgh, including lack social control and concentrated disadvantage, set them apart from other areas of the city. Other research has linked the concentration of gang members to increased levels of gun violence (Huebner et al., 2014) and homicides (Robinson et al., 2009; Pyrooz, 2012). Lastly, Brantingham et al. (2012) discovered that inter-gang violence clustered along the edges of gang territories.

Summary

The previous section details a number of potentially criminogenic places reviewed in the literature. Many of these places are consistently linked to higher levels of crime, including bars, alcohol outlets, cash businesses, fringe banks, schools, parks, public transportation stops, and gang territory. Others, such as entertainment places, public housing communities, drug treatment centers, and halfway houses, have a varying effect on crime patterns. Overall, the bulk of the evidence supports environmental criminology's notion that places play a role in the generation of criminal opportunity, thus influencing the spatial patterning of crime.

Crime Specific Outcomes

Many of the studies mentioned in the previous section grouped crime into broad indices (e.g. violent or property) or simply assumed homogeneity within single crime types. As discussed above, environmental criminology assumes offender decision-making is crime specific, and different crime types, even within a single legal category may have different opportunity structures.

Research to date has shown heterogeneity exists among incidents within crime types. Perhaps the first example of this came from Wolfgang's (1958) exploration of homicides in Philadelphia, PA. His analysis of five years of homicide data, encompassing 588 victims and 621 offenders, concluded that homicides were not unidimensional. Rather, they tended to vary greatly when examining the victims, offenders, and circumstances, suggesting that certain subtypes of homicides were more common than others. Wolfgang's work led to a large field of study within homicide research that emphasized the importance of incident disaggregation and the creation of homicide typologies (Pizarro, 2008).

Soon after Wolfgang (1958) published his findings on Philadelphia homicides, Normandeau (1968; 1969) replicated his methodology in the study of Philadelphia robberies. Normandeau discovered large amounts of variation in robberies, including sociodemographic differences, level of force used, amount of bodily harm inflicted, means of attack, and spatial patterning. He went on to emphasize the importance of robbery disaggregation by suggesting that if the overall robbery count in a city remains constant, but the offenses themselves become more violent (e.g. an increase in bodily harm towards victims), then a statement that crime has stayed the same would be misleading (Normandeau, 1968: pp. 90-91). Stated differently, increases or decreases in citywide robbery counts may be due to increases or decreases in specific types of robberies rather than an overall upwards/downwards trend.

Normandeau (1969) extended his work by disaggregating Philadelphia robberies into a five-category typology developed by McClintock and Gibson (1961) in their examination of London robberies. Their typology was based primarily on event-level differences in robberies, sorting incidents into one of five groups: 1) commercial robbery; 2) "street" robbery; 3) home invasion robbery; 4) "lure" robbery among relative strangers; and 5) "lure" robbery among friends, family, or coworkers. Compared to London robbery trends, which showed an inclination towards more professional, commercial-based robberies, most Philadelphia robberies were sorted into the street robbery category. Two things can be concluded from Normandeau's (1969) results. First, robberies are not a homogenous type with variation stemming from differences in robbery context or circumstance. Relatedly, comparisons of overall robberies across different jurisdictions potentially masks the heterogeneous nature of the crime.

Further robbery research disaggregated incidents into offender-based typologies that attempted to differentiate between different types of robbery offenders. Some sort offenders into categories that exemplify the types of robberies they commit or common *modus operandi* (MO) used during the incident. Conklin (1972) based his typology on interviews with convicted robbers in Massachusetts. He focused on the motivation, techniques, and commitment to criminal lifestyle, with categories ranging from professional robbers who carefully planned lucrative incidents to addicts and alcoholics who rob only to pay for their illicit substance habit. Similarly, Alison et al. (2000) examined narrative accounts of British robbers and categorized them as either 'Robin's men' (careful planners, organized), 'Bandits' (aggressive, quick to use language and violence to control situation), or 'Cowboys' (overly aggressive, attack victims needlessly). Gagnon and LeBlanc's (1985) typology was a hybrid of MO as well as robbery event type. They categorized robbers in Montreal into one of six categories: group bank robbers, solo bank robbers, group commercial robbers, solo commercial robbers, convenience store robbers, and street robbers.

Other offender-typologies have focused more exclusively on the M.O. of robbers (Luckenbill, 1980; Smith, 2003). Luckenbill (1980) based his typology on interviews and police records. Luckenbill (1980) identified three types of force used by robbers – threats, prodding, and incapacitation – and suggested the use of each was determined by the strength of the robber's coercive resources and the meaning of the target to robber. Smith's (2003) analysis and categorization of British robbery reports used two determining factors: the amount of interaction between the victim and offender and the level of violence used during the incident. Robbery incidents that included a large amount of interaction between the victim and offender were categorized as either confrontations (those with high levels of violence) or cons (those with low levels of violence). Alternatively, incidents with low levels of interaction were categorized as either blitzes (those with high levels of violence) or snatch thefts (those with low levels of violence).

Fuller (2014) suggested offenders are only one aspect of a criminal event (see Figures 2.1 and 2.2), and argued that offender-based prevention is difficult to accomplish, especially for robbery. Conversely, victim- or place-based robbery prevention strategies tend to yield better results. She then proposed a four-category typology based on the location of robbery incidents, including private space robberies, public space robberies, robberies occurring in insecure businesses (e.g. retail or convenience stores), and robberies occurring at secure businesses (e.g.

banks, post offices). Similar disaggregation methods can be found throughout the robbery literature. For example, McCluskey (2013) examined police reports in Detroit, Michigan and compared the use of physical coercion in street versus commercial robberies, finding that robbers tend to use force more in street robberies than commercial robberies. Typologies such as this are often seen in crime and place literature, as the location/context of a robbery plays an important role in opportunity formation. For example, home invasion robberies have a different opportunity structure than street robberies or commercial robberies. Bernasco and Block (2011) and Haberman and Ratcliffe (2015) focused exclusively on street robberies in their work linking criminogenic places to robbery patterns based on the idea that street robberies were more consistent with the crime pattern theory frame used in their works. On the other hand, Bernasco and Kooistra (2010) focused on the residential history of commercial robbers to predict offense location.

More recently, Haberman and colleagues (forthcoming) have assessed the heterogeneity of robbery types in official police data from Cincinnati, OH (2014-2016) using qualitative coding of location types (i.e. street, multi-family house, gas station, etc.), victim-offender relationships, property taken, and officers' narrative reports. Haberman and colleagues' (forthcoming) multi-cycle qualitative coding process suggested robbery incidents are best represented by the nature of the offender-victim interaction with additional insight gleaned from the environment in which the incident occurs.

Haberman et al. Typology Categories

After coding incidents during multiple coding cycles, ten distinct groups of robberies were distinguished from the Haberman et al. (forthcoming) typology based on emerging themes about offender-victim interactions and event environments. These categories are listed in Figure 2.1 below. The following section will detail these categories, including example narratives from the data. While these categories are not completely exhaustive (i.e. sub-categories could be created within each type), given certain limitations in the data, they accurately differentiate robberies based on the two dimensions stated above (see Chapter Five discussion on limitations).

Commercial Robberies

Commercial robberies are defined as those robberies occurring at a commercial facility. This is a commonly occurring category in robbery typologies (e.g. Normandeau, 1968) as their distinction lies primarily in the environment where which the incident takes place. Three distinct types of commercial robberies were found in the Cincinnati data. First were bank robberies. While bank robberies themselves varied, often based on offender *modus operandi*, they generally followed the same pattern in regards to environment and interaction:

> LISTED SUSPECT PASSED A NOTE TO THE TELLER DEMANDING MONEY. TELLER GAVE THE SUSPECT AN UNKNOWN AMOUNT OF US CURRENCY. SUSPECT FLED SCENE WB ON E 4TH ST.

A second type of commercial robbery involved the robbery of a commercial business. In these cases, either the business itself or the employee was the listed victim. However, these incidents primarily consisted of offenders "sticking up" the business:

> REPORTING PERSON STATES SUSPECT CAME INTO UDF, THROW BAG ONTO THE COUNTER, PULLED OUT HANDGUN AND DEMANDED MONEY.

The third type of commercial robbery included shoplifting incidents that turned into robberies due to physical confrontation between the offender and victim, usually a store employee. Had the offender left the store without being noticed, these incidents would not fit the legal definition of robbery:

ARRESTED WAS CAUGHT STEALING ITEMS FROM LISTED LOCATION, WHILE FLEEING CAUSED SERIOUS PHYSICAL HARM TO TWO EMPLOYEES OF THE STORE.

Delivery Driver Robberies

The next category of robberies are those of delivery drivers. While these could also fall under the category of lure robberies (see below), they were distinguishable due to the specific interactions and circumstances involved. Delivery driver robberies most often involved the robbery of pizza delivery drivers:

UNKNOWN SUBJECTS CALLED LAROSA'S AND PLACED AN ORDER TO BE DELIVERED TO LISTED ADDRESS. WHEN VICTIM ARRIVED TO DELIVER ORDER, SUBJECTS ROBBED HIM AT GUNPOINT AND FLED.

Dispute Robberies

Some robberies were the result of a dispute. These disputes ranged from verbal sparring to physical fighting. Most dispute robberies involved offenders and victims with a prior relationship, including family members, boyfriends/girlfriends, or friends/acquaintances:

VICTIM STATED THAT HER AND HER BOYFRIEND GOT INTO AN ARGUMENT AND HE CHOKED HER AND PUSHED HER TO THE GROUND. HE THEN TOOK HER WALLET AND LEFT THE SCENE IN A VEHICLE.

Alternatively, some dispute robberies involved parties that only briefly knew each other, oftentimes due to a physical fight between the two:

3 VICTIMS WERE WALKING HOME FROM WALMART WHEN 5 MALE BLACK SUSPECTS APPROACHED THEM AND ASKED THEM IF THEY WANTED TO

> FIGHT. ONE SUSPECT BEGAN PUNCHING VICTIM 1 IN THE FACE AND HEAD KNOCKING HIM TO THE GROUND LEAVING HIM UNCONSCIOUS AND TOOK LISTED PROPERTY FROM ALL 3 VICTIM'S.

Importantly, dispute robberies occurred at all three primary environments: streets, facilities, and residences.

Home Invasion Robberies

Another robbery type commonly found in previous literature are home invasion robberies. These incidents are defined as robberies where an unknown party enters the residence of the victim without permission. Home invasion robberies occur exclusively at one environment, a residence:

> VICTIM STATED THAT HE HEARD A KNOCK AT HIS DOOR AND WHEN HE OPENED IT 3 MALE BLACKS IN ALL BLACK, INCLUDING FACE MASKS, CAME IN AND POINTED GUNS AT VICTIM TELLING HIM TO LAY ON FLOOR. ONCE ON THE FLOOR ONE OF THE SUSPECTS TOOK 2 CELL PHONES AND US CURRENCY FROM THE VICTIM'S PANT POCKETS. THE SUSPECTS THEN LEFT AND DROVE TOWARDS READING RD IN A NEW MODEL CHEVY.

Home Invasion (Prior Relationship) Robberies

While uncommon, another type of home invasion robbery could be parsed from the data: those where the victim and offender had a prior relationship. Unlike typical home invasion robberies, offenders were often invited in to the residence, where they then committed the robbery:

> VICTIM INVITED SUSPECTS IN HER HOME. DURING WITH TIME, SUSPECT 2 WALKED TO VICTIM'S BEDROOM, TOOK VICTIM'S CURRENCY AND POINTED A GUN TO HER HEAD. SUSPECTS THEN FLED WITH VICTIM'S MONEY.

Lure Robberies

Similar to robberies of delivery drivers, lure robberies involve the offending party drawing the victim to a specific location where the robbery takes place. How the offender lured the victim to the location varied greatly within the data. Among the more common luring techniques involved the robbery of taxi drivers. In these cases, offenders would have taxi drivers take them to a location where upon the driver was robbed:

> SUSPECT WAS CUSTOMER IN A TAXI. WHEN THE CAB DRIVER (VICTIM #1) REACHED THE DESTINATION, SUSPECT DISPLAYED HANDGUN AND DEMANDED MONEY. SUSPECT THEN FLED ON FOOT IN UNKNOWN DIRECTION

In other instances, victims were lured by some form of online communication, such as through Craigslist in an attempt to purchase or sell property:

> VICTIM STATES THAT UNKNOWN SUSPECTS LURED HIM TO LISTED LOCATION TO COMPLETE A CRAIGS LIST DEAL BUT WAS HELD UP AT GUN POINT AND SUSPECTS TOOK LISTED PROPERTY WITHOUT VICTIMS PERMISSION.

Finally, the data revealed a small number of instances where a victim was lured to a location for the purpose of purchasing narcotics. It is possible that more robberies fit into this category but are not coded as such, as the purchase of narcotics is itself a crime, thus the lure (or even the robbery itself) may not be reported to the police. As an example of a narcotics-lure robbery narrative:

> VICTIM ENGAGED IN PURCHASE OF MARIJUANA FROM SUSPECTS WHEN HE WAS PUNCHED AND KNOCKED TO THE GROUND AND LISTED PROPERTY TAKEN.

Officer as Victim Robberies

Included in the robbery data were incidents where an offender, during the course of an arrest, attempted to take something from the arresting officer. As these instances fit the legal definition of robbery, they are categorized as such. However, due to the special circumstances surrounding these incidents, they were grouped together as "officer robberies":

> ARRESTEE ATTEMPTED PULL OFFICER'S TASER FROM HIS HAND TWICE AS HE WAS BEING PLACED UNDER ARREST FOR RESISTING ARREST AND THEFT.

Opportunistic Robberies

Incidents labeled as opportunistic robberies include those where an offender took property by force or threat of force from a victim in a public or semi-public location. These are often labeled street robberies in the literature. However, as discussed below, this label misidentifies these robberies, which occur in many different environments. Rather, these robberies can be identified better by the interaction between the offender and victim. That is, the interaction and crime itself are due to the opportunity created by the nearby environmental backcloth, as predicted by CPT. A final note in the label "opportunistic robbery". Environmental criminology suggests that all crimes are the result of an opportunity for the behavior to occur. Thus, all robberies are technically "opportunistic". However, this term is used to emphasize the notion that these incidents are the result of criminal opportunities created by the environmental backcloth and the crime generators and attractors that make up the physical space.

Opportunistic robberies often fell into one of two categories (when the police data allowed for sub-categorization of opportunistic robberies). First, there were "traditional" armed or strong-armed robberies where an offender approached the victim and demanded property:

> VICTIM STATED UNKNOWN SUSPECT POINTED A GUN TO THE BACK OF HER HEAD AND DEMANDED HER MONEY.

These "traditional" robberies often included the taking of a vehicle, commonly known as carjacking:

> VICTIM STATES UNKNOWN SUBJECT TOOK VEHICLE AT GUN POINT WHILE SHE WAS PARKED ON SIDE OF EASTERN AVE.

Second, there were incidents where offenders attempted to "snatch" property away from victims but had to use force due to resistance on the part of the victim:

> VICTIM STATED THAT AS SHE WALKED WITH THE WITNESS, THE SUSPECTS RAN UP ON HER FROM THE REAR, AND SNATCHED HER PURSE FROM OFF OF HER ARM, AND TOOK THE LISTED PROPERTY WITHOUT HER CONSENT.

Other Crime

The final category of robberies includes incidents where a robbery took place only after the commission of another crime. These incidents differ from the other categories in that primary crime being committed was not the robbery itself. For instance, a number of incidents involved victims walking up to their vehicles during a theft from automobile:

SUSPECT ENTERED VICTIM'S CAR ATTEMPTING TO TAKE VALUABLES FROM CAR. SUSPECT WAS DISCOVERED BY VICTIM. SUSPECT THREW VICTIM TO THE GROUND WHEN SHE APPROACHED HIM.

The results of the Haberman et al. (forthcoming) typology illustrate the multifaceted nature of robbery. First, it is apparent that robbery is far too complex in and of itself to be grouped with other crime types in multi-crime indices, as seen in much of the crime and place literature described above. The variation in environments and offender-victim interactions make it difficult to assume that the opportunity structures needed for these events to occur are the same for those as homicides, rapes, or assaults, which are themselves complex crime types (e.g. Wolfgang, 1958).

Table 2.1: Haberman et al. (forthcoming) Robbery Classifications

Name	Definition
Commercial	Robbery occurred at or on the premises of a commercial facility: includes bank robberies, robberies where an employee was the victim, and shoplifting incidents categorized as robberies
Delivery Drivers	Robberies where a delivery driver was lured to a location by the offender
Disputes	Robberies that occur after a verbal or physical dispute between known parties
Home Invasion	Robberies where an unknown offender enters the residence of the victim without permission
Home Invasion – Prior Relationship	Robberies where an known offender enters the residence of the victim with permission
Lure	Robberies where the victim was lured to the location by the offender
Officer as Victim	Robberies where the offender attempts to take property during the course of an arrest
Opportunistic	Robberies where offender takes property by force from a victim in a public or semi-public location
Other	Robberies that were uncodeable due to lack of information in police data
Other Crime	Robberies committed during the course of or in connection with another crime, such as kidnapping, sexual assault, or theft

Second, the same can be said for research using total robberies as a dependent variable. The variation in robbery, as seen in the typologies reviewed above, makes it difficult to assume that all robberies share the same opportunity structure. More importantly, the use of total robberies, especially in studies examining the influence of facilities on crime, may lead to misguided conclusions. For example, the notion that commercial robberies can be predicted by commercial places (e.g. retail stores) is tautological. That is, we should expect commercial places to significantly predict robberies if commercial robberies are included by definition.

Thus, when testing opportunity theories of crime, it follows that disaggregated measures would have the most construct validity. For example, Cohen and Felson (1979: p. 589) emphasized that RAT was designed to explain "direct-contact predatory violations", defined as acts where someone wrongly takes or damages another person and/or their property. More recent literature has recognized the need to differentiate among types of robberies when using a framework based in environmental criminology. This lead to the use of street robberies as a common dependent variable in crime and place research based on the theoretical underpinnings of environmental criminology. Street robberies, as often defined in the literature, were chosen due to how their opportunities organically stem from the environmental backcloth and how potential offenders and victims move through it (Bernasco et al., 2017).

The issue, however, lies with the operationalization of street robberies. For example, Bernasco and Block (2011) operationalized street robberies as all robberies occurring in a public location. Alternatively, Cincinnati Police Department crime analysts define street robberies as those that (1) were coded as "street", "parking lot", or other public environments, and (2) incidents where the victim type was coded as "individual" and not one of the other codes pertaining to nonindividual victims.[1] Recall, of course, that most research simply lacks clarity regarding their definition of robbery, thus making it difficult to assess the construct validity of their work.

While these operationalizations may approximate the impulsive, opportunistic robberies suggested by environmental criminology, evidence from the Haberman et al. (forthcoming) coding suggests that it may potentially include robberies that fail to conform to and/or exclude robberies that fit the definition of opportunistic violations. For instance, while some of these interactions exclusively occurred in a particular environment (e.g. commercial robberies exclusively at commercial facilities), other types of interactions occurred in multiple environments (e.g. armed robberies among strangers occurred in the streets, in/at facilities, or in/at residences). In other words, the nature of robbery incidents based on their descriptions by officers in narrative reports may not align with their classifications based on simple nominal variables capturing location and victim types. Additionally, robbery classifications based on official police data assumes perfect inter-rater reliability amongst police officers. Using the Cincinnati data as an example, an armed robbery occurring outside of a gas station could be coded as "street", "gas station", or "parking lot" by different officers. If coded as "gas station", this incident would not be included in the CPD-based coding scheme of street robberies, as it did not occur on the street or other public area.

If the operationalization of robberies is exclusively based on environment codes, it is possible that the measure does not truly measure the type of crime emphasized by environmental criminology. Rather, dependent variables should also focus on the offender-victim interaction, specifically if a particular incident represents the dynamic highlighted in opportunity theories of crime. Monk, Heinonen, and Eck (2010) accurately portrayed the dual importance of environments and offender-victim interactions when defining street robberies characteristics. Their definition of

[1] The Cincinnati Police Department follows National Incident Based Reporting System coding procedures.

street robberies included crimes with the following characteristics: (1) an offender targets a victim; (2) the victim is a pedestrian and a stranger; (2) the offender attempts or completes a theft of cash or property; (4) the offender uses force or the threat of force against the victim; and (5) the offense occurs in a public or semi-public place (Monk et al., 2010: p. 1). Thus, while environment plays a role (i.e. the robbery occurs in a public or semi-public place), the offender-victim interaction is also important (i.e. victims and offenders are unknown to one another; meeting is chance rather than specifically targeted) in determining which robberies are more opportunistic in nature.

The coding scheme (and data) used by Haberman et al. (forthcoming) allows for the examination of the types of robberies emphasized by environmental criminology. To do so, certain robbery categories must be excluded from analysis. These decisions are based on incident characteristics specified within the typology, including the offender-victim interaction and environment. Jacques and Wright (2008) suggest that one way to differentiate violent predatory acts is by comparing the amount of deception used preceding the crime. Two of the robbery categories in the Haberman et al. (forthcoming) typology, robberies of delivery drivers and lure robberies, involve a level of deception greater than that in the other robbery categories. This deception creates a different opportunity structure whereby offenders choose the place specifically and bring the victim to that location. This is vastly different from opportunistic robberies, which occur at or near places that generate opportunities organically or attract those looking for opportunities.

Dispute robberies, robberies of police officers, and robberies committed during the course of another crime should also be removed from analysis due to changes in the opportunity structure resulting from the offender-victim interaction. In each of these cases, the initial intent of the offender was not to commit a robbery. Rather, the altercations occurring before the robbery (e.g.

a dispute, an arrest, or the commission of another crime) were the result of circumstances unrelated to robbery or its opportunity structure(s).

Finally, commercial robberies and home invasion robberies are unique due to their environments. These robberies exclusively occur indoors, are more targeted/less opportunistic in nature, and occur in a closed and predictable environment (Monk et al., 2010). Thus, their opportunity structure differs from robberies that occur in an outdoor public or semi-public place. As such, they are often excluded from crime and place research[2] that focuses on spatial patterns and the role of potentially criminogenic facilities on those patterns.

This leaves only those robberies that organically develop based on the routine activities of offenders and victims and the opportunities created by the environmental backcloth. However, they do not necessarily happen on the street. As described above, many of these occurred on the premises of commercial facilities (e.g., gas station parking lot) or residences (e.g., public housing community's walking paths). Rather, these robberies, labeled "opportunistic" for lack of a better word, follow a similar crime script. A victim or victims, being in a public or semi-public place, are approached by an offender or offenders. The offender uses force, or threat of force, to assure compliance when attempting to take personal items from the victim(s). Once completed, the offender(s) leave the scene. Thus, while the environment alone may include/exclude certain types of robberies, the offender-victim interaction clearly indicates the type of robbery best explained by opportunity theory.

[2] These and other robberies are not summarily excluded from all crime and place research. For instance, research focusing on the role of place management or situational crime prevention could benefit from focusing on commercial robberies.

Current Study

The previous review demonstrates a number of key points that, when taken together with limitations of past studies, reveal the need for further exploration of spatial robbery patterns. First, environmental criminology suggests that crime concentrates in space (Sherman et al., 1989; Weisburd et al., 2012), and that this concentration is, at least in part, related to the presence of potentially criminogenic places (Bernasco & Block, 2011; Haberman & Ratcliffe, 2015). Second, environmental criminology suggests that offending decisions and criminal opportunity are crime specific (Clarke & Cornish, 1985; Felson & Clarke, 1998) and the different opportunity structures that facilitate different offending decisions vary across space (Brantingham & Brantingham, 1993). However, most crime and place research has used crime-general dependent variables to measure spatial concentration and how potentially criminogenic places influence this concentration. Even those studies that used crime-specific dependent variables like street robbery to measure spatial concentration (e.g. Braga et al., 2011) or how potentially criminogenic places influence crime patterns (e.g. Bernasco & Block, 2011; Hart & Miethe, 2014) may be limited in their scope due to reliance on police recorded data rather than qualitatively coded measures that validly capture the dependent variable under study. Therefore, the current study used the Haberman et al. (forthcoming) event-based typology to assess the extent to which the results of crime and place research might be sensitive to the operationalization of robbery, with a specific focus on spatial crime clustering and how different potentially criminogenic facilities link to robbery at the micro-level.

CHAPTER 3: DATA AND METHODS

The previous chapters made two overall points. First, past research has shown crime concentrates at places (Sherman et al., 1989; Weisburd et al., 2012) and specific types of facilities predict that concentration (e.g., see Bernasco & Block, 2011) as hypothesized by environmental criminology. Second, this research is limited because it has mostly ignored environmental criminology's emphasis on crime specific measures and focused on multi-crime indices (e.g., Part I violent crime) or broad crime types (e.g., all robberies). Haberman et al. (forthcoming) used qualitative coding techniques to identify a robbery typology and concluded that robberies could be categorized predominantly by how the offender and victim interact and the environment where they occurred (also see Eck & Clarke, 2003). Using this typology, the current study was designed to address the utility of disaggregated robbery measures in the crime and place literature. The following section details the study's research questions, site, data, and analytic methods.

Research Questions and Hypotheses

The research questions in this study focused on the distinct spatial patterns of three different robbery measures: (1) total robberies (2) police-designated street robberies (3) qualitatively coded opportunistic contact robberies. The first category, total robberies, is a crime-general measure that does not take into account different types of robberies. The second type, police-designated street robberies, is a crime-specific measure that can be created using regularly recorded police data according to the analytical practices of the police department supplying the analyzed data. However, it is narrowly defined based on the location (outdoor) and victim-type (individual)[3], and does not consider qualitative differences amongst robbery incidents. The third

[3] Police-based street robbery coding procedures were obtained from crime analysts at the Cincinnati Police Department.

measure uses the Haberman et al. (forthcoming) typology (see above for description) and includes only those robberies defined as opportunistic (see Chapter 2), which falls in line with the original conception of both routine activities theory (Cohen & Felson, 1979) and crime pattern theory (Brantingham & Brantingham, 1993; 1995).

Research Question 1: Do different robbery measures cluster spatially?

The first research question examined the spatial patterning of robbery incidents using all three measures listed above. Previous research suggests that robberies, like other types of crime, cluster in space. In order to test the value of disaggregated and qualitatively coded crime types, and whether or not they cluster as predicted by the law of crime concentration (Weisburd, 2015), the first step was to assess if and how each measure concentrated in space.

Research Question 2: Is the spatial clustering of robbery sensitive to the operationalization of the different measures?

Research question two examined how spatial clustering differed among the three robbery measures. Some similarity in spatial patterns was inherent due to the nested nature of the data. For instance, because police-designated street robberies and qualitatively coded opportunistic robberies are included in the total robberies measure, there should have been some overlap in hot spots between and among the different robbery types. Nevertheless, how often and where these hot spots exist may depend on which measure is examined. Therefore, it was important to see not only if each type clustered in space (research question 1), but also how these clusters changed depending on the measure examined. Overall, answering research questions 1 and 2 has important implications for identifying and studying crime concentrations by assessing the sensitivity of crime concentrations to the operationalization of robbery.

This is potentially informative for those looking to prevent opportunistic robberies. That is, for prevention efforts attempting to curb opportunistic robbery clusters, are the other robbery measures generating accurate hot spots or are they instead made up of "false positives" (i.e., numerous types of robberies)? Similar research and analyses were conducted by Klinger and Bridges (1997), who demonstrated that calls for service data, often assumed to be more accurate than officially recorded police data, often resulted in false positives when comparing crime types for dispatched calls and actual encounters.

Research Question 3: Is the relationship between facilities and robbery sensitive to the operationalization of different measures?

The third research question focused on the environmental backcloth (Brantingham & Brantingham, 1993) of where robbery events occur. Specifically, this research question examined the influence of potentially criminogenic places on the different robbery measures. Whether or not certain types of places predict robbery locations may be dependent upon the measure being used. Variation in opportunity structures due to the presence of certain crime generators or attractors may account for these differences. Research question 3 investigated the importance of potentially criminogenic places using two common analytic strategies: (1) by analyzing different combinations of facilities on street blocks (see Hart & Miethe, 2014; 2015) and (2) by testing the influence of places on street block robbery counts (see Bernasco & Block, 2011; Haberman & Ratcliffe, 2015). The results of these analyses indicate whether robbery operationalization alters the relationships among potentially criminogenic facilities and the spatial patterning of robbery.

Study Site

Cincinnati, Ohio is the current study's setting. Situated on the Ohio River in southwest Ohio, Cincinnati is roughly 80 square miles. Cincinnati has a population of approximately 300,000 residents, which makes it the third largest city in Ohio. Cincinnati is a relatively diverse city. Nearly half (49.3%) of its residents identify as white, while slightly fewer (44.8%) identify as black. The median household income in Cincinnati is $34,000, which is $10,000 less than the national median household income. An estimated 30.9% of Cincinnati residents live in poverty (US Census Bureau, 2015).

Dependent Variables

This study focused on robbery, both at the aggregate and disaggregated level. First, it is important to detail why robbery generally is the focus of this study. Robberies are a useful crime to study when exploring the link between crime and place for a number of reasons. The theoretical underpinnings of crime and place research emphasize the importance of offender decision-making as well as the congruence of offenders, targets, and low guardianship in time and space (Clarke & Cornish, 1985; Cohen & Felson, 1979). Routine activities theory, as originally postulated, focused on "direct-contact predatory violations", a category in which many robberies belong. This led to the use of robberies as a dependent variable in much of the crime and place research discussed in Chapter 2 (albeit often operationalized as an item in a multi-crime index or all robberies). Second, interviews with active robbers indicates differential decision-making in terms of crime locations and targets (Wright & Decker, 1997), which is an important part of the theoretical frame that underpins this proposed dissertation. Third, robbery concerns many citizens, so developing a deep understanding of robbery may lead to more effective crime control responses.

While robbery is generally a useful dependent variable to study, it is important to remember that it is not a homogenous category of crime. As discussed in the Chapter 2 section about crime-specific outcomes, previous research suggests that robberies vary on a number of dimensions, including those outlined by the Haberman and colleagues study (forthcoming). Additionally, previous crime and place research has focused on a certain robbery-specific outcome: street robbery. Thus, while robberies are a useful measure to study, it is also important to examine them at a disaggregated level.

This study used Cincinnati Police Department (CPD) robbery incident data from January 1, 2014 to December 31, 2016 (N = 4,086). Three dependent variables were examined. First, the total robberies variable includes all recorded robberies. Second, police-designated street robberies includes only robberies with a CPD designated location code representing a public/semi-public location and victim-type of individual (see Appendix A for police-designated street robbery coding procedure). Third, qualitative opportunistic robberies were identified based on Haberman and colleagues' (forthcoming) data.

For spatial analysis, the data were geocoded using ArcGIS. A dual-ranges address locator with 5 feet offset was used to geocode the data. Robbery incidents were geocoded at a 99.5% success rate, well beyond the suggested hit-rate of 85% hit-rate (Ratcliffe, 2004). Table 3.1 shows the breakdown of robbery measures by year. In total, 4,066 robbery incidents were examined, which included 1,422 in 2014, 1,305 in 2015, and 1,339 in 2016. Overall, robberies dropped from 2014 to 2015, with a slight uptick in 2016. Similar patterns occurred for both police-designated street robberies and qualitatively coded opportunistic robberies. Also evident from Table 3.1 is the general trend in the type of robbery seen in Cincinnati. When using the police-designated operationalization, street robberies made up between 70.3% and 74.2% of total robberies in the study period. Similarly, qualitatively coded opportunistic robberies accounted for 75.1% to 77.2% of robberies. Thus, it appears that Cincinnati's robbery problem consists of those robberies that environmental criminology attempts to explain.

Table 3.1: Robberies by Year and Operationalization

Year	Total	Police-Designated	Opportunistic
2014	1422	1055	1098
2015	1305	920	990
2016	1339	941	1005
Total	4066	2916	3093

Compared to similarly-sized cities in the United States, Cincinnati's robbery problem is among the worst. Figure 3.1 displays Cincinnati's robbery rate percentiles compared to cities[4] with populations between 250,000 and 499,999 residents for 2012 through 2016. Cincinnati's robbery rate percentiles ranged from 84 in 2014 to 93 in 2013. Figures 3.2 through 3.6 below show the distributions of robbery rates from 2012 to 2016 for these same cities. Cincinnati's robbery rate ranged from a high of 58.2 robberies per 10,000 residents in 2012 to 42.3 robberies per 10,000 residents in 2015. Generally, Cincinnati's robbery rate trended downwards from 2012 to 2016. Only 2016 saw a higher robbery rate than the year before, and this increase was very minimal (42.3 to 42.8). When comparing to similarly sized cities, Cincinnati remains on the higher end of the distributions, which are right-skewed, indicating that most mid-sized cities have robbery rates at the lower end of the distributions. Taken together, Figures 3.1 through 3.6 indicate that Cincinnati, when compared to cities with similar populations, has a consistently worse robbery problem.

[4] Data were obtained from the FBI Uniform Crime Report for each year. 35 cities, including Cincinnati, were within the population parameters AND reported data to the FBI each of the five years.

Figure 3.1: Cincinnati Robbery Rate Percentiles for U.S. Cities with Populations between 250,000 and 499,999 Residents by Year

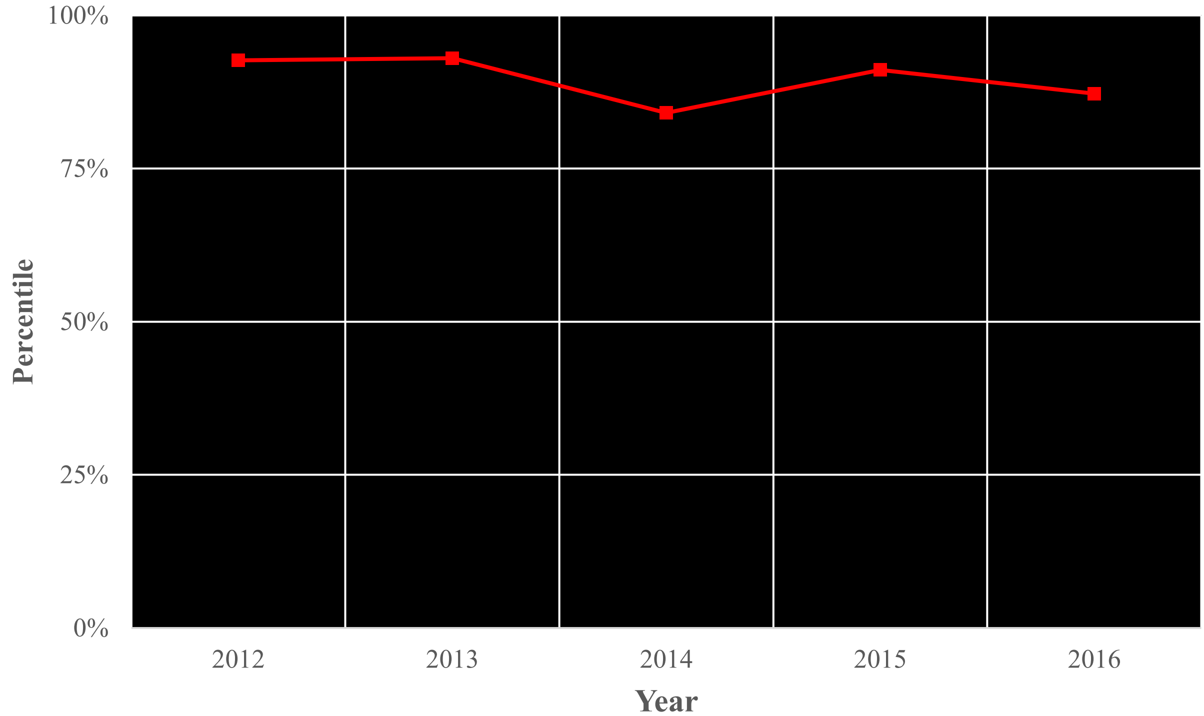


Figure 3.2: 2012 Robbery Rate Distribution for U.S. Cities with Populations of 250,000 to 500,000

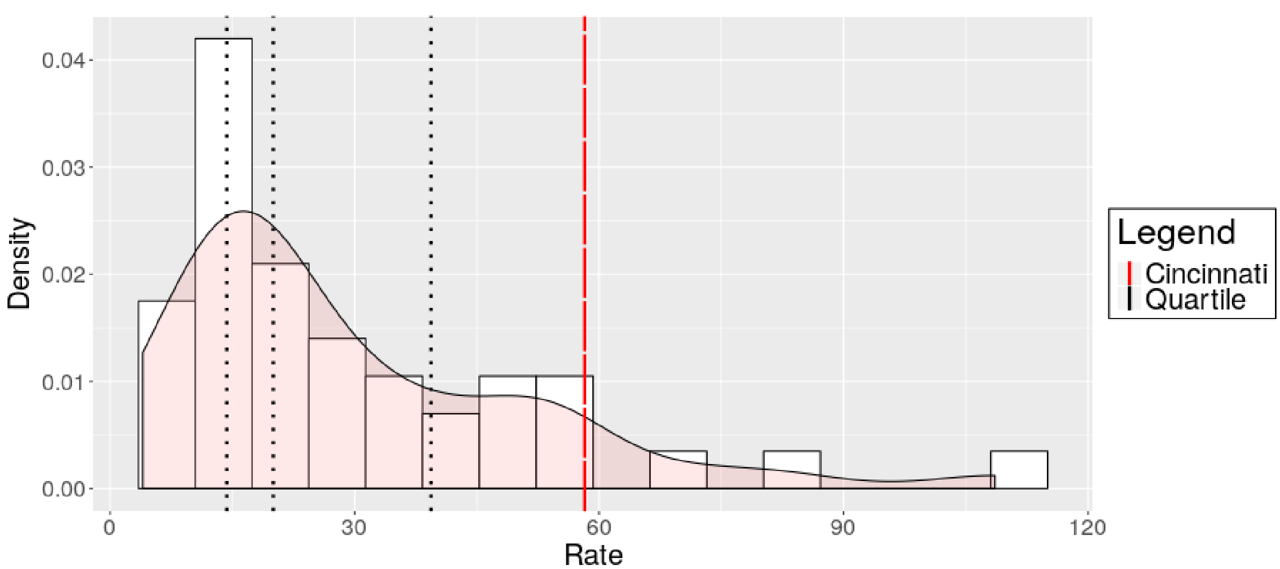


Figure 3.3: 2013 Robbery Rate Distribution for U.S. Cities with Populations of 250,000 to 500,000

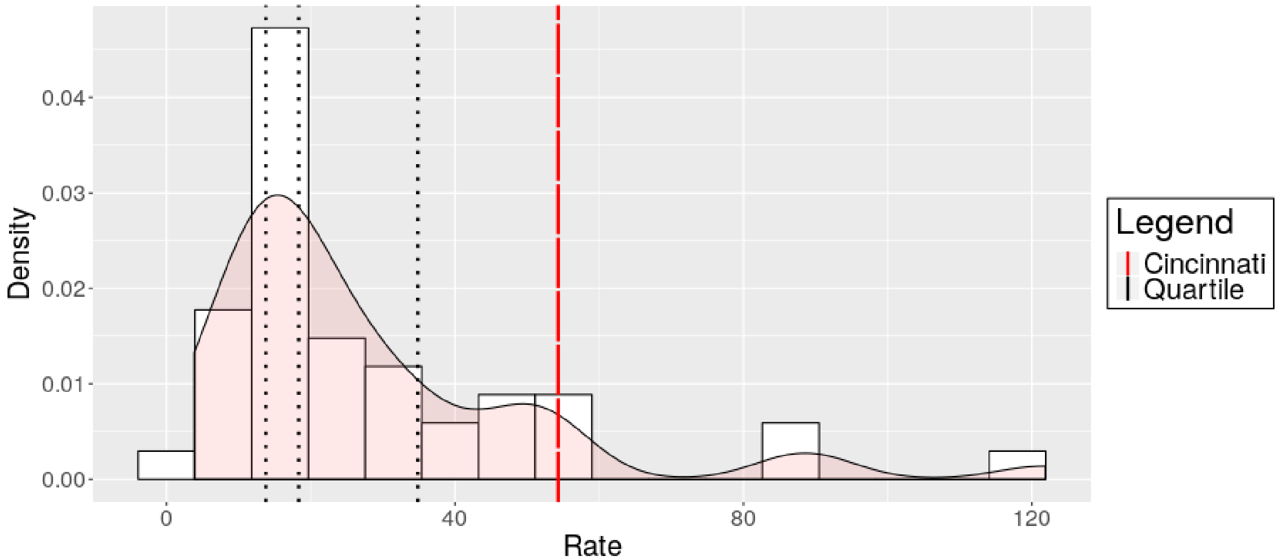


Figure 3.4: 2014 Robbery Rate Distribution for U.S. Cities with Populations of 250,000 to 500,000

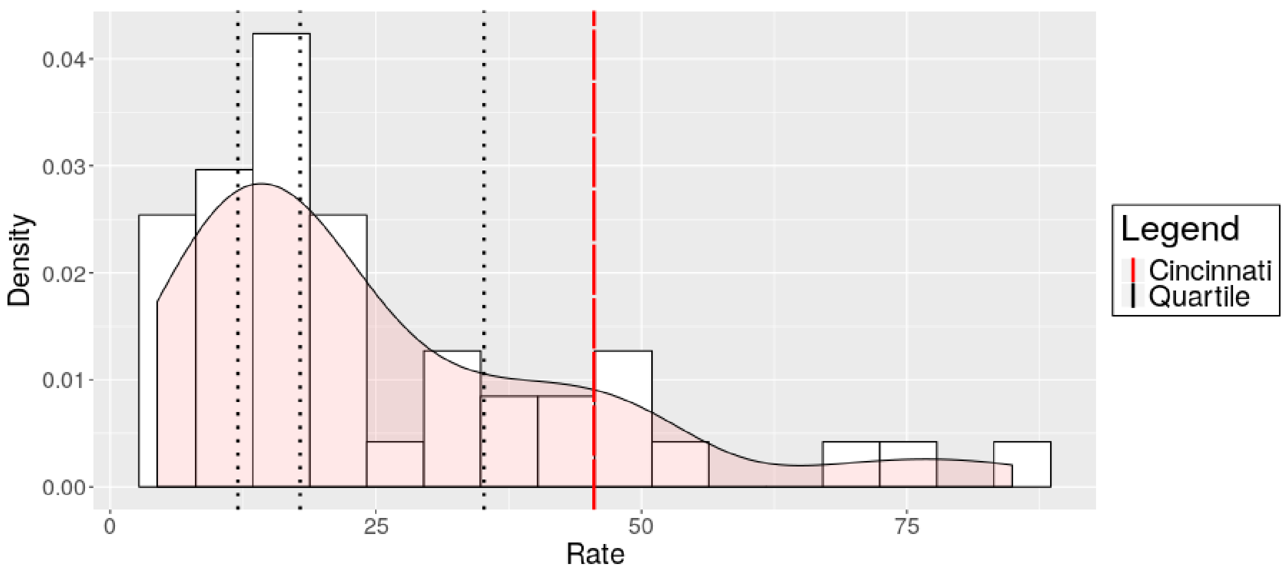


Figure 3.5: 2015 Robbery Rate Distribution for U.S. Cities with Populations of 250,000 to 500,000

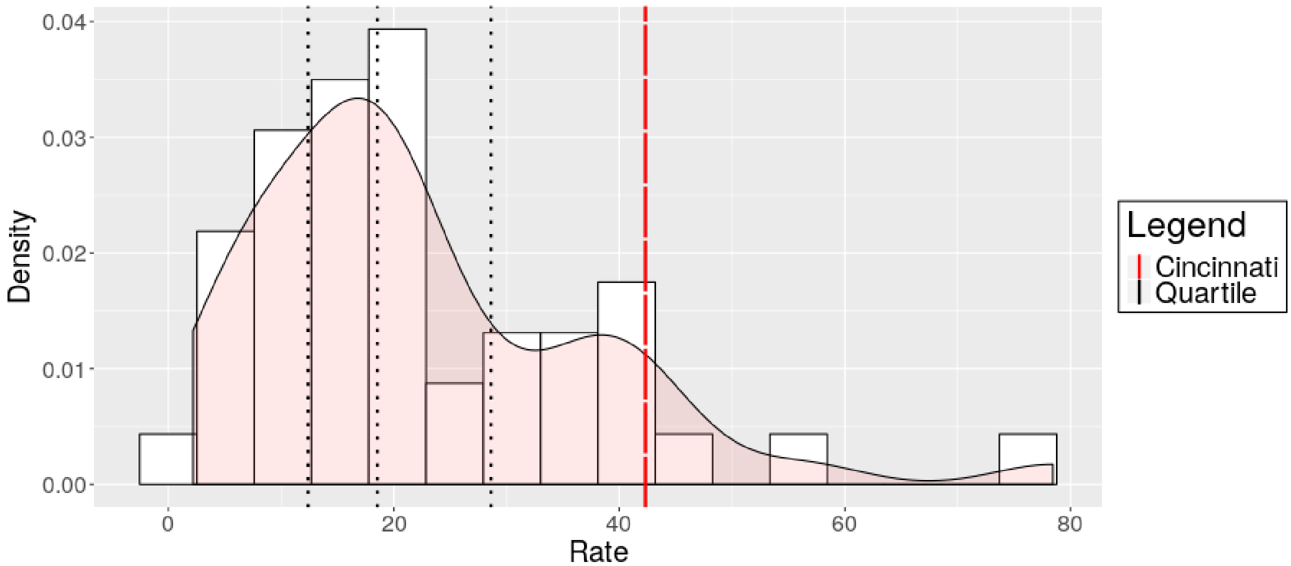
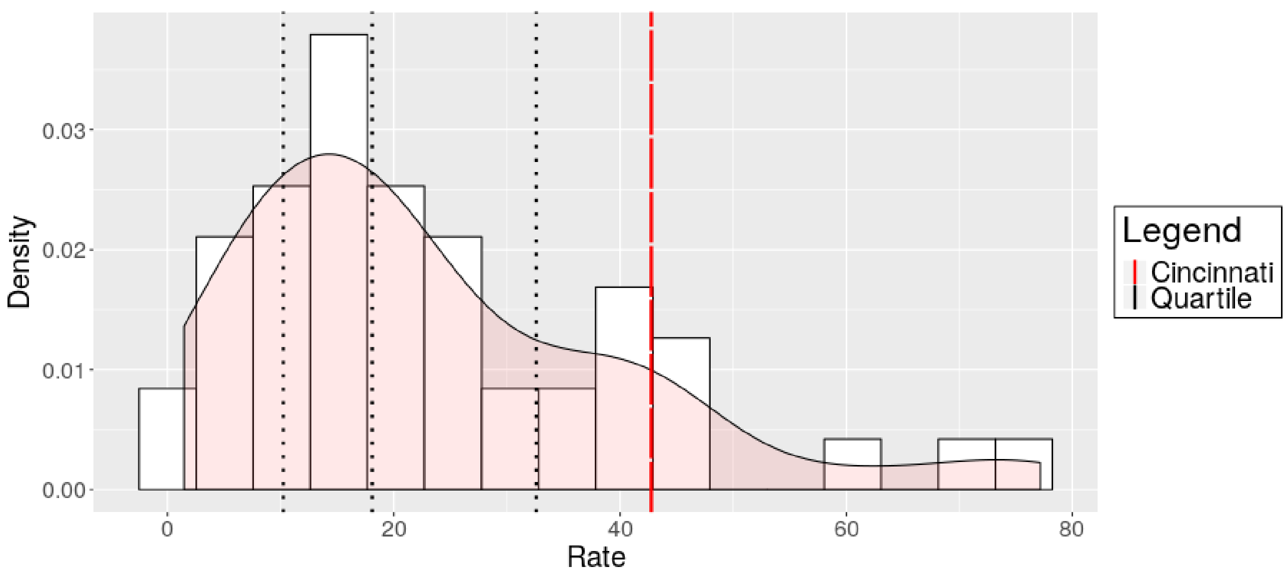


Figure 3.6: 2016 Robbery Rate Distribution for U.S. Cities with Populations of 250,000 to 500,000



Facilities Data

In addition to the robbery data described above, the current study required data on potentially criminogenic facilities in order to examine research question 3. The facility data came from a number of sources, which are summarized in Table 3.2

The majority of the facility data came from the Ohio Department of Taxation. Data for all businesses that collect sales taxes in Hamilton County were obtained in early January 2016, resulting in an initial list of 12,778 “businesses”. These data were coded, cleaned, and checked by researchers at the University of Cincinnati. This produced 2,392 unique businesses in the City of Cincinnati as described below.

Bars (N = 153), entertainment sites (N = 76), and restaurants (N = 575) captured places where individuals go for entertainment purposes. Businesses were coded as bars if their primary function was the sale if alcohol and if the business stayed open later than midnight on weekends, allowing for a differentiation between bars and restaurants that serve alcohol. Restaurants included both sit-down (or full service) and fast food restaurants, which were differentiated based on whether the restaurants had a wait staff, had a drive-thru, delivered food, and/or had less than 10 tables inside the establishment. Entertainment sites included art galleries, arcades, amusement parks, bowling alleys, batting cages, landmarks and attractions, mini-golf, museums, sports arenas, theaters, and a casino.

Other businesses from the tax dataset included everyday stores (N = 364), barbershops and salons (N = 181), grocery stores (N = 25), hotels (N = 27), pawn shops and check cashing stores (N = 20), laundromats and dry cleaners (N = 32), body art stores (N = 18), and retail stores (N = 694). Everyday stores included convenience stores, gas stations, small/ethnic grocery stores, pharmacies, and tobacco/vape stores. Retail stores included those that sell consumer electronics, clothing, household items, jewelry, office supplies, recreational equipment, as well as thrift stores, florists, and dollar stores.

Other data sources provided information on places not driven by economic activity. The following data were all represented as polygons. In order to code these data to street blocks, any street block that was directly accessible from the facility was be coded "1" and all other, non-accessible street blocks were coded "0". Data on high schools (N = 35) and higher education institutions (N = 9) were obtained from Ohio Department of Education and the U.S. Department of Education's Office of Postsecondary Education, respectively. Parks (N = 47) data were obtained from the Cincinnati Area Geographic Information System (CAGIS) as well as the Cincinnati Parks Department. Finally, public housing communities (N = 22) were obtained from the Cincinnati Metropolitan Housing Authority.

The remaining non-economic place data were represented as points or polylines, thus not requiring additional cleaning. Data for bus stops (N = 3,166) came from the Southwest Ohio Regional Transit Authority. Original coding of this data included multiple stops at a single location if buses traveled in multiple directions or if multiple lines used the same stop. Thus, bus stop data are operationalized as a dummy variable where presence of a bus stop on street block equaled 1 and absence equaled 0. Drug treatment facilities (N = 43) were obtained from the Ohio Mental Health and Addiction Services department. Data on the locations of public libraries (N = 22) were obtained from The Public Library of Cincinnati and Hamilton County. Only libraries within city limits were included. Recreation centers and city pools (N = 38) were obtained from the Cincinnati Recreation Commission. Unlike bus stops, these data were coded as counts.

Finally, gang territory (N = 2,215), represented as polylines, were obtained from the Cincinnati Police Department. These data were collected during intelligence gathering sessions stemming from the city's group and gang violence reduction strategy, the Cincinnati Initiative to Reduce Violence (Engel, Tillyer, & Corsaro, 2013). During these meetings, officers identified gang-controlled areas in their respective districts. To do this, officers marked on district maps which street blocks were gang-controlled. Cincinnati Police Department crime analysts took these maps and created a citywide polyline shapefile of gang territory where streets marked by officers (thus, operationalized as gang territory) equaled 1 whereas unmarked streets (not gang territory) equaled 0.

The facilities data shown in Table 3.2 and discussed above were used to construct variables for the analysis conducted for research question 3. While introduced here, the operationalization of these variables, and how they will be used, is introduced later in this chapter. That is, depending on the analytic technique, these data were structured in different ways, as either a dummy variable or count. This operationalization depended on the original coding as well as analytic technique. See Table 3.4 and the discussion for research question 3 for more information.

Table 3.2: Cincinnati Facilities Data by Type, Operationalization, and Data Source

Name	Source
Barbershops/Salons	Ohio Department of Taxation
Bars	Ohio Department of Taxation
Body Art Stores	Ohio Department of Taxation
Bus Stops	Southwest Ohio Regional Transit Authority
Drug Treatment Facilities	Ohio Mental Health and Addiction Services
Entertainment Sites	Ohio Department of Taxation
Everyday Stores	Ohio Department of Taxation
Gang Territory	Cincinnati Police Department
Grocery Stores	Ohio Department of Taxation
High Schools	Ohio Department of Education
Higher Education Institutions	US Department of Education
Hotels	Ohio Department of Taxation
Laundry	Ohio Department of Taxation
Parks	Cincinnati Parks Department
Pawn Shops/Check Cashing Stores	Ohio Department of Taxation
Public Housing Complexes	Cincinnati Metropolitan Housing Authority
Public Libraries	The Public Library of Cincinnati and Hamilton County
Recreation Centers and Pools	Cincinnati Recreation Commission
Restaurants	Ohio Department of Taxation
Retail Stores	Ohio Department of Taxation

Spatial Unit

Some of the analyses described below required robbery incidents to be allocated to a spatial unit. The current study used street blocks as its spatial unit of analysis. Street blocks are defined as both sides of a street between two intersections (Taylor, 1997; 1998). Street blocks have also been referred to as street segments (e.g. Weisburd et al., 2012) or face blocks (e.g. Bursik & Grasmick, 1993).

Street blocks are commonly used in crime and place research for a number of reasons. Second, street blocks are practical due to the nature of robbery events. Research suggests that certain types of places, such as bars, have an effect beyond their specific location (e.g. Groff, 2011; Ratcliffe, 2012). That is, a facility's role in the creation of robbery opportunity does not stop at the end of its property line. Other research links crime that occurs inside and outside facilities, suggesting that some places "radiate" criminal opportunity (Bowers, 2014). The use of street blocks as a spatial unit allow for an examination of how places may influence crime beyond their immediate area, especially when the exact location of an event may be "fuzzy". For example, the following incident "started" at a bus stop, yet the robbery took place further down the street:

> VICTIM WAS WALKING HOME FROM BUS STOP, WHEN UNKNOWN SUBJECTS WALKED UP FROM BEHIND AND STARTED PUNCHING HER. THE SUSPECTS TOOK HER WORK BAG AND CELL PHONE AND FLED NORTHBOUND.

Second, some scholars suggest street blocks follow the "smaller is better" criteria (Oberwittler & Wikstrom, 2009). Even within high crime neighborhoods, crime can vary from street to street (e.g. see Weisburd et al., 2004; et al., 2010). Some studies have even reported more variation in crime levels at smaller units of analysis than larger units of analysis, such as census tracts or neighborhoods (Steenbeek & Weisburd, 2016; Schnell, Braga, & Piza, 2017). Thus, street blocks allow researchers to better understand and unmask this spatial variation in crime levels.

Third, street blocks are a practical unit of analysis for the proposed research questions. Street blocks are easily identifiable when compared to larger areal units (Taylor, 1988). Larger areal units of analysis are often artificially defined for purposes outside the study of crime (Brantingham et al., 2009) or subjectively decided on by residents or researchers (Coulton et al., 2001; Campbell et al., 2009). Street blocks, as narrowly defined here, do not suffer from the same issues as larger units of analysis.

Cincinnati street block data were collected from CAGIS. The CAGIS street centerline shapefile covers all of Hamilton County and is the official street network dataset of the Hamilton County government. The following process was used to clean the street centerline file. First, all street centerlines outside of the City of Cincinnati were excluded. Next, all centerlines without valid address ranges were excluded (e.g., Interstates, highways, exit ramps, etc.) because these street blocks will never experience recorded crime due to the inability to geocode to the segments. Third, all streets digitized as multiple segments/lanes were reduced to a single centerline to ensure all streets blocks were only counted once. This left 11,008 street segments that averaged a length of 480 feet, slightly less than one-tenth of a mile.

Analytic Plan

The following section details the analyses used to answer the research questions. Because each research question requires a different set of analyses, the analytic plan is organized by research question. Each research question and subsequent analyses use the data and street block unit of analysis described above as appropriate.

Analysis Plan for Research Question 1

Recall research question one asks: Do different robbery types cluster spatially? Answering this question required describing the spatial patterning of each robbery variable separately. Therefore, spatial analyses describing the spatial clustering of each robbery type was conducted.

First, the overall level of clustering of robberies in the city was assessed by determining the percentage of street blocks that make up 25%, 50% and 100% of the total number of robberies within each robbery type. This was similar to previous research showing how crime clustering generally follows the law of crime concentration (Sherman et al., 1989; Weisburd et al., 2004; 2012; Weisburd, 2015).

Second, data visualizations were created to illustrate the spatial patterning of each robbery type across Cincinnati. Two types of maps were generated for each robbery type. The first maps illustrated the address points for each robbery type. The second maps illustrated the street block robbery counts, showing those street blocks that experienced larger amounts of robberies by type. With all maps displayed in a small-multiples format, it was possible to view and describe potential differences in robbery concentration across robbery types.

Third, Ripley's K analysis was used to describe the spatial clustering of each robbery variable. Ripley's K is a global measure of spatial clustering over different spatial scales (Ripley, 1976). Ripley's K allows for the testing of point data to see if patterns are significantly clustered or dispersed when compared to the assumption of complete spatial randomness (Bailey & Gattrell, 1995). The K function itself is a measure of the average number of events (in this case, robberies) within a specified distance of an arbitrary event.

The estimated value of Ripley's K[5] is:

$$K(d) = \lambda^{-1}(\text{number of events within distance } d \text{ of a randomly chosen event}) \qquad (3.1)$$

Where λ is the density of events (number of events divided by study area). This process is completed over a range of *d* distance bins, creating a cumulative function of points divided by the density. Assuming complete spatial randomness (CSR), the expected value of *K(d)* for a homogenous Poisson process is:

$$E\,[K(d)] = \pi d^2 \qquad (3.2)$$

At this point, Ripley's K is often transformed into Ripley's L, a square root function that creates a linear plot (Levine, 2015). The estimated value of Ripley's L is:

$$L(d) = [K(d)/\pi]^{1/2} \qquad (3.3)$$

Where the expected value of L is equal to the distance bin, thus creating a plot where CSR is illustrated as a straight line set at zero.

The L-function, then, summarizes the number of events within a given distance, taking into account both the area of the circle/buffer as well as the sample size. The size of the L-function may vary among distances, illustrating differential spatial patterns of clustering, dispersion, or randomness. The observed L value at each distance is then compared to an expected L value based on the assumption of CSR. The expected distribution of points is most commonly created via simulations of randomly distributed points throughout the study area. This allows for a test of whether or not an observed pattern of events is significantly different (either clustered or dispersed) from a random distribution. These simulated L values are used to create an "envelope" of minimum and maximum values to compare to the observed L value. The output for these tests are a graph

[5] The current study uses Wheeler, Worden, and McLean's (2016) notation, which borrows from Dixon (2002).

with distances on the X-axis and L values on the Y-axis. Both the observed L function and the simulation envelopes are plotted. Observed L values falling outside of this envelope can be considered either statistically significantly spatially clustered or dispersed where L values falling above the envelope are said to be spatially clustered and L values falling below the envelope are said to be spatially dispersed. Ripley's K analysis was completed in CrimeStat IV (Levine, 2015).

Fourth, hot spots will be identified using nearest neighbor hierarchical clustering (Nnh). Nnh is a point pattern tool found in the CrimeStat IV software package that uses the distances among points to identify hot spots (Levine, 2015). Specifically, the Nnh process begins by users specifying a minimum threshold distance where any two points are considered close, the geographic area of the study site, the minimum number of points needed per cluster, and output shape type. (Levine, 2015). Two options exist in specifying the minimum threshold distance: random nearest neighbor distance and fixed distance. Consistent with previous uses of Nnh in crime and place research (e.g. Haberman, 2017), the random nearest neighbor function will be used. This distance is defined as:

$$d_{NN(ran)} = 0.5\sqrt{\frac{A}{N}} \qquad (3.4)$$

where A is the user-defined study area and N is the number of events (Levine, 2015).

The threshold distance is obtained by selecting the appropriate one tailed confidence interval around the distance measure found above. This confidence interval is defined as:

$$d_{NN(ran)} \pm t\left(\frac{0.26136}{\sqrt{\frac{N^2}{A}}}\right) \quad (3.5)$$

where A is the study area, N is the number of events, t is the Student t-value for a given probability level, and 0.26136 is a constant. This confidence interval determines the probability that the distance between any two events is less than the random nearest neighbor distance. If the events are randomly distributed throughout the study area and the user selects a significance of $p \leq .05$, then only 5% of events would be expected to be closer than the threshold distance (Levine, 2015).

The next decision in the process is to define the study area. The area is either defined by the user based on the study region or is based on a bounding rectangle based on the minimum and maximum XY values in the data. The use of a bounding rectangle typically results in a larger area, which in turn usually results in a greater number of clusters, albeit less dense than clusters in a small area (Johnson, 2012). A value of 79.54 square miles (the geographic area of Cincinnati) was used rather than the minimum bounding rectangle.

The next step is choosing the minimum number of points needed to create a cluster. Levine (2015) states this criterion is necessary to eliminate very small clusters. That is, the use of large datasets may lead to the creation of thousands of clusters if the only criterion is distance. As this decision is relatively arbitrary, the default (ten points per cluster) will be used. In practice, it is likely that crime analysts will choose default values, thus choosing the default renders the resulting hot spots practically useful. The final decision prior to analysis is the output cluster type. Three options exist for visual output of Nnh clusters: (1) ellipses, (2) convex hulls (polygons), or (3) both. Convex hulls will be used, as they take on the actual shape of the point distribution, thus providing hot spots with more robust face validity (see Haberman, 2017).

The Nnh process begins by creating first-order clusters based on the above criteria. Once first- order clusters are identified, the process is repeated using the same parameters to create second-order clusters[6]. These clusters are based not in individual robbery points, but rather the centroids of first-order clusters. This process is repeated to create higher-order clusters until the clustering process fails (Levine, 2015). This Nnh process was repeated for each robbery type. Due to the size of higher-order clusters, only 1st order clusters were examined in the analysis presented below. That is, the size of higher-order clusters (second-order clusters), some of which spanned entire neighborhoods, does not fit into the micro-level focus of this dissertation.

Analysis Plan for Research Question 2

Recall research question two asks whether the clustering described by the analysis in research question is influenced by robbery operationalization. Before comparing any differences in spatial clustering, it was important to examine the overlap among robbery measures. Because all police-designated street robberies and qualitatively coded opportunistic robberies were included in the total robbery measure, some clustering was expected be similar among measures. Additionally, because the two disaggregated robbery measures were not mutually exclusive (i.e. an incident can be coded as both a police-designated street robbery and a qualitatively coded opportunistic robbery), it was important to assess the number of robberies that shared the different operationalizations.

This was especially important for the two crime-specific measures, police-designated street robberies and qualitatively coded opportunistic robberies. If, on one hand, the same robberies were captured using both definitions, then one could assume that environment alone was the driving factor in robberies defined by Haberman et al. (forthcoming) as opportunistic. On the other hand, if sufficient variation existed between the two crime-specific measures, then one could argue that

[6] The exception to this is the minimum number of "points" needed to create a cluster. Points in this case are the midpoints of each first-order cluster, and a minimum of three "points" are needed to create a second- or higher-order cluster.

future crime and place research needs focus on the offender-victim interaction as well as the environment. Because of this, it was important to see how these robberies were nested within one another.

Once robberies were scrutinized for their overlap in coding, the spatial concentration of robbery outcomes was assessed a number of ways. First, data visualizations were produced to examine the spatial patterning of first-order Nnh clusters. These produced a visual representation of how differentially operationalized robberies were clustered throughout the city. Further analysis was conducted to examine the relative concentration of robbery measures within street blocks. This went beyond the street block concentration of robberies in general (as examined for research question 1) by breaking down robberies by measure. This allowed for a comparison of each type of robbery to see if the clustering by street block differed by operationalization.

The next analysis of concentration compared street block hot spots of the three robbery outcomes. The first step in this analysis was to specify which street blocks should be considered hot spots. Hot spots can be measured using a number of analyses, and specification is a relatively arbitrary technique (Eck et al., 2005). For ease of understanding the relative concentrations of different measures, a basic hot spot technique was used: street block counts. This technique uses a cutoff whereby a street block is considered a hot spot only if a certain number of events occurred on it. Robbery counts are relatively low once aggregated to micro-units, such as street blocks. To ensure that the results are not sensitive to any one cutoff, analyses were completed using cutoffs of at least two, three, four, and five robberies per street block. This was done for each robbery measure, thus allowing for a comparison of street block hot spots, including if certain street blocks were hot spots for some measures but not others.

The final set of analyses for research question 2 examined the Nnh clusters from research question 1 in-depth. First, data visualizations were created to see if and how hot spots of different robbery measures co-occurred together in space. Second, total robbery and police-designated street robbery clusters were examined individually to determine the type of robberies that make up clusters within each type. In essence, this analysis determined if certain spatial clusters are general robbery hot spots or if they are instead made up of specific types of robberies (e.g. see Weisburd et al., 1993).

Analysis Plan for Research Question 3

The final research question further examined the sensitivity of robbery operationalization by exploring the possibility that potentially criminogenic places exhibit a differential effect on robbery patterns depending on how they were operationalized. This was accomplished using two statistical techniques found in recent crime and place literature: (1) conjunctive analysis of case configurations (CACC) and (2) count regression models. These two methods are described in detail below. Data used for these techniques included the facilities data mentioned above (see Table 3.2).

Conjunctive Analysis of Case Configurations

Developed by Miethe et al. (2008) but based on Ragin's (1987) qualitative comparative analysis, CACC serves as one way to confirm the importance of certain categorical variables and their influence on crime incident locations. In this case, CACC was used to explore how often certain places appeared on streets that experienced different types of robbery incidents.

CACC analysis has three steps. First, the CACC process begins by creating all possible case configurations, based on the number of independent variables and their operationalization (i.e. how many categories within each variable). If all variables are dichotomous (as they are in the current analysis: see Table 3.4), then the number of possible case configurations can be determined using equation 3.6:

$$\# \text{ Configurations} = X^Y \qquad (3.6)$$

In this equation, X represents the number of categories and Y represents the number of categorical variables being studied.

Second, all records/events (e.g. robbery incidents) are classified into a configuration. Once all records/events are classified, a data matrix where each configuration as well at the number (nci) and average number of cases (y1/nci) falling within each configuration is created. Finally, decision rules are created to indicate common and rarely observed profiles. The decision rules are based on the application of minimum cell frequency rules and depend on sample size. That is, the researcher must choose a cutoff where configurations with few cases are removed from analysis, leaving only those where most events are clustered. Miethe et al. (2008) label these "dominant profiles". Once the rule is set, the table and subsequent analysis includes only dominant profiles that contain the majority of cases.

It is helpful to use an example to understand the CACC process. In the present case, crime events were classified by the types of facilities that were located on the street blocks in which the crimes occurred. In this brief example, there are three variables (X1, X2, and X3) coded dichotomously for presence (=1) or absence (=0) on a street block. Three dichotomous independent variables results in eight potential case configurations ($2^3 = 8$). Table 3.3 illustrates the structure of the data matrix with three dichotomous independent variables. Using Table 3.3 as an example, an incident where all independent variables are present would be placed into configuration 8. Alternatively, an incident where no independent variables are present would be placed into configuration 1. After placing all incidents into their respective configurations, the researcher would then examine only those where the total number of cases fell above the minimum cell frequency rule.

Table 3.3: Case Configuration Data Matrix Example

Configuration #	X1	X2	X3	N_Cases	Y
1	0	0	0	nc1	y1/nc1
2	0	0	1	nc2	y1/nc2
3	0	1	0	nc3	y1/nc3
4	0	1	1	nc4	y1/nc4
5	1	0	0	nc5	y1/nc5
6	1	0	1	nc6	y1/nc6
7	1	1	0	nc7	y1/nc7
8	1	1	1	nc8	y1/nc8

*adapted from Miethe et al., 2008

Similar to Hart and Miethe (2014; 2015), the current study examined profiles of potentially criminogenic places for each of the disaggregated robbery types using CACC. Specifically, using the potentially criminogenic facilities data described below, CACC analysis was conducted for each robbery measure. To construct the data matrix, all independent variables (i.e. all facilities in the analysis) must be operationalized. These data were operationalized as dummy variables where 1 equals the presence of a facility on a street block and 0 equals its absence on a street block. The resulting data matrix of case configurations is quite large (2^{20} = 1,048,576 configurations). Each row represented a unique street block profile based on the combination of facilities located on that street block. Next, robberies were allocated to a specific configuration based on their spatial location. For example, if a robbery occurred on a street block where all facilities were absent, that case was allocated to the configuration where all independent variable coding equaled zero. After classifying incidents for each robbery category, the number of total observed street block profiles, dominant street block profiles, and proportion of events within dominant profiles were examined to assess whether different robbery measures cluster within certain behavior settings. The CACC reported here focuses on the average number of robberies per configuration rather than the count. Some configurations had high counts of robberies that exceeded the minimum cutoff, but the average number of robberies per street within the configuration was quite small due to a high amount of streets in that configuration. Therefore, the average number of robberies per configuration was used in order to assess which types of facilities and combinations, on average, produce a high number of robbery events. The minimum cell frequency cutoff was five for all analyses. Previous research has used 10 (Miethe et al., 2008; Hart & Miethe, 2014) or 5 (Hart & Miethe, 2015) depending on the total number of cases in the study. These studies, however, analyzed counts within configurations rather than averages. Five was chosen as the cutoff primarily due to the use of average number of robberies per configuration rather than the count. This produced a larger number of dominant profiles to examine. Results for count-based CACC can be found in Appendix B.

Count Regression Models

The second method to examine the potentially variable influences of places on different robbery types involved the use of count regression models seen in other crime and place research (e.g. Bernasco & Block, 2011). Counts of street block robberies for all three robbery variables were modeled using negative binomial regression models. Based on the Poisson model, negative binomial models allow for modeling of count variables with overdispersion (i.e., where the variance exceeds the mean; Osgood, 2000; Stucky & Ottensmann, 2009; Bernasco & Block, 2011; Haberman & Ratcliffe, 2015).

A number of model diagnostics indicated a better fit for negative binomial regression over Poisson regression. Specifically, observed and predicted probabilities of expected street block counts were graphed for all three dependent variables, each of which indicated negative binomial as the preferred model. This was also supported by likelihood-ratio tests directly comparing model fit between the two options (Long & Freese, 2014).

Additional model diagnostics were performed to rule out issues concerning multicollinearity, outlier influence, and spatial autocorrelation. Variance inflation factor (VIF) scores verified that multicollinearity was not an issue in any of the models. Outlier analysis indicated a number of street blocks in the final models required further assessment. However, the removal of outliers from the final models did not indicate they were substantially influencing results. Finally, spatial autocorrelation in the models' residuals was examined using Local Moran's I tests in GeoDa 1.12.1.59 (Anselin, Syabri, & Kho, 2006). This assessment of model residuals, including standardized Pearson, standardized deviance, and Anscombe residuals, was conducted using four types of spatial weights matrices: first-order queen contiguity and k-nearest neighbors using orders of 4, 5, and 6. All results indicated that spatial autocorrelation was not problematic.

The same place data used for CACC analyses was used for the count models. However, there are two major differences in how these data were used. First, whereas all place variables in the CACC analyses were operationalized as dummy variables, these data were operationalized in the count models as either dummy or count variables depending on their representation in the underlying dataset. For instance, data represented as polylines (e.g. gang territory) and polygons (e.g. high schools, higher education institutions, parks, and public housing complexes) remained dummy coded due to the nature of the data. Additionally, bus stops remained dummy coded due to the issues with duplicates in their dataset. That is, some bus stops in the data were counted multiple times depending on the direction each bus travels or if multiple buses traveled to the same stops. Finally, some place variables were essentially dummy coded because the maximum number of places on a street block was one. The remaining variables were operationalized as count variables. Place variable operationalization can be found in Table 3.4.

Table 3.4: Place Variable Operationalization by Statistical Analysis

Name	CACC	Negative Binomial
Barbershops/Salons	Dummy	Dummy*
Bars	Dummy	Count
Body Art Stores	Dummy	Dummy*
Bus Stops	Dummy	Dummy
Drug Treatment Facilities	Dummy	Dummy*
Entertainment Sites	Dummy	Dummy*
Everyday Stores	Dummy	Count
Gang Territory	Dummy	Dummy
Grocery Stores	Dummy	Dummy*
Hotels	Dummy	Dummy*
High Schools	Dummy	Dummy
Higher Education Institutions	Dummy	Dummy
Laundry	Dummy	Dummy*
Parks	Dummy	Dummy
Pawn Shops/Check Cashing Stores	Dummy	Dummy*
Public Housing Complexes	Dummy	Dummy
Public Libraries	Dummy	Dummy*
Recreation Centers and Pools	Dummy	Dummy
Restaurants	Dummy	Count
Retail Stores	Dummy	Count

Notes: * While operationalized as counts, variable acted as dummy due to maximum count of one on any street block

Accounting for potential spatial autocorrelation was the second difference between the usage of facilities data in CACC and count regression models. Spatially lagged variables of the facilities were created for both theoretical and practical reasons. Theoretically, previous crime and place research has shown that the criminogenic effect of places often extends into nearby areas (Groff, 2011; Bernasco & Block, 2011; Ratcliffe, 2012; Haberman & Ratcliffe, 2015). For example, violence from a bar on one street may spill over onto nearby streets. Failure to account for this effect reduces the applicability of count regression models, as important features of places are thus left out of statistical models. Practically, spatial autocorrelation violates the assumption of independent observations, thus, statistical models failing to account for it may lead to biased estimates (Anselin, 1988). In other words, without accounting for the potential influence of nearby places, the relationship between crime and place is not fully specified. The current study followed the lead of Bernasco and Block (2011) and Haberman and Ratcliffe (2015) by creating spatially lagged predictors, which have been shown to minimize spatial dependence.

Creating spatially lagged variables required creating a contiguity matrix that defined which units were considered neighbors. The current study used a first-order queen contiguity spatial weights matrix. In this case, spatial units defined as adjacent were those that "touch" the focal spatial unit at any point or edge. In terms of street blocks, adjacency simply meant those streets that intersect with one another. If the spatially immediate variable was operationalized as a count, then the spatially lagged version was also operationalized as a count of the variable across a unit's neighbors. For independent variables originally operationalized as indicator variables, spatially lagged predictors were only counted if the place was located on an adjacent block *but not* on the focal block. This is due to the operationalization of polygon data, which uses an indicator variable if that facility is accessible from a given street block. Thus, since multiple street blocks can experience a focal effect for the same facility, these street blocks were not double counted for spatial lag creation.

Previous crime and place research has recognized that even when accounting for potentially criminogenic facilities and land uses, certain structural variables remain important determinants of spatial crime patterns (e.g. Weisburd et al., 2012; Rice & Smith, 2002). Therefore, the current study accounted for the structural makeup of street blocks. Data for these measures came from the 2015 American Community Survey 5 year Census Block Group estimates. The four sociodemographic variables used in the current study were socioeconomic disadvantage, residential mobility, racial heterogeneity, and total residential population. Socioeconomic disadvantage was measured by the percentage of the population living at or below the poverty line. Residential mobility was measured as the percentage of the population that reported living at another location in the previous year. The racial heterogeneity measure used Gibbs and Martin's (1962) heterogeneity index, which subtracts from one the sum of the squared proportions of 1) white only; 2) African-American only; 3) Hispanic only; 4) Asian only; and 5) all other races. This created a variable with a lower bound of 0.0, indicating racial homogeneity, and an upper bound of 0.8, indicating racial heterogeneity. Recent crime and place research uses this same measure (Chainey and Ratcliffe, 2005; Haberman and Ratcliffe, 2015). Finally, the baseline population was captured in order to gauge the number of individuals living in the area. To create these measures, street blocks were assigned the above measures based on the census block in which it was located. In the case that a street block fell between two or more census blocks, they were assigned the mean of demographic measures of all adjacent census blocks.

Negative binomial regression models were estimated for each of the three measures to assess the extent to which certain facilities and control variables contributed to street block robbery patterns. Using Bernasco and Block's (2011) approach, models within each robbery measure were ran sequentially to assess the effects of each predictor as the model became more complex. Models for each robbery measure followed this order: (1) only spatially immediate place variables; (2) spatially immediate and lagged place variables; and (3) spatially immediate, spatially lagged, and sociodemographic controls. Only results from the full models were presented. Results tables include coefficients, standard errors, and incident-rate ratios (IRRs). IRRs were interpreted as the expected count change for a unit change in the independent variable. Subtracting one from the IRR and multiplying by 100 results in the percentage change of the dependent variable. A positive value is interpreted as the percentage increase in the expected count of street block robberies per unit-increase in the predictor, while negative values are the percentage decrease in the expected street block robbery count (Long & Freese, 2014).For example, an IRR of 1.7500 for the bars variable (operationalized as a count) would indicate that for every additional bar on a street block, the expected robbery count would increase 75% ((1.7500 - 1)*100 = 75). Table 3.5 shows the descriptive statistics for all variables used in the count regression models.

Table 3.5: Descriptive Statistics for All Model Variables

	Min	Max	Mean	SD
Total Robbery	0.0000	32.0000	0.3694	1.1939
PD Street Robbery	0.0000	18.0000	0.2649	0.8189
QC Opportunistic Robberies	0.0000	24.0000	0.2810	0.8855
Barbershops/Salons	0.0000	1.0000	0.0131	0.1136
Bars	0.0000	4.0000	0.0139	0.1404
Body Art Stores	0.0000	1.0000	0.0014	0.0369
Bus Stops	0.0000	1.0000	0.2876	0.4527
Drug Treatment Facilities	0.0000	1.0000	0.0037	0.0609
Entertainment Sites	0.0000	1.0000	0.0068	0.0823
Everyday Stores	0.0000	6.0000	0.0330	0.2159
Gang Territory	0.0000	1.0000	0.2012	0.4009
Grocery Stores	0.0000	1.0000	0.0023	0.0476
High Schools	0.0000	1.0000	0.0100	0.0995
Higher Education Institutions	0.0000	1.0000	0.0137	0.1163
Hotels	0.0000	1.0000	0.0023	0.0476
Laundry	0.0000	1.0000	0.0028	0.0530
Parks	0.0000	1.0000	0.0285	0.1665
Pawn Shops/Check Cashing Stores	0.0000	1.0000	0.0017	0.0415
Public Housing Complexes	0.0000	1.0000	0.0085	0.0920
Public Libraries	0.0000	1.0000	0.0015	0.0393
Recreation Centers and Pools	0.0000	1.0000	0.0035	0.0587
Restaurants	0.0000	15.0000	0.0522	0.3940
Retail Stores	0.0000	17.0000	0.0630	0.4944
SL Barbershops/Salons	0.0000	4.0000	0.0652	0.2813
SL Bars	0.0000	7.0000	0.0698	0.3456
SL Body Art Stores	0.0000	2.0000	0.0067	0.0828
SL Bus Stops	0.0000	1.0000	0.2592	0.4382
SL Drug Treatment Facilities	0.0000	2.0000	0.0187	0.1421

Table 3.5 (continued)

	Min	Max	Mean	SD
SL Entertainment Sites	0.0000	4.0000	0.0324	0.1900
SL Everyday Stores	0.0000	8.0000	0.1659	0.5223
SL Gang Territory	0.0000	1.0000	0.1191	0.3239
SL Grocery Stores	0.0000	2.0000	0.0109	0.1081
SL High Schools	0.0000	1.0000	0.0205	0.1418
SL Higher Education Institutions	0.0000	1.0000	0.0084	0.0910
SL Hotels	0.0000	2.0000	0.0122	0.1169
SL Laundry	0.0000	2.0000	0.0139	0.1216
SL Parks	0.0000	1.0000	0.0350	0.1837
SL Pawn Shops/Check Cashing Stores	0.0000	2.0000	0.0084	0.0920
SL Public Housing Complexes	0.0000	1.0000	0.0108	0.1034
SL Public Libraries	0.0000	1.0000	0.0078	0.0880
SL Recreation Centers and Pools	0.0000	1.0000	0.0160	0.1254
SL Restaurants	0.0000	18.0000	0.2573	1.0551
SL Retail Stores	0.0000	31.0000	0.3003	1.2486
Disadvantage	0.0000	93.8356	30.8944	20.2121
Residential Mobility	0.0000	78.3440	22.3156	13.0565
Racial Heterogeneity	0.0331	0.6720	0.3808	0.1619
Population/1000	1.5700	36.5500	10.8464	4.7448

Notes: Unit of analysis is street blocks (N = 11,008); SL = Spatially Lagged

Conclusion

The research questions proposed above were an attempt to assess the need for crime-specific dependent variables in crime and place research. While crime-general measures, such as multi-crime indices or broad crime categories, have been used in past research, they ignore the potential importance of crime specificity within criminal opportunity structures. The same can be said for police-designated street robbery measures, which may lack sufficient detail to accurately portray the types of crimes emphasized in environmental criminology. The current study was an attempt to test the sensitivity of robbery measures in Cincinnati, Ohio for crime and place research. The statistical analyses allowed these questions to be answered, allowing for an assessment of how crime and place research results may be sensitive to how crime is operationalized as well as a more precise understanding of how varying opportunity structures and behavioral settings influence the spatial locations of robbery events.

CHAPTER 4: RESULTS

Recall this study sought to address three main research questions:

RQ1: Do different robbery measures cluster spatially?

RQ2: Is the spatial clustering of robbery sensitive to the operationalization of the different measures?

RQ3: Is the relationship between facilities and robbery sensitive to the operationalization of the robbery dependent variable?

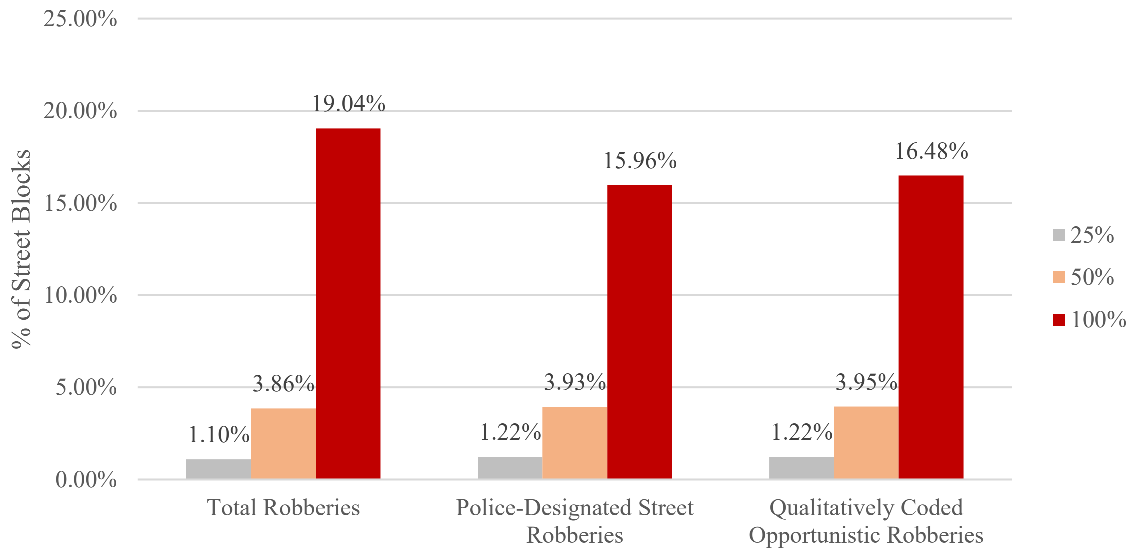
Chapter 4 presents the results of the analyses detailed in the previous chapter. The results are reported by research question.

Research Question 1: Do different robbery measures cluster spatially?

Robbery Concentration

Figure 4.1 illustrates each robbery measure's level of concentration at the street block level. The X-axis includes the three robbery measures as well as the percentage of robberies in the 25^{th}, 50^{th} and 100^{th} percentile. The Y-axis shows the percentage of street blocks that account for each percentile. Each robbery measure suggests a high level of concentration as predicted by environmental criminology (Weisburd, 2015). Half of total robberies from 2014 through 2016 occurred at only 3.86% of street blocks, and all robberies occurred at only 19%. A similar pattern emerged for both disaggregated robbery categories. Half of all police-designated street robberies and qualitatively coded opportunistic robberies occurred at 3.93% and 3.95% of street blocks, while all incidents within these categories occurred at 15.96% and 16.48%, respectively. These patterns closely follow the law of crime concentration, as it suggests an overwhelming majority of street blocks experienced few, if any, robbery events from 2014 through 2016. Robbery, no matter the operationalization, appears to cluster spatially.

Figure 4.1: Street Block Robbery Concentration by Measure



Data Visualizations

Next, data visualizations were created in ArcMap 10.5.1 in order to display the spatial concentration of robberies throughout Cincinnati. Figures 4.2 to 4.7 visualize this spatial patterning using two types of data visualizations. First, maps of incident location points were created for each measure (Figures 4.2 to 4.4). For ease of interpretation, three point maps for different areas of the city are displayed: (1) the western, (2) central, and (3) eastern. Generally speaking, the western maps show the area of Cincinnati west of downtown/uptown areas, while the eastern maps show the area of Cincinnati east of those areas. These cutoffs were also chosen because they roughly coincide with the city's six police districts. Visualizations of the west side generally cover District 3, while visualizations of the east side generally cover District 2. The remaining police districts (Districts 1, 4, 5, and the Central Business District) are found in visualizations of central Cincinnati. Second, because these maps can be potentially difficult to interpret due to incident points “falling” on top of one another, another set of data visualizations show choropleth maps of street block robbery counts for each measure. The choropleth maps cover the entire city.

The point maps are discussed first. To aide this discussion, specific areas on the visualizations are marked by letters. [7] While the clustering discussed below is qualitative and open to interpretation, it generally suggests that robbery patterns in Cincinnati, no matter the operationalization, were clustered. Starting with Figure 4.2, Areas A-D show different parts of the west side where robberies tend to concentrate no matter which operationalization was used. That is, while these areas are only pointed out on the map for total robberies, they are also concentrations of both disaggregated categories. Area A, the intersection of Colerain Avenue and W. North Bend Road, is primarily commercial, although the areas immediately surrounding the intersection are residential. Area B includes a large number of robberies off Harrison Avenue, a major artery that runs through the west side. Harrison Avenue includes both commercial and residential places. Area C consists of commercial and residential areas east of Ferguson Road and south of Queen City Avenue, another major thoroughfare running through the west side. Finally, Area D points out a much larger cluster of robberies located in two Cincinnati neighborhoods, East Price Hill and West Price Hill. This area is also mixed in terms of commercial and residential areas, and includes a number of major streets, such as Glenway Avenue. Roughly 500 of the 4,066 robberies occurred in Area D.

Figure 4.4 includes five areas pulled out for further examination. Area A is located in the College Hill neighborhood of Cincinnati and includes the region south of W. North Bend Road near Hamilton Avenue. A majority of the over 100 robberies in this area were coded as either

[7] Letters depicting areas of the city for discussion were only included in one of the three maps within each small multiple. This was done simply as an aesthetic choice: each area discussed includes clusters for all three types of robbery

police-designated street robberies or qualitatively coded opportunistic robberies, hence why it appears to be a cluster for all three operationalizations. Area B includes two smaller clusters, both in the Winton Hills neighborhood. Unlike many of the previously discussed clusters, Area B is almost entirely residential. Both the northern and southern clusters of Area B are located at public housing communities. Area C is located in the Northside neighborhood of Cincinnati. This cluster is comprised of a number of busy commercial streets, including Colerain Avenue to the west and Hamilton Avenue near the middle of the cluster. This cluster is primarily commercial areas with interspersed residences throughout. Areas D and E are large clusters of robbery activity and include the neighborhoods of Avondale and Walnut Hills (Area D), and Over-the-Rhine, West End, and the Central Business District (Area E). These neighborhoods are locally known as high-crime areas (each in the top 10 of most robberies by neighborhood) and collectively include over 30% (N = 1,227) of the total robberies in the city from 2014 to 2016.

Figure 4.5 includes four areas highlighted for further analysis. Areas A, B, C, and D are similar in terms of their clusters and makeup. Area A includes the neighborhoods of Pleasant Ridge and Kennedy Heights, Area B shows a cluster in the Madisonville neighborhood, Area C is located in Evanston, and Area D is in Mt. Washington. The robberies in each area cluster around a major road that houses many commercial businesses. Areas A and C are located near Montgomery Avenue, while Area B is located near Madison Road, and Area D is located near Beechmont Avenue. While most robberies in these areas occurred in commercial areas off these streets, the other robberies occurred primarily in residential areas a few blocks away.

Figures 4.5, 4.6, and 4.7 illustrate the street block concentration of total robberies, police-designated robberies, and qualitatively coded robberies, respectively. Street blocks were visualized based on the number of robberies that occurred on the segment. The street block count choropleth maps make visualizing overall spatial patterns much simpler. Grey streets indicate street blocks with no robberies over the three year study period, while those that did experience a robbery were coded from dark green to dark red, depending on the robbery count. These maps visualize the concentration suggested in Figure 4.1: while most street blocks were crime-free (grey) or low-crime (green), very few experienced a majority of robbery events from 2014 to 2016 (orange/red). These visualizations also suggest that while certain areas in the western and central portions of the city experienced high street-block level robbery concentrations, the problem of robbery itself is not entirely a neighborhood issue. While not a statistical test, this generally supports Groff et al. (2010) and Weisburd et al. (2012), who note that crime varies greatly from street block to street block.

Figure 4.2: Robbery Incident Locations (Westside)

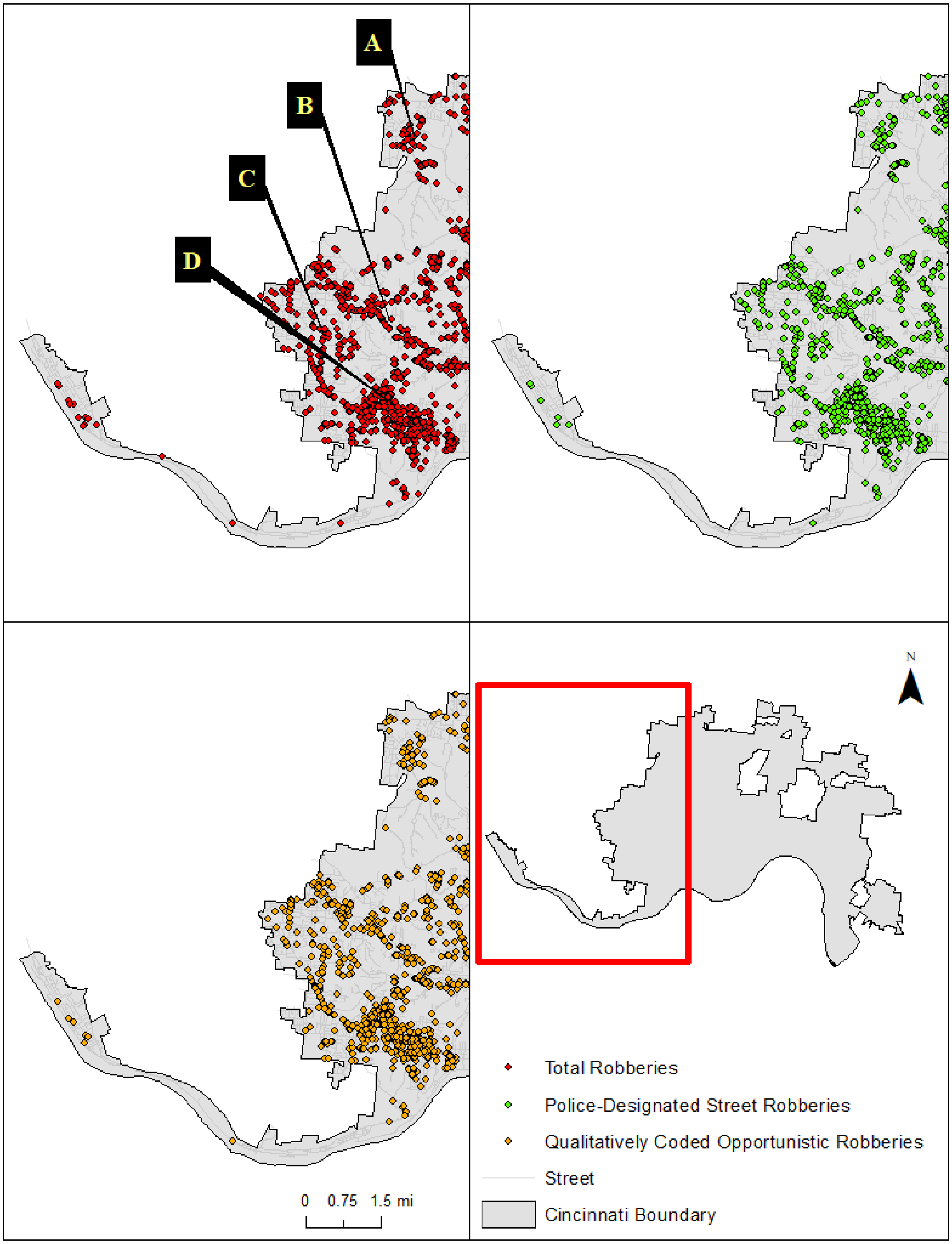


Figure 4.3: Robbery Incident Locations (Central)

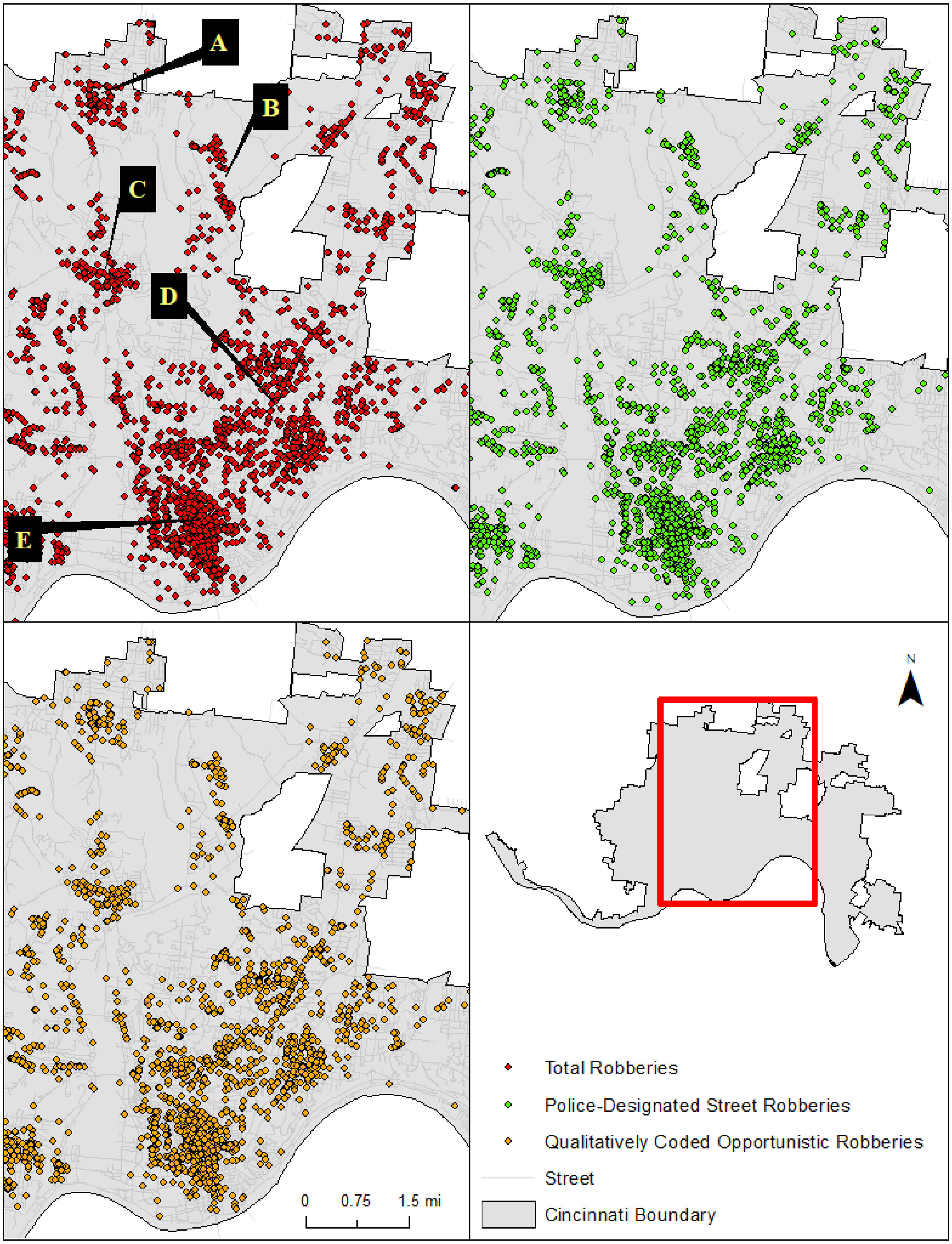


Figure 4.4: Robbery Incident Locations (Eastside)

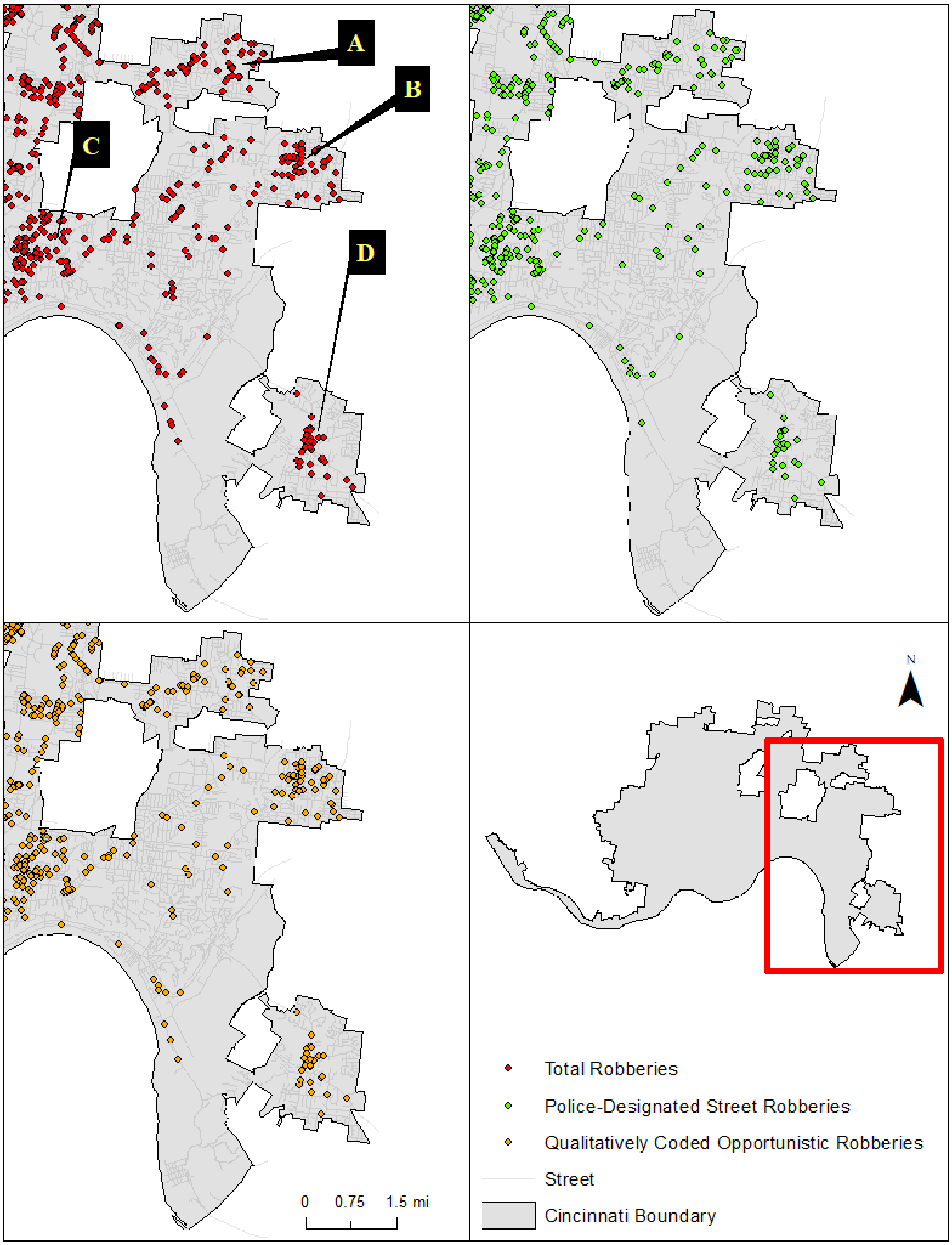


Figure 4.5: Total Robbery Street Block Counts

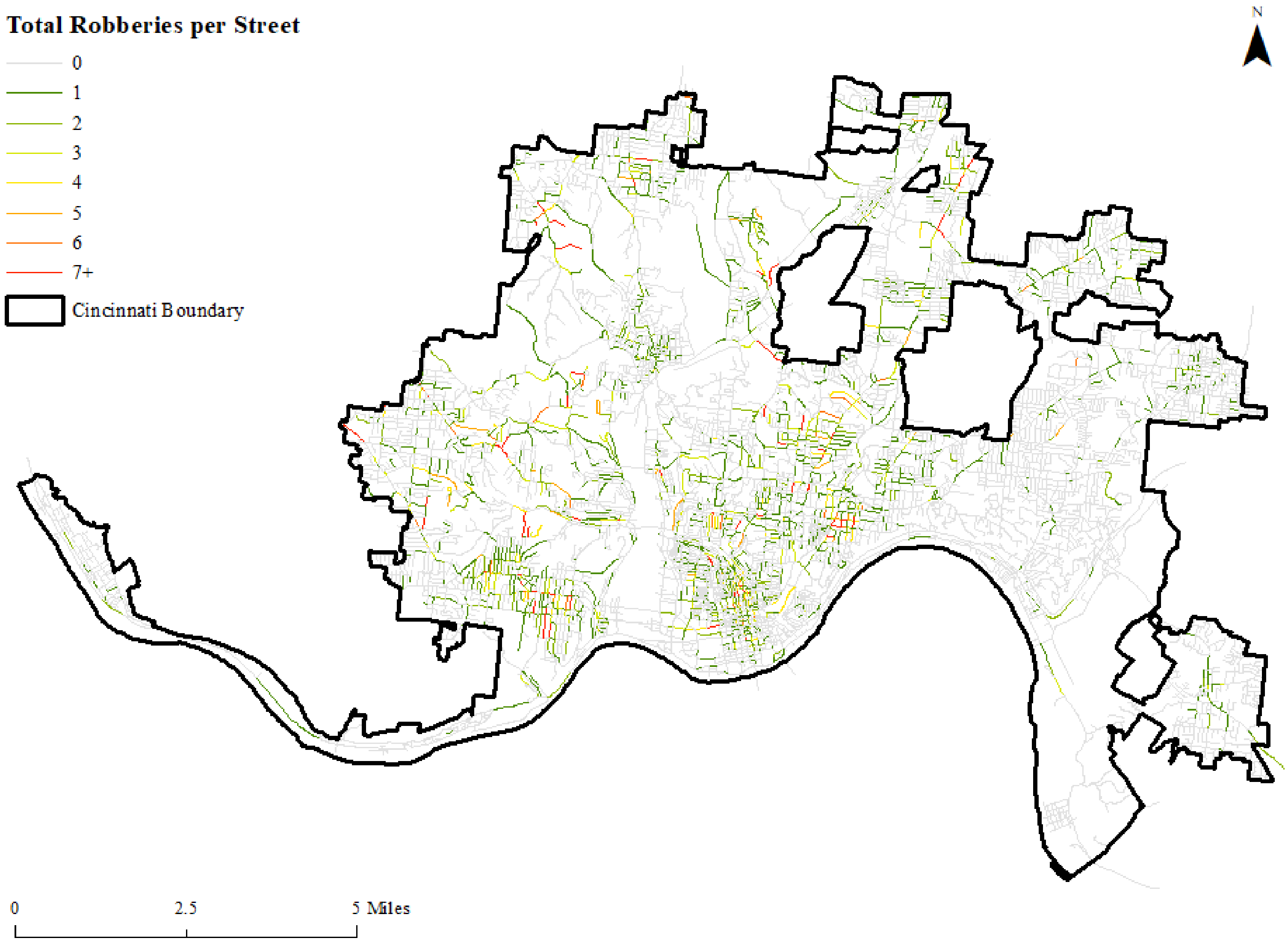


Figure 4.6: Police-Designated Street Robbery Street Block Counts

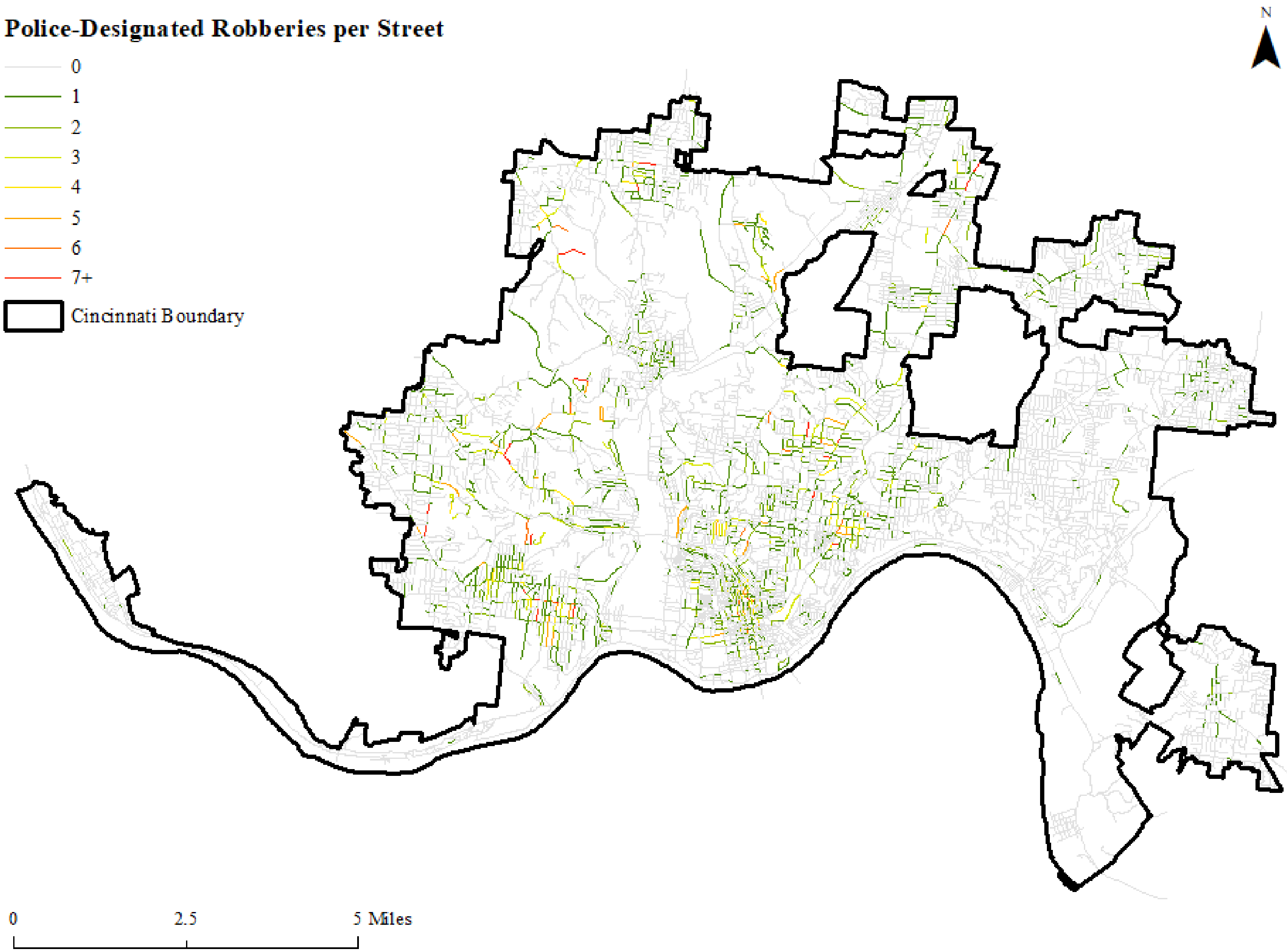
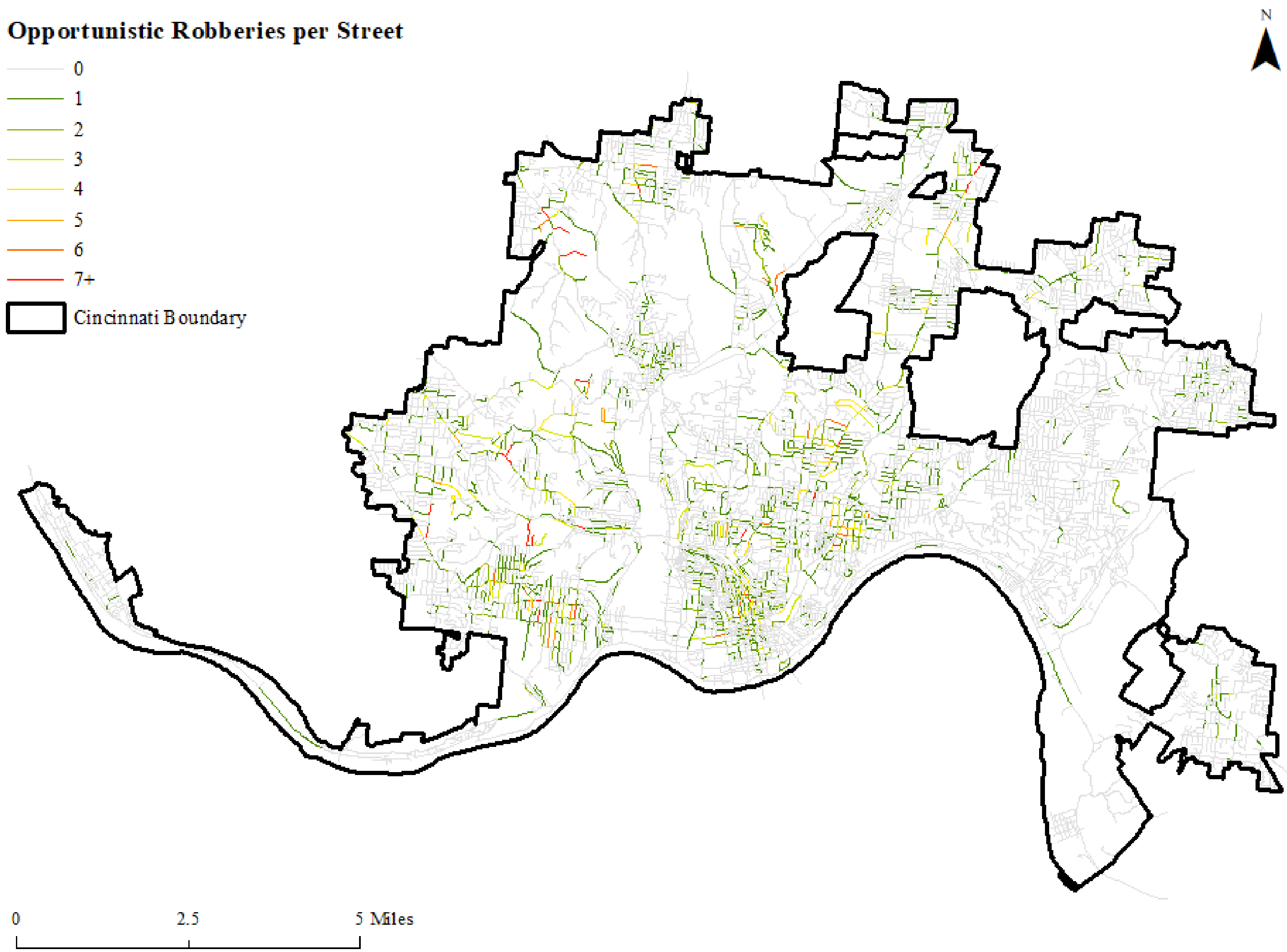


Figure 4.7: Qualitatively Coded Opportunistic Robbery Street Block Counts



Ripley's K

Ripley's K is a statistic showing the non-randomness of point data at different spatial scales (Levine, 2015). Figures 4.8, 4.9, and 4.10 show the Ripley's K analysis for total robberies, police-designated street robberies, and qualitatively coded opportunistic robberies, respectively. Each figure consists of four lines: the L(t) function, a line representing complete spatial randomness, and the minimum/maximum boundaries for the distance band created using 100 simulations. Comparing the L(t) function to the minimum/maximum "envelope" is essentially a non-parametric/simulated significance test, allowing for an approximate consideration regarding whether the distribution of points is clustered based on chance or not (Levine, 2015).

Analyses of Ripley's K for all robbery measures indicate a large amount of spatial clustering. The amount of spatial clustering increases up to around .8 miles then begins to decline as distances increase. That is, the highest amount of clustering occurs within a mile of each robbery incident for all measures. The level of clustering approaches complete randomness as one nears a distance of three miles. In sum, the Ripley's K analysis suggests that all three robbery measures are spatially clustered, which was would be expected based on previous research on crime patterns. This mirrors the findings of street block concentration levels shown in Figure 4.1.

Figure 4.8: Ripley's K Analysis for Total Robberies

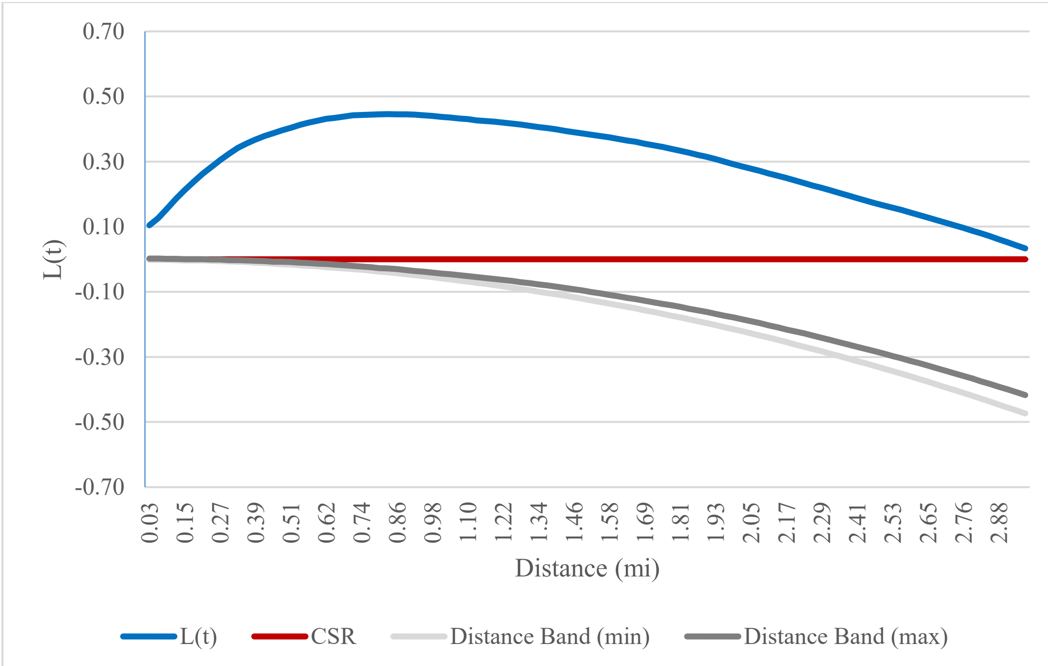


Figure 4.9: Ripley's K Analysis for Police-Designated Street Robberies

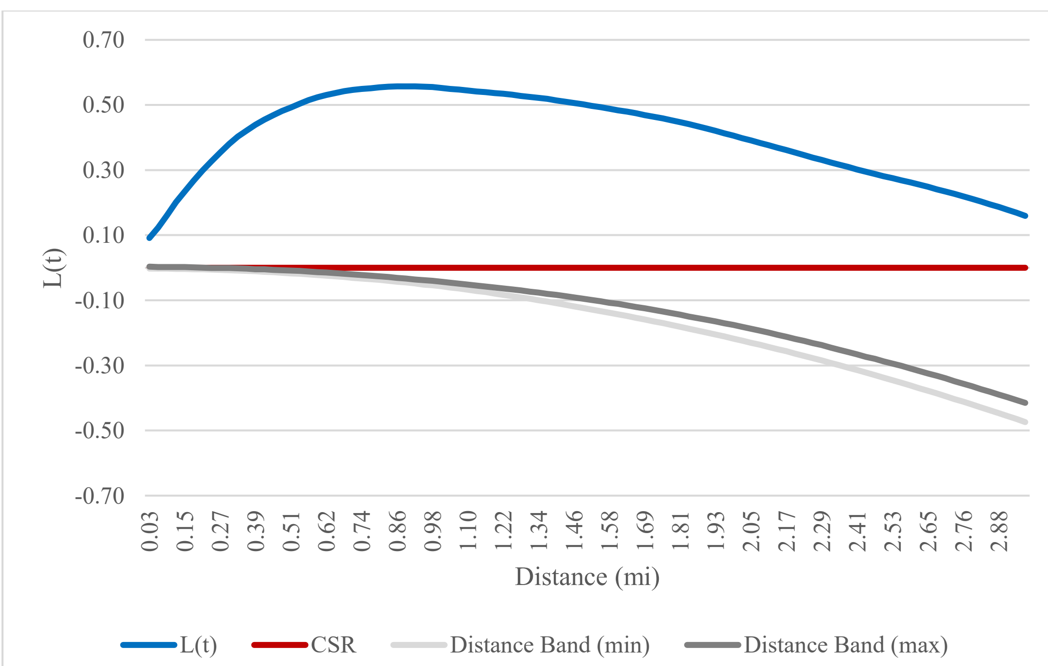
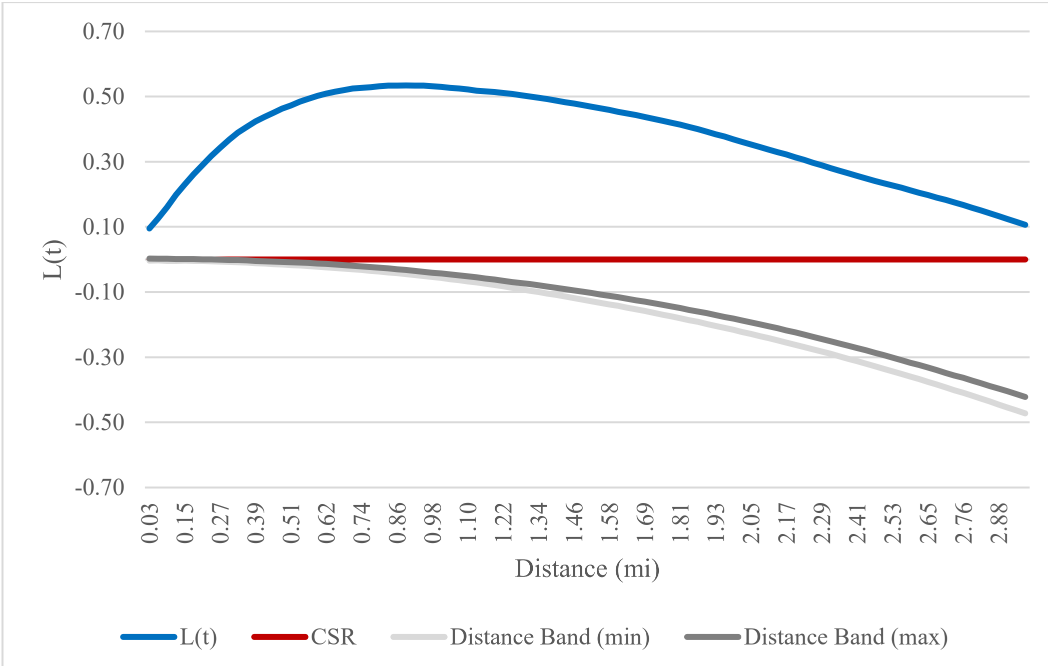


Figure 4.10: Ripley's K Analysis for Qualitatively Coded Opportunistic Robberies



Hierarchical Nearest Neighbor Clusters

First-order cluster information is provided in Table 4.1. Overall, the results suggest that while total robberies appear to differ, at least in terms of the number of first-order clusters and their average size, both disaggregated robbery types demonstrated very similar patterns. The overall number of total robbery clusters (N = 72) exceeded the number of police-designated (N = 44) and qualitatively coded clusters (N = 45), although their average area in square miles (N = 0.0038) was smaller than the disaggregated robbery categories (0.0065 and 0.0069). As an example, an American football field is roughly 0.0021 square miles, thus the average total robbery first-order cluster was roughly the size of two American football fields, while the size of an average disaggregated robbery cluster was about three football fields (Goodell, 2017). Other descriptive information indicates clusters for all measures are similar. For instance, the average cluster included around 17 incidents, no matter which robbery type was examined. Some first-order clusters were almost negligible in terms of area. These tend to occur on high-crime street blocks, thus creating a small, street-sized cluster. Most, however, were much larger than a single street block. Going back to the NFL field analogy, 50 total robbery clusters, 40 police-designated robbery clusters, and 40 qualitatively coded robbery clusters were larger than a football field.

Table 4.1: Nnh 1st Order Cluster Descriptive Statistics

	Total Robberies	Police-Designated Street Robberies	Qualitatively Coded Opportunistic Robberies
Number of clusters	72	44	45
Mean robberies per cluster	16.68	16.86	17.04
Mean area (square miles)	0.0038	0.0065	0.0069
Total area (square miles)	0.27	0.30	0.29
Percentage of robberies	29.54	25.45	24.80
Percentage area	0.34	0.38	0.36

Research Question 2: Is the spatial clustering of robbery sensitive to the operationalization of the different measures?

<u>Overlap Analysis</u>

As the analyses for research question 1 suggested, all robbery outcomes exhibited spatial clustering. Therefore, to better understand the clustering of the three robbery measures, research question two focused on whether clustering differed by robbery type. First, it was necessary to examine the overlap among robbery outcomes. Again, all police-designated street robberies and qualitatively coded opportunistic robberies were included in the total robbery outcome, and those two disaggregated robbery types were not mutually exclusive. If, for example, an overwhelming majority of total robberies were included in one or both of the disaggregated outcomes, then spatial clustering would look the same. Additionally, if police-designated robberies and qualitatively coded opportunistic robberies were perfectly correlated, those clusters would be the same as well.

Table 4.2 shows the overlap amongst the three robbery outcomes. The first two rows show the percentage of total robberies that were coded as police-designated street robberies and qualitatively coded opportunistic robberies, respectively. The majority of total robberies in Cincinnati were classified as the CPD definition of street robbery (N = 2,916; 71.72%) or the Haberman et al. (forthcoming) definition of opportunistic robberies (N = 3,093; 76.07%). Further, the third row shows that of the 2,916 police-designated street robberies, 2,640 (90.53%) were also operationalized as opportunistic robberies. Thus, while a sizeable percentage of total robberies were included in one or both of the disaggregated categories, a fair number of robberies in the city did not fit these definitions. These non-street, non-opportunistic robberies may influence the spatial patterning of total robberies while not affecting the patterning of either disaggregated robbery category.

Table 4.2: Robbery Variable Overlap Comparison

Overlap Variables	Count	Percentage
Police-Designated within Total	2,916	71.72
Qualitatively Coded within Total	3,093	76.07
Qualitatively Coded within Police-Designated	2,640	90.53

Notes: Total N = 4,066; Police-Designated N = 2,916; Qualitatively Coded N = 3,093;

Row 3 in Table 4.2 suggests a large amount of overlap between the two disaggregated robbery types, at least in terms of opportunistic robberies that are also street robberies. Table 4.3 further explores the overlap between these two robbery outcomes. In other words, how many robberies were only in police-designated street robberies, only in qualitatively coded opportunistic robberies, in both measures, or were in neither measure.

Overall, 3,369 robberies fell into at least one of the two crime-specific operationalizations (N = 82.86%), mirroring the results above. Nearly three quarters of those (N = 2,640) were coded as both police-designated street and qualitatively coded opportunistic. However, a number of cases coded as police-designated street robberies were *not* operationalized as qualitatively coded opportunistic robberies, and vice versa. That is, 267 robberies were considered police-designated street robbery but not opportunistic, while 453 were considered opportunistic but not police-designated street robbery. So, while most robberies that fell into either/or disaggregated robbery categories fell into both (N = 78.36%; 2,640 of 3,369), over 20% (N = 729) fit only one of the two operationalizations. Thus, while these two robbery measures may share some patterns of spatial clustering, there exists the possibility that they differ in some ways.

Upon visual inspection of the data, the majority (N = 269; 59.38%) of the 453 robberies coded as opportunistic *but not* police-designated robbery had a CPD location code of a residence of some sort. Others failed to meet the CPD street robbery definition because of a facility-based location code. Thus, while these robberies involved offenders holding up victims in public or semi-public places, they were not captured by the police-designated, environmentally-based operationalization. Alternatively, the majority of robberies coded as street robberies by the police *but not* opportunistic robbery by Haberman et al. (forthcoming) involved disputes (N = 112; 40.58%) among known parties or incidents where the victim was specifically lured to the robbery location (N = 88; 31.88%), thus not representing the serendipitous nature of offender-victim convergence that is commonly used to describe "street robberies". In sum, Table 4.3 suggests that simply using categorical variables in police data fails to capture the types of robbery emphasized by environmental criminology.

Table 4.3: Overlap Comparison of Robberies Coded as Police-Designated Street Robbery and/or Qualitatively Coded Opportunistic Robbery (2014 to 2016 Three-Year Totals)

		Qualitatively Coded Opportunistic Robberies	
		Yes	No
Police-Designated Street Robberies	Yes	2,640 (64.93%)	276 (6.79%)
	No	453 (11.14%)	697 (17.14%)

Note: Robberies in the No/No cell are all robberies that failed to meet either operationalization

The next step in analysis of research question 2 used the first-order Nnh clusters described above. Visualizations of all clusters, including areas where all cluster measures overlap, are located in Figures 4.11, 4.12, and 4.13. Like the location maps above, these visualizations are separated by area of the city and include letter call-out boxes for ease of interpretation. These visualizations allow the viewer to see how and where hot spot clusters differ or overlap based on operationalization.

Figure 4.11 shows the western portion of the city and includes three areas for further analysis. Area A includes a grouping of clusters in East Price Hill and West Price Hill, most occurring near Warsaw Avenue and Glenway Avenue. Eight “overlap clusters” can be seen here, indicating that these areas of the city are robbery hot spots no matter which operationalization was used. Five of these overlap clusters occur directly off Warsaw Avenue, a busy thoroughfare in western Cincinnati. Areas B and C, however, indicate places where a total robbery cluster and qualitatively coded opportunistic cluster are in close proximity, but where no police-designated street robbery clusters were located. It appears in these areas, operationalization influenced whether or not these places were considered hot spots or not. Figure 4.12 shows Nnh clusters in central Cincinnati, with two areas highlighted for explanation. Area A includes the neighborhoods of Over-the-Rhine, West End, Pendleton, and the Central Business District. There are a large number (N = 54; 33.54% of all first-order clusters) of clusters, albeit not all overlapping. This is clearly a robbery problem area. The variation in cluster type demonstrates that, depending on robbery operationalization, some streets/blocks/places may be considered a hot spot for one robbery definition but not others. Area B, a grouping of clusters in Walnut Hills, demonstrates the same point.

Figure 4.13 shows the only two clusters on the eastern side of the city. Area A shows two clusters in the Evanston neighborhood located on Montgomery Avenue just south of Dana Avenue. Two clusters overlap here: a total robbery cluster and a police-designated street robbery cluster. Again, it appears that operationalization influences some hot spot clustering locations. Area B indicates a small cluster the size of a street block. This cluster (while difficult to see) is a total robbery cluster only. Overall, despite the high level of overlap among measures (see Tables 4.2 and 4.3), the locations of Nnh spatial clusters suggest the importance of operationalization on spatial clustering.

Figure 4.11: First-Order Nnh Cluster Locations (Westside)

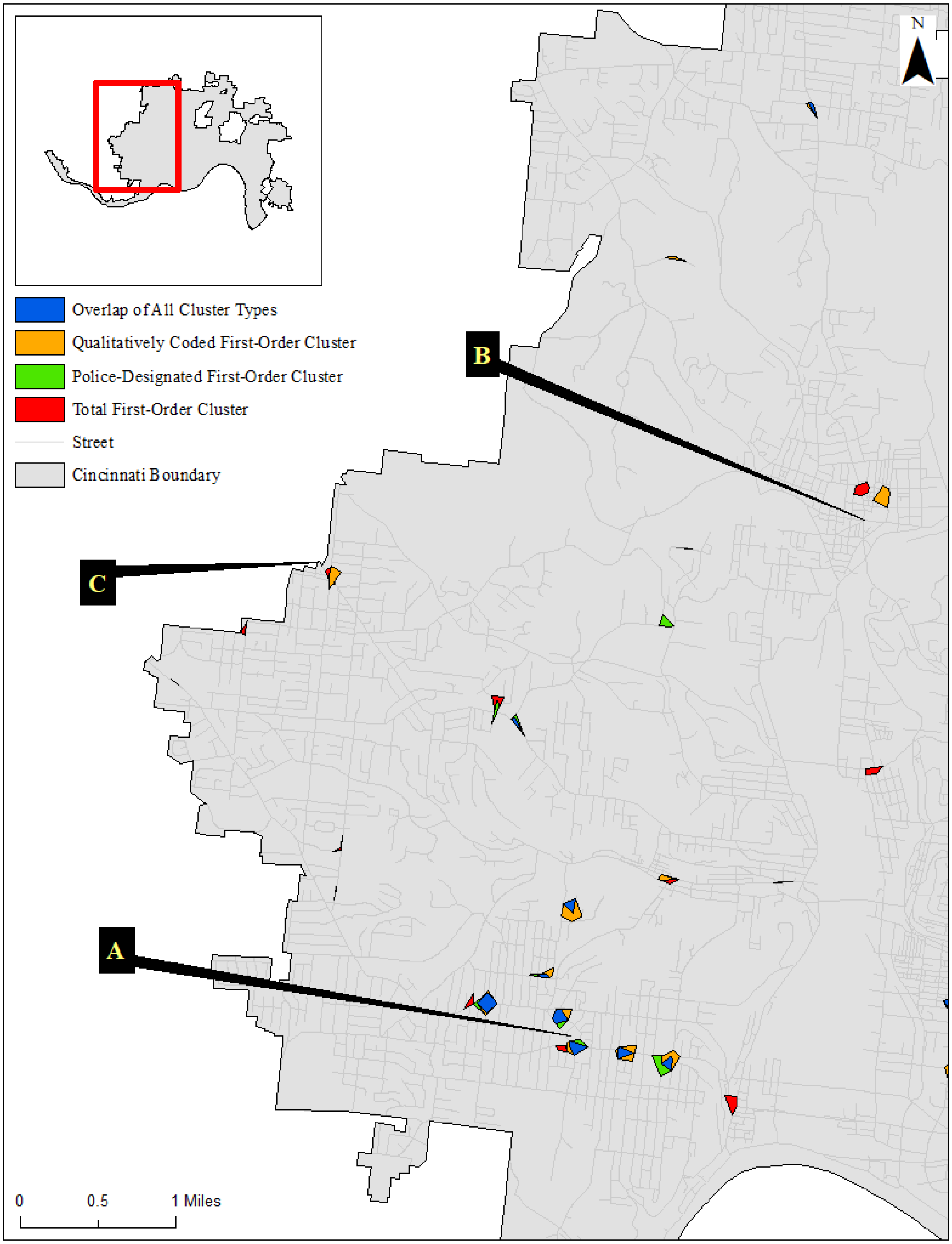


Figure 4.12: First-Order Nnh Cluster Locations (Central)

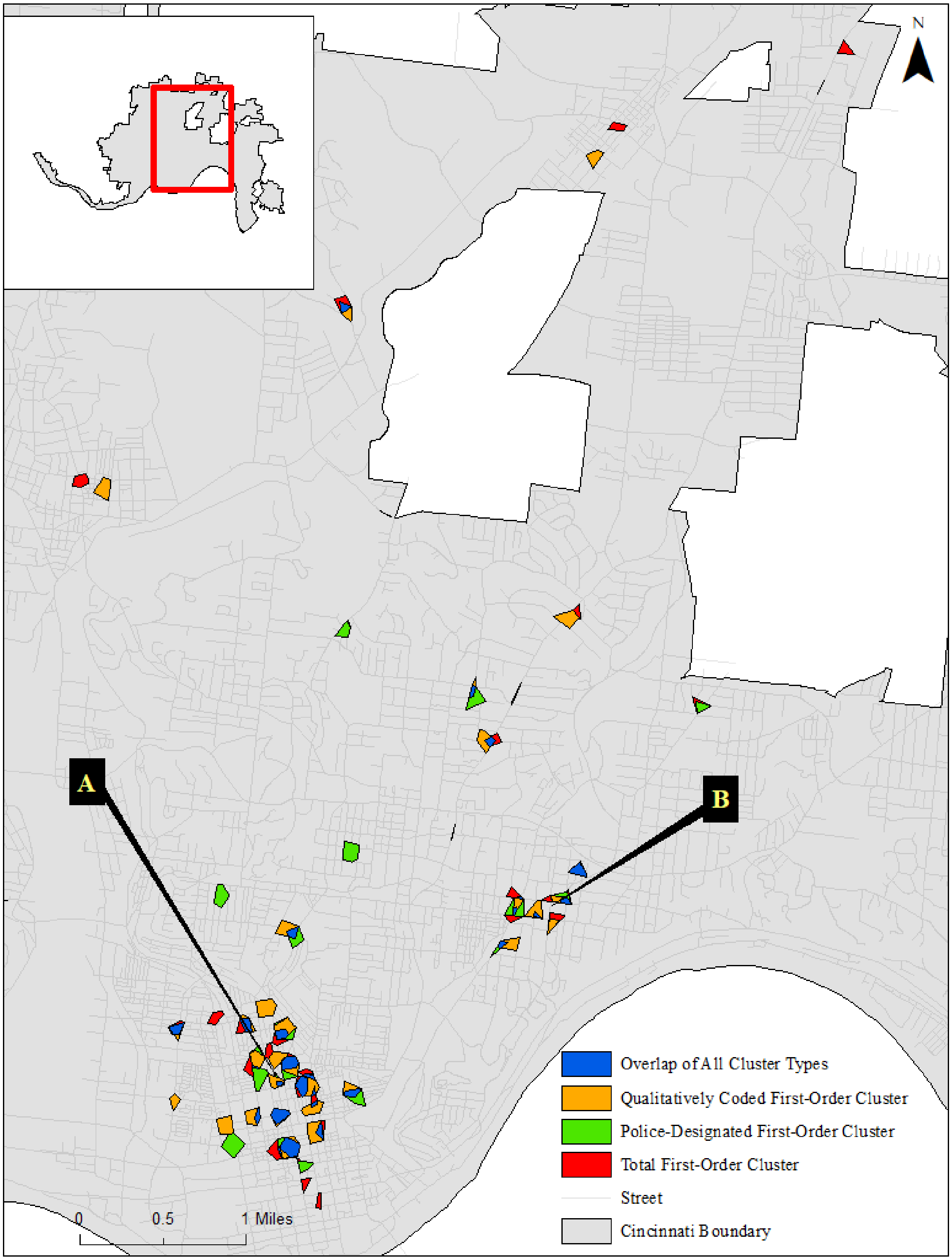
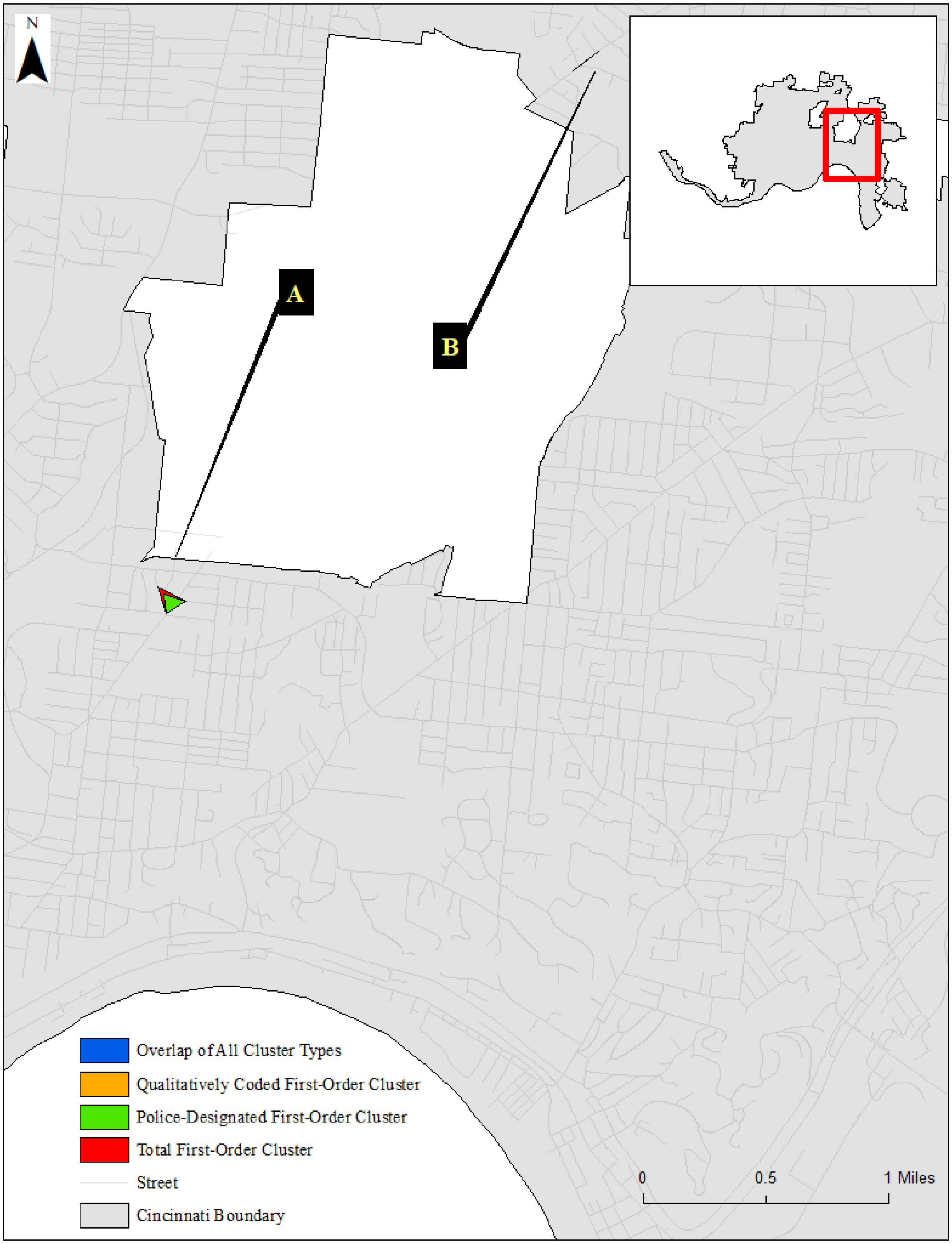


Figure 4.13: First-Order Nnh Cluster Locations (Eastside)



Concentration Comparison

Next, street block robbery counts were examined by robbery measure to assess the level of spatial clustering. Figure 4.1 suggested that robberies for all measures were highly concentrated at the street block level. Table 4.4 below further illustrates that concentration by breaking down each robbery measure by street block count. That is, street blocks were categorized based on the number of robberies they experienced over the study period. Consistent with previous research, no matter the measure used, the overwhelming majority of street blocks in Cincinnati did not experience a robbery of any type over the three-year study frame (80.96% for total robberies, 84.04% for police-designated street robberies, and 83.52% for qualitatively coded opportunistic robberies). When examining counts for those street blocks that did experience at least one robbery event, some patterns emerged that suggest the disaggregated measures differ slightly from the total robbery measure in terms of street block concentration. A comparison of street blocks that experienced two or more robberies shows that high total robbery street blocks (N = 787) outnumber high police-designated (N = 568) or qualitatively coded (N = 602) robbery street blocks. When looking at the highest street block count category (7+ robberies on a street block), this pattern continues; a higher percentage of street blocks experiencing 7+ total robberies (N = 0.64%) was seen when compared to police-designated (N = 0.21%) and qualitatively coded (N = 0.24%) robberies. One potential explanation for this is the lack of commercial robberies in the police-designated and qualitatively coded measures. That is, street blocks that experienced large numbers of commercial robberies, but no other types, would be categorized into the robbery-free row for the disaggregated measures.

Table 4.4: Distribution of Robberies by Frequency of Occurrence on Street Blocks

	Total Robberies (N = 4,066)			Police-Designated (N = 2,916)			Qualitatively Coded (N = 3,093)		
# of Robberies	**# of Street Blocks**	**Pct.**	**Cum. Pct.**	**# of Street Blocks**	**Pct.**	**Cum. Pct.**	**# of Street Blocks**	**Pct.**	**Cum. Pct.**
0	8912	80.96	80.96	9251	84.04	84.04	9194	83.52	83.52
1	1309	11.89	92.85	1189	10.8	94.84	1212	11.01	94.53
2	389	3.53	96.38	315	2.86	97.70	316	2.87	97.40
3	169	1.54	97.92	109	0.99	98.69	132	1.20	98.60
4	82	0.74	98.66	63	0.57	99.26	74	0.67	99.27
5	42	0.39	99.05	37	0.34	99.60	29	0.27	99.54
6	34	0.31	99.36	21	0.19	99.79	25	0.22	99.76
7+	71	0.64	100.00	23	0.21	100.00	26	0.24	100.00

Notes: # of Robberies = Number of robberies that occurred on a street block, ranging from zero to seven or more; # of Street Blocks = number of street blocks (N = 11,008) that experienced *x* # of robberies; Pct. = percent of observed street blocks that experienced *x* # of robberies; Cum. Pct. = cumulative percent

<u>*Hot Spot Analysis*</u>

The next set of analyses grouped robberies into hot spots at the street block level (see Tables 4.5 through 4.8). The tables are constructed as follows. The left column provides street block hot spot classifications by robbery outcome. In other words, the measures classify street blocks by whether or not the street block would have been classified as a hot spot for each of the robbery outcome measures. The possible classifications include: (1) street block was never a hot spot; (2) street block was a hot spot for all robbery operationalizations; (3) street block was only a hot spot for total robberies; (4) street block was a hot spot for total robberies and police-designated street robberies; and (5) street block was a hot spot for total robberies and qualitatively coded opportunistic robberies. As stated in Chapter 3, street blocks were considered hot spots if they experienced a certain number of robberies. To ensure that the results are not sensitive to any one cutoff, analyses were completed using cutoffs of at least two, three, four, and five robberies per street block.

Overall, these results suggest, to varying degrees, how robbery was operationalized influenced which streets one would consider a hot spot.[8] If operationalization did not matter, then all hot spots would fall into category 2 (hot spot for all measures) due to a complete overlap of operational definition. However, as discussed above, the overlap of disaggregated robbery types was not perfect. Because of this, a number of street blocks experienced higher amounts of one type of disaggregated robbery but not the other. To use an example from below, Table 4.8 shows the hot spot breakdown when using the strictest definition (HS >= 5). Nineteen street blocks experienced at least five robberies that fit the police designation, but less than five that were coded as opportunistic. Eighteen street blocks experienced at least five robberies that fit the opportunistic definition, but less than five that were coded as police-designated as well. If a crime analyst was attempting to find all the street block hot spots for police-designated street robberies, they would be missing out on 18 street blocks that fit a similar definition. In other words, operationalization can influence how researchers and crime analysts identify spatial clusters.

The analysis also suggests that using total robberies leads to a higher number of identified hot spots. Using Table 4.8 again, the number of hot spots identified using total robberies was 147. Alternatively, using only police-designated robberies or qualitatively coded robberies, one would end up with 81 or 80 hot spots, respectively. This could have multiple consequences for police, as it could both spread resources too thin as well as send officers to hot spots where their presence may not deter crime (see implications in Chapter 5). That said, Tables 4.5 through 4.8 generally suggest that the most frequent category of hot spots, no matter which definition used, is that where

[8] These results also provide further support to findings from research question 1, as most street blocks were never considered a hot spot no matter how defined

a street block is a hot spot for all robbery operationalizations. Thus, many of those hot spots identified using total robberies are also hot spots for the disaggregated robbery measures as well.

Table 4.5: Street Block Hot Spots by Robbery Operationalization (HS >= 2)

Hot Spot by Measure	# Street Blocks	Percentage
Never a Hot Spot	10,222	92.85
Hot Spot for All Measures	518	4.71
Total Only Hot Spot	135	1.23
Total & Police-Designated Hot Spot	50	0.45
Total & Qualitatively Coded Hot Spot	84	0.76

Table 4.6: Street Block Hot Spot by Robbery Operationalization (HS >= 3)

Hot Spot by Measure	# Street Blocks	Percentage
Never a Hot Spot	10,611	96.38
Hot Spot for All Measures	231	2.10
Total Only Hot Spot	90	0.82
Total & Police-Designated Hot Spot	22	0.20
Total & Qualitatively Coded Hot Spot	55	0.50

Table 4.7: Street Block Hot Spot by Robbery Operationalization (HS >= 4)

Hot Spot by Measure	# Street Blocks	Percentage
Never a Hot Spot	10,780	97.92
Hot Spot for All Measures	125	1.14
Total Only Hot Spot	56	0.51
Total & Police-Designated Hot Spot	19	0.17
Total & Qualitatively Coded Hot Spot	29	0.26

Table 4.8: Street Block Hot Spot by Robbery Operationalization (HS >= 5)

Hot Spot by Measure	# Street Blocks	Percentage
Never a Hot Spot	10,862	98.67
Hot Spot for All Measures	62	0.56
Total Only Hot Spot	48	0.44
Total & Police-Designated Hot Spot	19	0.17
Total & Qualitatively Coded Hot Spot	18	0.16

Nnh Robbery Cluster Analysis

Further assessment of how robbery operationalization potentially influenced spatial patterns involved analyzing the Nnh clusters described above. Both total robbery and police-designated street robbery Nnh clusters were inspected in detail to assess the types of robberies included in each cluster. The analysis of total robbery clusters focused on the proportions of disaggregated robberies that made up each cluster, whereas the analysis of police-designated clusters focused on the overlap of the two disaggregated robbery types.

Total robbery Nnh clusters were looked at in greater detail to assess the types of robberies that made up each cluster. If, on one hand, total robbery clusters primarily consisted of street or opportunistic robberies, then they could be reliably used as a hot spot technique. If, on the other hand, they produce "false-positives" for street or opportunistic hot spots, then their utility should be questioned. Table 4.9 shows the analysis of the total Nnh clusters and includes the following data: (1) total number of robberies, (2) number of police-designated street robberies, (3) number of qualitatively coded opportunistic robberies, (4) number of robberies coded as both police-designated street and qualitatively coded opportunistic, (5) number of robberies coded as neither police-designated street or qualitatively coded opportunistic, (6) proportion of police-designated street robberies in the cluster, (7) proportion of qualitatively coded opportunistic robberies in the cluster, and (8) proportion of police-designated street and qualitatively coded opportunistic robberies in the cluster.

Table 4.9: Total Robbery Nnh Cluster Analysis

Cluster	Total Robberies	P	Q	P&Q	Not P&Q	P Proportion	Q Proportion	P&Q Proportion
1	14	14	14	14	0	1.00	1.00	1.00
2	39	37	39	37	2	0.95	1.00	0.95
3	15	14	14	14	1	0.93	0.93	0.93
4	12	11	12	11	1	0.92	1.00	0.92
5	25	25	23	23	2	1.00	0.92	0.92
6	11	11	10	10	1	1.00	0.91	0.91
7	21	21	19	19	2	1.00	0.90	0.90
8	10	10	9	9	1	1.00	0.90	0.90
9	15	15	13	13	2	1.00	0.87	0.87
10	14	12	13	12	2	0.86	0.93	0.86
11	14	12	12	12	2	0.86	0.86	0.86
12	20	18	17	17	3	0.90	0.85	0.85
13	19	17	17	16	3	0.89	0.89	0.84
14	12	10	12	10	2	0.83	1.00	0.83
15	12	10	11	10	2	0.83	0.92	0.83
16	12	11	11	10	2	0.92	0.92	0.83
17	12	11	10	10	2	0.92	0.83	0.83
18	11	9	11	9	2	0.82	1.00	0.82
19	16	13	15	13	3	0.81	0.94	0.81
20	23	18	20	18	5	0.78	0.87	0.78
21	12	10	11	9	3	0.83	0.92	0.75
22	12	10	10	9	3	0.83	0.83	0.75
23	12	11	9	9	3	0.92	0.75	0.75
24	11	8	11	8	3	0.73	1.00	0.73
25	15	11	15	11	4	0.73	1.00	0.73
26	23	17	17	16	7	0.74	0.74	0.70
27	13	10	10	9	4	0.77	0.77	0.69
28	13	10	10	9	4	0.77	0.77	0.69
29	22	15	16	15	7	0.68	0.73	0.68
30	42	30	40	28	14	0.71	0.95	0.67
31	12	9	10	8	4	0.75	0.83	0.67
32	12	10	8	8	4	0.83	0.67	0.67
33	15	12	10	10	5	0.80	0.67	0.67
34	17	14	11	11	6	0.82	0.65	0.65
35	14	10	12	9	5	0.71	0.86	0.64
36	11	7	8	7	4	0.64	0.73	0.64
37	14	11	10	9	5	0.79	0.71	0.64
38	27	18	21	17	10	0.67	0.78	0.63
39	24	17	18	15	9	0.71	0.75	0.63
40	13	9	8	8	5	0.69	0.62	0.62
41	10	6	7	6	4	0.60	0.70	0.60
42	17	11	14	10	7	0.65	0.82	0.59
43	38	23	27	22	16	0.61	0.71	0.58

Table 4.9 Continued

Cluster	Total Robberies	P	Q	P&Q	Not P&Q	P Proportion	Q Proportion	P&Q Proportion
44	24	15	16	14	10	0.63	0.67	0.58
45	24	14	16	14	10	0.58	0.67	0.58
46	14	10	10	8	6	0.71	0.71	0.57
47	16	11	11	9	7	0.69	0.69	0.56
48	11	6	9	6	5	0.55	0.82	0.55
49	11	8	8	6	5	0.73	0.73	0.55
50	13	7	8	7	6	0.54	0.62	0.54
51	15	8	11	8	7	0.53	0.73	0.53
52	17	10	12	9	8	0.59	0.71	0.53
53	15	8	8	8	7	0.53	0.53	0.53
54	16	9	13	8	8	0.56	0.81	0.50
55	25	15	13	12	13	0.60	0.52	0.48
56	15	7	11	7	8	0.47	0.73	0.47
57	12	5	9	5	7	0.42	0.75	0.42
58	12	5	6	5	7	0.42	0.50	0.42
59	20	8	9	8	12	0.40	0.45	0.40
60	18	8	8	7	11	0.44	0.44	0.39
61	13	6	7	5	8	0.46	0.54	0.38
62	13	7	7	5	8	0.54	0.54	0.38
63	21	9	11	8	13	0.43	0.52	0.38
64	16	9	7	6	10	0.56	0.44	0.38
65	12	6	6	4	8	0.50	0.50	0.33
66	15	6	7	5	10	0.40	0.47	0.33
67	32	12	10	9	23	0.38	0.31	0.28
68	15	4	10	4	11	0.27	0.67	0.27
69	11	4	3	3	8	0.36	0.27	0.27
70	19	6	8	5	14	0.32	0.42	0.26
71	12	3	4	3	9	0.25	0.33	0.25
72	18	4	3	3	15	0.22	0.17	0.17

Notes: P = Police-Designated; Q = Qualitatively Coded; Table sorted by P&Q Proportion to show the range of clusters in terms of their ability to demonstrate potential for "false-positives"

Generally, total robbery clusters typically included a fair number of robberies coded as both police-designated street and qualitatively coded opportunistic robbery. Of the 72 total robbery Nnh clusters, 54 had a proportion of at least .5 of robberies that were coded as both police-designated street and qualitatively coded opportunistic robberies. In over 30% of total robbery Nnh clusters (N = 23) was the proportion .75 or higher. Similar proportions were found when using only police-designated or qualitatively coded robberies.

The influence of "false-positives", however, demonstrates the fallback of using total robberies. That is, how many of these 72 hot spots include less than 10 (the cutoff for Nnh cluster creation) disaggregated robbery types. In total, 28 clusters included less than 10 police-designated street robberies, and 23 included less than 10 opportunistic robberies. Thus, it appears that the issue of "false-positives" in using total robberies to identify hot spots in crime analysis may be a potential issue. That is, while the majority of total robbery Nnh clusters are made up of at least 50% of either/or disaggregated crime type, many of these clusters would not exist if solely relying on the types of robbery typically studied in environmental criminology. This might have the detrimental effect of sending limited police resources to areas where they are less effective.[9]

A similar question can be asked about the make-up of police-designated street robbery clusters and whether they produce "false-positive" hot spots for opportunistic robberies. Table 4.10 includes a similar analysis of police-designated street robbery Nnh clusters. The table includes the following information for all 44 first-order Nnh clusters of police-designated street robberies: (1) total police-designated street robberies, (2) robberies coded as both police-designated street and qualitatively coded opportunistic, (3) robberies coded as only police-designated street robbery, and (4) the proportion of incidents per cluster coded as both police-designated street and qualitatively coded opportunistic. In essence, this allowed for a further examination of the usefulness of crime analysis that focuses exclusively on environment-based coding of data. Overall, most of the police-designated street robberies that made up first-order clusters were also coded as opportunistic (N = 682; 91.91%). The lowest proportion of incidents per cluster coded as both was 0.71, with the majority (N = 30) of clusters having a proportion of 0.90 or higher.

[9] See Appendix B for further analysis of total robbery Nnh clusters, which focuses on comparing clusters with varying proportions of qualitatively coded opportunistic robberies.

However, while most of the robberies in these clusters fit both disaggregated definitions, it does not mean that one can substitute for the other. Figure 4.14 below visualizes only police-designated and qualitatively coded Nnh clusters in order to understand their overlap. While many Nnh clusters for both robbery categorizations overlap, there are still multiple areas throughout the city where the two do not converge. The orange clusters below in particular are hot spots that would not be obtained using only the police-designated street robbery definition. Thus, while overlap exists among clusters of the different robbery operationalizations, these analyses indicate that they are not perfect substitutes for one another. Therefore, researchers should fall back on the measure that best supports their research framework. In the current study, one that uses a framework based on environmental criminology, that measure is opportunistic robberies.

Table 4.10: Police-Designated Street Robbery Nnh Cluster Analysis

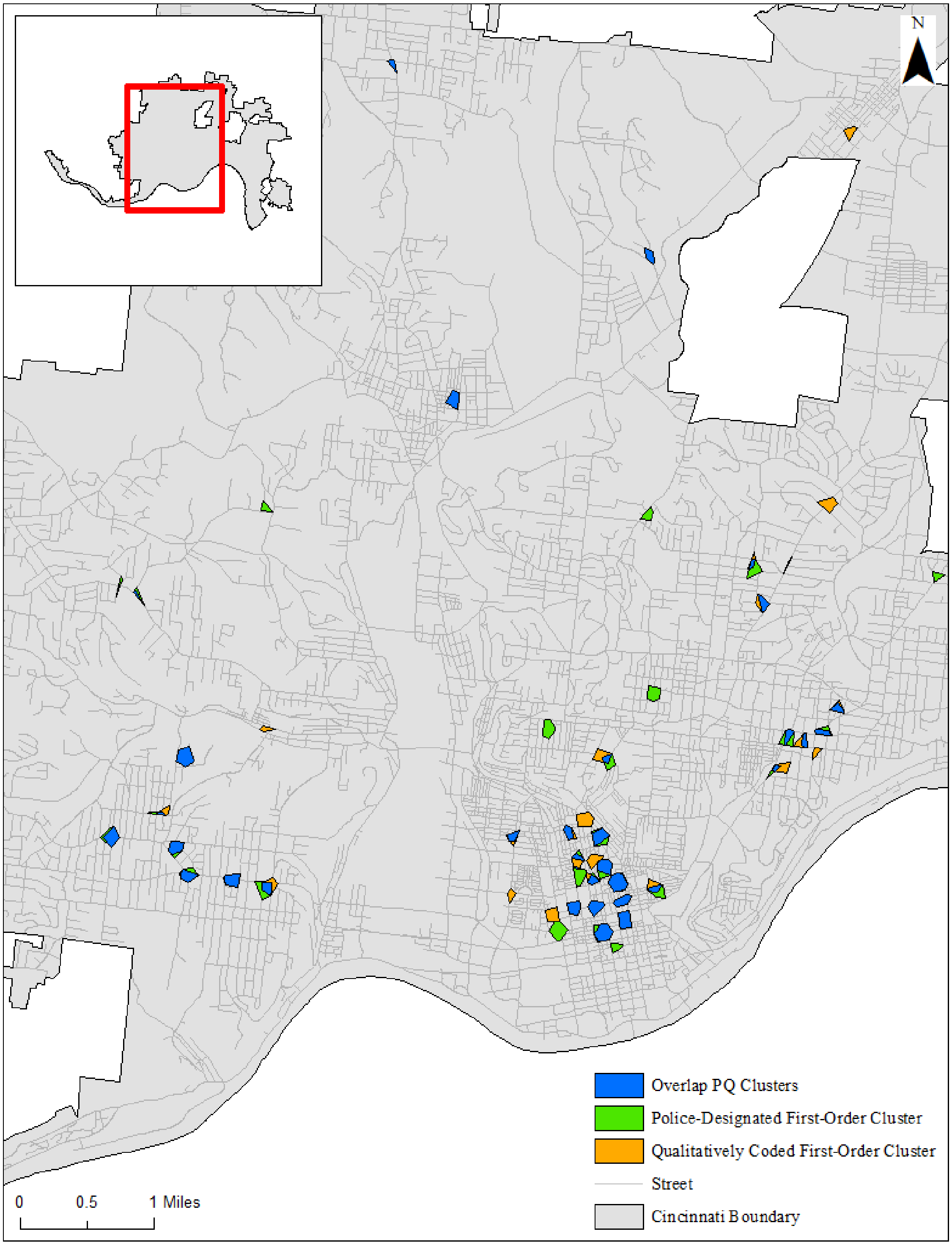
Cluster	Total N (P)	P&Q	P not Q	Proportion P and Q
1	46	45	1	0.98
2	31	29	2	0.94
3	35	33	2	0.94
4	22	20	2	0.91
5	26	24	2	0.92
6	26	25	1	0.96
7	23	21	2	0.91
8	23	23	0	1.00
9	21	20	1	0.95
10	10	8	2	0.80
11	20	19	1	0.95
12	20	19	1	0.95
13	19	15	4	0.79
14	19	17	2	0.85
15	14	12	2	0.86
16	18	18	0	1.00
17	17	16	1	0.94
18	10	9	1	0.90
19	17	17	0	1.00
20	10	8	2	0.80
21	16	15	1	0.94

Police-Designated Street Robbery Nnh Cluster Analysis (cont'd)

Cluster	Total N (P)	P&Q	P not Q	Proportion P and Q
22	16	16	0	1.00
23	16	15	1	0.94
24	15	13	2	0.87
25	15	13	2	0.87
26	14	14	0	1.00
27	14	12	2	0.86
28	14	14	0	1.00
29	14	11	3	0.79
30	14	13	1	0.93
31	14	10	4	0.71
32	13	10	3	0.77
33	13	10	3	0.77
34	13	13	0	1.00
35	13	11	2	0.85
36	12	12	0	1.00
37	12	12	0	1.00
38	11	10	1	0.91
39	11	9	2	0.82
40	11	10	1	0.91
41	11	10	1	0.91
42	11	10	1	0.91
43	11	11	0	1.00
44	11	10	1	0.91

Notes: P = Police-Designated; Q = Qualitatively Coded

Figure 4.14: Police-Designated and Qualitatively Coded Nnh Cluster Overlap



Note: Overlap PQ Clusters = areas where both police-designated and qualitatively coded Nnh clusters overlapped with one another; created by merging police-designated and qualitatively coded clusters together.

Research Question 3: Is the relationship between facilities and robbery sensitive to the operationalization of different measure?

The final research question was concerned with whether robbery operationalization had a differential impact on the relationship among potentially criminogenic places and crime. To assess this potential effect, two sets of analyses were performed: conjunctive analysis of case configurations (CACC) and count regression models. These analyses allowed for a comparison among robbery outcomes in terms of which, if any, facilities linked to crime. The facility data and operationalization of these data can be found in Table 3.4.

Conjunctive Analysis of Case Configurations

Results from the CACC analyses can be found in Tables 4.11, 4.12, and 4.13. Only dominant profiles are shown for ease of viewing. Of the 1,048,576 potential configurations possible with 20 dummy coded independent variables, only 288 were found in Cincinnati. The majority of streets in the city belong to the configuration with zero facilities located on the block (N = 5,959; 54.13%). An additional 14.83% (N = 1,632) of street blocks included only a bus stop and no other facility.

The CACC process for total robberies produced 37 profiles that met the minimum cell frequency cutoff of five. That is, 37 CACC "types" of streets in Cincinnati had average of at least five incidents per street. That said, as shown in the *n* column, *configurations meeting the cutoff are almost exclusively due to one or two problem streets within the same configuration*. For example, at the top of the list (sorted by average total robberies per configuration) is the configuration that includes the following facilities: restaurants, retail stores, grocery stores, bus stops, and gang territory. However, only one street in the city fit that configuration. That street, however, experienced 32 total robberies over the three-year period. This is generally the case for all configurations that met the cutoff. One configuration stands out, however. This configuration included restaurants, corner stores, bus stops, and gang territory. There were nine streets fitting this configuration that averaged over five robberies throughout the study period. Among the most common facilities found in the 37 dominant configurations were bus stops (33 profiles), everyday stores (28 profiles), restaurants (21 profiles), retail stores (20 profiles) and gang territory (20 profiles). Two types of facilities, body art stores and higher education institutions, were not found in any dominant profiles for total robberies.

There were far fewer (N = 14) dominant profiles of police-designated street robberies throughout the city. However, like the majority of total robbery dominant profiles, the CACC analysis showed that certain streets with rare combinations of facilities experienced very high levels of street robbery. For instance, two street block configurations experienced 13 street robberies over the study period. The first configuration included restaurants, retail stores, grocery stores, bus stops, and gang territory – the same configuration as the total robbery dominant profile with the highest number of incidents (see above). The second configuration included bars, restaurants, corner stores, retail stores, barbershops and salons, and bus stops. Unlike the total robbery CACC analysis*, no high-robbery CACC profile included more than two similar street blocks.* Some facilities, however, were common among the 14 dominant profiles, including bus stops (N = 12), gang territory (N = 11), restaurants (N = 10), retail stores (N = 9), and everyday stores (N = 8). Facilities not found in any dominant profiles included hotels, body art stores, laundromats and dry cleaners, public libraries, high schools, higher education institutions, and public housing communities.

The CACC results for qualitatively coded opportunistic robberies were nearly identical to the police-designated street robbery CACC results. Thirteen dominant profiles were found, almost all of which were street blocks with rare combinations of facilities. That is, no configuration had more than two street blocks that included that particular mixture of places. The most dominant profile (13 robberies; 2 streets in configuration) included the following places: everyday stores, retail stores, grocery stores, barbershops and salons, bus stops, and gang territory. Similar to dominant street robbery profiles, common facilities among the 13 configurations included gang territory (N = 12), bus stops (N = 11), everyday stores (N = 11), restaurants (N = 8), and retail stores (N = 8). Facilities not found in any of the dominant profiles included entertainment places, hotels, body art stores, public libraries, higher education institutions, and public housing communities.

Table 4.14 summarized the results of the CACC analyses and includes the number of dominant profiles as well as the occurrence of each facility in those profiles. Overall, the CACC analysis suggests that particular combinations of facilities do not necessarily drive robberies in Cincinnati no matter how they are operationalized. Rather, configurations with high occurrence (rather than high crime) tended to experience very low average levels of robbery. That said, the CACC analysis suggested that certain facilities potentially link to robbery regardless of the other facilities on the street block. These include bus stops, gang territory, everyday stores, retail stores, and restaurants. These five facilities were the most common facilities found in dominant profiles for each of the analyses, suggesting that their presence on a street block may produce higher than normal levels of robbery opportunity.

Table 4.11: Dominant Profiles for Total Robbery CACC Analysis

#	Bar	Rest	Chk	Evdy	Retail	Groc	Ent	Hotel	Rec	Laundry	Barber	T'x	Lib	Bus	HS	Parks	PubHou	Gang	*n*	Avg
1	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	1	1	32
2	0	1	0	1	1	0	0	0	0	0	1	1	0	1	0	0	0	1	1	20
3	0	0	0	1	1	1	0	0	0	0	1	0	0	1	0	0	0	1	2	19
4	0	1	0	1	1	1	0	0	0	0	1	0	0	1	0	0	0	0	2	15
5	1	1	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0	1	15
6	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	13
7	0	1	1	1	1	0	0	0	0	0	1	0	0	1	0	0	0	1	1	11
8	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	1	10
9	1	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	1	1	10
10	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	1	9
11	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1	2	8.5
12	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	7
13	0	1	0	1	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1	7
14	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	7
15	0	1	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	7
16	0	1	0	0	1	1	0	0	0	0	1	0	0	1	0	0	0	1	1	7
17	0	1	0	1	1	0	0	0	0	1	1	0	0	1	0	0	0	1	1	7
18	0	0	0	1	1	1	0	0	0	0	1	0	0	1	0	0	0	0	2	6.5
19	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	6
20	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	1	1	6
21	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	6
22	0	1	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	6
23	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	1	1	6
24	0	1	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	1	6
25	1	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	6
26	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	9	5.3
27	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	1	3	5.3

Table 4.11 Continued

#	Bar	Rest	Chk	Evdy	Retail	Groc	Ent	Hotel	Rec	Laundry	Barber	T'x	Lib	Bus	HS	Parks	PubHou	Gang	*n*	Avg
28	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	1	5
29	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	1	5
30	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	5
31	0	1	0	1	0	0	0	0	0	1	0	0	1	1	0	0	0	1	1	5
32	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	5
33	1	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	5
34	0	1	0	1	1	0	0	0	0	1	1	0	0	1	0	0	0	0	1	5
35	0	1	0	1	1	1	0	0	1	0	1	0	0	1	0	0	0	0	1	5
36	0	0	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0	1	1	5
37	1	1	0	0	1	0	1	0	0	0	1	0	0	1	0	0	0	1	1	5

Notes: 0 = Absence of facility in configuration; 1 = Presence of facility in configuration; *n* = number of streets in Cincinnati within the particular configuration; Avg = average number of robberies per street within each configuration; Facilities that were not present in any dominant profiles for total robberies were excluded, including body art stores and higher education institutions

Table 4.12: Dominant Profiles for Police-Designated Street Robbery CACC Analysis

#	Bar	Rest	Chk	Evdy	Retail	Groc	Ent	Rec	Barb	T'x	Bus	Park	Gang	*n*	Avg
1	0	1	0	0	1	1	0	0	0	0	1	0	1	1	13
2	1	1	0	1	1	0	0	0	1	0	1	0	0	1	13
3	0	1	0	1	1	0	0	0	1	1	1	0	1	1	11
4	0	0	0	1	1	1	0	0	1	0	1	0	1	2	10
5	1	1	1	1	1	0	0	0	0	0	1	0	1	1	7
6	0	0	0	0	1	0	0	0	0	0	1	1	1	1	6
7	0	1	0	1	0	0	0	0	0	0	1	1	1	1	6
8	0	1	0	1	0	0	0	1	0	0	0	0	1	1	5
9	0	1	0	0	1	0	1	0	0	0	1	0	0	1	5
10	0	0	0	0	0	0	0	0	0	1	1	0	1	1	5
11	1	0	0	1	0	0	0	0	0	0	0	0	1	1	5
12	0	1	1	0	0	0	0	0	1	0	1	0	1	1	5
13	0	1	0	1	1	1	0	0	1	0	1	0	0	2	5
14	1	1	0	0	1	0	1	0	1	0	1	0	1	1	5

Notes: 0 = Absence of facility in configuration; 1 = Presence of facility in configuration; *n* = number of streets in Cincinnati within the particular configuration; Avg = average number of robberies per street within each configuration; Facilities that were not present in any dominant profiles for total robberies were excluded, including body art stores, high schools, higher education institutions, hotels, laundromats and dry cleaners, public housing complexes, and public libraries

Table 4.13: Dominant Profiles for Qualitatively Coded Opportunistic Robbery CACC Analysis

#	Bar	Rest	Chk	Evdy	Retail	Groc	Rec	Laundry	Barber	T'x	Bus	HS	Park	Gang	*n*	Avg
1	0	0	0	1	1	1	0	0	1	0	1	0	0	1	2	13
2	1	1	0	1	1	0	0	0	1	0	1	0	0	0	1	13
3	0	1	0	1	1	0	0	0	1	1	1	0	0	1	1	12
4	0	1	0	0	1	1	0	0	0	0	1	0	0	1	1	10
5	1	1	1	1	1	0	0	0	0	0	1	0	0	1	1	9
6	0	1	0	1	1	0	0	1	1	0	1	0	0	1	1	7
7	0	0	0	0	1	0	0	0	0	0	1	0	1	1	1	6
8	0	0	0	1	0	0	0	0	0	0	1	1	0	1	2	6
9	0	1	1	1	1	0	0	0	1	0	1	0	0	1	1	6
10	0	1	0	1	0	0	1	0	0	0	0	0	0	1	1	5
11	0	1	0	1	0	0	0	0	0	0	1	0	1	1	1	5
12	0	0	0	1	0	0	0	0	0	1	1	0	0	1	1	5
13	1	0	0	1	0	0	0	0	0	0	0	0	0	1	1	5

Notes: 0 = Absence of facility in configuration; 1 = Presence of facility in configuration; *n* = number of streets in Cincinnati within the particular configuration; Avg = average number of robberies per street within each configuration; Facilities that were not present in any dominant profiles for total robberies were excluded, including body art stores entertainment places, higher education institutions, hotels, public housing communities, and public libraries.

Table 4.14: Facilities Common Among Dominant Profiles for All Robbery Outcomes

Variable	Total Robberies % (N)	Police-Designated % (N)	Qualitatively Coded % (N)
Barbershops/Salons	37.84 (14)	42.86 (6)	38.46 (5)
Bars	16.22 (6)	28.57 (4)	23.08 (3)
Body Art Stores	0.00 (0)	0.00 (0)	0.00 (0)
Bus Stops	89.19 (33)	85.71 (12)	84.62 (11)
Drug Treatment Facilities	16.22 (6)	14.29 (2)	15.38 (2)
Entertainment Sites	5.41 (2)	14.29 (2)	0.00 (0)
Everyday Stores	75.68 (28)	57.14 (8)	84.62 (11)
Gang Territory	54.05 (20)	78.57 (11)	92.31 (12)
Grocery Stores	21.62 (8)	21.43 (3)	15.38 (2)
High Schools	5.41 (2)	0.00 (0)	7.69 (1)
Higher Education Institutions	0.00 (0)	0.00 (0)	0.00 (0)
Hotels	2.70 (1)	0.00 (0)	0.00 (0)
Laundry	16.22 (6)	0.00 (0)	7.69 (1)
Parks	5.41 (2)	14.29 (2)	15.38 (2)
Pawn Shops/Check Cashing Stores	13.51 (5)	14.29 (2)	15.38 (2)
Public Housing Complexes	2.70 (1)	0.00 (0)	0.00 (0)
Public Libraries	2.70 (1)	0.00 (0)	0.00 (0)
Recreation Centers and Pools	5.41 (2)	7.14 (1)	7.69 (1)
Restaurants	56.76 (21)	71.43 (10)	61.54 (8)
Retail Stores	54.05 (20)	64.29 (9)	61.54 (8)

Notes: Total Robbery Dominant Profile N = 37; Police-Designated Street Robbery Dominant Profile N = 14; Qualitatively Coded Opportunistic Robbery Dominant Profile N = 13

Count Regression

The following section details the count regression analysis for Cincinnati street blocks. As discussed in Chapter 3, sequential modeling was conducted for the three robbery measures. For ease of interpretation, only the final models, which consisted of spatially focal, spatially lagged, and socio-demographic measures, are presented. AIC and BIC statistics indicated the final models were the best fit for each measure. Overall descriptive statistics for all model variables were shown in Table 3.5 in Chapter 3. Tables 4.15 through 4.17 show the negative binomial regression results estimating the effect of street block variables on total robberies, police-designated street robberies, and qualitatively coded opportunistic robberies, respectively. Table information includes variable coefficients, standard errors, and incident-rate ratios (IRRs).

Table 4.15 shows the results from the final negative binomial model that used total robberies as the dependent variable. Fourteen of the twenty spatially immediate facility variables were significantly linked to robbery. Expected robbery counts were higher for each additional bar (~68%), everyday store (~162%), restaurant (~21%), the presence of a bus stop (~190%), drug treatment facility (~140%), gang territory (~164%), grocery store (~203%), hotel (~139%), park (~36%), pawn shop/check cashing store (~107%), public housing complex (~117%), public library (~354%), or recreation center/pool (~155%). Additionally, the presence of a higher education facility on a street block significantly decreased the expected robbery count by around 53%. The spatially lagged variables for eight of these facilities (bars, bus stops, everyday stores, gang territory, hotels, parks, public libraries, and recreation centers/pool) were also significantly linked with higher expected robbery counts. Finally, all sociodemographic variables were positively and statistically significantly associated with higher robbery counts.

Table 4.16 illustrates the results from the final count models for police-designated street robberies. Twelve of the fourteen spatially immediate facility variables that were significant for total robberies were also significant (and in the same direction) for police-designated street robberies: grocery stores and hotels were no longer significant in this final model. IRRs for these variables were fairly consistent with those from the total robbery models, save for everyday stores, which saw a slight decrease in the expected count of street robberies per unit increase (~83%), as well as public libraries, whose presence on a street block led to higher counts of expected street robberies (~432%). Similarly, all but one spatially lagged facility (recreation centers/pools) were also positively associated with higher expected street robberies. All sociodemographic controls were significant and had similar IRRs to their counterparts in the total robbery model.

The final count regression model for qualitatively coded opportunistic robberies is shown in Table 4.17. Eleven spatially immediate facility variables obtained significance in the final model, all of which were also significant (and in the same direction) in the final models for total robberies and police-designated street robberies. In this model, pawn shops/check cashing stores dropped out of significance. In the case of the final opportunistic robbery model, the IRRs for significant variables remained fairly consistent as well, save for a few facilities. Drug treatment facilities obtained a lower IRR in this model, while the IRRs for everyday stores and public libraries mirrored those from the final police-designated street robbery model, both of which differed from their respective IRRs in the total robbery model. Spatially lagged were similar as well with a few exceptions. Unlike the total robbery and street robbery models, the spatially lagged effect of hotels disappeared in the opportunistic robbery model. Like total robberies, however, the spatially lag effect of recreation centers/pools was significantly and positively associated with expected opportunistic robbery counts. Interestingly, the spatially lag of laundromats and dry cleaners produced a significant but negative effect on expected opportunistic robberies. This effect was seen in the partial models for total robberies and police-designated street robberies, but disappeared once sociodemographic variables were introduced. Finally, like the other models, all sociodemographic controls were significant and positive.

Table 4.15: Total Robbery Negative Binomial Full Model

	Coef.	S.E.	IRR
Barbershops/Salons	0.0765	(0.1726)	1.0795
Bars	0.5197***	(0.1286)	1.6815
Body Art Stores	0.0690	(0.4260)	1.0715
Bus Stops	1.0631***	(0.0612)	2.8955
Drug Treatment Facilities	0.8765***	(0.2553)	2.4025
Entertainment Sites	0.2724	(0.2437)	1.3131
Everyday Stores	0.9624***	(0.0814)	2.6180
Gang Territory	0.9718***	(0.0556)	2.6427
Grocery Stores	1.1069***	(0.3015)	3.0251
High Schools	0.3061	(0.1904)	1.3581
Higher Education Institutions	-0.7593***	(0.2198)	0.4680
Hotels	0.8718*	(0.3567)	2.3911
Laundry	-0.1332	(0.3330)	0.8753
Parks	0.3050*	(0.1377)	1.3566
Pawn Shops/Check Cashing Stores	0.7298*	(0.3576)	2.0747
Public Housing Complexes	0.7757***	(0.1804)	2.1722
Public Libraries	1.5137***	(0.3701)	4.5436
Recreation Centers and Pools	0.9380***	(0.2819)	2.5548
Restaurants	0.1940***	(0.0589)	1.2141
Retail Stores	0.0874	(0.0448)	1.0913
SL Barbershops/Salons	-0.0500	(0.0887)	0.9512
SL Bars	0.1938**	(0.0620)	1.2138
SL Body Art Stores	0.0078	(0.2214)	1.0078
SL Bus Stops	0.5814***	(0.0645)	1.7885
SL Drug Treatment Facilities	0.1571	(0.1273)	1.1701
SL Entertainment Sites	-0.0331	(0.1178)	0.9675
SL Everyday Stores	0.2498***	(0.0408)	1.2838
SL Gang Territory	0.3945***	(0.0724)	1.4836
SL Grocery Stores	-0.1139	(0.1810)	0.8923
SL High Schools	0.2039	(0.1391)	1.2262
SL Higher Education Institutions	0.1362	(0.2147)	1.1460
SL Hotels	0.4080*	(0.1683)	1.5038
SL Laundry	-0.3424	(0.1894)	0.7100
SL Parks	0.2808*	(0.1169)	1.3242
SL Pawn Shops/Check Cashing Stores	-0.0085	(0.1977)	0.9915
SL Public Housing Complexes	0.2466	(0.1742)	1.2796
SL Public Libraries	0.5299**	(0.2000)	1.6987
SL Recreation Centers and Pools	0.3068*	(0.1534)	1.3591
SL Restaurants	-0.0075	(0.0245)	0.9925
SL Retail Stores	0.0198	(0.0222)	1.0200
Disadvantage	0.0183***	(0.0014)	1.0185
Residential Mobility	0.0060**	(0.0021)	1.0061
Racial Heterogeneity	0.9417***	(0.1584)	2.5643
Population/1000	0.0246***	(0.0047)	1.0249
Constant	-3.7933***	(0.1092)	0.0225
Ln(alpha)	0.5070***		
AIC	14018.0310		
BIC	14354.1240		

Notes: ***p < .001; **p < .01; *p < .05. SL = Spatially lagged.

Table 4.16 Police-Designated Street Robbery Negative Binomial Full Model

	Coef.	S.E.	IRR
Barbershops/Salons	0.1434	(0.1846)	1.1542
Bars	0.4607**	(0.1432)	1.5852
Body Art Stores	0.1393	(0.4467)	1.1495
Bus Stops	1.0367***	(0.0666)	2.8198
Drug Treatment Facilities	0.7582**	(0.2701)	2.1345
Entertainment Sites	0.3217	(0.2595)	1.3795
Everyday Stores	0.6044***	(0.0864)	1.8302
Gang Territory	1.0236***	(0.0602)	2.7832
Grocery Stores	0.6425	(0.3326)	1.9012
High Schools	0.2661	(0.2066)	1.3049
Higher Education Institutions	-0.7874***	(0.237)	0.4550
Hotels	0.6426	(0.4049)	1.9014
Laundry	-0.8466	(0.4511)	0.4289
Parks	0.3605*	(0.1454)	1.4341
Pawn Shops/Check Cashing Stores	0.7792*	(0.3763)	2.1798
Public Housing Complexes	0.7911***	(0.1901)	2.2058
Public Libraries	1.6712***	(0.3797)	5.3185
Recreation Centers and Pools	0.9684**	(0.2950)	2.6338
Restaurants	0.1805**	(0.0607)	1.1978
Retail Stores	0.0234	(0.0481)	1.0237
SL Barbershops/Salons	0.0611	(0.0976)	1.0630
SL Bars	0.2580***	(0.0660)	1.2943
SL Body Art Stores	0.0570	(0.2314)	1.0586
SL Bus Stops	0.5900***	(0.0703)	1.8039
SL Drug Treatment Facilities	0.1658	(0.1336)	1.1803
SL Entertainment Sites	0.0294	(0.1250)	1.0299
SL Everyday Stores	0.2312***	(0.0443)	1.2601
SL Gang Territory	0.4427***	(0.0784)	1.5569
SL Grocery Stores	-0.2150	(0.2053)	0.8065
SL High Schools	0.1784	(0.1498)	1.1954
SL Higher Education Institutions	0.1062	(0.2333)	1.1120
SL Hotels	0.4334*	(0.1799)	1.5426
SL Laundry	-0.3227	(0.2055)	0.7242
SL Parks	0.3189*	(0.1252)	1.3755
SL Pawn Shops/Check Cashing Stores	-0.0021	(0.2080)	0.9979
SL Public Housing Complexes	0.2050	(0.1863)	1.2275
SL Public Libraries	0.6339**	(0.2091)	1.8849
SL Recreation Centers and Pools	0.3056	(0.1636)	1.3575
SL Restaurants	-0.0253	(0.0273)	0.9750
SL Retail Stores	-0.0077	(0.0249)	0.9923
Disadvantage	0.0185***	(0.0015)	1.0187
Residential Mobility	0.0081***	(0.0023)	1.0081
Racial Heterogeneity	1.0733***	(0.1736)	2.9252
Population/1000	0.0217***	(0.0050)	1.0219
Constant	-4.1240***	(0.1197)	0.0162
Ln(alpha)	0.4987***		
AIC	11871.1210		
BIC	12207.2150		

Notes: ***p < .001; **p < .01; *p < .05. SL = Spatially lagged.

Table 4.17 Qualitatively Coded Opportunistic Robbery Negative Binomial Full Model

	Coef.	S.E.	IRR
Barbershops/Salons	0.1805	(0.1837)	1.1978
Bars	0.5194***	(0.1332)	1.6811
Body Art Stores	0.2098	(0.433)	1.2334
Bus Stops	1.0110***	(0.0653)	2.7484
Drug Treatment Facilities	0.6365*	(0.2721)	1.8898
Entertainment Sites	0.1943	(0.2644)	1.2145
Everyday Stores	0.6864***	(0.0861)	1.9865
Gang Territory	1.0294***	(0.0594)	2.7995
Grocery Stores	0.6232	(0.3333)	1.8649
High Schools	0.3413	(0.2009)	1.4068
Higher Education Institutions	-0.7051**	(0.2336)	0.4941
Hotels	0.7585	(0.3932)	2.135
Laundry	-0.2715	(0.3801)	0.7623
Parks	0.3437*	(0.1455)	1.4102
Pawn Shops/Check Cashing Stores	0.5241	(0.3796)	1.689
Public Housing Complexes	0.7573***	(0.1897)	2.1324
Public Libraries	1.6621***	(0.377)	5.2705
Recreation Centers and Pools	1.0810***	(0.287)	2.9476
Restaurants	0.1737**	(0.0606)	1.1897
Retail Stores	-0.0062	(0.0488)	0.9938
SL Barbershops/Salons	0.0591	(0.0959)	1.0609
SL Bars	0.2818***	(0.0647)	1.3255
SL Body Art Stores	-0.0286	(0.2346)	0.9718
SL Bus Stops	0.5254***	(0.0694)	1.6911
SL Drug Treatment Facilities	0.2215	(0.1314)	1.2480
SL Entertainment Sites	0.0127	(0.1243)	1.0127
SL Everyday Stores	0.2554***	(0.0438)	1.2910
SL Gang Territory	0.4570***	(0.0771)	1.5794
SL Grocery Stores	-0.3008	(0.2073)	0.7402
SL High Schools	0.2230	(0.1472)	1.2498
SL Higher Education Institutions	0.2736	(0.2216)	1.3147
SL Hotels	0.2916	(0.1876)	1.3385
SL Laundry	-0.4383*	(0.2075)	0.6451
SL Parks	0.3346**	(0.1240)	1.3974
SL Pawn Shops/Check Cashing Stores	0.0217	(0.2047)	1.0219
SL Public Housing Complexes	0.2886	(0.1826)	1.3345
SL Public Libraries	0.5295*	(0.2113)	1.6981
SL Recreation Centers and Pools	0.3431*	(0.1616)	1.4093
SL Restaurants	-0.0177	(0.0268)	0.9825
SL Retail Stores	-0.0076	(0.0248)	0.9924
Disadvantage	0.0185***	(0.0014)	1.0186
Residential Mobility	0.0063**	(0.0023)	1.0063
Racial Heterogeneity	1.1588***	(0.1708)	3.1860
Population/1000	0.0233***	(0.0050)	1.0235
Constant	-4.0716***	(0.1178)	0.0171
Ln(alpha)	0.5071***		
AIC	12239.5600		
BIC	12575.6540		

Notes: ***p < .001; **p < .01; *p < .05. SL = Spatially lagged

Of the 20 spatially focal place variables, 11 were significant across the three final models. This indicates that these variables, no matter the operationalization of robbery, influenced the expected street block robbery count net of the other variables in the models. This should be expected for many of these places for a number of theoretical and practical reasons. Three other places, grocery stores, hotels and pawn shops/check cashing stores, were significantly linked to some types of robberies but not others. Hotels only significantly linked to total robberies, but not police-designated street robberies or qualitatively coded opportunistic robberies. This is potentially due to the fact that many hotels in Cincinnati are located downtown in heavily commercial areas. The same can be said for grocery stores, which typically experienced only commercial robberies. The pawn shop/check cashing variable, on the other hand, was not consistently significant across models within each dependent variable. Review of the model building process revealed that this effect was not robust across models, thus, its relative significance should thus be taken with caution.

Spatially lagged variables also illustrated varying results across outcome measures. Six spatially lagged variables demonstrated robust effects across robbery outcome measures: (1) bars, (2) bus stops, (3) everyday stores, (4) gang territory, (5) public libraries, and (6) parks. As the focal versions of these variables were also significant, the results of these analyses suggest that no matter the type of robbery being examined, these places consistently predict increased expected street block counts on both focal and nearby street blocks. Three other variables were only significant for one or two robbery measures: spatially lagged hotels (total robberies and police-designated street robberies), laundromats/dry cleaners (qualitatively coded opportunistic robberies), and recreation centers/pools (total robberies and qualitatively coded opportunistic robberies.) Finally, in all models, socio-demographic variables were significantly linked to robbery, suggesting that places indicative of social disorganization experienced higher levels of robbery no matter the makeup of the environmental backcloth.

CACC & Count Model Results

When comparing the CACC and count regression results, a number of things were apparent. To reiterate, the CACC analysis identified five places that were often included in dominant profiles: bus stops, everyday stores, gang territory, restaurants, and retail stores. Count regression results generally supported these places' link to crime, save for retail stores. Additionally, the crime-saving impact of higher education places seen in the count regression was evident in the CACC results, whereby no dominant profiles included this variable. Even though these two types of analyses test different links to crime and place (CACC examines the combination of places, count regression controls for them), the results suggest that similar facilities predicted the occurrence of differentially operationalized robbery no matter the method.

Summary of Results

When discussing the specifics of the analyses as they pertain to each research question, it is important to take into account three general findings taken from this study. First, from both a qualitative and quantitative standpoint, numerous differences exist between robberies defined solely by the environment in which the incident takes place (i.e. police-designated street robberies) and those defined by the victim-offender interaction as well as the environment (i.e. qualitatively coded opportunistic robberies). A general comparison of these two disaggregation strategies was illustrated in Table 4.3. When looking at the number of incidents coded as either/or police-designated and opportunistic (N = 3,369), almost 22% (N = 729) were not coded as both. That is, they were either coded as only police-designated (N = 276) or opportunistic (N = 453). This difference is clarified when examining the types of robberies coded as either police-designated or opportunistic. Most of the police-designated-only robberies were domestic incidents that occurred on the street, whereas most of the opportunistic-only robberies occurred at a residence with a non-outdoor location code in the data. Further evidence from hot spot analysis underscored this point. While most street block hot spots, no matter how they were defined, were clusters of both disaggregated types, a number of street blocks were hot spots for either police-designated or opportunistic. While these numbers were small, they have larger implications for police and crime analysis (see below). Thus, at least qualitatively speaking, a large enough difference was found between these two operationalizations to suggest that using an environment-only coding system both fails to account for *and* falsely includes robberies that do not conform to the theoretical framework.

Research questions two and three examined if robbery operationalization influenced spatial patterns and the effect of potentially criminogenic facilities, respectively. The results from the analyses bring about the second general finding, which is that there were few differences when using either police-designated or opportunistic robberies as the dependent variable in the quantitative analyses. This was evident in a number of ways. Figure 4.1 and Table 4.6, comparing differing percentages and counts of street block robbery concentration, shows very similar levels between the two measures. The Ripley's K analysis demonstrated similar findings or that all three outcomes were spatial clustered (see Figures 4.15, 4.16, and 4.17). Nnh cluster analysis also suggested similarity between the robbery measures. The number, size, and makeup of clusters for both types were quite similar. Finally, the CACC and count regression analyses did not suggest that certain potentially criminogenic places produce more or less criminal opportunity for either robbery measure. Thus, while qualitative (and some quantitative) evidence suggests a difference between police-designated and opportunistic robberies, other evidence suggests that environment-only operationalizations of robbery do a fairly good job of approximating the types of robberies highlighted by CPT. This should not be too surprising as a large number (N = 2,640, 78%) were coded as both types of robbery.

As mentioned in Chapter 2, the use of total robberies in crime and place research may be unwarranted due the heterogeneity of robbery incidents, be it due to differences in terms of environment, victim-offender interaction, etc. The results from this study bring about a third finding that informs on the utility of total robberies as a crime outcome. In support of the applicability of total robberies to crime and place research, this study found general consistency in terms of spatial patterns and facility predictors of robbery locations. However, some differences were evident, primarily when looking at number of street block hot spots (see Tables 4.5 through 4.8), Nnh clusters for all outcomes (see Table 4.1), and dominant profiles in CACC (see Tables 4.11, 4.12, and 4.13). The use of total robberies produced far more hot spots and dominant configurations than either disaggregated robbery measure. Further review of total robbery Nnh hot spots indicated that many of the clusters would have gone away when using only those robberies that more neatly fit into an environmental criminological framework.

CHAPTER 5: DISCUSSION AND LIMITATIONS

The following section first summarizes the main findings from the analyses in Chapter 4 as they pertain to the theoretical framework and research questions asked. Then, potential implications from the findings are considered. Finally, limitations of the current study are discussed, including avenues for future research, as well as concluding remarks.

Discussion

<u>Explanations</u>

Research question 1

Recall research question 1 focused on the spatial clustering of robbery measures. Results from these analyses lend further support to the law of crime concentration (Weisburd, 2015) in that all measures were highly spatially clustered. This was true no matter how robbery was operationalized or how clustering was defined. This finding was not surprising given the history of crime and place research. Dating back to the mid-1800s (see Guerry, 1833; Quetelet, 1831; 1842), researchers have shown that crime is non-randomly distributed. This has held even at different spatial units, from communities (e.g. Shaw & McKay, 1942) down to the address level (Sherman et al., 1989). Environmental criminology helps explain this phenomenon. Offenders choose areas and targets that are within their awareness/activity space and rich in criminal opportunity. These opportunities stem from the presence of activity nodes along highly trafficked paths (Brantingham & Brantingham, 1981; 1984; 1993). When offenders and targets meet at these places, and when guardianship, management, and offender handling are low, crime is more likely to take place (Cohen & Felson, 1979; Felson, 1986; 1995; Eck, 2003).

Research question 2

Research question 2 delved further into the spatial concentration of robbery outcomes by investigating whether that clustering was sensitive to how robbery was operationalized. That is, do different types of robbery cluster in different places throughout the city? Little, if any, previous research has examined the spatial clustering of different sub-types of the same crime category. That said, research suggests that crime hot spots of different crime types rarely overlap with one another (Haberman, 2017).

The results presented above were mixed. The mutual overlap among robbery measures studied here led to many instances where robbery clusters themselves overlapped. In these cases, robbery operationalization (as defined here) mattered little. Referring back to Table 4.2, the amount of overlap in spatial clustering is not surprising. 71.62% and 76.07% of total robberies were coded as police-designated street robberies and qualitatively coded opportunistic robberies, respectively. The spatial patterning of these robberies created clusters for each of the three robbery measures, as they were in fact "made" from the same robbery incidents. The same can be said for the overlap among police-designated street robberies and qualitatively coded opportunistic robberies. In essence, both operationalizations attempt to capture the same types of robbery (simply labeled street robberies in the current literature). Again, this created a high degree of overlap in terms of spatial clustering.

However, the results also suggested locations of clusters throughout the city where operationalization did matter. This was most apparent when comparing total robbery hot spots/clusters with those of the disaggregated measures (see Tables 4.1, 4.5 through 4.8). In all instances, the total robbery measure produced more clusters than either disaggregated measure. This suggests that the types of robberies left out of either disaggregated definition are a product of different opportunity structures, thus creating clusters in different areas of the city. This further supports the importance of crime specificity in environmental criminology, as the use of a crime-general measure (i.e. total robberies) masks the heterogeneity evident in the characteristics of robbery events.

Slight differences in the locations of spatial clusters were also evident when comparing police-designated street robberies to qualitatively coded opportunistic robberies. This was due to the fact that, while many robberies fit both disaggregated operationalizations, the overlap was not perfect. For instance, some streets were hot spots for opportunistic robberies *but not* police-designated street robberies, and vice versa, despite the similarities in the initial reasoning for their operationalization (i.e. robberies adhering to environmental criminology). These clusters and hot spots were influenced by those robberies that fit only one of the disaggregated robbery operationalizations.

Given what is known about decision-making processes of criminals, this result is not surprising. A number of elements go into these decisions, including area familiarity, target familiarity, and distance to incident location from home, to name a few (see Wright & Decker, 1997; St. Jean, 2007; Bernasco et al., 2013). Slight differences in the types of robbery (via differences in operationalization) could alter how, when, where, and why these decision are made, thus influencing the location of spatial patterns. Additionally, referring back to Chapter 4, patterns emerged regarding the types of robberies left out of one operationalization but included in the other. For example, most robberies included in the qualitatively coded measure (excluded in the police-designated measure) were incidents at residential places. Thus, any definitional change in the how robbery is operationalized may lead to differences in where these incidents take place.

Research question 3

Research question 3 focused on how, if at all, the relationship between robbery and potentially criminogenic facilities is sensitive to robbery operationalization. For similar reasons discussed above, changes in how robbery is defined could lead to different facilities producing different types of opportunities for robbery. Overall, there did not appear to be many differences among the three robbery measures in terms of which facilities significantly linked to expected robbery counts on Cincinnati street blocks. This could have been due to a number of reasons, the primary explanation the significant overlap of the robbery measures. That is, a majority of total robberies (N = 82.86%) were coded as either/both a police-designated street robbery or/and a qualitatively coded opportunistic robbery. Thus, since the measures highly overlapping, it makes sense that the same types of potentially criminogenic facilities predict all three types. In terms of which specific facilities were linked, the findings from the count regression analysis were consistent with prior research. While some places shown to be linked to crime were not (e.g. entertainment sites, high schools, retail stores), others have been routinely associated with crime.

A cursory review of crime and place literature that focuses on the impact of potentially criminogenic places on spatial patterns lends credence to this finding. As noted in Chapter 2, a number of different measures have been used in these studies, some crime-general (e.g. crime indices, total robberies) and some crime-specific (e.g. street robberies). In many cases, they converge on similar findings. That is, many studies identify the same types of facilities that link to higher crime. For example, bars have been linked to higher crime using crime-general outcomes (e.g. Roncek & colleagues, 1981; 1989; 1991) as well as crime-specific measures (e.g. Bernasco & colleagues, 2011; 2013; 2017). Thus, some potentially criminogenic facilities may be "crime-general opportunity creators", whereby different types of crime are influenced by their presence.

The review of crime and place literature from Chapter 2 also suggests similarities between the facilities that exhibited significant findings in the current study and those that have routinely predicted crime in past studies. Bars, for instance, have been linked to crime in past studies, both when focusing exclusively on their role (e.g. Roncek & Maier, 1991) or when including them along with other facility predictors (e.g. Bernasco & Block, 2011). This link is predicated on two notions. First, bars are activity generators where large amounts of people come together, thus creating more opportunity. Second, because users of bars are often inebriated, they make for suitable targets (e.g. Mustaine & Tewksbury, 1998).

Other facilities that were found to be significantly linked to higher expected robbery counts, including bus stops, everyday stores, parks, public housing complexes, recreation centers, and restaurants are other examples of high activity places. That is, people use these facilities often, thus making them important activity nodes in the environmental backcloth. Like bars, these places have been linked to crime in previous studies (e.g. Hart & Miethe, 2014; Groff & McCord, 2012; Haberman et al., 2013; Haberman & Ratcliffe, 2015). Other facilities, specifically drug treatment centers and gang territory, act more as crime attractors than crime generators or activity nodes.[10] That is, offenders are drawn to these places due to the potential for criminal opportunity. Again, both have been linked to crime in previous studies (e.g. Furr-Holden et al., 2016; Taniguchi et al.,2011; Haberman & Ratcliffe, 2015).

Interestingly, one facility type, higher education institutions, produced a consistent *negative* effect on expected street block robberies. That is, the presence of a college or university on a street block was predictive of lower than expected robberies. This is potentially due to the fact that many colleges and universities in Cincinnati have their own police force (or, for others, a

[10] Parks have also been viewed as potential crime attractors, as they may attract offenders looking for places with low levels of control (e.g. Groff & McCord, 2011)

campus security force). Thus, these places have high levels of guardianship, which may push criminal opportunities off campus.

The current study supports the importance of these places and their role in predicting expected crime counts and micro-units of analysis. However, a number of facilities that have previously predicted crime were not significantly linked in the current study. For example, previous research suggests the presence of high schools influences crime locations (e.g. Roncek & LoBosco, 1983; Roncek & Faggiani, 1985; Bernasco & colleagues, 2011; 2013; 2017; Haberman & Ratcliffe, 2015). However, the finding that not all places link to crime is not surprising given what is known about crime opportunity and the role that facilities play in crime patterns. For instance, Haberman and Ratcliffe (2015) and Bernasco et al. (2017) illustrated that the link between facilities and crime is dependent upon the time of day and day of week, including for high schools.

Perhaps the one facility that could have been linked to total robbery but not the others was retail stores. This is due to the nature of robberies occurring at or near retail stores; that is, robberies at these places tend to be commercial. Interestingly, retail stores demonstrated a positive significant link to total robberies in the first two models (spatially proximate, spatially proximate + spatially lagged). However, once controlling for street block socio-demographics, this significant relationship disappeared. This reduction of significance did not happen during the model building process for the disaggregated robbery measures; retail stores were never significant in any model. Thus, while not significant, retail stores did exhibit some relationship with total robberies, as would be expected with a robbery measure that included commercial robberies.

Relatedly, there were instances where significance patterns differed across outcomes. This was especially noticeable in the count regression models. Specifically, six variables exhibited different significance patterns based on the robbery variable used: the focal predictors of (1) grocery stores, (2) hotels, (3) pawn shops/check cashing stores, and the spatial lags of (4) hotels, (5) laundromats/dry cleaners, and (6) recreation centers and pools.

This could be due to a number of factors, both theoretical and empirical. Theoretically, the differences may suggest that these places create an opportunity structure that fits certain types of robberies but not others. For example, the opportunity structures of crime at and around grocery stores in Cincinnati might have been better tailored for commercial robbery than for police-designated or opportunistic. This could explain why grocery stores predicted higher total robberies (which included commercial robberies) but not police-designated or opportunistic (which did not include commercial robberies). This follows Felson and Clarke's (1998) proposal that opportunities for crime are highly specific as well as Eck and Madensen's (2009) suggestion that opportunity structures were crime-specific. As the overlap among robbery types was not perfect, differences in opportunity structure for robberies in one type but not the other may drive the differences in significance patterns.

It could also be due to the differences in spatial clusters of different robbery types as seen in the results for research question 2. That is, the differences in significance patterns could be due to the slight differences in category overlap, which caused slight differences in the locations of robbery patterns. For instance, pawn shops and check cashing stores were significant for total and police-designated robberies, but not opportunistic robberies. The robberies included in the former types, but not the latter, may have tended to cluster on street blocks containing pawn shops and check cashing stores. If this was the case, it could potentially explain the difference in significance patterns. This would also support Haberman's (2017) work that suggested hot spots are crime-specific. While he looked at the overlap of hot spots among more general crime types, the same lack of overlap among disaggregated crime types might also lead to differences in whether or not a facility significantly predicts certain types of robbery.

Alternately, these differences may simply be picking up on "noise" in the models. That is, these differences may simply be due to unexplained variance rather than real differences in the facilities, their opportunity, and the robberies that cluster near them. As there were a large number of variables included in the final models (20 focal facilities, 20 lagged facilities, and 4 sociodemographic controls), the number of significance tests was also high. When this happens, the chances of making a Type-I error increase in likelihood (Bernasco et al., 2017). Thus, it is possible these significance differences (as well as other variables and their significance/non-significance) are due to error.

Implications

This dissertation's implications can be sorted into two categories: (1) implications for research and (2) implications for practice. That is, the current work can inform those conducting crime and place research in the future as well as crime analysts and those who direct crime control and prevention resources. While other cities may experience variation in robbery types, or even if Cincinnati experiences a change in robbery types in the future, the issues presented here should be considered before further work.

Before reviewing the theoretical implications, it is important to discuss why spatial patterns of different robbery outcomes may diverge. The three theories framing the current study (rational choice perspective; routine activity theory, and crime pattern theory) all emphasize the role of crime specificity. That is, the decisions made by offenders differ by crime type (Cornish & Clarke, 1985) and crime opportunities are highly specific (Felson & Clarke, 1998). The importance of examining spatial patterns of different crime types has been emphasized in previous research (e.g. Weisburd et al., 1993; Andresen & Linning, 2012; Haberman, 2017). These studies suggest the theoretical mechanisms explaining spatial patterning differ by operationalization (Weisburd et al., 1993), that aggregating crime types may be inappropriate for micro-level research (Andresen & Linning, 2012), and that hot spots of different types of crime may not occur in the same spatial locations (Haberman, 2017). Taken together, how researchers operationalize crime variables has multiple theoretical implications.

The current results suggest that while some differences were observed in analyses comparing police-designated street robberies and qualitatively coded opportunistic robberies (e.g. street block hot spot analysis; Nnh cluster overlap), there were also a number of commonalities. For instance, spatial clustering at the street block level was quite similar between the measures, as were the CACC and count regression model results which linked similar facilities to both robbery outcomes. This was due, primarily, to the high overlap in cases coded as either type. While some analyses (such as the hot spot analysis) indicated certain street blocks were high for one type and not the other, the results generally conclude that police-designated coding of robbery incidents did a fairly good job of capturing the types of robberies emphasized by CPT.

Thus, researchers who use environment-based coding of robberies, whether due to lack of better data, lack of time for a qualitative analysis, or any other reason, should be confident that their work is generally capturing the phenomena that environmental criminology set out to explore. That said, it should be noted in their limitations that their robbery measure variable is not without fault. Similarly, previous research using this robbery coding scheme (e.g. Bernasco & Block, 2011) should not be “thrown out” due to construct validity critiques of their dependent variable. Rather, those reading these studies should acknowledge that street robberies, in this case, are a close approximation of opportunistic robberies.

The same confidence in dependent variable cannot be said for studies using total robberies, at least when used within a CPT framework. As detailed above, CPT stresses the importance of the human activity patterns structured by the environmental backcloth for the spatial patterning of criminal opportunities (Brantingham & Brantingham, 1981). This has led researchers to examine, among other avenues, the influence of potentially criminogenic places on spatial crime patterns. As this line of research developed, scholars recognized the need for an appropriate dependent variable, one that conformed to the CPT framework. As such, street robberies, loosely defined as incidents occurring in public or semipublic places were chosen (also see Monk et al., 2010).

Much of the early research in crime and place, and even more recent studies, have failed to take this into account, thus leading to the use of crime general measures such as crime indices or total robberies. The use of crime indices, as it pertains to studies using a CPT framework, have little predictive power in terms of the impact that places have on crime. CPT and other theories within environmental criminology emphasize crime specificity as it pertains to the creation of opportunities. Thus, findings from facility-based studies using crime indices merely suggest that particular places produce some sort of opportunity for some types of crime – not exactly the level of specificity stressed by the theory.

Even still, the results from robbery typology research, including the Haberman et al. (forthcoming) typology, suggest that the use of total robberies is far too general to be used in research using a CPT framework. The Haberman et al. (forthcoming) typology showed a number of robbery types that are not organically created by the environmental backcloth, such as lure robberies or domestic dispute robberies. Other types, such as commercial robberies, would produce a tautological argument, whereby commercial places predict commercial robberies, which can only occur at commercial places.

The current study examined this by testing if crime patterns of total robberies were similar to those of disaggregated types that approximate (at least in part) opportunistic robberies. These findings demonstrated mixed results. Generally, total robberies followed a similar pattern of clustering to that of both disaggregated robbery types, especially when looking at levels of street block concentration. The facilities analyses also suggested that the same types of places that predict disaggregated robberies also predicted total robberies. However, the increased number of street block hot spots and Nnh clusters for total robberies (as compared to both disaggregated robbery measures) suggest that differences between the measures do exist. This over-estimation of robbery hot spots can have a large impact in practice (see below), but also suggests theoretical implications if using a theoretical framework based in environmental criminology. That is, a total robbery measure may include a number of incidents whose opportunity did not stem from the environmental backcloth, but rather from some other source.

It should be said, then, that future research examining the influence of potentially criminogenic places should rely exclusively on disaggregated crime incidents. If possible, these incidents should be categorized based on victim-offender interaction as well as the environment in which the incident took place. This is note to say that other crime and place research is wrong for using crime general measures. Many of these studies are highly informative on the spatial patterning of crime (e.g. Weisburd et al., 2012). However, their results should be taken as generally as possible. That is, they should be viewed as a starting point for the study of spatial patterns of crime. Further evidence is then warranted as to how and why certain places produce crime-specific opportunity. This contribution also plays a larger role in terms of the use of disaggregated crime types, which may be more appropriate for certain types of analyses (Andresen & Linning, 2012). Overall, as easy as total robberies are to use practically (that is, no data cleaning is required for an outcome with a typically large N), they should be used sparingly, if at all, in crime and place research, and should be noted as a limitation of the study.

The implications for crime analysis, on the other hand, paint a slightly different picture. This contribution, related to the increased specification of robbery patterns, is useful for crime prevention strategies, including Situational Crime Prevention (SCP) (Clarke, 1980; Cornish & Clarke, 2003) and Problem-Oriented Policing (POP) (Goldstein, 1979; Eck & Spelman, 1987; Spelman & Eck, 1987). Both SCP and POP are predicated on the fact that opportunity structures and problems need to be as specifically identified as possible. These and other strategies are of primary importance to both law enforcement and public prevention efforts.

Again, recall both the Nnh cluster and hot spot identification analyses demonstrated that the total robbery measure produced a great deal more hot spots and clusters For example, the Nnh cluster analysis found 72 first-order clusters for total robbery, while identifying only 44 and 45 for police-designated street robberies and qualitatively coded opportunistic robberies, respectively. This suggests an over-estimation of robbery hot spots when using total robberies. In practice, this could lead to police resources being spread too thin to cover all hot spots, when a more precise measure (one based soundly on environmental criminology) would produce *less* hot spots that would be *more* susceptible to police intervention. Overall, this suggests that crime analysis of total robbery patterns should only act as a starting point for the identification of spatial patterns. Any further analyses and subsequent responses should be based on more specific incident types.

Appendix C also illustrates the need for more specific crime measures in problem identification. While all three clusters were high-robbery areas, the incidents that made them so varied greatly. It follows that any prevention efforts geared to address those hot spots would need to be different from each other as well, as effective interventions should be crime-problem-specific (Clarke, 1995; Eck & Madensen, 2009). Crime prevention and control responses for a commercial robbery hot spot should differ from those of a "mixed-type" robbery hot spot, which would also differ from a hot spot made up of opportunistic robberies in a residential parking lot. Without this added specification, prevention resources, which are spread thin to begin with, would potentially be wasted in some areas. For instance, sending police to commercial robbery hot spots, when other strategies (e.g. SCP or improve place management) would be better suited, should be avoided.

While the utility of total robberies to crime analysis is minimal, it should also be noted that environment-based disaggregated robberies are also potentially problematic. Even though academic researchers can be somewhat confident in using these types of robberies as an approximation of opportunistic robberies, the same should not be said for crime analysts. Results from the street block hot spot and Nnh cluster analysis indicated a number of instances where one measure created a hot spot/cluster where the other did not, and vice versa. While many hot spots and clusters did overlap, the correlation between the two was not perfect. This matters, again, because of the importance of crime specificity in prevention efforts. The types of robberies included in one definition but not the other is non-random. For example, most of the incidents left out of the police-designated street robberies in the current analysis were coded as occurring at a residential location. Because of their location code in the data, they would not be considered police-designated street robberies, even if the victim-offender interaction suggested the incident fit the definition of street robberies that CPT suggests (e.g. Monk et al., 2010). These are important types of robberies that law enforcement strategies could combat, as opposed to dispute and lure robberies, which come about via different opportunity structures (thus, potentially require a different solution).

Limitations

The current study is not without limitations, which can broadly be grouped into one of three categories: (1) data concerns, (2) analysis concerns, and (3) interpretation concerns. The following section discusses these limitations as well as potential future steps that research could take in the future.

Potential data limitations exist for both the dependent variables (robbery and its classification) as well as those variables used to predict robbery locations in Chapter 4. The first and most obvious data limitation dealing with the robbery data is that this study is reliant upon official police data. While robberies are typically reported to police at a higher rate than other crime types (Truman & Morgan, 2016), there still exists the potential that not all robbery incidents are captured in official police data. Typically referred to as the "dark figure of crime" (Biderman & Reiss, 1967), incidents not reported to the police are not captured here. One particular type of robbery incident that could be severely underreported are those where the victim is a criminal, such as the robbery of drug dealers. Ethnographic research suggests some robbers specifically target drug dealers *because* they will not report the incident (Goldstein, 1985; Wright & Decker, 1997; Rosenfeld, Jacobs, & Wright, 2003). Thus, there are potential robbery hot spots not seen in the data. Much of the research surrounding robberies involving drug dealers has relied on interviews with active offenders (e.g. Wright & Decker, 1997). A potential strategy to capture these types of robberies and their patterns would be to interview active robbers and/or drug dealers. While this level of data may be less precise than incident data, it could lead to a more compelte picture of the robbery problem within a city.

A comparable limitation is the fact that other types of crimes, quite similar to robbery, are not specifically explored here. For instance, assaults, shoplifting, larceny/theft, and motor vehicle theft share many behavioral similarities with robberies, including similar environments and victim-offender interaction. Similarly, many robberies include instances where assaults, thefts, or motor vehicle thefts took place during the course of the robbery. While these incidents are similar in nature to robbery, they are not captured in its classification or legal definition (29 O.R.C. § 2911.02), thus are not included in the data. However, because of the similarities in behaviors, it may be beneficial in the future to include these types of incidents in analyses. This would start by applying the Haberman et al. (forthcoming) typology (or a revised version of it) to crime types that share similarities with robbery. From there, the same analyses performed above can be completed on each crime type individually as well as jointly to better understand the nature of these incidents.

The next set of limitations discussed here relate to the robbery typology used for analysis. These data were qualitatively coded based primarily on narrative information and location codes provided by CPD officers. As such, the typology is only as good as the information given by officers. Errors or disagreement in location coding, for example, could lead to differences in whether a robbery is considered “street” or not by crime analysts. This could lead to inaccurate analysis when using environment-based robbery coding. Similarly, errors in narrative information could equally influence analysis. If, for example, the narrative information leaves out the fact that the victim and offender were in a relationship, that incident could be coded differently from a dispute. Thus, there exists the possibility that some robberies are miscoded, which could affect the above analyses. The most obvious future step for this potential limitation is for better and easier coding procedures for police officers when entering incident data. If done correctly, the data pulled out above via qualitative coding procedures (which tend to consume large amounts of time and manpower) could be obtained directly from structured components of the data.

The next typology-based limitation is the level of detail for each category. In every typology or categorization procedure, there exists the possibility of either adding or removing detail. This is the same for the Haberman et al. (forthcoming) typology used in the current study. Take, for example, the category of opportunistic robberies. Even within this disaggregated sub-type of robbery which share a common theme (robberies where offender takes property by force from a victim in a public or semi-public location), there exist a number of dimensions one could potentially study. For example, researchers could disaggregate this category based on whether or not the offender used a weapon, how the offender made his or her approach/getaway, or what was taken during the robbery. Many robbery typologies already go into this detail (e.g. Luckenbill (1980), who examined types of force used), albeit not in an attempt to differentiate spatial crime patterns. Thus, the typology used above is but one way to examine disaggregated robbery incidents. The current study can only speak to the differences in robberies disaggregated on general victim-offender interactions. While future work could examine spatial patterns of a more highly defined robbery disaggregation, at some point, the decision must be made as to the disaggregation used or even the terminology used within that categorization (Bowker & Star, 2000).

A final note on the use of the Haberman et al. (forthcoming) typology and CPD data. As described above, conversations with CPD crime analysts led us to their definition of "street robberies". Their use of this definition was strictly based on the data available to them. That is, without delving into the data qualitatively, the best CPD crime analysts could do to obtain incidents that approximate opportunistic robbery was to use public, outdoor location codes. Other cities' robbery data may include more information whereby their "police-designated street robberies" include incidents where the victim-offender interaction is taken into account. Therefore, it should be stated that the current study is in no way critical of CPD, its crime analysts, or police crime analysts in general. Rather, this study and Haberman et al. (forthcoming) agree that collecting better data upfront could eliminate this issue entirely.

The potentially criminogenic places used in study provide their own potential limitations. While this study controls for a large number of facilities, there may be places that influence certain robbery patterns missing from analysis. An additional limitation involves the use of all facility types in analysis, which ignores well-documented evidence showing the variation within facility-type (Eck et al., 2007). Research examining the 80/20 rule suggests that not all places within a facility type contribute evenly to crime. Thus, future research examining the link between potentially criminogenic places and crime may benefit from a better understanding of which places contribute to criminal opportunity (see Henderson, forthcoming). Another potential issue, one found in much crime and place research, including the proposed dissertation, lies with the static nature of place and land use data, most of which was obtained in early 2016. While previous research suggests little change over time in places (e.g. Weisburd et al., 2012), it is possible that changes in the environmental backcloth increase or decrease nearby criminal opportunities (e.g. Poister, 1996; Billings et al., 2011).Similarly, changes in place management has been theorized to effect crime at places (Madensen, 2007) and been shown to explain varying levels of crime at apartment complexes (Payne, 2010). Avenues for future research should include moving beyond cross-sectional crime and place models by controlling for possible changes in facilities, land uses, place managers, or other concepts integral to environmental criminology.

The final data-related limitation focuses not on what was included in the analysis, but rather other data that may help inform on the findings. As stated previously, crime opportunities are highly specific (Felson & Clarke, 1998; Eck and Madensen, 2008). That is, different types of crime (and sub-types within crime categories) require a different opportunity structure for the offense to take place. This assumption is fundamental in environmental criminology and the research using it as a framework. In reality, however, opportunity is in the eye of the beholder (Johnson & Bowers, 2003). In other words, there is variation in how offenders view crime opportunity, just as there is variation in the opportunity for different types of crime (Felson & Clarke, 1998). The current study, and much of the crime and place research this study is based on, fails to account for the offender's perspective in crime opportunity. The addition of how offenders view differential opportunity in future research may help researchers better understand the importance of crime specificity in crime patterns.

Limitations stemming from the chosen analytical techniques are also present in the current study. One analytical limitation is the use of a large number of potentially criminogenic facilities, including those rarely seen in previous literature or theorized to influence crime patterns. While some may say controlling for more types of places is better, including this large a number (20 facilities, plus 20 lagged variables) of places increases the likelihood of making a Type-I error in the count regression models (Bernasco et al., 2017). The inclusion of 20 facility variables also exponentially increased the number of potential configurations in the CACC analysis. Comparatively, in their CACC analysis of criminogenic microenvironments, Hart and Miethe (2015) used ten total variables: eight place variables, a land use variable, and the day of week. Their results appear much more stable than those presented above, and are less susceptible to those streets that are alone in their configuration yet are also high crime. Thus, it could be argued that, rather than adding in all potentially criminogenic places (e.g. all those where the potential for victims and offenders to interact with one another), researchers should only add in those that are theoretically or practically useful.

The final two of limitations arise from interpretation issues. As with all studies, there are issues of external validity. Variation in robbery type as well as other predictors used in the analyses differs from city to city. For example, certain types of street robbery may be more or less present in Cincinnati than in other cities, thus justifying the need to replicate these findings elsewhere. Normandeau (1968) warned of this, using it as an example as to why the study of disaggregated robberies was important. Barnum et al. (2017) came to a similar conclusion for potentially criminogenic places, finding that certain types of places influenced robberies in some cities but not others. This underlies the importance of replication in social research, including crime and place research.

Finally, the interpretations themselves are subject to debate. While some differences were evident between the police-designated and qualitatively coded robberies, their spatial patterns (and facilities that predicted them) were similar. Others may argue that *any* difference in patterns is evidence that environment-based coding of incidents is lacking, and therefore all results from previous and future studies should be abandoned. Others may say that the two disaggregated categories tested here are essentially the same, and therefore differences between them are a statistical artifact. There is no correct answer in this case. Qualitatively speaking, there appears to be a difference in *some* of the robberies included in an environment-based coding system when compared to a coding system based on victim-offender interaction. That said, most of the robberies in one type also occur in the other. Thus, where one stands on this issue depends on the level of precision they expect in their dependent variable.

Finally, many of the differences examined and discussed above were subjective in nature, and not supported by statistical testing. That is, the "eyeball test" was used when discussing similarities and differences among spatial patterns among outcomes. Thus, while differences in crime patterns may *appear* similar or dissimilar, they may not be so, statistically speaking. One difficulty in empirically validating differences among the measures used in the current study was the lack of mutual exclusivity. That is, most of the robberies in Cincinnati from 2014 through 2016 were included in all three measures (N = 2,640; 64.93%). As many statistical tests assume data independence, the nested nature of the robbery data used here was an issue. That said, the subjective nature of comparisons across outcomes among research questions is still a limitation.

Conclusion

Environmental criminology has shown its importance as a way to understand the spatial patterning of criminal events and opportunities. The theories that compose this framework, including CPT, have led to a large body of research, including studies that attempt to link certain types of places with robbery incidents. These studies have been generally supportive of CPT and other environmental criminological theories by showing that some places, such as bars, bus stops, or gang territory, increase nearby crime levels.

Important to these studies is what crime variable is actually being tested. CPT and other theories emphasize the importance of crime specificity, even though many crime and place studies have used crime-general measures as the dependent variable. Other studies have attempted to use a crime-specific measure, usually loosely defined "street robberies", to combat this misspecification. However, evidence from Haberman et al.'s (forthcoming) study on a robbery typology indicates that defining street robberies solely on their environment has potential issues, as it both includes and excludes some types of robbery that either should or should not be included.

The current study took the Haberman et al. (forthcoming) typology of robbery events to examine the sensitivity of operationalization on crime patterns. Using different methods, three robbery measures were assessed to determine the amount of spatial clustering, differences in spatial clustering, and the impact that facilities had on this clustering. The results indicated both similarities and differences among measures. All measures supported the law of crime concentration (Weisburd, 2015) and were predicted by similar types of facilities. That said, despite a high degree of overlap among the measures, evidence from hot spot and spatial cluster analysis indicated a number of instances where these spatial patterns did not match. It is suggested, then, that future crime and place research should attempt to define crime measures as narrowly as possible, preferably in a way that matches the framework put forth by environmental criminology.

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APPENDIX A

Creation of the police-designated street robbery variable was based on conversations with CPD crime analysts who suggested how they would pull "street robberies" from the data. They suggested a two-step process: first, remove all incidents where the location code was not an outdoor location. This left the following possible location codes:

- 05 – Garage/Shed
- 13 – Parking Garage
- 43 – Yard
- 44 – Construction Site
- 46 – Field/Woods
- 47 – Street
- 48 – Parking Lot
- 49 – Park/Playground
- 50 - Cemetery
- 52 – Other Outside Location
- 56 – ATM Machine (separate from bank)

The second step was to remove incidents where the victim-type code was not an individual. Not-individual codes included business, financial institutions, government, and police officers.

APPENDIX B

The following appendix illustrates an alternate CACC analysis, one which focuses not on the average number of robberies per configuration, but rather the total count. Average-based CACC results were discussed in the body of the text because they better accounted for which configurations were truly robbery generators as opposed to those discussed here, many of which are both high in the number of robberies as well as the number of streets in Cincinnati matching that configuration.

Table B1 shows the count-based CACC analysis for total robberies. Included in this table are the configuration, whether the facility was present or not, the count of streets fitting that configuration, the count of robberies in that configuration, and the average number of robberies in that configuration. Using a minimum cell frequency of 10 robberies per configuration, 50 configurations made the list. These configurations accounted for 3,510 total robberies, or 86.33%. An overwhelming number of these 3,510 robberies came from four configurations: (1) Configuration 1 consisted of no facility variables; (2) Configuration 2 only included the presence of gang territory; (3) Configuration 3 only included the presence of a bus stop; and (4) Configuration 4 included streets that had a bus stop and were in gang territory. These configurations experienced 2,298 robberies over the course of the three-year study period.

However, when looking at the number of streets within these configurations and their mean number of robberies per street, these numbers are deceiving. That is, while these configurations accounted for a majority of robberies, their averages suggest that the configurations themselves may not be driving these robberies, as the average robbery per street in each configuration is quite low. Results from CACC count-based analyses for the disaggregated robbery measures, shown in Tables B2 and B3, mirror these findings, including the same configurations (albeit in different orders) accounting for a high percentage of the robbery count all the while experiencing a low average per street. While informative to the overall distribution of different robbery measures across Cincinnati, these results suggest that count-based CACC cannot be relied upon as a measure of which configurations, and the places within them, are generating or attracting robbery opportunity.

Table B1: Total Robbery Count-Based CACC Analysis

Config	Bar	Rest	Chk	Evdy	Retail	Groc	Ent	Rec	Barber	T'x	Lib	Bus	HS	Univ	Parks	PubHou	Gang	*n*	Avg	Total
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5959	0.1255	748
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1258	0.4587	577
3	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1632	0.3266	533
4	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	591	0.7445	440
5	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	60	2.4167	145
6	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	49	1.8980	93
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	23	2.2609	52
8	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	9	5.3333	48
9	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	62	0.6935	43
10	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	10	3.9000	39
11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	20	1.9500	39
12	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	69	0.5652	39
13	0	0	0	1	1	1	0	0	1	0	0	1	0	0	0	0	1	2	19.0000	38
14	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	57	0.6140	35
15	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	21	1.6667	35
16	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	27	1.2222	33
17	0	1	0	0	1	1	0	0	0	0	0	1	0	0	0	0	1	1	32.0000	32
18	0	1	0	1	1	1	0	0	1	0	0	1	0	0	0	0	0	2	15.0000	30
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	187	0.1497	28
20	0	1	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	6	4.5000	27
21	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	10	2.6000	26
22	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	18	1.3889	25
23	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	17	1.1765	20
24	0	1	0	1	1	0	0	0	1	1	0	1	0	0	0	0	1	1	20.0000	20
25	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	24	0.8333	20
26	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	31	0.6452	20
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	24	0.7917	19
28	0	1	0	1	1	0	0	0	1	0	0	1	0	0	0	0	0	9	2.0000	18
29	0	1	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	6	3.0000	18
30	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	5	3.4000	17
31	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1	2	8.5000	17
32	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	1	3	5.3333	16
33	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	21	0.7619	16
34	1	1	0	1	1	0	0	0	1	0	0	1	0	0	0	0	0	1	15.0000	15
35	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	9	1.6667	15
36	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	44	0.3182	14
37	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	4	3.2500	13
38	0	0	0	1	1	1	0	0	1	0	0	1	0	0	0	0	0	2	6.5000	13

Table B1 Continued																				
Config	Bar	Rest	Chk	Evdy	Retail	Groc	Ent	Rec	Barber	T'x	Lib	Bus	HS	Univ	Parks	PubHou	Gang	*n*	Avg	Total
39	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	1	13.0000	13
40	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	9	1.3333	12
41	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0.9231	12
42	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	8	1.5000	12
43	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	6	2.0000	12
44	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	1	5	2.2000	11
45	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	4	2.7500	11
46	0	1	1	1	1	0	0	0	1	0	0	1	0	0	0	0	1	1	11.0000	11
47	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0.4545	10
48	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	5	2.0000	10
49	0	1	0	0	1	0	1	0	0	0	0	1	0	0	0	0	0	1	10.0000	10
50	1	1	1	1	1	0	0	0	0	0	0	1	0	0	0	0	1	1	10.0000	10

Notes: *n* = number of streets in configuration; Avg = average number of robberies per configuration; Total = total number of robberies per configuration; Body art stores, hotels, and laundromats/dry cleaners were not included in any dominant profiles.

Table B2: Police-Designated Street Robbery Count-Based CACC Analysis

Config	Bars	Rest	Evdy	Retail	Groc	Barber	T'x	Lib	Bus	HS	Univ	Parks	PubHou	Gang	*n*	Avg	Total
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5959	0.1030	614
2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1258	0.3545	446
3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1632	0.2463	402
4	0	0	0	0	0	0	0	0	1	0	0	0	0	1	591	0.6142	363
5	0	0	1	0	0	0	0	0	1	0	0	0	0	1	60	1.3333	80
6	0	0	1	0	0	0	0	0	1	0	0	0	0	0	49	0.9184	45
7	0	0	0	0	0	0	0	0	0	0	0	0	1	1	23	1.6957	39
8	0	0	0	0	0	0	0	0	1	0	0	0	1	1	20	1.8000	36
9	0	0	0	0	0	0	0	0	1	0	0	1	0	0	57	0.5439	31
10	0	1	0	0	0	0	0	0	1	0	0	0	0	0	62	0.4355	27
11	0	0	0	1	0	0	0	0	1	0	0	0	0	1	27	0.9630	26
12	0	0	0	1	0	0	0	0	1	0	0	0	0	0	69	0.3623	25
13	0	1	1	0	0	0	0	0	1	0	0	0	0	1	9	2.5556	23
14	0	0	1	1	0	0	0	0	1	0	0	0	0	1	10	2.3000	23
15	0	0	0	0	0	0	0	0	0	0	0	1	0	0	187	0.1230	23
16	0	0	1	1	1	1	0	0	1	0	0	0	0	1	2	10.0000	20
17	1	0	0	0	0	0	0	0	1	0	0	0	0	0	24	0.7500	18
18	0	0	0	0	0	0	0	0	1	1	0	0	0	0	31	0.5806	18
19	0	1	1	0	0	0	0	0	1	0	0	0	0	0	21	0.8095	17
20	0	1	0	0	0	0	0	0	1	0	0	0	0	1	18	0.9444	17
21	0	0	1	1	0	0	0	0	1	0	0	0	0	0	10	1.6000	16

Table B2 Continued

Config	Bars	Rest	Evdy	Retail	Groc	Barber	T'x	Lib	Bus	HS	Univ	Parks	PubHou	Gang	*n*	Avg	Total
22	0	0	0	0	0	0	0	0	1	0	0	0	1	0	17	3.2500	16
23	0	0	0	0	0	0	0	0	0	0	0	0	1	0	24	13.0000	13
24	0	0	0	0	0	0	0	1	1	0	0	0	0	0	4	13.0000	13
25	0	1	0	1	1	0	0	0	1	0	0	0	0	1	1	0.2727	13
26	1	1	1	1	0	1	0	0	1	0	0	0	0	0	1	2.0000	13
27	0	0	0	0	0	0	0	0	1	0	1	0	0	0	44	1.8333	12
28	0	1	1	1	0	0	0	0	1	0	0	0	0	1	6	1.8333	12
29	0	1	1	1	0	0	0	0	1	0	0	0	0	0	6	1.3750	11
30	1	0	0	0	0	0	0	0	1	0	0	0	0	1	6	11.0000	11
31	1	1	0	0	0	0	0	0	1	0	0	0	0	0	8	1.1111	11
32	0	1	1	1	0	1	1	0	1	0	0	0	0	1	1	0.4762	11
33	0	1	0	1	0	0	0	0	1	0	0	0	0	1	9	2.0000	10
34	0	1	0	1	0	0	0	0	1	0	0	0	0	0	21	5.0000	10
35	1	0	1	0	0	0	0	0	1	0	0	0	0	0	5	0.1030	10
36	0	1	1	1	1	1	0	0	1	0	0	0	0	0	2	0.3545	10

Notes: *n* = number of streets in configuration; Avg = average number of robberies per configuration; Total = total number of robberies per configuration; Body art stores, check cashing stores, entertainment places, hotels, laundromats/dry cleaners, and recreation centers/pools were not included in any dominant profiles.

Table B3: Qualitatively Coded Opportunistic Robbery Count-Based CACC Analysis

Config	Bars	Rest	Evdy	Retail	Groc	Rec	Barber	T'x	Lib	Bus	HS	Univ	Parks	PubHou	Gang	*n*	Avg	Total
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5959	0.1061	632
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1258	0.3776	475
3	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1632	0.2623	428
4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	591	0.6514	385
5	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	60	1.5500	93
6	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	49	0.9796	48
7	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	23	1.6087	37
8	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	20	1.7500	35
9	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	57	0.5439	31
10	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	9	3.3333	30
11	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	62	0.4839	30
12	0	0	1	1	0	0	0	0	0	1	0	0	0	0	1	10	2.8000	28
13	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	27	1.0000	27
14	0	0	1	1	1	0	1	0	0	1	0	0	0	0	1	2	13.0000	26
15	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	69	0.3478	24
16	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	187	0.1283	24
17	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	21	1.0000	21

Table B3 Continued																	
Config	Bars	Rest	Evdy	Retail	Groc	Rec	Barber	T'x	Lib	Bus	HS	Univ	Parks	PubHou	Gang	*n*	Avg	Total
18	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	31	0.6129	19
19	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	17	1.0588	18
20	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	18	1.0000	18
21	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	24	0.7500	18
22	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	10	1.5000	15
23	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	24	0.6250	15
24	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	44	0.3182	14
25	0	1	1	1	0	0	0	0	0	1	0	0	0	0	1	6	2.1667	13
26	1	1	1	1	0	0	1	0	0	1	0	0	0	0	0	1	13.0000	13
27	0	1	1	1	0	0	1	1	0	1	0	0	0	0	1	1	12.0000	12
28	0	0	1	0	0	0	0	0	0	1	1	0	0	0	1	2	6.0000	12
29	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	6	1.8333	11
30	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	6	1.8333	11
31	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	4	2.7500	11
32	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	8	1.3750	11
33	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	9	1.2222	11
34	0	1	0	1	0	0	0	0	0	1	0	0	0	0	1	9	1.1111	10
35	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	21	0.4762	10
36	0	1	0	1	1	0	0	0	0	1	0	0	0	0	1	1	10.0000	10
37	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	5	2.0000	10
38	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	5	2.0000	10

Notes: *n* = number of streets in configuration; Avg = average number of robberies per configuration; Total = total number of robberies per configuration; Body art stores, check cashing stores, entertainment places, hotels, and laundromats/dry cleaners were not included in any dominant profiles.

APPENDIX C

As seen above in Table 4.9, the analysis indicates wide variation in terms of the types of crimes that made up total robbery Nnh clusters. When focusing solely on the proportion of qualitatively coded opportunistic robberies in total robbery Nnh clusters, the proportions ranged from 0.17 to 1. The secondary analysis performed here in Appendix C examines in depth a number of these total robbery Nnh clusters. Specifically, clusters with low, medium, and high proportions of opportunistic robberies were examined qualitatively.

The first cluster examined here is Cluster 25, which had the lowest proportion of robberies coded as opportunistic (N = 0.17; 3 of 18). This particular cluster is located on the 6100 block of Glenway Avenue on the west side of Cincinnati. It was entirely driven by robberies occurring at the Western Hills Plaza, a horseshoe-shaped shopping center comprised of a number of retail stores and restaurants. Further inspection of the robberies making up this Nnh cluster indicated that, as one would expect in a commercial shopping center, they were primarily either commercial robberies or shoplifting incidents coded as robberies due to incident characteristics. The robberies coded as opportunistic occurred in the parking lot of the shopping center. A final interesting note on this particular cluster/area; regression diagnostics identified the street block nearest this cluster as an outlier.

The second cluster examined here is Cluster 63, which had a proportion of 0.5 in terms of robberies coded as opportunistic (N = 6 of 12). This cluster is located primarily on 400 block of Walnut Street in downtown Cincinnati, between East 4th Street and East 5th Street. It is a block south of the southwest corner of Fountain Square, a popular entertainment site in Cincinnati. The 400 block of Walnut Street includes a number of stores and shops, a hotel, and, most important to this cluster, a number of banks. While this cluster includes six incidents coded as opportunistic, it also includes five bank robberies. The remaining non-opportunistic robbery in thus cluster was an incident where the victim was lured by a previous acquaintance to the location. Thus, while this location experienced a fair number of opportunistic robberies, the cluster was equally driven by bank robberies.

The third and final cluster examined here is Cluster 37, which had an opportunistic robbery proportion of 1, meaning all robberies (N = 15) that made up this total Nnh cluster were qualitatively coded as opportunistic. This cluster is drive primarily by fourteen robberies that occurred on Westmont Lane, which houses the Autumn Woods apartment complex. There were no commercial places near this location; that is, no businesses that one assumes links to predatory street robberies were located nearby. Rather, these robberies occurred almost exclusively in the parking lot of this apartment complex. In the CPD data, four of these robberies were coded as occurring at a multi-family apartment complex, meaning they were not included in the police-designated street robbery definition. The remaining had a location code of parking lot.

These three examples illustrate the importance of delving into crime patterns discerned from the use of total robbery data. While many of the total robbery Nnh clusters included a fair number of robberies qualitatively coded as opportunistic, others were primarily driven by the types of robberies not as well-explained by CPT, and thus not as well prevented or controlled by efforts based on CPT.