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I, Jillian S Desmond, hereby submit this original work as part of the requirements for the degree of Doctor of Philosophy in Criminal Justice.

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Risky people around risky places: The effects of crime-prone offenders and facilities on the spatial distribution of crime

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Risky people around risky places:
The effects of crime-prone offenders and facilities on the spatial distribution of crime

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ABSTRACT

Crime hot spots are the result of offenders repeatedly perceiving and exploiting criminal opportunity at the same location. Theory supports the notion that offenders interact with their proximal environment; in fact, some have suggested proximal offenders condition the criminogenic effects of some types of facilities. Empirical tests have failed to clearly integrate measures of offenders and criminal opportunity in explanations of crime concentrations. The current dissertation integrated measures of likely offenders, from information on formally incarcerated persons, and criminal opportunity to explain concentrations of robbery and theft from auto across street blocks in Cincinnati. In addition, it tests whether exposure to offenders conditioned the effects of criminogenic facilities. Overall, findings show exposure to likely offenders is important to account for in explanations of crime concentrations. Not only do the likely offender measures have significant main effects, but they interact with some criminogenic facilities to create higher crime counts, beyond the independent effects of likely offender and facility measures.

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CHAPTER 1: INTRODUCTION

For most of its existence, criminology has focused on explaining why some people are more crime-prone than others (Andrews & Bonta, 2003). More recently, one part of environmental criminology branched off to explain why certain places are more crime prone than other places in a city (see Andresen, 2014 for an overview). Importantly, this subfield of criminology does not omit offenders. Environmental criminology theories put forth that offenders interact with criminal opportunities within their immediate setting and these interactions lead to crime events. Though offenders are only one of the elements necessary for a crime to occur, they are integral to environmental criminology theory. Despite this, most research conducted using an environmental criminology framework focuses on places and most studies of crime and place fail to account for offender presence in their models. The scant environmental criminology empirical findings significantly related to offenders suggests the distribution of offenders has a main effect on spatial crime patterns. However, these studies have been limited by macro-level units of analysis inconsistent with the micro-level focus of environmental criminology theories and fail to incorporate measures of offender and opportunity in the same model. This dissertation attempts to fill these gaps and assess the offender's role in the geographic distribution of crime.

This dissertation is presented in four chapters. This chapter has introduced the dissertation's focus. Chapter 2 provides the environmental theory and empirical evidence that suggests people (offenders and non-offenders), criminal opportunity, and crime events are not randomly distributed in space. Rather, it is thought that some places facilitate the convergence of offenders and targets that are deemed as rewarding ("suitable") and relatively risk-free (little or no presence of “guardianship”). Offenders develop an understanding of the different types of criminal opportunity that are common at or near certain types of facilities. Despite crime and place research identifying some categories of facilities as criminogenic, like bars or schools, it has also been found that there is variation within these homogenous groups. One potential, but untested, hypothesis is that while criminogenic facilities present similar types of opportunity, they facilitate different types of patrons, some of which may be offenders. Chapter 2 concludes by discussing the scattered empirical findings that shed light on the spatial relationship between offenders and crime, directly and indirectly through criminogenic facilities. The gaps in the empirical literature present opportunities for the current study to advance environmental criminology by testing multiple elements under the same model.

Chapter 3 outlines the research questions, measures, and methods. Four research questions are posed. First, do offenders geographically concentrate in a small number of places? Second, if they do geographically concentrate, do these offender hot spots coincide with crime hot spots? Third, how do offender factors and facility factors explain crime across street blocks net of other variables that have been used to explain spatial crime patterns in past research? Fourth, are the effects of potentially criminogenic facilities on crime conditional on the spatial distribution of offenders?

I accounted for exposure to likely offenders by mapping the home locations of convicted offenders released by the Ohio Department of Rehabilitation and Correction in Cincinnati, Ohio between 2013 and 2015. Empirically validated “risk score” data was available for about half of the offenders released in this timeframe, which estimate the offender’s likelihood to reoffend after release. These offender measures were used in conjunction with a list of criminogenic facilities, road network data, and sociodemographic control variables to model robbery and auto-related crime street block counts for 2016 and 2017. I used spatial statistics to explore the univariate and bivariate spatial distribution of offenders and each crime type in order to answer my first two research questions. To answer the third research question, I used count regression models to estimate the effects two different offender conceptualizations on the two crime types, net of the other factors. Lastly, I introduced interaction terms between offender measures and significant facilities into the count regression models to assess whether the amount of nearby offenders condition the criminogenic effects of some facilities in order to answer research question four.

Chapter 4 presents the results of the methods above. First, offenders concentrated in a small number of areas and coincided with the distribution of robbery and theft from auto. Both offenders and criminogenic facilities exerted significant effects on crime, net of other factors. These findings were consistent with Brantingham and Brantingham's theory of hot spot formation, in that both the distribution of offenders and opportunity plays a role in overall spatial rime patterns. Lastly, there were a handful of significant interactions between offenders and criminogenic facilities with crime.

Chapter 5 concludes the dissertation with a discussion of the findings in light of prior literature, the implications, and limitations. Overall, the dissertation provided support for many of the assertions from Crime Pattern theory (Brantingham, Patricia L. & Brantingham, 1981; Brantingham, Patricia L. & Brantingham, 1991; Brantingham, Patricia L. & Brantingham, 1999; Brantingham, Patricia L. & Brantingham, 1995). In addition, there was some support for Madensen and Eck's (2008) explanation of risky facilities, but the relationship was more complex than originally conceptualized. There were a number of data and methodological limitations, which largely centered on shortcomings of the offender data. For instance, offender data only included home addresses, rather than other commonly used places or facilities. The potential implications greatly outweigh these shortcomings. Theoretically, this study shed light on the relationship offenders have with the spatial distribution of crime, advancing the empirical support for concepts in environmental criminology theory. It illuminated how offenders affect street-level crime counts and moderate the effect of criminal opportunity.

CHAPTER 2: LITERATURE REVIEW

To establish the proposed link between offenders and spatial crime patterns, in the following chapter I present the research and empirical findings related to environmental criminology. First, I present the theoretical foundation, which asserts the larger environmental backcloth shapes the distribution and patterns of potential offenders and criminal opportunity. Offenders, within their environment, take in cues to make decisions about which criminal opportunities to exploit or ignore. Next, I discuss the current state of crime and place research. This subsection will establish crime concentrates in a small number of places, and this concentration is largely explained by the presence of criminogenic facilities. The third section will present that establishments are not equally criminogenic, even within sets of homogenous facilities, like bars. Neighborhood context and place management have been tested explanations of this phenomenon. One plausible, yet untested, explanation for this variation is the uneven distribution of offenders. While largely untested, some research has hinted at the importance of the spatial distribution offenders for explaining the distribution of crime. This is the topic of the final section of the chapter. Overall, this chapter will present the current state of environmental criminology theory and research as it relates the spatial relationships among offenders, criminal opportunity, and crime. I end the chapter by presenting research gaps that need to be addressed in order to better understand how offenders, criminal opportunity, and the interaction of the two explain concentrations of crime. This is particularly important because offenders are often included in environmental criminology, but rarely tested among other common variables.

Environmental Criminology

According to environmental criminology, crime is spatially patterned around human behavior, movement, and perceptions of criminal opportunity. Offenders make rational decisions to commit crime based on calculations of risk and reward (Clarke & Cornish, 1985). In order for a crime to occur, an offender must converge with a suitable target in space and time (Cohen & Felson, 1979). In other words, a potential offender must happen upon a criminal opportunity in order to assess its risks and rewards. Situational cues within the immediate setting signal to the offender the target suitability and levels of guardianship, which together make a criminal opportunity (Clarke, 1997). Crime varies in space because offenders, criminal opportunities, and human travel patterns are not uniformly or randomly distributed in space (Brantingham, Patricia L. & Brantingham, 1981; Brantingham, Patricia L. & Brantingham, 1991; Brantingham, Patricia L. & Brantingham, 1999; Brantingham, Patricia L. & Brantingham, 1995). Movement between and usage of popular places allow for the convergence of offenders with targets deemed suitable and unguarded, leading to crime.

Rational Choice Perspective

The Rational Choice perspective is a framework used to understand how offenders make decisions, particularly with respect to where, when, and whom to victimize (Clarke & Cornish, 1985). The basic premise of this perspective is that individual actors develop schemas or preferences that guide their search for opportunities to maximize rewards while minimizing risks and harms. Clarke and Cornish (1985) modeled two different major decisions: (1) involvement decisions and (2) event decisions. Offenders' background and life experiences will shape assessments of rewards and risks, which will dictate future participation, persistence, and desistance in/from crime (involvement). Eventually, offenders build skills and preferences towards specific types of criminal opportunity based on environmental cues (crime event). According to the Rational Choice perspective, offenders exploit and search out criminal opportunities that satisfy their preferences (Clarke & Cornish, 1985).

The involvement decisions draw on sociological, psychological, and criminological concepts to explain the decision to begin, continue, and desist from offending. Initial involvement in crime is a process that involves the recognition of "readiness" to commit a crime followed by the actual commission of a crime, often without premeditation (Clarke & Cornish, 1985:167). Clarke and Cornish (1985) acknowledge there are predisposing factors that increase a person's likelihood to become involved in crime. These predisposing factors are those that classic criminologists theorize and test, such as poor upbringing, collections of personality traits, or presence of anti-social peers. People with these predisposing factors are more likely to learn about crime, including moral positions, techniques and planning, and expectations of the police. These people also develop general needs, which often precipitate criminal activity. These needs may include tangible items, like money or sex, and intangible goods, like respect or status. Next, a person considers the possible methods for obtaining those goals, including both legal and illegal options. With their knowledge of crime and law enforcement, they evaluate each solution in terms of effort needed, amount of risk and reward, and moral costs (Clarke and Cornish, 1985:168). At this point, an offender acknowledges whether or not they are "ready" to commit a crime.

Before an offender is involved in crime, the "ready" individual will likely encounter a series of early offending decisions, which will guide the continuation of offending (Clarke & Cornish, 1985). The ready person will first be presented with a chance event that they will likely exploit. Positive experiences with criminal offending, such as high rewards or evading detection, result in positive reinforcement and increased involvement. Thus, an offender receiving positive reinforcement will likely continue to offend after the initial offense. As offending increases, offenders will improve skills and knowledge, change their lifestyle around offending, and associate with other offenders. They will develop an understanding of the setting characteristics and "cues" that indicate rewards or risk of being caught.

The event decision is the offender's actual choice to commit a specific crime at a given place and time, which reflects a collection of environmental cues hinting at rewards and risks of a particular criminal opportunity (Clarke & Cornish, 1985). This decision explains why some situations are more favorable for offending (pp. 174). According to Clarke and Cornish (1985), situational aspects and settings vary dramatically by time, place, or victim. Some targets may carry valuable goods with strong security; others may carry low-value items that are easily accessible. Furthermore, some hours of the day may attract more targets to a specific area. The settings with more perceived reward than risk will be exploited and sought after more often. Opportunities that are most likely to be exploited are those with high reward, high excitement, low effort, and low risk of apprehension or danger (Clarke & Cornish, 1985; Clarke, 1997).

Clarke (1997) detailed specific elements or cues that affect perceptions of risk and reward to better advocate for their prevention. Known as Situational Crime Prevention, Clarke (1997) asserted that removing or altering the elements of opportunity might shift the balance away from offending. Rational Choice perspective models an offender's decision as an interaction between an offender's experiences and preferences and a place's environmental cues. Each offender has a unique set of predisposing factors and eventually an offending history. Over time, they will develop skills, peers, and new experiences that will guide the type of criminal opportunity they favor. Similarly, crime is more likely to occur at places that signal substantial or easy rewards with little effort or risk. These places have factors that cue offenders to these rewards and risks.

Routine Activities Perspective

Building on the assumptions that offenders make decisions based on perceptions of risk and reward, Routine Activities perspective is a framework to explain three aspects of criminal opportunity, including an offender, target, and place guardianship (Cohen & Felson, 1979)[1]. Cohen and Felson (1979) asserted that crimes occur when a motivated or "likely" offender converges in time and space with a suitable target, which lacks capable guardianship. According to Cohen and Felson, anyone could be "motivated" to commit a crime under the right circumstances, but some people have criminal inclinations or experiences that make them more likely to offend than others. Furthermore, these "motivated" offenders are not faced with a decision to offend until they encounter a target in space/time lacking capable guardianship. Different types of routines or activities will facilitate the convergence of different types of people or targets, at different times of the day in different locations (pp. 591).

Once convergence has occurred, potential offenders use clues from the setting to assess the suitability of the target and the capabilities (or presence) of guardians. Similar to explanations by Clarke and Cornish (1985), people, items, or places that are "suitable" are those that hold

[1] Cohen and Felson (1979) originally used Routine Activities perspective to explain macro-level changes in American crime patterns in the mid and late 1900's. For example, they found national levels of theft coincided with the price and size reduction of many electronic appliances. Their concepts evolved into a framework for specific crime events.

value, or are accessible and easy to conceal or move (Cohen & Felson, 1979). For example, research on shoplifting decisions assign target suitability based on the size or monetary value of items or goods (Clarke, 1999). The risk of offending can be increased to the point of a non-offense when capable guardians are present, access to targets is controlled, or the target is no longer valuable. Guardians, defined as individuals who have the perceived ability to step in, defend, and protect a crime, reduce the attractiveness of committing a crime despite a suitable target (Cohen & Felson, 1979; Hollis-Peel, Reynald, van Bavel, Elffers, & Welsh, 2011).

The framework laid out by Cohen and Felson (1979) transformed over time to explain certain behaviors or lifestyles associated with criminogenic convergence, target suitability, and guardianship (Averdijk, 2011; Bunch, Clay-Warner, & Lei, 2015; Hindelang, Gottfredson, & Garofalo, 1978; Lemieux & Felson, 2012; Miethe, Stafford, & Long, 1987; Mustaine & Tewksbury, 1998; Schreck & Fisher, 2004; Spano, Freilich, & Bolland, 2008). Early Routine Activities' research, like Messner and Blau (1987) found specific household activities, such as television viewing, were negatively associated with neighborhood crime. However, a handful of non-household activities, such as sporting events or other entertainment, were positively associated with neighborhood crime (Messner & Blau, 1987). Indoor and outdoor activities differentially altered guardianship of the home and likelihood of convergence with others. More recent research has assessed correlates with different types of crime in search of specific behaviors that increase risk of violent victimization (Bunch et al., 2015; Lemieux & Felson, 2012; Sampson & Wooldredge, 1987; Schreck & Fisher, 2004; Spano et al., 2008) or property crime victimization (Averdijk, 2011; Bunch et al., 2015; Mustaine & Tewksbury, 1998; Stein, 2013). Different "routine" behaviors, like gang involvement or party going, increase exposure to “differential opportunities for crime” or victimization (as explained by Messner & Blau, 1987:1047).

Crime Pattern Theory

Crime Pattern Theory assembles the different components of Rational Choice and Routine Activities perspectives into a spatial framework (Brantingham, Patricia L. & Brantingham, 1981; Brantingham, Patricia L. & Brantingham, 1995; Brantingham, Paul J. & Brantingham, 1993). The theory argues that the larger community context (“backcloth”) dictates where people, places, and criminal opportunity are spatially distributed (Brantingham, Patricia L. & Brantingham, 1999). Movement and usage of these places (“nodes”) via walkways and roads (“paths”) in turn put different locations at different risks for crime occurrences. Agreeing that offenders are rational and read cues from the environment about opportunity, the authors also highlight the importance of people’s perceptions of their immediate environment and their mobility patterns. Essentially, Brantingham and Brantingham (1999) argue that each component (offenders, victims or targets, nodes, and common paths) is spatially distributed and have varying degrees of “criminal potential”. If these components were layered on a map with transparency, the areas with the most overlap (darkest hues) would indicate areas with the highest cumulative criminal potential (Brantingham, Patricia L. & Brantingham, 1999).

Brantingham and Brantingham (1993) explain an environmental backcloth as a “mosaic” of demographic, social, physical, and economic factors. Factors ranging from zoning or land use to racial makeup can influence the distribution of criminogenic features, which will pattern crime hot spot locations (Brantingham, Patricia L. & Brantingham, 1999). Most importantly, the immediate physical setting guides the distribution, movement and interaction of potential offenders, victims, and targets. Other dynamics, such as social or cultural factors, can influence people's informal norms, types of routines, and other personal behavior. They can also affect the behavior of groups and organizations, like the police for example (Brantingham, Patricia L. & Brantingham, 1981). While not directly associated with Crime Pattern Theory, Wikstrom (2004) also explained the integration of individuals inside their environment. He argued that broad social conditions (exposure to criminal settings) influences an individual's development of a criminal propensity or attitudes. Overall, the larger environmental context affects the distribution and interaction of offenders, victims, and other targets.

The environmental backcloth is comprised of a number of spatial features that shape the movement of individuals: nodes, paths, and edges. "Nodes" are places central to a person's life, such as one's home, school, work, or gym (Brantingham, Patricia L. & Brantingham, 1995:10). Nodes carry different characteristics that emit environmental cues about criminal opportunity, making them either crime generators or attractors (Brantingham, Paul J. & Brantingham, 1993). "Paths" are streets, walkways, or public transportation lines that facilitate the movement of people between nodes (Brantingham, Paul J. & Brantingham, 1993). As people move along paths, to and from nodes, they acquire knowledge of the physical and social world around them (Brantingham, Patricia L. & Brantingham, 1995:11). "Edges" are both literal and figurative thresholds that separate areas, which neighbors use to determine who is or is not an outsider (Brantingham, Patricia L. & Brantingham, 1995:12).

Individuals are positioned inside a larger environmental context and interact with its characteristics (Brantingham, Paul J. & Brantingham, 1993; Wikstrom, 2004). According to

Brantingham and Brantingham, offending and non-offending populations move routinely around their nodes and common paths, which make up their “activity space”. Because of the frequent exposure, people know a great deal about their action spaces and the social dynamics governing them. This activity space can be extended to include areas that individuals may not regularly use, but gain awareness of due to their proximity to common nodes and paths (known as “awareness space”) (Brantingham, Paul J. & Brantingham, 1993:10). Wikstrom’s Situational Action Theory argued that some people are predisposed to seeing crime as a viable activity, and these people are more likely to recognize and seek out criminal opportunity in their environment (Wikstrom, 2004). Together, these theories suggest the environment patterns movement of people, but offenders (those with a propensity to see crime as a viable action) passively identify or actively search out criminal opportunity in and around their activity space (Brantingham, Paul J. and Brantingham, 1993; Wikstrom, 2004).

There are a handful of homogenous types of places that link to more crime. These facility types share common functions and characteristics, such as attracting large volumes of people, hosting risky routines or activities, or emitting cues about suitable or ungraded targets (Bernasco & Block, 2011; Brantingham, Patricia L. & Brantingham, 1995; Brantingham, Paul J. & Brantingham, 1993). “Crime generators” are sites that attract a larger number of people for reasons unrelated to criminal offending, such as shopping malls (Brantingham, Patricia L. & Brantingham, 1995). Due to the large influx of people and targets, offenders may passively exploit opportunities that present themselves. “Crime attractors” are sites, which have the explicit reputation for providing criminal opportunity. Offenders actively seek out these places and their patrons, because of the known opportunity associated with them (Brantingham, Patricia L. &

Brantingham, 1995). "Crime neutral areas" are sites that have occasional crime, but lack ample and reputable criminal opportunity to be consistent targets of offending. Instead, local residents or "insiders" sporadically exploit opportunities (Brantingham, Patricia L. & Brantingham, 1995).

Offenders' decision-making, including criminogenic behavior, and routine activities are all contextualized by their environment (Brantingham, Patricia L. & Brantingham, 1981; 1995; 1993). Elements that contribute to offenders' decisions to commit crime are drawn from their awareness spaces, which are dictated by movement to and from common nodes (Brantingham, Paul J. & Brantingham, 1993; Clarke & Cornish, 1985). Some places are more crime-prone because they attract more people, have suitable targets and poor guardianship, or facilitate criminogenic routine activities (Brantingham, Paul J. & Brantingham, 1993; Clarke & Cornish, 1985; Cohen & Felson, 1979). Taken together, these environmental criminological theories explain the distribution of crime as a function of human movement and the offenders' perceived distribution of criminal opportunity.

Crime & Place Research

Crime and place research has focused on identifying and explaining spatial crime patterns. Regardless of the unit of analysis, research has found a small number of neighborhoods, census units, street blocks, or addresses/land parcels account for the majority of a city's crime, while most places are relatively crime-free. To explain these patterns, crime and place research has first established that the environmental backcloth influences crime directly and indirectly. Furthermore, the street network patterns movement between important nodes. A majority of crime and place research seeks to explain crime concentrations with the presence of criminogenic facilities, such as bars, public housing communities, and open-air drug markets. Variation within facility types, however, suggest not all establishments within a homogenous category are equally criminogenic. Instead, something, such as the facilities' exposure to likely offenders, may be conditioning the relationship between facility types and crime.

Crime Concentrations at Varying Scales

One of the most salient findings in crime and place research is that a small portion of a city's total geographic area contains the majority of a city's crime (Weisburd, 2015). These patterns exist among regions and cities, neighborhoods and census-units, and even streets and address or parcels. As the geographic scale moves from cities and regions to neighborhoods and streets, criminologists continue to find crime concentrated in a few units (Weisburd, Bernasco, & Bruinsma, 2009). Over time, some environmental criminologists have favored the use of micro-units, such as street blocks or land parcels (see Weisburd, 2009). Many argued street blocks better reflect the nature of micro-communities, movement patterns, and dynamics of criminal opportunity (Taylor, R. B., 1997).

Early spatial examinations of crime trends and patterns focused on explaining spatial distributions at "macro-places" and "meso-places" (Weisburd, 2015). Macro-places included cities, counties and states, while meso-places included neighborhoods, census blocks and tracts. The early 1800's research found crime, structural disadvantage, and other social processes concentrated more heavily in some cities and regions of a country (Weisburd et al, 2009). Eventually, the use of macro-places progressed to meso-places, like neighborhoods and census-units. One the largest contributions to environmental criminology came from Shaw and McKay's

(1942) work in Chicago, IL. First, they found offender home addresses concentrated in the disadvantaged portions of Chicago (known as the “Zone of Transition”). More importantly, they discovered these patterns remained stable despite the migration of different racial and ethnic groups into and out of the “Zone of Transition”. Crime-free areas remained relatively crime-free, even after residents moved into them from the “Zone of Transition”. This led Shaw and McKay to conclude that there must be something about the geographic place leading to crime, rather than people in the area. Later, studies continued to find that crime and disadvantage consistently concentrated in similar parts of each respective city (Mazerolle, Wickes, & McBroom, 2010a; Rountree & Warner, 1999; Sampson & Groves, 1989; Sampson, Raudenbush, & Earls, 1997; Veysey & Messner, 1999; Warner & Rountree, 1997).

More recently environmental criminologists have examined the spatial distribution of crime at a finer unit of analysis, known as “micro-places” (Weisburd, 2015). Micro-places include clusters of street blocks, street segments, and unique addresses or land parcels. In the late 1980’s, a number of researchers found that the same crime concentrations which occur at the macro- and meso-levels, also occur at the address-level as well (Pierce, Spaar, & Briggs, 1988; Sherman, Gartin, & Buerger, 1989). In Minneapolis, for example, three percent of addresses accounted for 50 percent of the city’s calls for police service (Sherman et al., 1989). Crime concentration findings at street segments have been so consistent that Weisburd (2015) has deemed the pattern the “Law of Crime Concentration at Places”. Essentially, this criminological law proposes that a small proportion of streets disproportionately account for the majority of a jurisdiction’s crime. This finding has been replicated at different units of analysis, using different types of crime data, and in different types of cities, sizes of cities, and regions of the world (Weisburd, 2015).

While macro- and meso-level analyses described between neighborhood variation in crime, findings from micro-level analyses now suggest that research needs to account for within-neighborhood variation in crime. Weisburd and colleagues (2004) tested the distribution and stability of crime at street segments, defined as both sides of the street between two intersections (Taylor, R. B., 1997). First, they found that four percent of street segments accounted for 50 percent of crimes between 1989 and 2002 and remained relatively stable. In many cases, high-crime streets directly neighbor low-crime or crime-free streets. These findings were later replicated using different localities, time periods, and crime types (For representative examples see Weisburd, 2001; Andresen & Malleson, 2011; Andresen & Malleson, 2011; Curman, Andresen, & Brantingham, 2015; Curman et al., 2015; Weisburd & Green-Mazerolle, 2001).

Environmental Backcloth

According to Brantingham and Brantingham (1993) the larger social, political, and structural context influence the distribution of facilities and people, as well as peoples' usage and movement. Structural disadvantage is one such environmental backcloth element that affects crime. Structural disadvantage often refers to a collection of adverse neighborhood conditions, which results in fewer resources and impedes a community's ability to better itself (Krivo & Peterson, 1996). Universally, these areas also tend be historically crime-ridden (Krivo & Peterson, 1996; Pratt & Cullen, 2005a). Within research, it is established that different forms of structural disadvantage tend to concentrate (Krivo & Peterson, 1996; Wilson, 1987). For example, areas that have high poverty levels tend to have low property values, higher residential turnover, and therefore less education funding. Because the effects are so strong (Pratt & Cullen, 2005a), structural controls are nearly universal in environmental criminology. According to Crime Pattern theory, structural factors, disadvantage in particular, affect how people move, interpret, and interact with their environment (Brantingham, Paul J. & Brantingham, 1993)

The environmental backcloth influences the distribution of facilities and offenders (Kubrin & Hipp, 2016; Loukaitou-Sideris, Liggett, Iseki, & Thurlow, 2001; Ousey & Lee, 2002; Ray, Boshari, Gozdyra, Creatore, & Matheson, 2013; Tillyer & Walter, 2018; Tita & Radil, 2011; Woo & Joh, 2015). The needs and desires of residents, in addition to the ability for facilities to make money, influences the types of facilities common in different communities. For example, check-cashing facilities tend to be located in neighborhoods where residents need cash fast and do not typically have saving accounts to draw from (Kubrin & Hipp, 2016; Lee, Gainey, & Triplett, 2014; Ray et al., 2013). In the 1960's and 1970's, the location of high-rise public housing communities tended to be located in disadvantaged areas because the demand for affordable housing coupled with low land prices and/or government subsidies offered owners immense potential to profit (Freeman,2004; Goetz, 2003). Correctional research has also established offenders released from prison tend to reside in disadvantaged neighborhoods, marked by high residential turnover, familial disruption, low employment levels, and high rates of crime (Clear, 2007; La Vigne, Mamalian, Travis, & Visher, 2003; La Vigne, Kachnowski, Travis, Naser, & Visher, 2003; La Vigne, Thomson, Visher, Kachnowski, & Travis, 2003; Rose & Clear, 1998; Travis, Keegan, Cadora, Solomon, & Swartz, 2003). For instance, Allard and colleagues (2017) found that the most chronic and costly offenders returned to the most disadvantaged neighborhoods, which were located in just five percent of Queensland, Australia.

Despite environmental criminology's attempt to fully explain why crime concentrates most heavily in disadvantaged areas, concentrated disadvantage and other structural issues continue to have an independent relationship with crime (Bernasco & Block, 2011; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; Haberman, Sorg, & Ratcliffe, 2018; Houser, McCord, & Sorg, 2018; McCord, Ratcliffe, Garcia, & Taylor, 2007; Wo, 2016). Shaw and McKay (1942) theorized that places with high residential turnover, poverty, and ethnic heterogeneity would be unable to recognize common values and therefore protect their community from criminals. Shaw and McKay (1942), and a handful of researchers failed to fully mediate the effect of disadvantage, even after controlling for community-level social factors (Anderson, 1999; Carr, Napolitano, & Keating, 2007; Kirk & Papachristos, 2011; Kubrin & Weitzer, 2003; Sampson et al., 1997; Veysey & Messner, 1999). This remained true in tests of criminogenic facilities (Bernasco & Block, 2011; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Houser et al., 2018; McCord et al., 2007; Wo, 2016). Bernasco and Block (2011) showed the strength and significance of some facilities changed after the introduction of sociodemographic disadvantages.

Paths

In Crime and Place research, paths facilitate the movement of people to and from nodes (Brantingham, Patricia L. & Brantingham, 1981; Brantingham, Patricia L. & Brantingham, 1991). Theoretically, people, including offenders, travel among paths and develop familiarity and understanding of the streets in which they use. These paths facilitate the convergence of offenders and targets, and emit environmental and situational cues for criminal opportunity. For example, more highly traveled streets present more opportunity for offenders to find vehicles to break into or people to victimize. Paths with poor lighting, blind spots, and poor visibility by others reduce the amount of guardianship and increase the suitability of targets.

Of research that examines the relationship between paths and crime, most focus on components of permeability, or the total potential movement in a space, including street networks and general city layouts (Groff, Taylor, Elesh, McGovern, & Johnson, 2014). These studies measure permeability in different ways, but generally find more connected, accessible or highly used streets tend to have more crime, particularly burglary (Agnew, 2018; Beavon, Brantingham, & Brantingham, 1994; Groff et al., 2014; Johnson, S. D. & Bowers, 2010; Summers & Johnson, 2017; White, 1990). This relationship is stronger on streets that are connected to major thoroughfares, highway ramps, or other public transportation (Agnew, 2018; Beavon et al., 1994; Groff et al., 2014; Johnson, S. D. & Bowers, 2010; Summers & Johnson, 2017). In addition to the support for importance of paths, this suggests connected streets support more usage (by offenders and targets) and provide easier escapes. Taken together these studies suggest places and neighborhoods are more easily accessed and highly traveled have more crime.

It should be noted there are a number of studies that do not agree with the general findings or Crime Pattern Theory's conceptualization of movement (Chang, 2011; Hillier & Shu, 2000; Sohn, Yoon, & Lee, 2018; Summers & Johnson, 2017; Van Nes, 2006). For example, Van Nes (2006) found burglars who targeted homes near their own, tended to favor more secluded and hidden areas. Sohn and colleagues (2018) attempted to address the inconsistencies in permeability and crime research. They found higher permeability reduced the risk of burglary. They argued higher permeability could lead to more ‘eyes on the street’ or higher degrees of guardianship (Sohn et al., 2018:32). Birks and Davies (2017) suggested these mixed results indicate there may be threshold or “sweet spot” for street permeability, meaning offenders target streets that are well traveled and provide targets, but avoid streets that are “too” traveled and provide targets with ample guardianship.

With the mixed findings, it is not surprising that some crime and place research simply include street characteristics as a control variable in their models (Andresen, Curman, & Linning, 2017; Bernasco & Block, 2011; Braga, Hureau, & Papachristos, 2011; Curman et al., 2015; Groff & Lockwood, 2014; Weisburd, Groff, & Yang, 2014). [2] Unlike the studies presented above, which give an idea of how the effect of streets vary, these studies examine their effect net of criminogenic facilities. Even after removing the main effects of facilities, these studies find that major streets or “arterial” streets are associated with more violent, property, and disorder crimes (Andresen et al., 2017; Bernasco & Block, 2011; Braga et al., 2011; Curman et al., 2015; Groff & Lockwood, 2014; Weisburd et al., 2014). Compared to lesser-traveled streets or less accessible highways, these types of streets are travelled by more people, often connect major nodes, and are walkable by both offenders and victims.

[2] Curman et al (2015) found that the effect of street type did not have a consistent “global” effect on crime. While many of the chronically high street segments were arterial streets, they found low or decreasing streets were also arterial streets in some pockets of Vancouver. Braga et al (2011) found arterial streets were associated with less street robberies, but more commercial robberies.

Facilities

Studies linking facilities with spatial crime patterns are one of the most common study types in the crime and place literature. Facilities are groups or categories of homogenous establishments that share primary functions, such a grocery stores or bars and clubs (Eck, Clarke, & Guerette, 2007). Along with shared functions, facilities often share similar layouts, encourage the same types of behaviors or actions, have similar business practices, and attract relatively similar crowds. This is especially true when comparing one facility type to another. While a nightclub might be structured differently than a pub or tavern, they appear relatively similar in comparison to a bank or school. A subsection of crime and place literature examines the criminogenic effects of some facilities. Those that have heightened risk for crime are known as "criminogenic facilities" or "crime generators or attractors" (CGAs). Some facilities may accommodate the convergence of people, others may elicit situational cues or encourage risky behaviors that offenders exploit or search out, and some simply anchor people to the surrounding areas.

The wide breadth of facilities and crime literature, all with different units of analysis and methods, come to the same conclusion: criminogenic facilities are important in understanding the spatial distribution of crime. Facilities pattern people throughout space and bring offenders and victims or targets together. To test the impact of various criminogenic facilities, most research has measured criminogenic facilities differently (aggregate measures or specific facility types), use different statistical approaches (regression or pre-post analyses), and account for different spatial extents (testing distance effects). These points are elaborated below.

The first way researchers have measured criminogenic facilities is by accounting for aggregate measures of facility types and different land uses that theoretically present more crime opportunities (Browning et al., 2010; Kinney, Brantingham, Wuschke, Kirk, & Brantingham, 2008; McCord et al., 2007; Stucky & Ottensmann, 2009). As expected, different land uses, have been linked to the locations of different crime type concentrations. For example, land uses associated with higher densities of people and housing or entertainment activities were associated with more violent crime (Browning et al., 2010; Kinney et al., 2008; Stucky & Ottensmann, 2009). Likewise, McCord and colleagues (2007) aggregated different facilities into crime generators or crime attractors and found they had a "substantial" effect on incivilities in the respective neighborhoods, net of other sociodemographic factors (pp. 312). Together, the studies showed the importance of land uses and facilities for attracting or generating opportunities for different crime types.

More commonly, researchers test the independent effects of individual criminogenic facilities using regression analyses (Cameron, Cochrane, Gordon, & Livingston, 2016; Kubrin & Hipp, 2016; Ousey & Lee, 2002; Ratcliffe & Taniguchi, 2008; Roncek & Lobosco, 1983; Roncek & Faggiani, 1985; Stucky & Smith, 2017; Taniguchi & Salvatore, 2012). Because CGAs facilitate different types of criminal opportunity, focusing on a single facility sheds light on more nuanced relationships among facilities, criminal opportunity, and crime. This often involves comparing units with the specific facility to those without it. For instance, Roncek and colleagues (Roncek & Lobosco, 1983; Roncek & Faggiani, 1985) found blocks with schools (particularly public schools) had significantly higher rates of different types of crime. Roncek used the same methodology to assess the effect of bars and taverns on crime (Roncek & Maier, 1991). In sum, this methodology has linked crime to different facilities, such as liquor stores (Cameron et al., 2016; Gruenewald & Remer, 2006; Lipton & Gruenewald, 2002; Lipton et al., 2013; Pridemore & Grubesic, 2013; Toomey, Erickson, Carlin, Lenk et al., 2012; Toomey, Erickson, Carlin, Quick et al., 2012), fringe banking (Kubrin, Squires, Graves, & Ousey, 2011; Kubrin & Hipp, 2016; Lee et al., 2014; Ray et al., 2013), public transportation hubs (Kooi, 2013; Stucky & Smith, 2017), substance treatment facilities (Taniguchi & Salvatore, 2012), illicit markets (Johnson, L. T., 2016; Martínez, Rosenfeld, & Mares, 2008; Ousey & Lee, 2004), and gang territories (Block, 2000; Taniguchi, Ratcliffe, & Taylor, 2011), among others.

Other studies have used a pre-post design to assess changes in crime after a facility has been opened or closed (Aliprantis & Hartley, 2015; Sandler, 2017; Santiago, Galster, & Pettit, 2003). Unlike using a regression-style approach, this method provides a more robust analysis of how crime changes when opportunity associated with these criminogenic facilities are removed or introduced. For example, this approach is common in understanding how crime is associated with public housing communities (Aliprantis & Hartley, 2015; Sandler, 2017; Santiago et al., 2003), transportation nodes (Phillips & Sandler, 2015), pubs or taverns (Burgason, Drawve, Brown, & Eassey, 2017; Kypri, Jones, McElduff, & Barker, 2011), gang territories (Tita & Ridgeway, 2007), and legal brothels in Spain (Soto & Summers, 2018).

Other researchers examine multiple facilities within the same regression analysis to assess the relationship between each facility and crime, while controlling for structural and street network factors (Bernasco & Block, 2011; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Steenbeek, Völker, Flap, & Oort, 2012; Wo, 2016). While these studies come from a select number of study sites, they included a handful of the same facilities and found many facilities are related to more crime among neighborhoods, census units, and streets. While the studies identified over 15 different criminogenic facilities, the most consistently criminogenic facilities included bars or other alcohol establishments, ATMs and banks, corner stores, transportation hubs, and illicit markets (Bernasco & Block, 2011; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Steenbeek et al., 2012; Wo, 2016). Each of the individual studies examined the relationship from a slightly different angle. For instance, some found crime was patterned based on facility usage during different times of day or seasons of the year (Haberman & Ratcliffe, 2015; Haberman et al., 2018), and others found criminogenic facilities influenced crime at different spatial ranges (Groff & Lockwood, 2014). These findings led to and aided in the discussions about the moderated effects of criminogenic facilities and crime.

As hinted at above, a handful of studies have examined the effect criminogenic facilities have on the surrounding area (Bernasco & Block, 2011; Bowers, 2014; Groff & Lockwood, 2014; Groff, 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Houser et al., 2018). Groff and Lockwood (2014) tested how criminogenic facilities relate to crime counts within 400, 800, and 1200 feet buffers of each street[3]. Only two facilities (bars and subway stops) were significantly associated with increases in violent, property, and disorder crime at each of the three distances. The remaining three facilities had mixed association with different crime types and at different spatial extents. Bernasco and Block (2011) modeled a similar relationship among multiple criminogenic facilities including counts of facilities per census block and sums of all facilities in

[3] These distances roughly represent one additional block of distance.

adjacent census blocks. They included over 10 facility types and found only two were not associated with higher robbery counts, even when including surrounding census blocks (pp. 46). Haberman and colleagues (2015; 2018) captured different spatial extents by including spatially lagged criminogenic facility variables. Similar to the other studies, different facility types interacted with their surrounding environment in different ways.

Houser and colleagues' (2018) multi-level model replication of a previous study (McCord et al., 2007) suggested however, there are spatial extents that are too big to accurately model individuals' perceptions. Houser, McCord and colleagues (2018; 2007) modeled the same relationship between perceived incivilities and aggregate measures of criminogenic facilities in two different ways. Using a multi-level approach, Houser and colleagues (2018) found individuals living near criminogenic facilities reported significantly more incivilities, but the neighborhood-level counts of criminogenic facilities were no longer significant (Houser et al., 2018:18). While Groff and Lockwood (2014) suggest criminogenic facilities affect surrounding areas, this also restricts the distance of criminogenic facility's effect. Individuals' perceptions of their environment are much smaller than a city's pre-defined neighborhoods.

Overall, despite different methodologies, each with different strengths and limitations, facilities and crime studies have consistently found many facilities are criminogenic. These facilities include alcohol establishments, convenience or corner stores, transportation hubs, check-cashing facilities or payday lenders, schools, public housing communities, and illicit markets, among others (see Haberman et al., 2015; 2018 for a comprehensive list). The studies also uncover small nuances, such as radiating effects of some criminogenic facilities (Bowers, 2014) or some facilities have different relationships with different types of crime (Groff &

Lockwood, 2014). Overall, this body of literature stresses the importance of facilities in modeling the spatial distribution of criminal opportunity via the importance of facilities for structuring human activity patterns.

Risky Facilities

On the other hand, Eck and colleagues introduced the notion of "risky facilities" (Clarke & Eck, 2007; Eck et al., 2007; Madensen & Eck, 2008; Wilcox & Eck, 2011). According to the risky facility phenomenon, only a small portion of establishments will account for the majority of crime and disorder problems associated with the group of facilities as a whole (Clarke & Eck, 2007:4). [4] For example, while bars have been identified as criminogenic, it is likely that only a handful of bars in a city contribute to crime, while most will have little or no crime. Thus, not all establishments within homogenous group of facilities are equally criminogenic and treating them as such may be simplifying their effects (Clarke & Eck, 2007; Eck et al., 2007). One potential explanation for this unequal distribution of crime within facilities is the unequal concentration of offenders, which leads to different patronage. It is this potential relationship that the current dissertation proposes investigating.

There is some research that supports the risky facility phenomenon (see Eck et al., 2007:255-264). Alcohol establishments, particularly bars, have received the most attention within criminology. Madensen (2007) examined the distribution of crime among Cincinnati bars,

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[4] Clarke, Eck, Madensen and colleagues refer to specific establishments or places with a single address as "places" (Clarke & Eck, 2007; Eck et al., 2007; Madensen & Eck, 2008; Wilcox & Eck, 2011). Furthermore, the Risky Facility phenomenon eventually came to be called the Law of Troublesome Places (Wilcox and Eck, 2011). To maintain consistency with other terms in this dissertation, I use establishment as synonymous with place, and risky facility phenomenon as synonymous with the Law of Troublesome Places.

finding 20 percent of bars (n = 36 bars) accounted for 56 percent of all crime in the city. The proportions varied by crime type, but generally a small number of "risky" bars accounted for most crime in the city. This finding was also present in small businesses (Taylor & Mayhew, 2002), motels (Bichler, Schmerler, & Enriquez, 2013), apartment complexes (Clarke & Bichler-Robertson, 1998), and many other facility types (see Eck et al., 2007:255-264). This phenomenon appears to exist regardless of the crime type, facility type, size of facility, chain or local, public or private (Wilcox & Eck, 2011).

Madensen and Eck (2008) reviewed four hypotheses to explain the risky facility phenomenon (Eck et al., 2007; Madensen & Eck, 2008). The neighborhood hypothesis argues that facilities in disadvantaged, crime-prone neighborhoods will produce more high-crime facilities than upper- and middle-class neighborhoods. The management hypothesis argues that crime-prone facilities are the result of poor and negligent management, while crime-free facilities have management who actively prevents crime. The patron hypothesis states that risky facilities attract more motivated and likely offenders than their counterparts (similar to Brantingham and Brantingham (1995) conception of crime attractors). Lastly, the behavior Setting hypothesis states that crime-prone places will develop a set of criminal norms due to the characteristics of the neighborhood, place management, and patrons. These norms or standards of behavior either encourage or discourage deviant or criminogenic behavior.

In 2010, Eck and colleagues produced a report for the National Institute of Justice on the situational aspects of crime concentrations among bars and apartments in Cincinnati, Ohio (Eck et al., 2010). They collected various crime data, census data, and parcel data, surveyed bar managers, and observed each site. The report provided a number of insights into the plausibility of the hypotheses listed above. In light of other crime and place findings, the report provides context with their rigorous methodology.

First, Eck and colleagues (2010) found that neighborhood context was “loosely coupled” with violence. They found crime-prone bars concentrated in different neighborhoods than crime-free neighborhoods, on average. Furthermore, violent crime at bars increased by about 40% per incremental increase in their neighborhood’s disadvantage (pp. 91). While untested, the authors propose neighborhood context likely affects place characteristics and management, which in turn are also linked to crime (pp. 106-107). For example, they suggest local laws and policies likely effect place management decisions, such as occupancy, location, and staffing. This has also been found in a number of facilities and crime studies, which found sociodemographic factors had direct and indirect effects on crime (Contreras & Hipp, 2019; Ousey & Lee, 2002; Papachristos & Kirk, 2006; Stucky & Smith, 2017; Taniguchi & Salvatore, 2012; Tillyer & Walter, 2018). On the contrary, Eck and colleagues (2010:48-49) also found the micro-concentration of bars, apartments, and crime were inconsistent with the neighborhood hypothesis. A number of high-crime bars and apartments were located on the same or a nearby street with crime-free bars and apartments, even in the same neighborhood. While neighborhood context mattered, it did not explain how high-crime and low-crime facilities could exist on the same street.

Eck and colleagues (2010) then considered the management hypothesis. As theorized, management practices largely varied among bars and apartments. The situational characteristics resulting from management practices were significantly related to violent crime in both settings. Managers who provided security and protective measures often had safer facilities (pp. 65; pp. 101). For example, bars could prevent crime if they staffed security, while those that had fewer or no security staff had higher levels of violence (Eck et al., 2010:64). Similarly, apartments with managers on-site had significantly lower violent crime rates. These findings are situated in a body of crime prevention evaluation literature that supports the link between place manager decision-making and crime (Mazerolle & Ransley, 2005). Unlike Eck and colleagues (2010), this body of literature provides a large number of case studies and some randomized control trials that show changing place management practices produced crime prevention benefits (Eck & Wartell, 1998; Mazerolle, Price, & Roehl, 2000).

Eck and colleagues (2010), like other research, did not explicitly test the patron hypothesis; however, they did find evidence patron characteristics mattered. Bars and apartments that attracted "unwanted" or potentially criminal patrons had higher levels of violence.[5] For instance, when bar managers reported they were not attracting their "ideal" customer, they reported about three more violent incidents than their counterparts (pp. 61). Furthermore, crime-prone apartments were also less likely to screen for potentially criminal residents, and more likely to have residents who were delinquent on rent or previously evicted (pp. 98, 101). In fact, apartments that did not perform criminal background checks on their residents had six times more violent crime than those that did. Theory and some research has established the importance of offenders, but no study to date has explicitly tests the patron hypothesis.

Similarly, Eck and colleagues (2010) did not explicitly test the Behavior Setting hypothesis;

[5] Eck and colleagues (2010) discussed these variables as practices within the managers control and do not discuss them as proxies for types of patrons. Instead, they argue bar managers that attract unwanted customers fail to successfully market their bar, and failing to screen apartment residents is an apartment manager's security practice.

however, their collective findings suggest there are no single set of characteristics that are solely responsible for risky bars or apartments (Eck et al., 2010). More likely than not, each element (community context, situational characteristics dictated by place management, and offenders) interact together to create standards of behavior and perceptions related to criminal opportunity. Theoretically, offenders are one set of important factors and required for crime to occur (Cohen & Felson, 1979). According to environmental theory, offenders routinely travel through space and absorb cues from the environment about the potential risks and rewards of committing crimes (Brantingham, Patricia L. & Brantingham, 1981). Applying findings from Eck and colleagues (2010), both the community context and situational characteristics of specific places are related to crime. Empirically, however, crime and place research has not tested the influence of offenders or patrons on risky facilities. They are rarely tested in assessments of crime concentrations, including the risky facility phenomenon.

Offenders & Crime Concentrations

While the importance of offenders and their perceptions of the immediate environment are evident in environmental criminology, they are rarely used to explain the spatial distribution of crime. Even among the most comprehensive studies discussed above, the presence of offenders were not included in the models, with two exceptions (Bernasco & Block, 2011; Weisburd et al., 2014). There is, however, a handful of scattered findings that suggest the volume of offenders is associated with crime, and may interact with criminogenic facilities (Chamberlain, 2018; Eck et al., 2010). For instance, early tests of community-level theories of crime patterns and correctional studies both included proxy measures of offenders. Lastly, a rigorous study of criminogenic bars and apartments in Cincinnati, Ohio suggest the patrons using particular establishments may be related to higher levels of crime (Eck et al., 2010). However, this section will show none of these tests control for sociodemographic and street network controls, criminogenic facilities and the presence of offenders, nor do they examine micro-level patterns smaller than a census block.

Main Effects of Likely Offenders on Crime

Two bodies of research have examined the relationship between the concentration of offenders and crime. In communities and crime literature, measures of unsupervised teens, truant students, and young males commonly serve as controls for likely offenders (Bellair, 1997; Bursik & Grasmick, 1993; Krivo, Lauren J. & Peterson, 1996; Lowenkamp, Cullen, & Pratt, 2003; Mazerolle, Wickes, & McBroom, 2010b; Slocum, Rengifo, Choi, & Herrmann, 2013; Sun, Triplett, & Gainey, 2004; Taylor, R. B. & Covington, 1993; Veysey & Messner, 1999; Weisburd et al., 2014). These studies examine the role neighbors or neighborhood-groups play in preventing crime and tend to control for things like guardianship or likely offenders. These studies have been mostly conducted at a macro-level of analysis, which is inconsistent with the micro-level approach required to assess criminal opportunities. Nonetheless, the study results are still informative for the current dissertation.

Though they are mostly treated as control variables, offender measures in these studies are consistently found to have a significant relationship with crime; in some cases, they have even had the strongest effect among sociodemographic and social control variables (Lowenkamp et al., 2003; Sampson & Groves, 1989; Veysey & Messner, 1999). The consistency and strength of the findings imply offenders have a direct role, net of other factors, but are rarely discussed or elaborated. Instead, scholars focused on how residents exert protective factors and how potential offenders can hinder those protective abilities (Warner and Rountree, 1997; Veysey and Messner, 1999; Venaktesh, 1997; Warner, 2014).

The correctional field has assessed how offenders' environments influences them after their release (Drakulich, Crutchfield, Matsueda, & Rose, 2012; Hipp & Yates, 2009; Kovandzic, Marvell, Vieraitis, & Moody, 2004; Raphael, Stoll, Duggan, & Piehl, 2004; Rosenfeld, Wallman, & Fornango, 2005). In addition to finding recently-released offenders concentrate in space (Clear, 2007; Hesseling, 1992; La Vigne et al., 2003; La Vigne et al., 2003; La Vigne et al., 2003; Rose & Clear, 1998; Travis et al., 2003), study findings also support the idea that the volume of offenders is associated with neighborhood-level crime patterns (Drakulich et al., 2012; Hipp & Yates, 2009; Kovandzic et al., 2004; Raphael et al., 2004; Rosenfeld et al., 2005). Generally, these studies find that the number of parolees or recently released offenders in a neighborhood or census unit are positively associated with crime. However, the findings are not situated along side other measures of environmental theory or among smaller units of analysis, making it hard to discern their effects, net of criminogenic facilities or street network characteristics.

There are two studies that notably include the presence of offenders and criminogenic facilities while analyzing micro units of analysis (Bernasco & Block, 2011; Weisburd et al., 2014). Both find offenders have a significant, positive relationship with crime, but neither explore an interactive relationship between the offender and facilities measures. Bernasco and Block (2011), for example, included a measure of known offenders along with measures of 14 facilities and illicit markets. The presence of known offenders was measured by summing the number of home addresses of recently arrested robbers in each Census block. Additionally, a spatially lagged version of the known offender measure was also included the model. Along with many of the facilities, the offender measure were found to be positively related to robbery, and fully mediated the effect of gang territories. Likewise, Weisburd and colleagues' (2014:40) assessed crime on Seattle street blocks over time and included multiple offender measures, criminogenic facilities, and proxies for social control. Weisburd et al. (2014) accounted for offenders by summing the number of truant juveniles and summing the number of truant or low-achieving students ("high-risk juveniles"). In addition, they accounted for criminal opportunity by including land uses (such as commercial or residential), aggregates of public facilities, sums of retail store profits, and the presence of bus stops. They found that the presence of at least one truant juvenile on a street segment doubled the odds of it being a crime hot spot. Both groups of researchers acknowledged their findings as preliminary evidence towards the importance of offenders in micro-space. However, they did not examine any conditional or interactional effects between offenders and facilities (Bernasco & Block, 2011; Weisburd et al., 2014).

Taken together, studies from the communities and crime and corrections literatures suggest that offenders could affect spatial crime patterns. This is especially important knowing offenders tend to target places nearby or at which they have some degree of familiarity. Known as an offender's "journey-to-crime" or "crime journey" (see Bernasco, 2014 for an overview), offenders are more likely to offend within a short distance of their homes (Bernasco, 2010; Block, Galary, & Brice, 2007; Groff & McEwen, 2006; Lu, 2003; Pizarro, Corsaro, & Yu, 2007; Townsley & Sidebottom, 2010; Van Koppen & Jansen, 1998). Search behaviors and distances have been found to range between ½ mile and two miles, but findings largely vary by study methodology, offender type, and crime type (see Groff & McEwen, 2006:7-8 for an overview). Furthermore, offenders are more likely to target places they are familiar with firsthand, like their family members' neighborhoods (Bernasco, 2010; Menting, Lammers, Ruiter, & Bernasco, 2016; Menting, 2018) or places that have similar demographic make-ups (Baudains, Braithwaite, & Johnson, 2013; Bernasco & Block, 2009; Chamberlain & Wallace, 2016; Clare, Fernandez, & Morgan, 2009; Johnson, S. D. & Summers, 2015; Townsley, Birks, Ruiter, Bernasco, & White, 2016). Advancing the empirical understanding of how offenders interact with criminal opportunity requires filling in gaps surrounding the offender's role in the spatial distribution of crime.

Moderating Effect of Offenders on Crime

In addition to these studies, there are two other studies, one rooted in environmental criminology theory and the second in correctional research, that suggest the criminogenic effects of offenders and facilities may be moderated by offender characteristics (Chamberlain and Boggess, 2018; Eck et al, 2010). Chamberlain and Boggess (2018) controlled for sociodemographic factors and used the conviction offense and intensity of community supervision to proxy variation in offender preferences. Overall, they found that the relationship between presence of parolees and crime counts per census block group was contingent on the type of parolee (offense specialization and level of supervision) and the structural advantage of their neighborhood (Chamberlain & Boggess, 2018). In some cases, crime was found to be negatively associated with more offenders, particularly drug or property offenders. This relationship was further conditioned by neighborhood disadvantage. Parolees re-entering poor and disadvantaged neighborhoods were associated with increases in crime. While Chamberlain and Boggess (2018) detailed the importance and nuanced relationship offenders have with community crime, they failed to account for criminogenic facilities or street network characteristics. The paper does not shed light on how offenders interact with criminal opportunity or whether criminal opportunity is more influential than the presence of offenders.

In 2010, Eck and colleagues produced a report for the National Institute of Justice on the situational aspects of crime concentrations among bars and apartments in Cincinnati, Ohio (Eck et al., 2010). Eck and colleagues (2010), like other researchers, did not explicitly test the impact of offenders on crime; however, they found evidence that the "risky facility phenomenon" may be the result of different types or volumes of patrons. Bars and apartments that attracted "unwanted" or potentially criminal patrons had higher levels of violence.[6] For instance, when bar managers reported they were not attracting their "ideal" customer, they tended to report about three more violent incidents than their counterparts (pp. 61). Furthermore, crime-prone apartments were also less likely to screen for potentially criminal residents, and more likely to have residents who were delinquent on rent or previously evicted (pp. 98, 101). In fact, apartments that did not perform criminal background checks on their residents had six times more violent crime than those that did.

In sum, theory and some research have suggested offenders link to spatial crime patterns, but no study to date has explicitly tested the patron hypothesis. Neither the environmental criminology nor correctional literature have explicitly explored the spatial relationship among

[6] Eck and colleagues (2010) discussed these variables as practices within the managers control and do not discuss them as proxies for types of patrons. Instead, they argue bar managers that attract unwanted customers fail to successfully market their bar, and failing to screen apartment residents is an apartment manager's security practice.

offenders, criminogenic facilities, and crime. Bit by bit, environmental criminology and correctional literature has shown the presence of offenders are likely related to community crime levels. This evidence, however, is piecemeal; in some cases, it is drawn from studies that use imprecise measures of offenders, omit measures of criminal opportunity, or use large units of analysis. A smaller subset of studies has suggested the effects of offenders or criminogenic facilities are moderated by offender characteristics. While these studies explore variation among offenders and the distribution of opportunity, they fail to put all the pieces together under the same umbrella. This limits the ability to understand how all pieces (offenders, streets, and opportunity) act together and separately, net of each other's influence.

Why have the tests of micro-crime concentrations failed to use the collection of offender and opportunity variables despite the consistency among opportunity theories? This could be occurring for a number of reasons. First, some colleagues have suggested the field does not gain new information by finding offenders are associated with higher crime rates. More likely, however, data and methodological limitations are more likely to restrict full tests of offenders, criminal opportunity, and the distribution of crime. Gathering facility data is time-consuming and meticulous. Offender home addresses are often not collected, kept, or available for research purposes. These get significantly more difficult when using smaller units of analysis, like street blocks. This now requires more precise location data, and the skills to map each bit of data.

It is important to note the reasons these tests have not been conducted because it provides insights into the dissertation's value. Without proper inclusion of variables, models may be misspecifying or "biasing" effects of offenders, criminogenic facilities and/or controls. Some studies have included proxy measures, such as the proportion of youth or "unsupervised" teens, but continue to risk biasing results. The current dissertation combined multiple data sources at the street block-level. These tests improved our understanding of street block crime levels. Rather than understanding independent effects, we are able to see how offenders, criminogenic facilities, and controls influence street block crime levels.

Summary

Environmental criminology theory tells us that offenders are an essential element of the crime triangle. Crime is expected to be patterned around criminogenic places and paths to the extent that likely offenders take advantage of the criminal opportunities they present. Empirically, we know that crime is concentrated, and these concentrations have been explained mostly by assessing the presence of different criminogenic facilities and street network characteristics. Rarely are offenders considered. The little research that has been done assessing the link between the spatial distribution of offenders and crime concentrations has been limited in that it has failed to account for measures of criminal opportunity under the same model, particularly among micro spatial units. Thus, one relatively untested idea in the environmental criminology literature is that variations in offender presence can interact with the effects of criminogenic facilities to impact crime. In actuality, the presence of offenders influences nearby crime levels and interacts with some facilities to indirectly impact nearby crime levels. The findings, however, prove to be more complex than originally conceived by Brantingham and Brantingham or Madensen and Eck. This proposed study seeks to address this gap in the literature by answering four general research questions. The research questions are designed to understand how offenders relate to crime and their surrounding environment. It also examines how offenders may interact with their environment, making some individual establishments riskier than those in the same homogenous group of facilities. It reduces the potential of model misspecification inherent in models that do not include theoretically relevant variables like offenders, criminogenic facilities, street network characteristics, and structural controls.

CHAPTER 3: RESEARCH QUESTIONS, DATA, AND METHODS

The proposed study's main goals are to examine the spatial distributions of offenders and test if the spatial patterning of offenders can be integrated with past correlates of spatial crime patterns to explain micro-level crime counts. This chapter presents the proposed study's research questions, data, and methodology. First, the chapter begins by outlining the research questions and hypotheses the proposed dissertation will address. Second, the proposed study's period, site, and various data sources are outlined. Third, the unit of analysis and measures are described. Fourth, the proposed analytic plan for answering each of the three questions is presented.

Research Questions and Hypotheses

Crime Pattern theory suggests that crime, facilities, and offenders are not evenly distributed in space. Prior literature has established three major conclusions, which are the basis of the research questions. First, there is strong evidence that micro-level crime concentrations are the result of the distribution of risky facilities or criminogenic facilities (Bernasco & Block, 2011; Bowers, 2014; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Kinney et al., 2008; McCord & Ratcliffe, 2007; Steenbeek et al., 2012; Wo, 2016). Second, there is a small body of evidence that suggests likely or motivated offenders also play a role in the spatial distribution of crime (Bursik & Grasmick, 1993; Drakulich et al., 2012; Hipp & Yates, 2009; Kovandzic et al., 2004; Lowenkamp et al., 2003; Raphael et al., 2004; Rosenfeld et al., 2005; Veysey & Messner, 1999; Weisburd et al., 2014). Third, the relationships between crime, criminogenic facilities, and offenders appear to vary largely in space, whether related to structural disadvantage or other unmeasured neighborhood variables (Cameron et al., 2016; Chamberlain, 2018; Haberman, Groff, & Taylor, 2013; Houser et al., 2018; Johnson & Summers, 2015; McCord & Ratcliffe, 2007; Tita & Greenbaum, 2009). The following research questions are based on both Crime Pattern theory and the prior empirical literature.

1) Do likely offenders geographically concentrate in a small number of places?

H_0: Recently released offender home addresses are randomly distributed in a city.

H_1: Recently released offender home addresses are geographically clustered in a city.

2) Do offender hot spots overlap with crime hot spots?

H_0: The geographic distribution of recently released offender home addresses does not overlap with the geographic distribution of crime in a city.

H_1: The geographic distribution of recently released offender home addresses overlaps with the geographic distribution of crime in a city.

Research questions 1 and 2 are inter-related. Together, both research questions focus on the univariate spatial distribution of likely offenders and bivariate relationship between the spatial concentration of offenders and crime. Previous literature suggests that recently released offenders do spatially concentrate in some parts of a city, particularly in low-income and disadvantaged neighborhoods (Irvin-Erickson & La Vigne, 2015; La Vigne et al., 2003; La Vigne et al., 2003; La Vigne et al., 2003). Some research also suggests that crime and recidivism patterns were positively associated with the number of parolees or recently released offenders at the macro- and meso-level (Drakulich et al., 2012; Hipp & Yates, 2009; Kovandzic et al., 2004; Raphael et al., 2004; Rosenfeld et al., 2005). Before modeling the relationship between spatial concentrations of offenders and spatial concentrations of crime, however, I will use exploratory spatial data analyses to investigate these research questions.

3) Does the spatial distribution of likely offenders link to spatial distribution of crime net of other variables that have been used to explain spatial crime patterns in past research?

H_0: The spatial distribution of recently released offenders is not significantly related to crime, after controlling for structural factors, street characteristics, and the presence of criminogenic facilities.

H_1: The spatial distribution of recently released offenders is significantly related to crime, after controlling for structural factors, street characteristics, and the presence of criminogenic facilities.

Building on past work, this research question will indicate if the presence of motivated offenders has a main effect on spatial micro-crime patterns. As outlined in the previous chapters, this is a key but relatively untested proposition in environmental criminology.

4) Are the effects of potentially criminogenic facilities on crime conditional on the spatial distribution of likely offenders?

H_0: There is not an interactive effect between the spatial distribution of recently released offenders and facilities on crime.

H_1: The effect of potentially criminogenic facilities on crime is conditional on the spatial distribution of recently released offenders.

The last research question seeks to understand the interactive effect between spatial distribution of likely offenders and facilities on crime. While research has established a list of criminogenic facility types, Eck and colleagues (Clarke & Eck, 2007; Eck et al., 2007; Madensen & Eck, 2008; Wilcox & Eck, 2011) pointed out the "risky facility phenomenon", the notion that not all facilities of a homogenous type are equally criminogenic. The patron hypothesis presented that facilities of the same type may be more criminogenic than others due to the nearby presence of offenders (Madensen and Eck, 2008). It was not aimed at specific facility types, but rather applied generally to all facility types that followed the "risky facility phenomenon". According to Wilcox and Eck (2011), crime and place literature has yet to find a facility type that does not follow the pattern, gaining the label the "Iron Law of Troublesome Places". Therefore, there is no theoretic or empirical literature to suggest the patron hypothesis applies to one criminogenic facility and not another. This dissertation will explore the relationship between offenders and crime, adding further evidence to this relatively understudied environmental criminology proposition.

Study Site

Cincinnati, Ohio is the current study's site. Located along the Ohio River, north of Kentucky, Cincinnati is a mid-sized city in Southwest Ohio. Cincinnati has approximately 300,000 residents (U.S. Census Bureau, 2018). According to the US Census, about half of Cincinnati's population was white (50.7%) or black (46.8%) in 2010. Only 2.8 percent of the City's population was Latino/a. The city was approximately 80 square miles. Overall, the neighborhoods were quite diverse in their economic and racial makeup. [7] According to two Cincinnati news outlets, the City ranked among the top 10 most segregated urban cities, with higher proportions of white home ownership and employment than that of minorities, and significantly higher proportions of black and Hispanic residents living at or below the poverty line (Campoy, 2016; Kent & Frohlich, 2015; Swartsell, 2015).

Unit of Analysis

The proper spatial unit of analysis has been highly debated since the beginning of crime and place research. Historically, the unit of analysis slowly has become smaller, starting with large neighborhoods and census units to street segments or single addresses (Eck, 2017; Weisburd et al., 2009). The unit of analysis is often dictated by available data or researcher's preference with little or no consideration of the problems associated with different units of analysis. Researchers should consider how a unit of analysis can overlook the limitations of data (accuracy and precision), change measurements based on the shape and location of unit boundaries (Modifiable Areal Unit Problem) or lead to misspecification of causality (ecological or exception fallacies). Street blocks reflect natural paths and boundaries used by people, but also restrict the impact offenders can have on a larger unit of analysis, like a neighborhood. After considering both technical challenges and theory, the current study uses street blocks as the unit of analysis. Street blocks are defined as both block faces between two intersections (Taylor, 1997).

Street blocks are theoretically a better representation of human movement. As reviewed above, Crime Pattern Theory and supporting research suggested citizen movements and the

[7] The 52 neighborhoods are aligned with census demarcations making comparisons more reliable.

effects of criminogenic facilities are distributed tightly across micro spaces (Brantingham, Patricia L. & Brantingham, 1991). People travel along streets and tend to develop knowledge and familiarity of streets, while they stay relatively blind and unfamiliar with the rest of a neighborhood (Brantingham, Patricia L. & Brantingham, 1991). Ethnographic research supports the notions that both citizen movement, offender searches, and guardian's social control operate at a micro-level (Duneier, Hasan, & Carter, 1999; Jacobs, 1961). Taylor (1997) suggested street blocks are "behavior settings", or places that facilitate interactions with proximal people and facilities and connect individual-level factors and neighborhood-level factors. The areas directly proximal to important places, such as homes, are the center of people's lives, tend to support homogenous groups of people, and facilitate repeated contact with those nearby people. Together these factors create a common understanding of the accepted behavior, attitudes and norms at the street level.

In addition, street blocks address a number of technical concerns in spatial research. First, the accuracy and precision of most crime data is best balanced at the street segment, rather than a smaller or larger unit of analysis. CPD officers inputted crime incident locations using a specific address. Some offenses, particularly violent offenses, develop and even occur over an area larger than a single address (see Jacobs, 2012; Luckenbill, 1981 for example); however, an officer is still required to enter a single address. While we cannot guess how officers assign a location in these situations, the street blocks incorporate multiples addresses and are more identifiable than unique addresses. Second, street blocks reduced the accuracy problem faced by using unique addresses. The Modifiable Areal Unit Problem (MAUP) refers to the bias associated with artificially chosen spatial boundaries of areal groupings (Openshaw & Taylor, 1979). Especially with continuous data, areal units can cut data into pieces even though it may not represent natural splits in a phenomenon. For example, residents of a neighborhood do not pattern movement or behavior based on government-defined boundaries. Human movement, however, does naturally occur along street blocks (Brantingham, Patricia L. & Brantingham, 1981). Therefore, street blocks provided a micro-unit of analysis that is rooted in theory and minimizes the geographic imprecision of police data and geocoding.

Street Reference Data

The Cincinnati Area Geographic Information System (CAGIS) provided updated street centerline data for all of Hamilton County (City of Cincinnati, 2018). While the City of Cincinnati's streets are updated on a quarterly basis, a team of graduate students at the University of Cincinnati cleaned the connectivity, address ranges, alternate street names, and eliminated duplicate streets to better reflect the City's street network. After cleaning, the dataset included only a single segment between intersections with street name aliases for segments that changed names over the course of the study period to provide a unit of analysis consistent with the definition of street blocks commonly used in the criminological literature. The street reference data was used to geocode both crime data and offender home addresses. In addition, it provided the unit of analysis, the street segment. All variables were joined or allocated to the intersecting street segment.

Data Sources and Measures

The current study used five different data sets (displayed in Figure 1 and Table 1). First, the Cincinnati Police Department (CPD) provided 2016-2017 official crime incident data to derive the dependent variables and 2015 official calls for service data to derive drug and prostitution markets. Second, data on facilities at the address level were derived from the 2015 Ohio Department of Revenue and various municipal and state government offices. Third, the Ohio Department of Rehabilitation and Correction (ODRC) supplied offender records for all individuals released from ODRC supervision to a Cincinnati address between 2013-2015. Measures of offenders and offender motivation were derived from the collection of variables and home addresses in the ODRC data. Fourth, the U.S. Census Bureau provided sociodemographic data, which served as control variables. Fifth, the Cincinnati Area Geographic Information System (CAGIS) provided street centerline files (used to geocode all spatial data) which had categorized street types (arterial versus local roads) and served as a control variable.

Figure 1. Timeline of data sources, 2013 – 2018

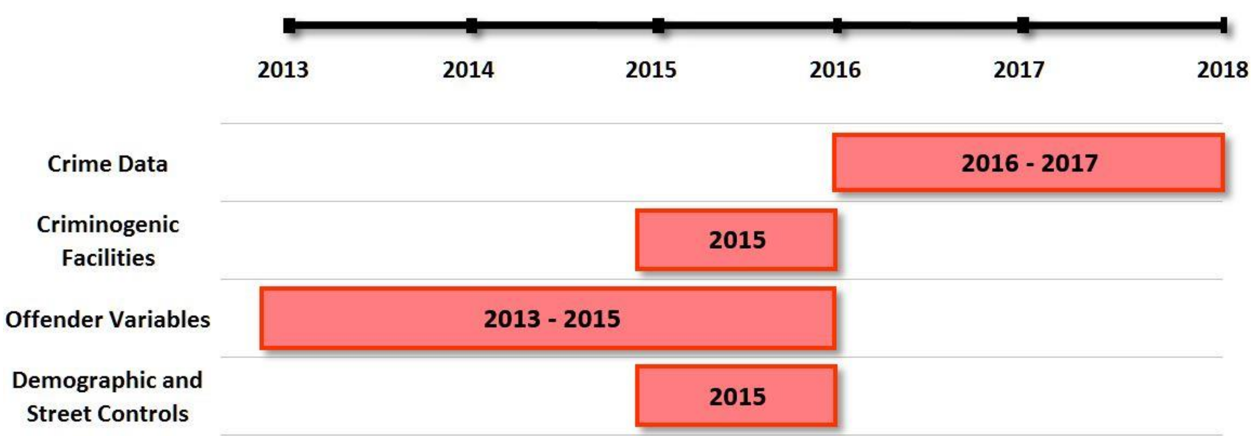

Table 1. Sources and Descriptions of Study Variables

Variable Type	Variable	Source	Operationalization
Dependent Variable	Robbery	CPD	Count of Incidents
	Theft from Auto	CPD	Count of Incidents
Criminogenic Facilities[a]	Bar/Club	ODT	Count
	Entertainment Facility	ODT	Count
	Fringe-Banking Store	ODT	Count
	Grocery Store	ODT	Count
	Everyday Store	ODT	Count
	Restaurant	ODT	Count
	Retail Store	ODT	Count
	Bus Stop	SORTA	Dummy
	High School[b]	ODE	Dummy
	Drug Treatment Facility[b]	OMHAS	Dummy
	Parking Facility	CAGIS	Dummy
	Public Housing[b]	CMHA	Dummy
	Gang Territory	CPD	Dummy
	Prostitution Market	CPD	Count of CFS
	Drug Market	CPD	Count of CFS
Likely Offender Variables	Exposure to Likely Offenders	ODRC	IDW Scale
	Exposure to Cumulative Offender Risk	ODRC	IDW Scale
Control Variables	Total Population	ACS	Continuous
	Concentrated Disadvantage	ACS	Continuous
	Residential Stability	ACS	Continuous
	Racial Heterogeneity	ACS	Continuous
	Length of Street	CAGIS	Continuous
	Major Street	CAGIS	Dummy
	Highway Access	CAGIS	Dummy

Note: CPD = Cincinnati Police Department, ODT = Ohio Department of Taxation, SORTA = Southwest Ohio Regional Transit Authority, ODE = Ohio Department of Education, CAGIS = Cincinnati Areal Geography Information System, CMHA = Cincinnati Metro Housing Authority, ACS = American Community Survey, ODRC = Ohio Department of Rehabilitation and Correction.

[a] Each facility included will also include a spatially lagged version. Their coding schema will match that of their original coding. Facilities represented by polygons will only be coded if the focal street block does not house the facility and one or more adjacent street block does.

[b] Facilities represented by polygons are those whose geographic footprint span multiple blocks. Streets that have access to the respective facility are coded as "1".

Dependent Variables

The Cincinnati Police Department (CPD) provided 2016 and 2017 crime incident data for the City of Cincinnati. Crime incidents are records of a crime event discovered by police officers or reported by citizens that occurred within CPD's jurisdiction. Crime incidents are more restrictive than calls for service (Emergency-911 calls) because officers must decide there is enough evidence to suggest an offense likely occurred. Crime incidents are less restrictive than arrest data because crime incident data does not require a known or apprehended suspect. Crime incidents are more restrictive than calls for service, which do not require or verify a crime to have occurred during recording. The "Dark Figure of Crime" or the fact that not all crimes are detected and recorded, however, is a well-known limitation of crime incident data (Biderman & Reiss, 1967; Skogan, 1977).

The FBI provides definitions of the crime classifications that they require all police departments to report (see U.S. Department of Justice, 2018). Part one crimes include homicide, robbery, assault, rape, burglary, arson, and auto theft, which tend to be more accurately reported and comparable among different jurisdictions (Gove, Hughes, & Geerken, 1985; Hindelang, 1974; Wolfgang, 1963). A number of recent publications have noted the inappropriateness of aggregating crime types (Andresen & Linning, 2012; Andresen et al., 2017; Haberman, 2017). Crime hot spots are not located in the same locations when different crime types are disaggregated and analyzed using various spatial techniques (Haberman, 2017). In addition, Andresen and Linning (2012:279) found there were dramatic differences in the concentrations of substantively different crime types, such as robbery and theft of vehicle, but there are often negligible differences within a crime type like robbery. Therefore, the study used robbery, one

Part I violent crime type, and theft from auto, one Part I property crime type, as the dependent variables. Table 2 describes the Uniform Crime Reporting (UCR) codes and other characteristics used to operationalize robbery and theft from auto offenses.

Table 2. Operational Definitions of Dependent Crime Variables

Crime Type	Description	UCR Code	Other Fields
Robbery	Unlawful taking of goods, with a weapon and/or the use (or threat of) violence	300 series	N/A
Theft from Auto	Unlawful taking of a vehicle part or object within the confides of a vehicle	600 series	Theft Code = 23F, 23G, 24I

Note: UCR Code refers to code assigned by the FBI's Uniform Crime Reporting system. Theft codes, on the other hand, are assigned by the Cincinnati Police Department. The theft codes included include theft of an auto and theft of auto contents, parts, and license plate.

Robbery included all robbery incidents, regardless of victim type (commercial versus individual) or injury type (threaten, attempted or sustained). Robbery was chosen because its relative popularity in criminology, particularly in environmental criminology. This provided a point of reference for the current study, and extended findings from past literature. There has been recent research suggesting further disaggregating crime types based on qualitatively different event factors (Andresen & Linning, 2012; Clutter, Unpublished); however, Andresen and Linning (2012) found a substantial amount of overlap among the distribution of commercial and individual robberies in multiple Canadian jurisdictions. Correlates with robbery tend to be consistent across studies (Bernasco & Block, 2011; Clutter, Unpublished; Haberman & Ratcliffe, 2015; Haberman et al., 2018), which is consistent with Cornish (1994).

Theft from auto offenses were used as a representative of property crime.[8] Theft from auto included all thefts from an automobile, including parts and contents of a vehicle and a vehicle's license plate. It is less frequent in crime and place literature than residential burglary, but local stakeholders and frequency in Cincinnati led the choice to use theft from auto offenses. One possible limitation (which will be discussed further in Chapter 5) is auto thieves tend to be younger than other offenders (McCaghy, Giordano, and Henson, 1977; Fleming, Brantingham and Brantingham, 1994). According to Fleming and colleagues (1994), nearly half of auto thefts were committed by offenders under the age of 18. Johnson and Summers (2015) found that younger offenders were more likely to commit vehicle-related thefts only when they were near facilities commonly used by young people, such as schools. While prior research focuses on auto theft rather than theft from auto, this is a problem because the offender data only included adult offenders. This likely biases the results in favor of a weaker relationship between offender and theft from auto counts and will be further discussed in the limitations (Chapter 5).

The crime incident data included home addresses, which were geocoded to street blocks. The geocoding hit rate for the crime incident data was roughly 99.9%. For reference, a match rate above 85% has been deemed acceptable in criminology (Ratcliffe, 2004). It should be noted CPD does not use street intersections in their location data, which eliminated the need to allocate incidents falling at two streets' intersection. There were 2,437 robbery offenses between 2016 and 2017. Most streets had no robberies (N = 9,530), followed by one robbery (N = 945).

[8] In a previous version, theft from auto was aggregated with auto-related theft. Sensitivity checks showed dramatic differences among the geographic distribution and among significant predictors of auto theft and theft from auto. The correlation between theft from auto and auto theft among street blocks was weak-moderate (Pearson's Correlation = 0.34). Theft from auto was chosen over auto theft because of the frequency and age demographic related to common offenders.

Furthermore, there were 6,915 thefts from auto between 2016 and 2017. Similarly, most streets had no thefts from auto (N = 7,663), followed by one theft (N = 1,840).

Facilities

In 2016, Dr. Cory Haberman and a team of graduate students collected data on business licenses in the City of Cincinnati and provided access to the data set for this dissertation. The process began with a list of all businesses that collect sales taxes in Hamilton County, Ohio from the Ohio Department of Taxation. After geocoding, cleaning, and verifying all business details, the original 12,778 businesses in Hamilton County were reduced to 2,392 businesses in the City of Cincinnati. In addition, Dr. Haberman and the research team gathered information on facilities that were not economically-driven from a number of other sources: the Ohio Department of Education, the U.S. Department of Education's Office of Postsecondary Education, Cincinnati Area Geographic Information System (CAGIS), Cincinnati Parks and Recreation Department, the Cincinnati Metropolitan Housing Authority, Southwest Ohio Regional Transit Authority, and the Cincinnati Police Department. Table 3 presents univariate statistics for all study variables included in the dissertation.

Table 3. Univariate Statistics of Study Variables, Street Blocks in Cincinnati OH

Variable Name	Min	Max	Median	Mean	SD
Robbery	0	26	0	0.22	0.83
Theft from Auto	0	36	0	0.63	1.60
Bar/Club	0	4	0	0.01	0.14
Entertainment Facility	0	2	0	0.01	0.08
Fringe-Banking Store	0	2	0	0.00	0.04
Grocery Store	0	1	0	0.00	0.05
Everyday Store	0	6	0	0.03	0.22
Restaurant	0	15	0	0.05	0.39
Retail Store	0	17	0	0.06	0.50
Bus Stop	0	1	0	0.29	0.45
High School	0	1	0	0.01	0.10
Drug Treatment Facility	0	1	0	0.00	0.06
Public Housing	0	1	0	0.01	0.09
Parking Structure	0	1	1	0.51	0.50
Gang Territory	0	1	0	0.20	0.40
Prostitution Market	0	11	0	0.01	0.20
Drug Market	0	63	0	0.53	2.04
Bar/Club SL	0	7	0	0.07	0.35
Entertainment Facility SL	0	4	0	0.03	0.19
Fringe-Banking Store SL	0	3	0	0.01	0.10
Grocery Store SL	0	2	0	0.01	0.11
Everyday Store SL	0	8	0	0.17	0.52
Restaurant SL	0	18	0	0.26	1.06
Retail Store SL	0	31	0	0.30	1.25
Bus Stop SL	0	1	0	0.26	0.44
High School SL	0	1	0	0.02	0.14
Drug Treatment Facility SL	0	2	0	0.02	0.14
Public Housing SL	0	1	0	0.01	0.10
Parking Structure SL	0	1	1	0.95	0.21
Gang Territory SL	0	1	0	0.12	0.32
Prostitution Market SL	0	17	0	0.39	1.24
Drug Market SL	0	136	6	11.27	16.54
IDW Exposure to Likely Offenders	0	118.05	7.04	12.26	15.91
IDW Cumulative Offender Risk	0	180.19	8.19	14.88	20.83
Total Population/100	1.57	36.55	10.32	10.81	4.80
Concentrated Disadvantage	-5.88	15.70	-0.57	0.01	3.64
Residential Stability	-4.48	6.14	-0.23	-0.03	1.73
Racial Heterogeneity	0.02	0.74	0.43	0.39	0.17
Length of Street (feet)/100	0.13	188.08	3.47	4.79	5.01
Major Street	0	1	0	0.16	0.36
Access to Highway	0	1	0	0.02	0.13

Note: N = 10,940 street blocks; Min = Minimum, Max = Maximum, SD = Standard Deviation, SL = Spatial Lag

The dissertation included 15 total “potentially criminogenic” facilities or crime generator and attractors. These facilities had strong theoretic and empirical support as criminogenic facilities, as per the review in Chapter 2 (for example Bernasco & Block, 2011; Haberman & Ratcliffe, 2015; Lum, 2008; Taniguchi et al., 2011). The facilities derived from Dr. Haberman’s research team were coded in two ways. First, some facilities were summed per street segment. Others were only coded as dummy variables due to the nature of the facility type (e.g. gang territory) or the facility stretched multiple blocks (e.g. public housing community). A sum of facilities was favored because prior literature has found that collection of proximal risky facilities, such as “entertainment districts”, can have a heightened risk when compared to single, isolated facilities (Loukaitou-Sideris, 1999; Mazerolle, White, Ransley, & Ferguson, 2012).

Some of the facilities captured places that sell a large quantity of goods or items and therefore large numbers of patrons and vehicles: (1) grocery stores (N=25; count), (2) retail stores (N=694; count), (3) everyday stores (N=364; count), (4) parking structures (N=5,544; dichotomous). Grocery stores were facilities whose main purpose is to sell daily consumer goods, food products, and general household items. Retail and everyday stores aggregated multiple types of businesses. Retail stores captured stores that sell consumer electronics, clothing, household items, jewelry, office supplies, recreational equipment, and include thrift stores, florists, and dollar stores. Everyday stores, on other hand, sold quick use items, and included convenience stores, gas stations, small ethnic corner stores, pharmacies, and tobacco/vape stores. Parking structures included all parking garages and/or lots coded by CAGIS. They existed as both polygons, lines, and points. Therefore, streets within 50 feet of a polygon, line, or point was coded as access to a parking structure.

Additional facilities included places that "anchor" or attach motivated offenders to the general area, such as individuals at a crime-prone age or those with known prior involvement criminal offending: (4) high schools (N=35; dichotomous), (5) gang territories (N=2,215; dichotomous), and (6) drug treatment facilities (N=43; dichotomous). High schools' locations were gathered from the Ohio Department of Education and included all public, private and charter schools serving 9th – 12th grade. Drug treatment facilities were gathered from Ohio Mental Health and Addiction Services. High schools and drug treatment facilities spanned multiple blocks (represented as a polygon), therefore, any street with access to the facility. Gang territories were gathered from the Cincinnati Police Department (CPD). CPD tracked the street blocks that were occupied or unofficially claimed by Cincinnati groups or gangs during intelligence gathering sessions with analysts, specialists, and officers for the department's violent crime strategy (see Engel, Tillyer, & Corsaro, 2013). Both high schools and gang territories are indicated as a dichotomous dummy variable, where "1" = present and "0" = not present on a street block.

Another set of facilities were those that facilitate risky behaviors as patrons may consume alcohol or drugs, carry large amounts of cash, or illicit items like drugs or stolen items: (7) restaurants (N=575; count), (8) bars or clubs (N = 153; count), (9) fringe-banking facilities (N = 20; count), (10) drug markets (N = 5,799 calls for service), and (11) prostitution markets (N = 164 calls for service). Restaurants include both fast food and full menu, sit-down eating establishments. They often serve alcohol and facilitate a late-night entertainment crowd. Bars included facilities that sold alcohol for on-site consumption and stayed open past midnight on weekends. Fringe-banking facilities included any businesses identified as a pawnshop or check-cashing facility. Each of these facilities were summed to reflect the number of facilities per street block. Drawing from the similar procedures from multi-facility regression studies (Bernasco & Block, 2011; Haberman & Ratcliffe, 2015; Haberman et al., 2018), drug markets and prostitution markets were calculated by summing official police data. Prior literature has used a number of data sources, including incidents, arrests, medical examiner reports, surveys, and calls for service (Bernasco & Block, 2009; 2011; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Tita & Ridgeway, 2007; Martinez et al., 2008; Sevigny & Allen, 2015; Weisburd & Green-Mazerolle, 1995). Cincinnati Police Department provided both arrest and calls for service data; however, the crime analyst described recording errors among prostitution data.[9] To maintain consistency between the two illicit markets, the number of drug-related and prostitution-related calls for service was used to proxy drug and prostitution markets.

The remaining three facilities that prior research has linked to higher rates or count of crime. (12) Public housing communities (N=22; dichotomous) were gathered from the Cincinnati Metropolitan Housing Authority.[10] Public housing included any properties operated by Cincinnati Metropolitan Housing Authority and included apartments, single- and multi-family homes, and high-rise communities. Similar to high schools (N = 109; dichotomous) and drug treatment facilities (N = 41; dichotomous), public housing communities spanned multiple blocks; therefore,

[9] Because prostitution is misdemeanor offense, it requires an officer to directly witness the incident for an arrest to occur. Instead, prostitution is more often seen in citation or call for service data. Without a heightened enforcement operation (such as undercover or confidential informants buys), Cincinnati Police Department rarely target prostitution offenses. Drug offenses are similar, but are more often the target of special enforcement operations than prostitution.

[10] Prior literature has also used public housing vouchers as a measure of the distribution of low-income residents; however, these studies fail to consistently connect scattered site housing with crime (Lens, 2013; Van Zandt and Mhatre, 2013). This suggests there may be something different among structures and people in which they house.

any street with access to the facility was coded as "1" and those without access to any public housing communities were coded as "0". Generally, research has supported public housing communities as criminogenic facilities (Aliprantis & Hartley, 2015; Dunworth & Saiger, 1994; Roncek, Bell, & Francik, 1981; Sandler, 2017; Weatherburn, Lind, & Ku, 1999), but it should be noted that not all public housing in Cincinnati included high-rise or high-density structures.

In addition, (13) bus routes (N=3,166; dichotomous) were gathered from the Southwest Ohio Regional Transit Authority. Research has found bus stops are associated with higher rates of crime (Gerell, 2018; Hart, Timothy C. & Miethe, 2014; Kooi, 2013; Loukaitou-Sideris, 1999; Loukaitou-Sideris et al., 2001; Phillips & Sandler, 2015); however, Loukaitou-Sideris (2001) found the presence of other facilities was stronger predictor of crime than bus stop characteristics. Lastly, (14) entertainment facilities (N=76; count), drawn from the Ohio Department of Taxation, and included art galleries, arcades, amusement parks, bowling alleys, batting cages, landmarks and attractions, mini-golf, museums, sports arenas, theaters, and a casino. In addition to attracting large amounts of people, these facilities also encourage alcohol consumption, use cash exchanges, and distract patrons from self-protective behaviors. Entertainment facilities were summed per street; however, there were no streets that had more than two of these Facilities.

Likely Offender Variables

A number of scholars, including Cohen and Felson (1979), have argued that any person can be "motivated" to commit a crime, given the right circumstances. They have argued, however, that some people have higher propensities or criminal inclinations that make them more "likely" to be offenders. To capture "likely" offenders, this dissertation used people who have been formally incarcerated as a proxy for likely offenders. One likely offender measure captures the exposure to all recently released offenders, while a second weights each person by their "risk" score, which captures the likelihood to reoffend upon release.

Beginning in 2006, convicted offenders in the Ohio Department of Rehabilitation and Correction (ODRC) were evaluated for their unique risks and needs, using the Ohio Risk Assessment System (ORAS) (Latessa et al., 2005). These assessments occur at different stages and can change depending on the assessment goal, ranging from pre-trial assessment (designed to assess flight risk) and prison intake (used to assess internal risk for violence) to re-entry assessment (used to assess needs and risks related to recidivism). The second likely offender measure uses the Reentry Risk tool, which provides the most recent assessment and relates specifically to risk of re-offending or risk to the community (Desmarais, Johnson, and Singh, 2016; Latessa et al., 2009). There are a number of different tools, but this specific tool's goal aligns more closely to Brantingham and Brantingham's (1981, 1993, 1995) conception of variation in motivation or varying levels of criminal inclinations. For instance, Brantingham and Brantingham (1981:90) suggest motivation varies in strength and character, which are captured by the score and offense type.

Data on persons recently released from correctional supervision was obtained from the ODRC. These data included all persons released from ODRC with a Cincinnati address between 2013 and 2015, regardless of whether they were still under ODRC supervision or not (N=3,443). The ODRC oversees all state-run prison and community-corrections facilities, and maintains all data related to those individuals. The data provided included offense characteristics, home addresses, and a numeric and ordinal risk score associated with the likelihood of re-offending.

The data also provided each person's home addresses at multiple points in their ODRC tenure, including upon admission to a facility, upon release from a facility, and upon a probation/parole violation.

The most recent addresses for each likely offender was joined to street block midpoints.[11] After geocoding the home addresses, there was a match rate of 93.3 percent, resulting in 3,213 total matched offender addresses. Table 4 displays the geocoding results for the ODRC data. While geocoding hit rates were acceptable, only about half of the sample (57.5%) had a valid ORAS score. This data was not missing at random, but rather concentrated among offenders who were released upon completion of their sentence. This is important because the risk data was not fully accounting for older offenders or those charged with less serious crime. This bias is discussed in Chapter 5 as a major limitation.

Table 4. Geocoding Results of Likely Offender Addresses; ODCR, 2013 - 2015

	All years		2013		2014		2015	
	N	(%)	N	(%)	N	(%)	N	(%)
Total Sample	3,443		1,075		1,181		1,187	
Valid Address	3,213	(93.3%)	1,001	(93.1%)	1,108	(93.8%)	1,104	(93.0%)
Valid ORAS Score	1,980	(57.5%)	611	(56.8%)	672	(56.9%)	697	(58.7%)
Valid Address & ORAS Score	1,852	(53.8%)	569	(52.9%)	632	(53.5%)	651	(54.8%)
High Risk of Recidivating	671	(19.5%)	284	(26.4%)	236	(20.0%)	151	(12.7%)
Valid Address	627	(93.4%)	259	(91.2%)	226	(95.8%)	142	(94.0%)
Moderate Risk of Recidivating	842	(24.5%)	249	(23.2%)	284	(24.0%)	309	(26.0%)
Valid Address	791	(93.9%)	236	(94.8%)	265	(93.3%)	290	(93.9%)
Low Risk of Recidivating	467	(13.6%)	78	(7.3%)	152	(12.9%)	237	(20.0%)
Valid Address	434	(92.9%)	74	(94.9%)	141	(92.8%)	219	(92.4%)

Note: ORAS = Ohio Risk Assessment System

[11] Sensitivity checks were run for multiple coding schemes. This included creating offender measures using (1) all offender unique addresses, (2) a variety of distance measures, (3) the last known mailing address, and (4) separating offenders by offense types. They are discussed in Chapter 4.

The ODRC data was conceptualized and operationalized in two different ways. First, exposure to likely offenders captured the concentration of all cases. Second exposure to cumulative offender risk captured the varying strengths of motivation of the likely offenders. Both measures will use inverse distance weighting (IDW) to account for the effects of likely offenders living near a street block (see Groff, 2014; Groff & Lockwood, 2014). This method weights points within a distance threshold around each respective street block, so that the weight decreases as distance from the street block increases. This creates a natural buffer that corrects for geocoding or address errors. The accuracy of self-reported offender addresses has been questioned (Loza, Loza-Fanous, & Heseltine, 2007; Maxfield, Weiler, & Widom, 2000; Payne & Piquero, 2018; Peters, Kremling, & Hunt, 2015; Piquero, Schubert, & Brame, 2014). While research has generally found self-reported information tends to be accurate, there is no research on the accuracy of home addresses. Unlike a simple count of offenders per street segment, IDW count weights offenders based on their proximity to each street segment. Not only has research suggested weighting is a better measure of exposure than simple summations (Groff, 2014; Groff & Lockwood, 2014; McCord et al., 2007; Tita & Radil, 2010), but it reduces the reliance on fully accurate offender addresses. For both, measures 2,500 feet thresholds were assigned (as it is the length of approximately five blocks in Cincinnati).[12] The 2,500 feet cutoff was chosen for two reasons. First, it represents the distance around criminogenic facilities that research has established as search areas for offenders (Iwanski, Frank, Dabbaghian, Reid, & Brantingham,

[12] As stated in Footnote 11, multiple distances were assigned for the IDW measures. A distance of 1,000 feet was approximately two city blocks. A distance of 2,500 feet represented approximately 5 street blocks, while 4,000 feet represented the average distance from an offender and the closest facility. There were no large differences among model fit, coefficient strength, direction or significance. This is discussed further in Chapter 4.

2011; Reid, Frank, Iwanski, Dabbaghian, & Brantingham, 2014; Summers & Johnson, 2017). Second, it was a similar distance used in Groff (2014) that had strong and consistent model fit of the different search distance examined. Third, it fell between the two other distances that were assessed (1,000 feet, which provided the best model fit in Groff (2014) and 4,000 feet, which was the average distance of offenders' closest facility).

The first measure used IDW to quantify the possible exposure to any likely offender. It uses all offenders with a valid street address, regardless of risk scores (N=2,834). Each home address was assigned a weight, ranging from 0 to 1, for each street block. Likely offenders falling outside the 2,500 feet threshold was assigned a "0" and offenders falling on the respective street was assigned a "1". The remaining addresses within the threshold were assigned diminishing scores (1< weight >0) associated with their distance from the respective street. All offender weights will then be summed for each street block.[13]

The second measure of offenders used valid ORAS recidivism score, where low risk was coded "1", moderate risk was coded "2", and high risk was coded "3".[14] These scores were also weighted using the IDW process described above. After distance-related weights were assigned to each offender, the weight was multiplied by the ORAS score, and then summed for every street block. This attempted to account for the cumulative amount of offender motivation among offenders living in the area, but recall missing data may be biasing results. The important thing

[13] The formula used to calculate cumulative offender risk was: $\Sigma\left(ORAS * \left(1 - \sqrt{distance\ to\ focal\ street}\right)\right)$.

[14] The ordinal scale was a validated measure capturing likelihood to recidivate and is used in dictating different levels and types of treatment (Latessa et al., 2005). Therefore, the original conception (rank ordering) was used to preserve its original intent, rather than the continuous measurement.

to note is that approximately 40 percent of the study's sample is missing an ORAS recidivism score and thus was omitted from this measure's computation (see Table 4).

Sociodemographic and Street Network Control Variables

The proposed study used 2015 American Community Survey (ACS) 5-year estimates at the U.S. Census block group level to control for important socio-demographic measures. Block groups are the smallest geographic unit available. Block groups are approximately a ½ square mile and contain an average of 50 street segments. The ACS data was joined to street blocks. In cases where a street block are located in multiple block groups, the average of the variables from each block group was allocated to the street block. Using past research, four sociodemographic measures were created from the ACS data. Similar measures have been extensively used in criminology (Bernasco & Block, 2011; Groff & Lockwood, 2014; Haberman & Ratcliffe, 2015; 2018; Krivo, Lauren J, Peterson, & Kuhl, 2009; Morenoff, Sampson, & Raudenbush, 2001; Peterson, Krivo, & Harris, 2000; Sampson et al., 1997). The four sociodemographic control variables will include (1) total residential population, (2) concentrated disadvantage, (3) residential instability, and (4) racial heterogeneity.

Total population captured the number of people living in the surrounding census block groups. Concentrated disadvantaged will average the percentages of (1) persons unemployed, (2) persons without a high school diploma, (3) single female-headed households, (4) households below poverty line, and (5) persons receiving public assistance (Krivo, Lauren J. & Peterson, 1996; Morenoff et al., 2001; Peterson & Krivo, 2010; Pratt & Cullen, 2005b; Sampson et al., 1997; Warner, 2014). Higher values indicated higher degrees of disadvantage. Residential instability averaged two ACS variables: (1) percentage of rented households and (2) percentage of residents who lived in different houses in last 5 years. Higher values will represent higher residential turnover/instability. Lastly, racial heterogeneity was calculated as 1 minus the sum of the squared proportions of the populations of four racial groups: (1) White, (2) Black, (3) Hispanic, and (4) Other Races (Chainey & Ratcliffe, 2005). The measure is bounded between 0.00 and 1 minus the reciprocal number of racial categories used to create it. With four racial groups, the maximum heterogeneity is 0.75, where the maximum represents equal representation across all groups and higher degrees of racial heterogeneity and diversity.

In addition, I included three street block characteristic control variables capturing the length of street, accessibility, and potential usage. Longer street blocks are likely to house more facilities, potential addresses, and thus crime. The general "path" literature detail three important conclusions. Crime is more prevalent in (1) highly used and connected streets, (2) streets near interstate highway entrances, and (3) streets (regardless of type) near criminogenic facilities. Some research has found using street types (like arterial versus small roadways) do not accurately represent the permeability of street networks (see Davies & Bishop, 2013); however, street type still proxies usage, in that larger arterial streets are more often traveled (shown in simulation studies) (Iwanski et al., 2011; Reid et al., 2014). In addition to the length of street, I will include a control for major streets (major street = "1") and streets within 1,000 feet of highway entrance (highway accessible = "1").

Spatial Lag Control Variables

Spatial Lags for each facility was included to control for spatial autocorrelation and the crime "radiating" effect (Bernasco & Block, 2011; Bowers, 2014; Groff, 2011; Groff & Lockwood, 2014).[15] The crime and place literature discussed in Chapter 2 describes extended spatial effects criminogenic places can have on surrounding areas. Furthermore, Tobler (1970) noted that proximal places, things, and people tend to be more alike than those at farther distances (see Miller, 2004). The statistical worry is that these proximal points are no longer independent, an assumption for most regression analyses. If nearby points influence each other, the autocorrelation in regression residuals biases statistical estimates (Anselin, 2000). Therefore, it is important to control for this similarity, known as spatial autocorrelation (Askey, Taylor, Groff, & Fingerhut, 2018; Calder & Bauer, 1992; Rees & Schnepel, 2009; Schmerler, 2005).

Spatial lags for each facility variable were computed using a queen-contiguity first-order spatial weights matrix. This process treats a street as a neighbor if the two intersect with each other (Bellamy, 1996). Because some facilities are represented as counts and others dichotomously, their spatially lag version reflect those differences. For example, if the facilities were represented as a count, such as grocery stores, then the spatial lag variables would count all grocery stores among streets that intersect with the respective street. The spatial lag of dichotomous facilities, such as high schools, indicated the presence of any high school among the respective street and its intersecting streets. For facilities spanning multiple blocks (high schools, drug treatment facilities, and public housing communities), there is a risk of counting the same

[15] The inverse distance weighting process used to assign offender scores to street blocks account for the effects of all street blocks within 1,000 feet; therefore, these effects should already be controlled for in the offender measures.

facility twice. To avoid this, the spatially lagged variables were only coded as "1" if the adjacent street block reported access to the facility and the focal street block did not.

Analytic Plan

First, I used a collection of spatial analyses to address the first research question regarding the spatial concentration of offenders' home addresses. This included data visualizations (i.e., maps) and spatial statistics. Second, I used count regression analyses to address research questions 2 and 3. Table 5 outlines major components of each analyses used to assess the proposed research questions. This analytic plan attempted to understand the universal and spatially varying relationship between, offenders, criminogenic facilities, and crime.

Table 5. Description of Spatial Analyses

Name	RQ Answered	Statistical Program	Details
Kernel Density Estimation	RQ1	ArcGIS	Univariate, spatial analysis that visually depicts where and how features cluster in space
Ripley's K	RQ1	R - spatstat	Univariate, spatial analysis that assesses degree of spatial clustering/dispersion for a point pattern over a range of distances
Ripley's Cross K	RQ2	R - spatstat	Bivariate, spatial analysis that assesses degree of spatial clustering/dispersion between two point patterns over a range of distances
Global Count Regression Without Interactions	RQ4	r – MASS or pscl	Multivariate, count model for relationships between a set of variables and a dependent variable
Global Regression With Interactions	RQ4	r – MASS or pscl	Multivariate, count model for relationships between a set of variables and a dependent variable

Exploratory Spatial Data Analyses

Kernel Density Estimation

First and foremost, the spatial concentration of persons who formally incarcerated and crime was depicted in a series of kernel density maps produced in ArcGIS. Kernel density estimation (KDE) creates a continuous surface of values in grid cells using interpolation. The values of each cell represents the degree of concentration or density of values. The user must define two parameters in the computation of KDE. The cell size dictate the grids, which the values were calculated and then displayed. The bandwidth or search radius defines which features around the cell of interest was used to calculate its value. Within the bandwidth, a weighting schema will give closer points more influence than those farther from the cell of interest. Generally, the smaller search radius increases prediction accuracy but decreases the generalizability, while decisions related to the cell size do not significantly change the outcome (Chainey, 2013; Hart, Timothy & Zandbergen, 2014).

Despite the many recommendations on assigning cell sizes and bandwidth parameters of KDE (Bailey & Gatrell, 1995; Chainey & Ratcliffe, 2005; Chainey, 2013; Eck, 2005; Hart, Timothy & Zandbergen, 2014), Chainey and Ratcliffe (2005) provided recommendations that were more practical and easier to understand. This is important because the KDE is a descriptive visual process, when compared to the more advanced complex models used later in the dissertation. Chainey and Ratcliffe (2005) advised the cell size should be ½ the distance of the average block face. The search radii should reflect a K-order of the average nearest neighbor distance (ie. K-*n* order = nth closest nearest neighbor), depending on what scale the researcher is interested

(Chainey & Ratcliffe, 2005:158-160). Smaller K-orders will result in very fine details and larger K-orders will result in more general and smooth views of a phenomenon's distribution. Because the cumulative proportions table will describe spatial concentrations at the micro-level, I maintained consistency and a smaller k-order, such as the distance of the average K-5 order nearest neighbor. This will reflect the average of every point's 5^{th} closest neighbor.

The maps of recently released persons and each of the two crime types were presented below. The values on each map depicted the values using the top five deciles, so that grids with the top 50% highest values are visual and every change in colored hues (e.g. light red versus deep red) depict a tighter concentration. Concentrations of formally incarcerated persons were overlaid on crime concentration, making differences easier to see. The goal of this analysis was to begin understanding the degree and location of likely offender and crime concentrations in the city.

Cumulative Percentage Tests

A graph was used for the cumulative proportions of crime versus cumulative proportion of street blocks test. First, the cumulative proportions of likely offenders or crime were plotted against the cumulative percentage of street blocks containing those data. Next, an expected distribution for the cumulative proportions was obtained via simulation. Events (home addresses or crimes) were randomly assigned with replacement to a new street block (holding the total number of events constant). Next, the cumulative percentages of events located within the cumulative percentages of street blocks were computed for the simulated dataset. The simulation was then be repeated 1,000 times. Across all 1,000 simulated samples, the mean cumulative percentage of the outcome at each cumulative percentage of street blocks was then computed and plotted on graph. The mean line represented the expected cumulative percentage of the event hosted by the corresponding cumulative percentage of street blocks under the assumption of complete spatial randomness. Additionally, a 95% credible interval was obtained by rank ordering the cumulative percentage of events at each cumulative percentage of street blocks and selecting the 2.5 and 97.5 percentiles over the 1,000 simulated datasets to create a 95% credible interval. When the observed cumulative percentage of events falls above the expected line and outside the 95% confidence interval, then the outcome being evaluated was considered statistically more concentrated than expected under an assumption of complete spatial randomness. If the opposite relationship were shown, it indicated more spatial repulsion than expected under an assumption of complete spatial randomness the outcome. I specifically used the base packages provided by R-statistics program to calculate cumulative percentages, simulate the spatially random distributions of crime, and create the graphs.

Ripley's K

Ripley's K is a global measure of spatial clustering or dispersion. It statistically compares the observed number of likely offenders or crimes within a given distance of a feature to an expected count if we assumed complete spatial randomness (Fischer & Getis, 2010; Ripley, 1976). The statistical test is performed on a point pattern dataset at a range of distances to formally test for spatial clustering at different spatial scales (Ripley, 1976). More specifically, Ripley's K is a proportional measure of the number of observed features within a distance compared to the number of expected features, given complete spatial randomness (Fischer & Getis, 2010).[16] Because Ripley's K is a point pattern test, it does not require aggregating the cases to street blocks, which may be susceptible to the modifiable areal unit problem, like the simulation test described in the previous paragraph.

The user is required to set the range of distances as well as the increments. This will assign the "distance bins" to which Ripley's K was calculated. To capture micro-, meso-, and macro-level patterns, I set the minimum distance equal to half of the average length of street segment (250 feet), with increasing intervals to indicate increases in the unit of analysis. Ripley's K values are often transformed into a square-root function called the L-statistic. This transformation simply "rescales" the K function so the reference (randomness) line appears as a straight line at zero for each distance bin when plotting the distances on the x-axis and corresponding L-statistic on the y-axis.

The spatial statistics package (spatstat) in the R-statistical program provided all necessary functions to compute Ripley's K (Baddely et al, 2020). To assess the degree of spatial clustering of offenders and crime, a plot of the L-statistics provided the basis of the analysis. The L statistics of each distance was then be plotted with simulated L-statistics and their confidence intervals derived from the assumption of random distribution. Values that are greater than the confidence intervals of the random distribution indicate clustering, while values lower than the confidence intervals indicate dispersion (Fischer & Getis, 2010). Assuming both offenders and crime cluster

[16] Streets themselves, and the potential locations for crime, is not randomly distributed. Therefore, some researchers have simulated a Poisson distribution by conducting Ripley's K analysis on street blocks (Groff, 2010). This, however, does not include confidence intervals or provide significance tests. It was not used.

in space, we expected to see the L-statistic values remain greater than zero (the randomness estimates). We were also able to see at what distance the spatial distribution is most and/or least clustered.

Bivariate Ripley's K

The bivariate Ripley's K, also known as Ripley's Cross-K, was used to understand the spatial distribution of two point patterns. Using methodology presented in Dixon (2002), the Cross-K function tests the independence between likely offenders and each crime type. More simply put, it asks whether there is an interaction between the two data types (Dixon, 2002). Essentially this process now counts the number of one data type within distance bin of the second event type – or a marked point pattern (Cameron & Trivedi, 2013; Long & Freese, 2014). For instance, it will count the number of offenders within given distance of crime events. This is then compared to spatial randomness, to determine whether the data are clustered, random, or repulsed. It asks: are there more offenders near crime events than we would expect under complete randomness (i.e., are likely offenders and crime spatially (in) dependent)?

The spatial package (spatstat) in R-statistical program also provides all necessary testing for Ripley's Cross-K (Baddeley et al., 2020). Similar to the Ripley's K analysis above, the minimum distance will be set to half the average distance of a street block (2500 feet), with increasing distances. To assess the findings, the L-statistic was also used. Similar to the Ripley's K analysis above, this process rescales the K function so the reference (randomness) appears as a straight line at zero. The different distances were plotted on the x-axis and the corresponding L-statistic on the y-axis. When the observed line is above that of the reference line, the two data types are dependent, but if the line is below that of the reference line, the two data types are repulsed from each other. In addition, this showed the distances at which likely offenders and each crime type are most or least spatially dependent.

Similar to the significance testing in Ripley' K, the observed distribution are compared to Complete Spatial Randomness (CSR). This process randomly relocates the points, reassesses the distribution, and repeats the process 99 times. Wheeler and colleagues (2016) have argued this randomization process does not not accurately account for a bivariate relationship between two or more data sources because it completely reassigns the location of points. Instead, the authors argue significance tests should only reassign values to existing locations. Wheeler detailed the process and provided code to complete this task; however, the process required too much computing power and was not run. [17] Because this step was exploratory in nature, the standard Ripley's Cross-K procedure was used and the reassignment of points was an admitted limitation.

Count Regression Analyses

Next, count regression models were used to answer research questions 3 and 4. Recall, the dissertation's dependent variable was street block robbery and theft from auto counts. Therefore, Poisson or negative binomial regression models were appropriate for discrete count outcomes. Poisson models assume equidispersion, where the observed variance is equal to the mean (Cameron & Trivedi, 2013; Long & Freese, 2014:482). If this requirement is not met (and the variance is greater or less than the mean), standard errors can be biased, which influences

[17] Dr Wheeler's r-code and logic is provided on his personal website (https://andrewpwheeler.com/2015/10/27/the-spatial-clustering-of-hits-vs-misses-in-shootings-using-ripleys-k/).

statistical significance. Instead, crime data is often over-dispersed, where the conditional variance is greater than its mean.[18] In this case, the negative binomial distribution more correctly modeled the dispersed variance.

To determine whether the data fits a Poisson or negative binomial model, two steps were taken. First, the distributions of both dependent variables were visualized in a histogram, with that of simulated Poisson and Negative Binomial distributions. This initial step gave an idea of whether over- or under-dispersion exists. Next, likelihood-ratio test were used to determine if negative binomial models were superior to Poisson models (Long & Freese, 2014:547).

Two sets of models were estimated for each outcome (using MASS or pscl r packages; Ripley et al., 2019; Jackman, 2017). First, a model estimating the impact of the first likely offender measure, the potentially criminogenic facilities predictors, and socio-demographics control variables were estimated. Next, interactions between the likely offender measure and the statistically significant facility measures from Model A were estimated. All variables were estimated in the same model as none of the variables suffered from multi-collinearity as determined by examining variance inflation factor scores. The same modeling process was repeated for both proxy measures of likely offenders. The results of the count models are presented below with coefficients, standard errors, and incidence rate ratios (IRR). IRR simplify the interpretation of count models. These are calculated by exponentiating coefficient estimates (IRR = $\exp(\beta_k)$) (Long & Freese, 2014:490). An IRR can then be converted to a percent change in the outcome per unit increase in a predictor, by subtracting 1 from the IRR and multiplying by

[18] Under-dispersion where the variance of an outcome is less than its mean is also possible.

100 (percent change = IRR - 1 * 100) where positive values indicate percentage increases and negative values indicate percentage decreases (Long & Freese, 2014:491).

Summary

Overall, the analytic plan was broken into two main steps. First, exploratory spatial data analyses were conducted to assess the geographic distribution of likely offenders and crime in the city. Recall, likely offenders is proxied by using data on formally incarcerated persons. Cumulative portion tables and figures describe the proportion of likely offenders and crime falling in Cincinnati streets. These were compared to distributions described in Weisburd (2015). Kernel density analysis provided maps of the spatial concentrations of each data type. Each set of maps were assessed separately and jointly. Ripley's K and Cross-K provided our first significance test as to whether likely offenders, robbery, and theft from auto clustered in space.

The second major step used count regression models to assess the multivariate relationship among likely offenders, criminogenic facilities, control variables, and crime. A street block's exposure to formally incarcerated persons were coded in two ways, one of which attempted to capture variation in criminal inclinations or the likelihood to reoffend (via the ORAS scores). These models assessed the main effects of the variables on robbery and theft from auto. Next, the patron hypothesis was tested by introducing interaction variables (between likely offender measures and significant criminogenic facilities). This step was performed for both operationalizations of exposure to likely offenders and between robbery or theft from auto. It was designed to assess whether a street block's exposure to likely offenders conditioned or moderated the criminogenic effects of some facilities.

CHAPTER 5: RESULTS

Chapter 5 is split into three main parts. The first section presents results as it relates to the first two research questions. (1) Do likely offenders geographically concentrate in a small number of places? (2) Do likely offender "hot spots" coincide with crime "hot spots"? The second section presents the results aimed at answering the third research question. (3) How does the exposure to likely offenders and criminogenic facilities explain crime across street blocks, net of other factors? The last section will present results designed to answer the last research question. (4) Is there an interactive effect between likely offenders and criminogenic facilities that explain crime across street blocks, net of other factors?

Research Questions 1 and 2: Spatial Patterns of Offenders and Crime

Cumulative Percentage Tables

Figure 2 and Figure 3 present the concentration of formally incarcerated people and crime among street blocks in the study sample. Recall, likely offenders and the crime types were expected to be concentrated in a small number of streets, while most streets have few or no offenders and crime. Generally, all three variables roughly follow Weisburd's (2015) recommended percentages. More specifically, the addresses of recently released offenders (as a proxy measure of likely offenders) were concentrated much more than expected if offenders were randomly distributed. All reported home addresses (n = 3,213) were concentrated in just 16.5% of Cincinnati street blocks. In addition, robbery was also highly concentrated among street blocks with all robberies concentrating in just 12.9% of streets. Third, thefts from auto were concentrated, but to a slightly lesser extent of offenders and robbery. All thefts from auto were distributed among 29.9% of street blocks. Overall, offenders, robbery, and theft from auto were more concentrated than expected if they were randomly distributed among street blocks in the study area.

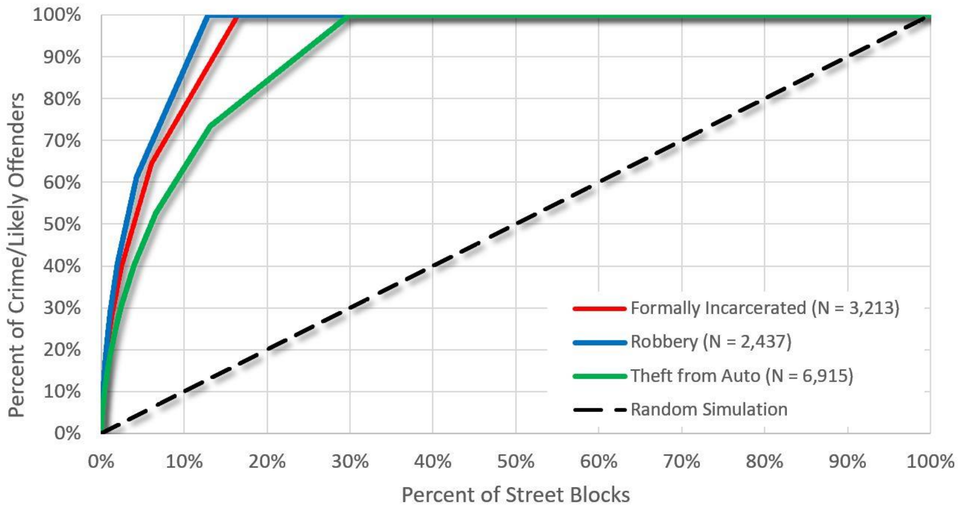

Figure 2. Cumulative Distribution of Likely Offenders, Robbery, and Theft from Auto among Street Blocks

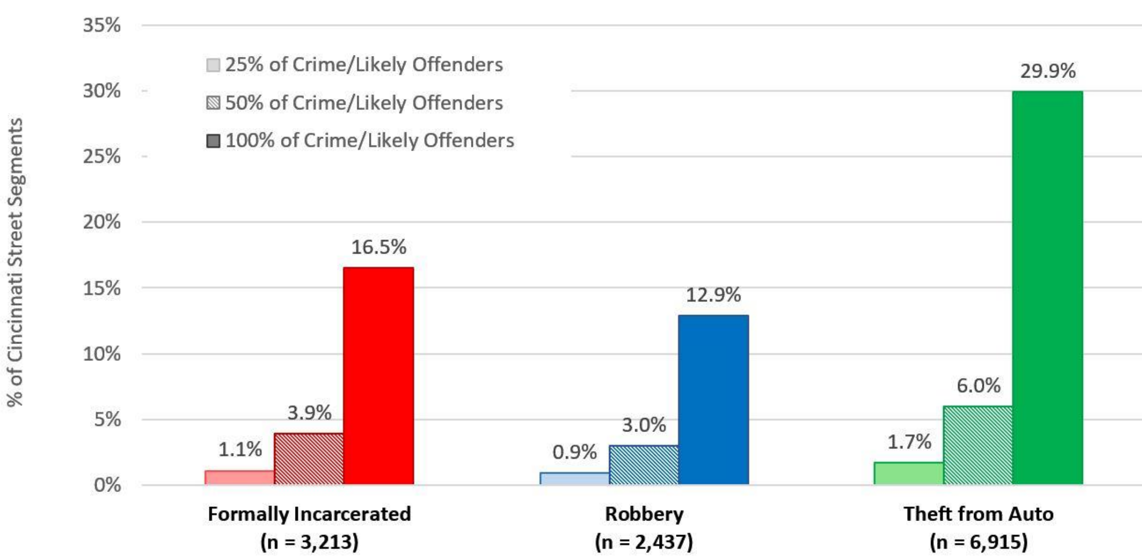

Figure 3. Law of Crime Concentration at Places among Likely Offenders, Robbery, and Theft from Auto

Ripley's K

Ripley's K was used to examine the degree in which likely offenders, robbery, and theft from auto clustered at different spatial extents (Dixon, 2002). The reported statistic is the L-statistic, a standardized value of Ripley's K (Dixon, 2002). Figure 4 shows the L(t) line for each data type, where values greater than the reference line (Y = 0) represent clustered point patterns, and values lower than the reference line represent dispersed point patterns.[19] The X-axis presents different spatial scales (ranging from 250 feet to about half a mile), while the Y-axis presents the corresponding L-statistic at each scale. According to Figure 4, offenders, robbery and thefts from auto were more clustered in space than we would expect if they were distributed by complete spatial randomness (CSR). At every distance band, offenders, robbery, and theft from auto were above both reference lines, indicating clustering.

Ripley's Cross-K

Next, Ripley's Cross-K was used to examine to bivariate spatial relationship between the crime types and the home addresses of recently released offenders.[20] This describes whether

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[19] Typically, the reference line is simulated to reflect point patterns with complete spatial randomness (CSR); however, street networks bind human movement and crime locations within databases. A CSR reference line and the L-statistic for all street midpoints are presented (as seen in Groff et al., 2010). No significance testing was available, so it was not discussed in detail here. However, the results were consistent. Offenders, robbery, and theft from auto were more concentrated than expected if data equally dispersed across all street blocks.

[20] Ripley's Cross-K compares the spatial relationship between two variables with the relationship based on complete spatial randomness (CSR). Wheeler, Worden, and McLean (2016) argued the original formulation of Cross-K as inappropriate because it reassigned the location of points to unrealistic locations when simulating CSR. Instead, the authors argue the points should be fixed and then randomly reassigned to truly simulate a randomly-distributed reference line. This process was attempted on multiple accounts, but computer power limited the ability to simulate randomness by reassigning offenders, robbery points, and theft from auto points. The code, provided by Wheeler's website, was running for multiple weeks before failing to compute. Dr. Wheeler's work and r-code can be found on his personal website (https://andrewpwheeler.com/2015/10/27/the-spatial-clustering-of-hits-vs-misses-in-shootings-using-ripleys-k/).

two different point patterns are *attracted* to each other (varying together) or *repulsed* (concentrated in different places). Figure 5 shows the L(t) lines depicting the spatial relationship between likely offenders and robbery, and likely offenders and thefts from auto. As with Figure 4, the X-axis denotes the spatial extent (in feet), and the Y-axis describes the corresponding L-Statistic for each relationship. Values falling above the reference line represent spatial attraction, while values falling below the reference represents spatial repulsion. Figure 5 shows that the relationships between likely offender home addresses and crime were attracted or "hung together" at every spatial extent.

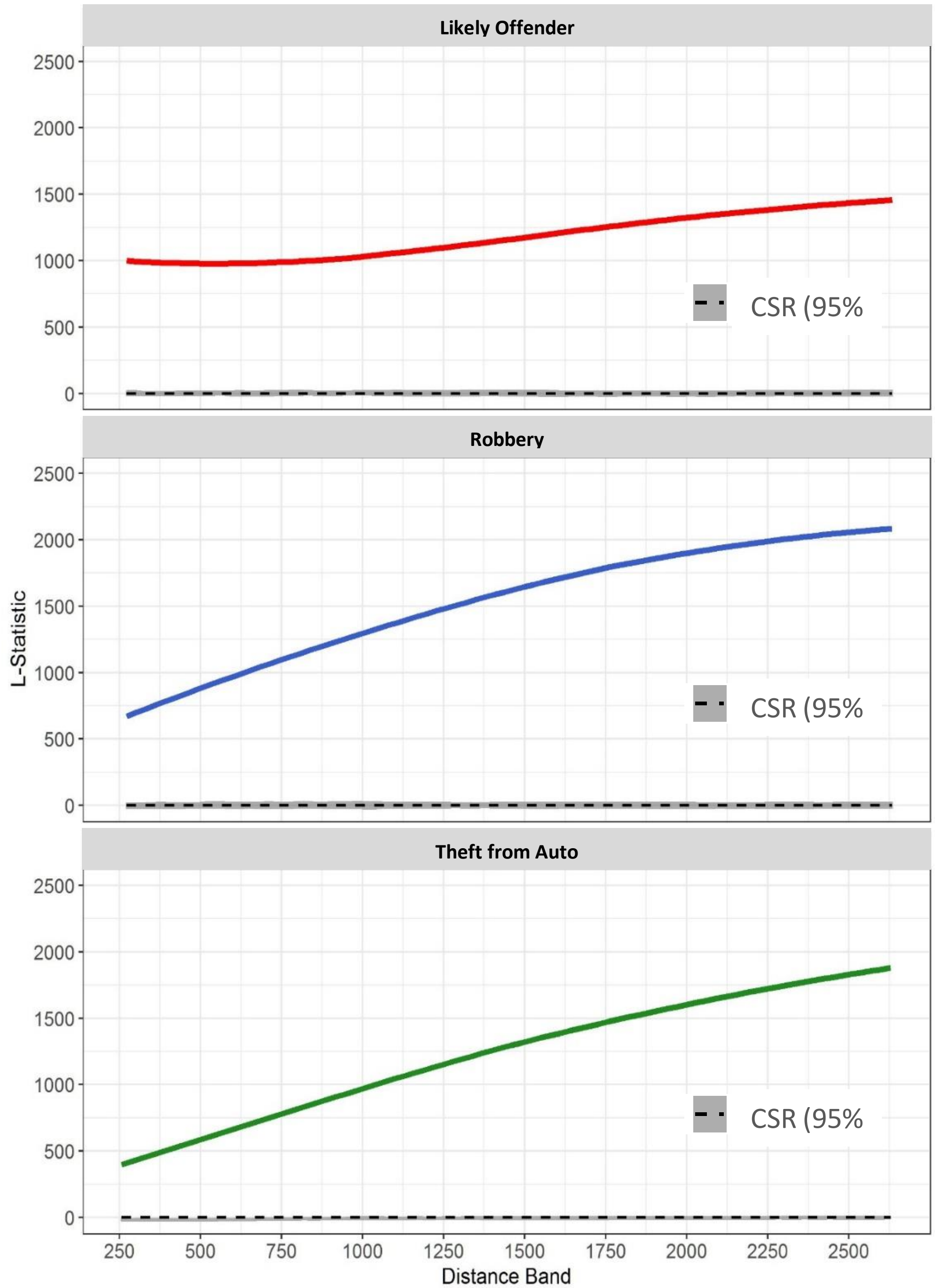

Figure 4. Results of Ripley's K Analysis; Spatial Distribution of Offenders, Robbery, and Theft

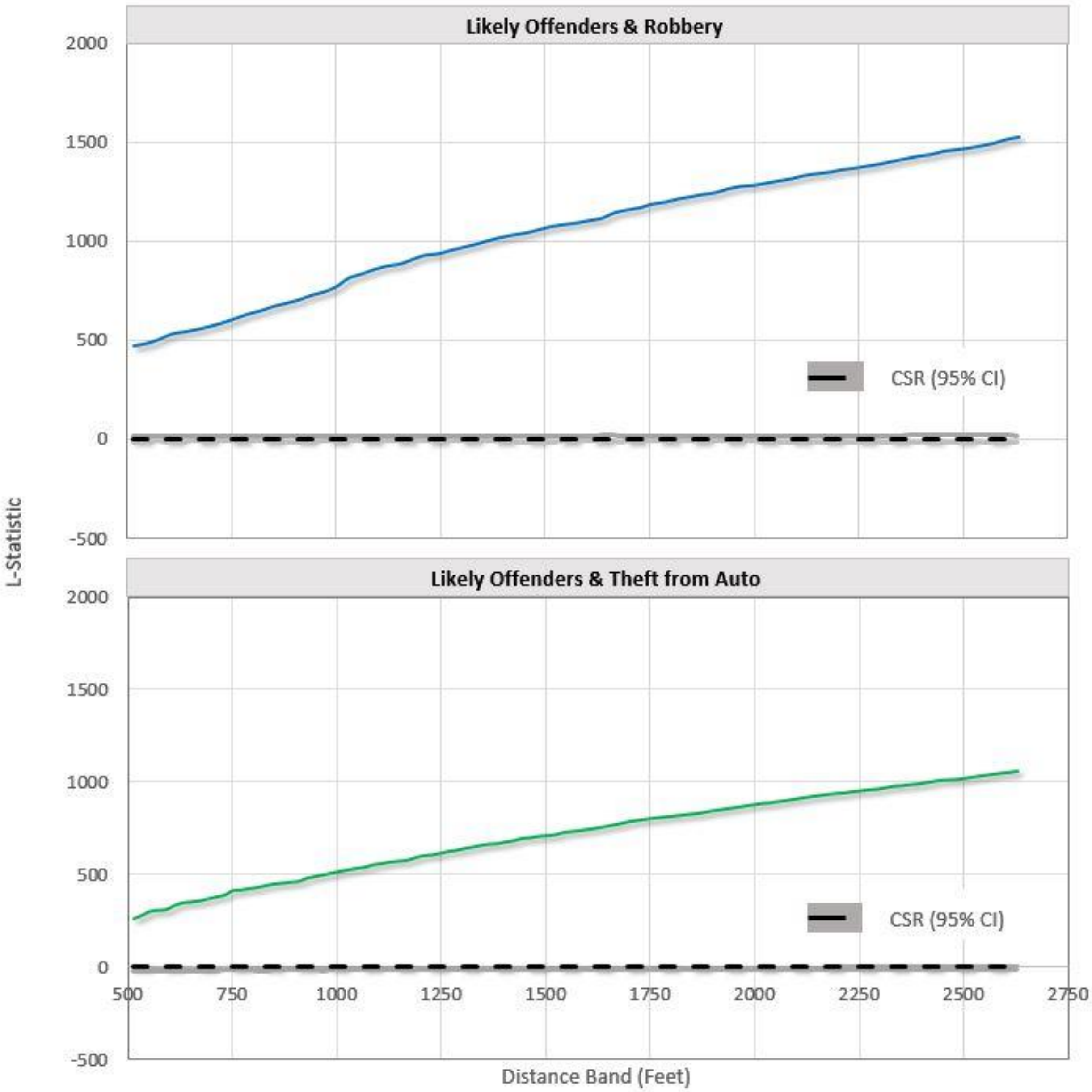

Figure 5. Results of Ripley's Cross-K; Bivariate Spatial Concentration between Offenders and Crime

Kernel Density

Figure 6, Figure 11, and Figure 13 display the locations of formally incarcerated persons' home addresses, robbery, and theft from auto hot spots. As discussed in Chapter 4, the cell size of kernel density analyses remained the same for each data source, 240 square feet (half the distance of the average block in the study sample). The search radius reflected the distance between the 5^{th} closest neighbor (recently released offenders = 682ft; robbery = 709ft; theft from auto = 470ft). The density results are displayed using the decile classifications, where only cells with the highest 30% of cell values are colored. A grid system is overlaid to simplify interpretation of the maps. Overall, these maps display the areas of Cincinnati with the highest clustering of likely offenders, robbery, and thefts from auto.

Figure 6 displays the geographic concentration of likely offenders. Ratcliffe (2004) classified crime hot spots into three different spatial patterns. Despite being more concentrated with most parts of the city, points were concentrated within hot spots at varying degrees. Inside hot spots, some points were dispersed throughout the area ("dispersed"), others concentrate at multiple addresses ("clustered"), and some concentrate at a single address ("hot point") (Ratcliffe, 2004). Each classification has slightly different mechanisms in describing why the hot spot is a hot spot. Both likely offender and crime hot spots in Cincinnati follow these classifications[21].

[21] It is important to note that offender home addresses were joined to the street block and analyzed at this level. Due to IRB restrictions, finer analyses were not allowed to protect the identity of the offender sample. Because of this, I am unable to assess spatial variation within a street block. This forces clustered or dispersed patterns to resemble hot point patterns in streets where offenders distributed or clustered within the street block.

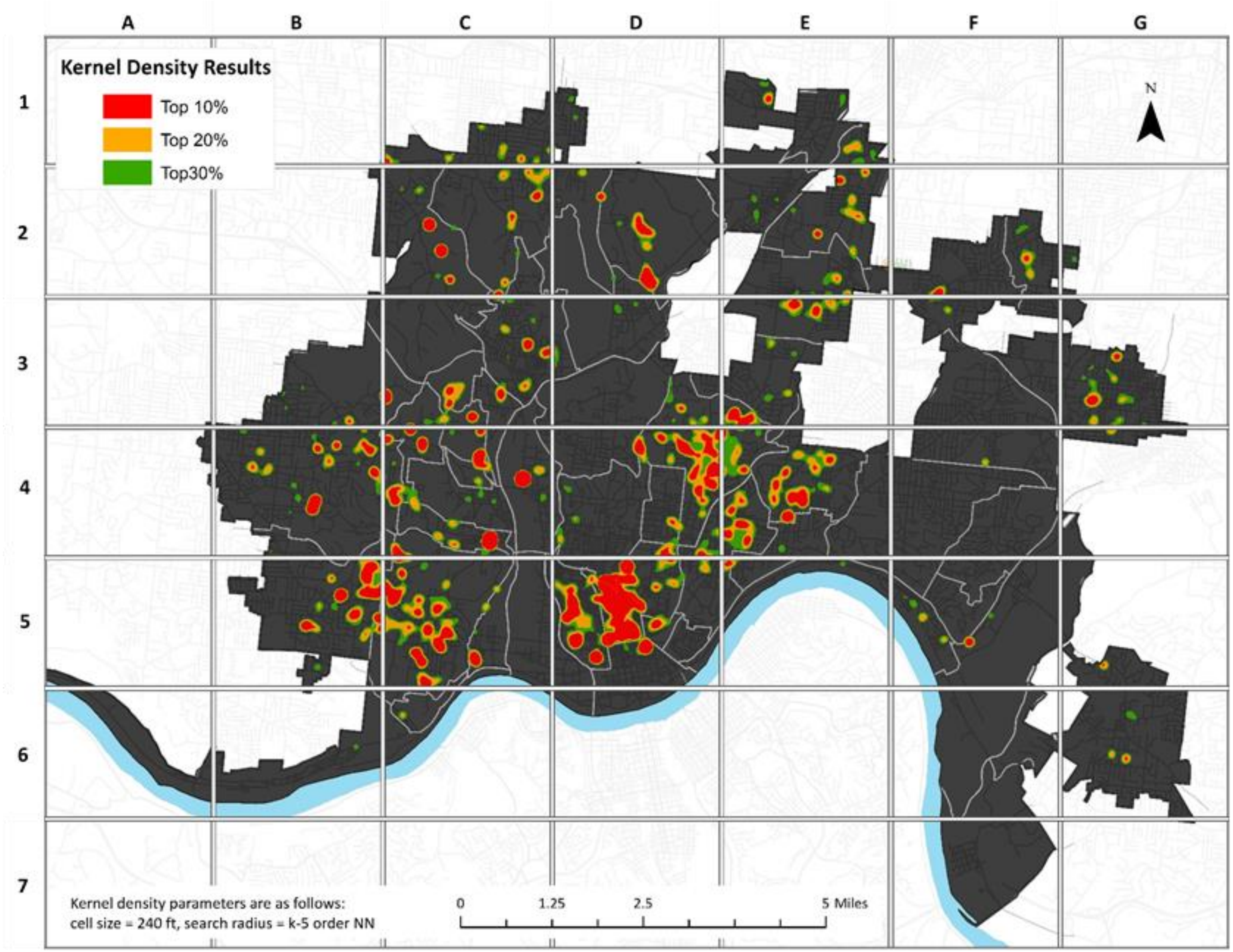

Figure 6. Distribution of Formally Incarcerated Persons' Home Addresses; Cincinnati, Ohio, 2013 -2015

The largest hot spot located in the central business district (Cell D5 in Figure 6) shows an example of a dispersed hot spot. Dispersed hot spots still house more offenders than most of the city, but they were distributed throughout the concentrated area. The southern edge of Cell D5 is the central business district, which largely houses office buildings. The northern area is mixed-use area, containing low-income housing, luxury apartments, restaurants, bars, corner stores, boutiques, and other commercial facilities.[22] Cell D4 in Figure 6 displays a second dispersed hot spot (northeast corner). This area contains a number of low-income, multi-unit apartment complexes and commercial facilities, but predominantly contains single- or multi-family homes. Figure 7 shows an aerial view of a collection of street blocks with a dispersed hot spot pattern. A mix of detached homes and apartment complexes reduce the ability to have specific addresses with large number of home addresses. A number of commercial facilities, such as fast food restaurants, a dollar store, and corner stores were nearby the area shown in Figure 7.

Ratcliffe (2004) also described "clustered" hot spots or those where points are distributed among multiple addresses inside the hot spot. While there were multiple addresses inside the hot spot that disproportionately housed likely offenders, these hot spots also had other offender homes elsewhere in the hot spot. Often times large multi-unit apartment, complexes housed a large number of likely offenders, but the adjacent area included single or multi-family homes as well. Unlike dispersed hot spots, the offender home addresses were not evenly or randomly

[22] The northern portion of Cell D5 (known as "Over-the-Rhine") went through dramatic changes between 2000 and 2010. In the early 2000's, the area was plagued with poverty and largely depilated. In 2001, there were a series of riots related to dissatisfaction with the police and results of redevelopment/gentrification. Despite this redevelopment continued, resulting in large scale improvements to specific blocks of Over-the-Rhine. It should be noted much the redevelopment occurred on a small number of major streets, but did not include adjacent streets. It is still common to have redeveloped streets adjacent to depilated streets and facilities.

distributed in the hot spot. Cell D4 in Figure 8 demonstrated a clustered hot spot (northeast corner of the cell). These areas contain proximal apartment complexes and/or street blocks with multi-family homes. Figure 8 displays this with a high-rise apartment located on the same street block as detached single- and multi-family homes.

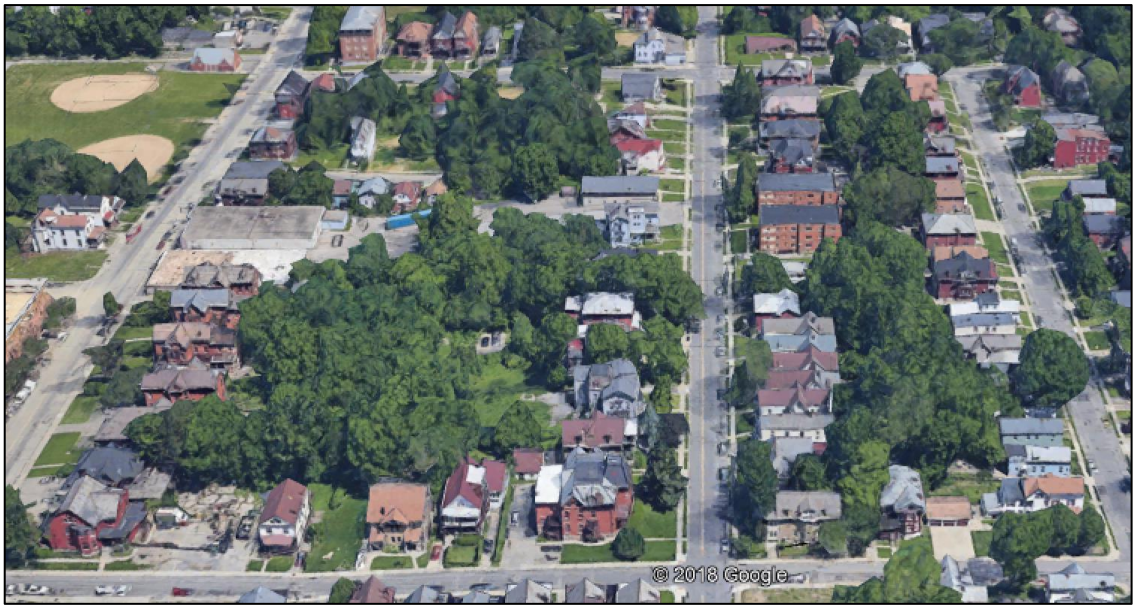

Figure 7. Aerial View of Hot Spot with a Dispersed Pattern

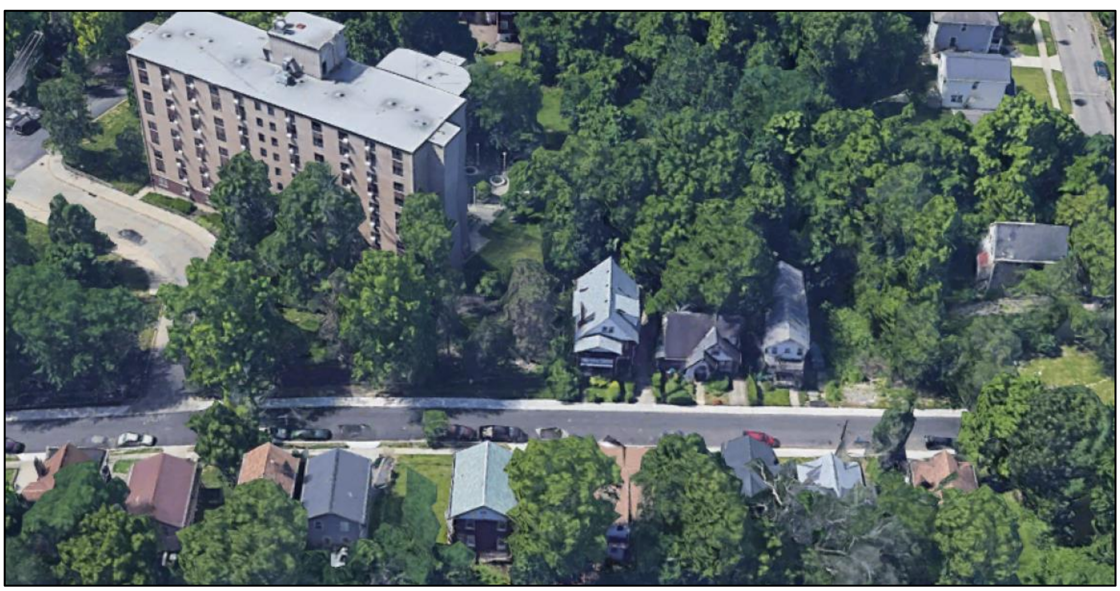

Figure 8. Aerial View of Hot Spot with a Clustered Pattern

Lastly, Ratcliffe (2004) classified some hot spots as “hot points”. Among crime hot spots, these tend to represent areas with a crime generator or attractor (Ratcliffe, 2004:11). There were a large number of hot spots that followed this pattern, which were largely located along the periphery of the city. Unlike clustered hot spots, those following a hot point pattern tend not to have incidents at other addresses inside a hot spot (Ratcliffe, 2004). This was also true among offender home addresses. Two examples of hot points were located in Cell C2 in Figure 6. Both hot spots contained low-income apartment communities housing a disproportionate number of likely offenders[23]. Unlike clustered hot spots, these tended to be more remote and did not include commercial facilities within a short distance. Figure 9 displays an aerial view of a community with a hot point pattern. Offender home addresses concentrated in this single street with the nearest offender living over 1,000 feet away. Recall, offender home addresses were joined to the street block, removing variation among this street block.

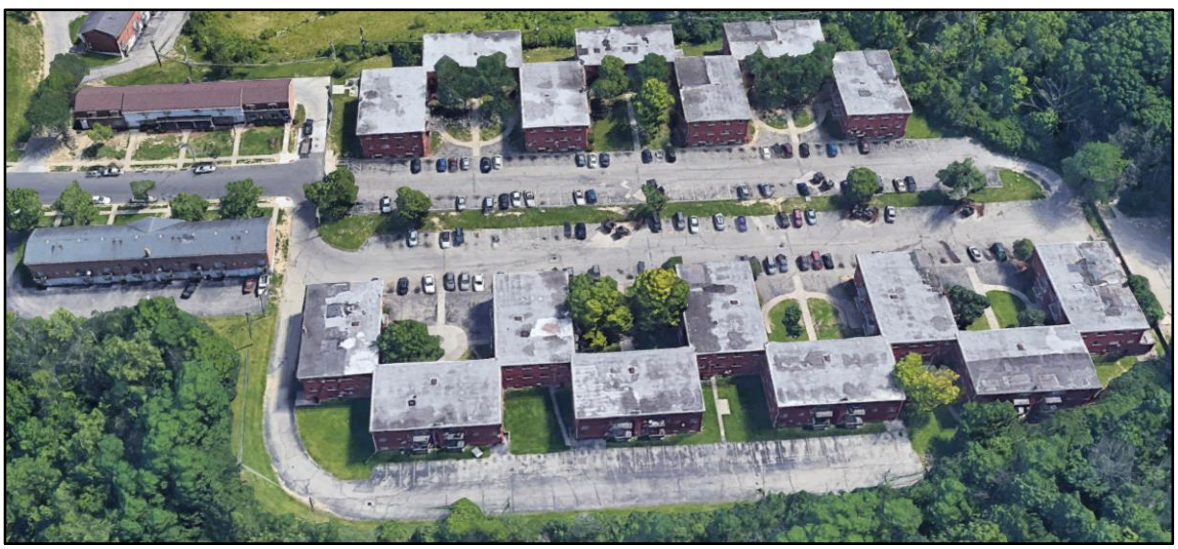

Figure 9. Aerial View of of Hot Spot with a Hot Point Pattern

[23] A third example of a hot point was centered at the Ohio Department of Rehabilitation and Correction Regional Probation Office, which is notable because it was not a residential facility. This likely reflected an error in my data.

Figure 11 displays the location of robbery hot spots in the red hues. Like offender addresses, robberies followed different point patterns (Ratcliffe, 2004). Examples are shown in Figure 10, where bigger points represent addresses with more incidents. The left panel of Figure 10 displays the dispersed pattern in Cell D5. This mixed-use area contains residential buildings and homes as well as a number of officer buildings, parks, bars, restaurants, and other commercial facilities. The bottom right panel displays an example of a clustered hot spot located in Cell C4 of Figure 11. There were multiple addresses with robbery incidents, but it was not dispersed among the full hot spot. For instance, two addresses (both gas stations) had six or more robberies, while remaining had at least one robbery. There was only one hot spot that resembled a hot point pattern (top right panel of Figure 10). Cell C3 (near east edge of the cell) in Figure 10 displays a hot point robbery hot spot. This hot spot contained a single address (gas station) with seven robberies.

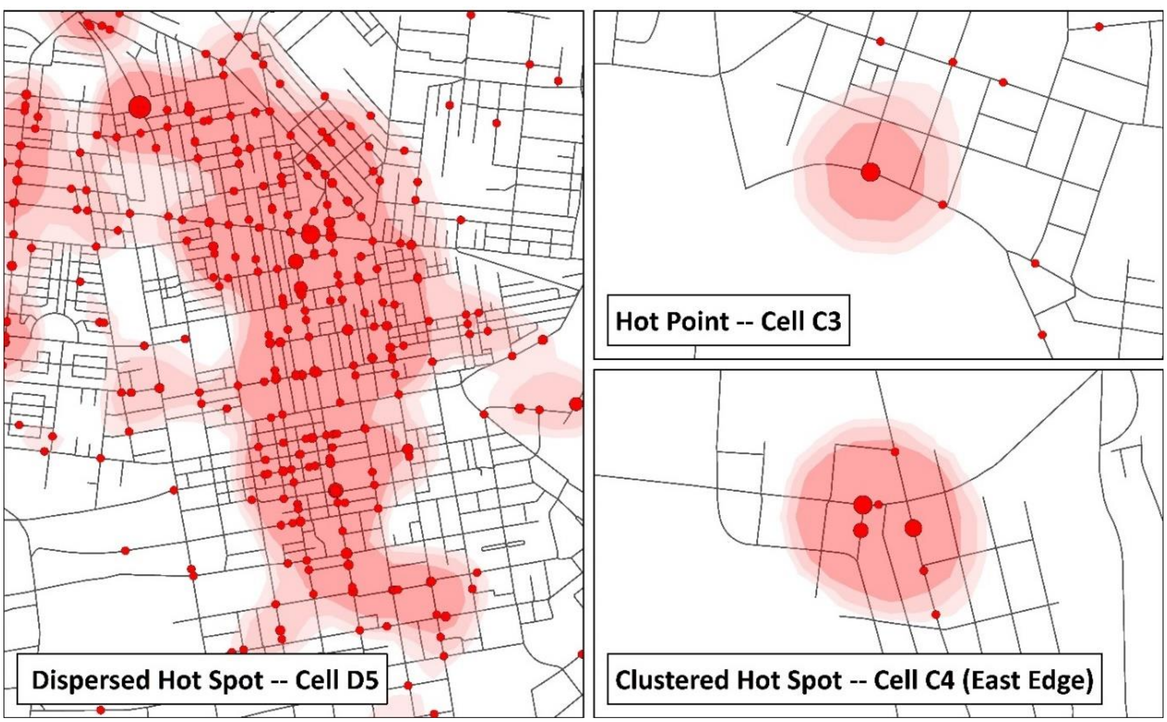

Figure 10. Distribution of Points within Select Robbery Hot Spots

Figure 11 also overlays the locations of home address and robbery hot spots. Some hot spots coincide closely with each other. For instance, both offender and robbery hot spots were located in Cell D5 in Figure 11 and follow dispersed hot spot patterns. This area houses both low-income residents and young professionals, and draws non-residential patrons to restaurants, bars, and specialty boutiques. In addition, the hot spots spanning across Cells B5 and C5 in Figure 11 coincide closely and both followed a clustered pattern. Both offender homes and robberies tended to be concentrated heavily on two major streets and along adjacent streets to a lesser extent. Lastly, a number of hot spots following the hot point were overlapping or proximal in Cell C2 and C4 in Figure 11. Offender homes concentrated in housing communities in these hot spots. Robberies also concentrated in these areas, but were concentrated within the community[24].

There were also areas that had little or no overlap between offender and robbery hot spots. Most notably this occurred in the southern area of Cell D5 in Figure 11. While the robbery hot spot in this cell extends into the southern portion of the cell, the offender hot spot did not. This area is the central business district; it does not contain a large amount of residential homes or buildings, but has restaurants, businesses, parking garages, and office buildings. In the center of Cell E4, there is a clustered offender hot spot, but only a small lightly concentrated robbery hot spot. This area located in and around Walnut Hills, is a mixed-use area. Despite having commercial facilities, primarily fast food restaurants, gas stations, corner stores, and a few bars, this area does not draw many non-residential patrons.

[24] The difference is likely the result of different data sources. Recall offender home addresses were joined to the street block. This removed variation within the street and mapped points to the same spot.

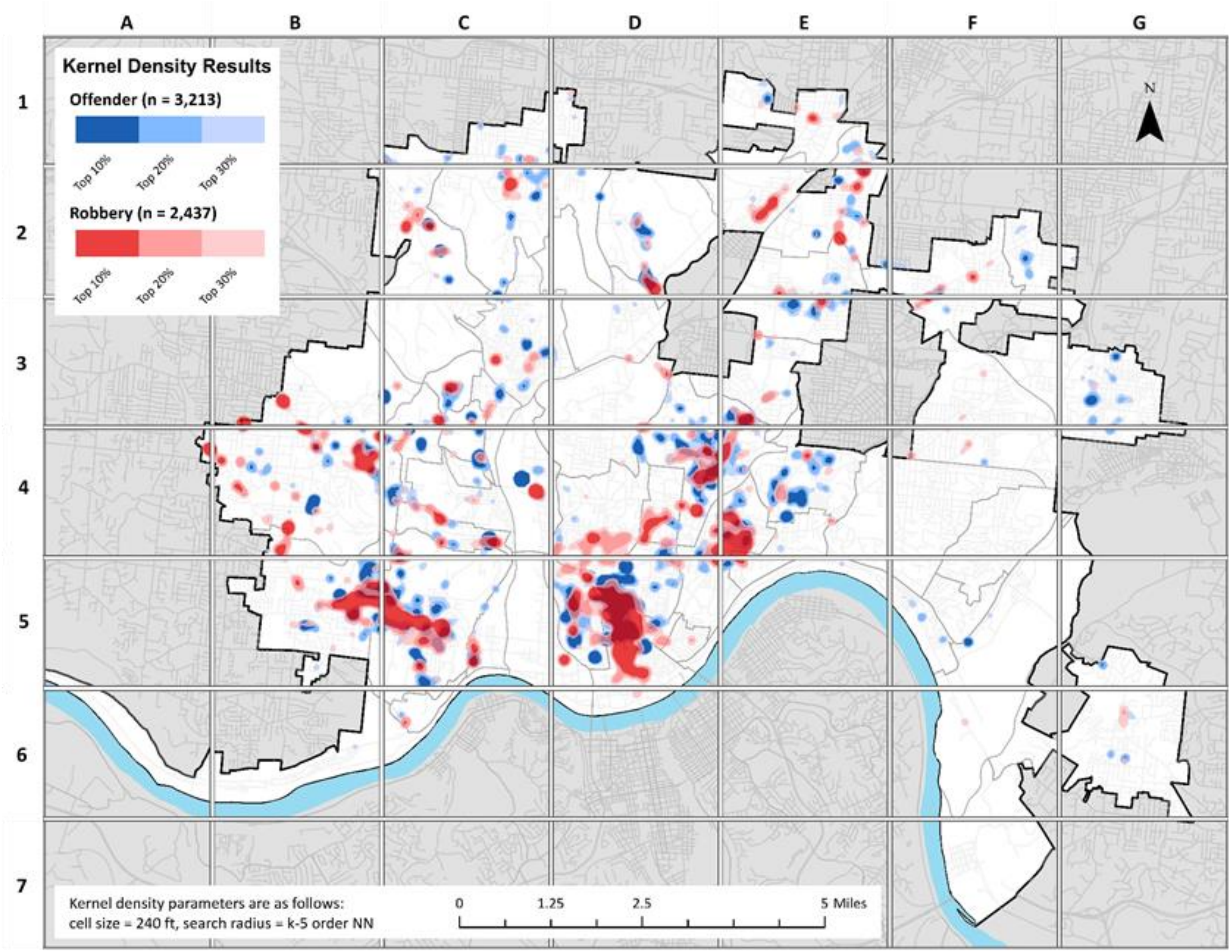

Figure 11. Distribution of Formally Incarcerated Persons and Robbery Hot Spots, Cincinnati, Ohio

Figure 13 shows the location of theft from auto hot spots in the green hues. Similar to the offender homes and robberies, these followed different spatial patterns. Most hot spots were either dispersed or clustered. Figure 12 shows three examples of hot spot patterns among theft from auto. The left panel in Figure 12 shows the downtown area. There were a handful of addresses with more points than other areas of the hot spot, one of which was a car rental facility and another was a large parking garage. However, theft from auto was generally dispersed in the hot spot. The bottom right panel shows a clustered hot spot pattern. This hot spot contained nine addresses with at least one theft from auto, one of which was a music venue with nine thefts. Most of these addresses clustered around the music venue. Lastly, hot points were present among theft form auto hot spots, but very rare. The top right panel displays a hot point, an apartment complex with six thefts from auto. The next closest theft from auto was about 1000 feet from the apartment complex.

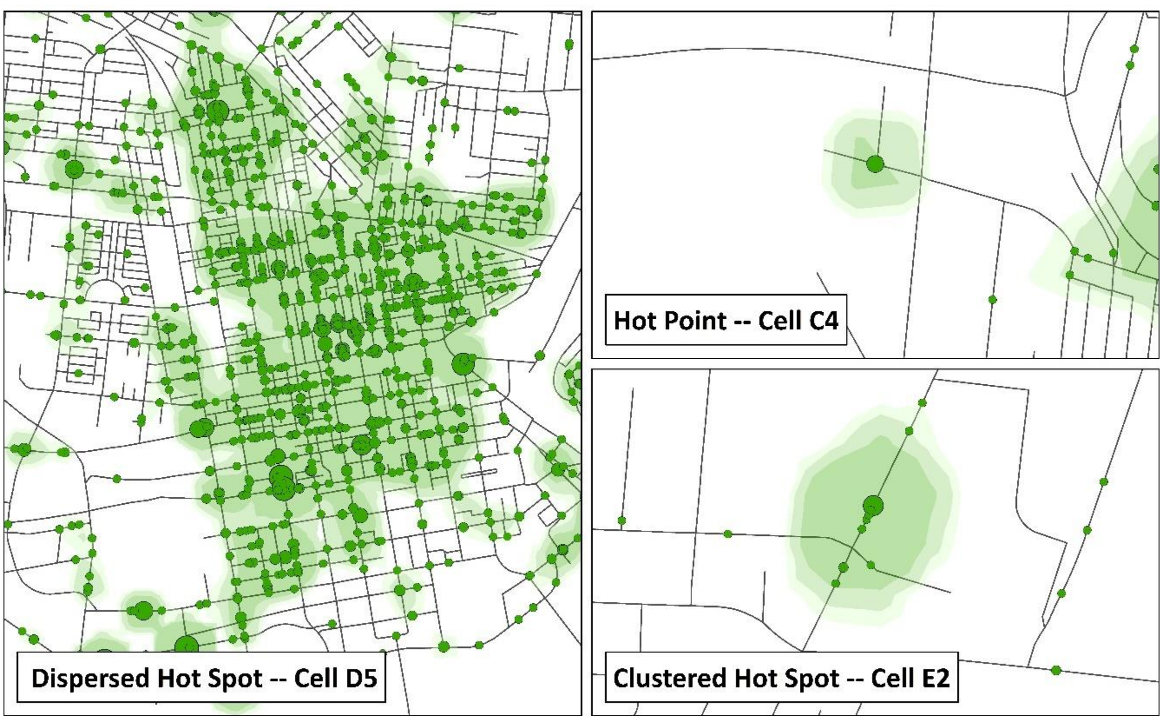

Figure 12. Distribution of Points within Select Theft from Auto Hot Spots

Figure 13 also shows how theft from auto and offender hot spots overlap. The hot spots overlapped the greatest in the northern area of Cell D5 (Over-the-Rhine neighborhood) and across Cells B5 and C5. This is the same area where offender and robbery hot spots overlapped. It contained both residents, office buildings, restaurants and bars, and garages to support the users. The hot spots across Cells B5 and C5 were located near residential area, a private and public school, and a shopping center. This area also mixed low and high-income residents with non-residents using the shopping center.

Despite the similarities between offender and theft from auto hot spots, there were a large number of hot spots that do not overlap. The dispersed theft from auto hot spot spans a much larger area than offender home addresses. In the southeast corner of Cell D5 in Figure 13, the central business district provides more opportunity for thefts from auto by drawing non-residents and employees to the area. It does not contain a large amount of residential apartments and homes, with the exception of a few "luxury" apartments. The thefts from auto hot spot extends north into the boundary of D4 and D5 in Figure 13. This area houses and supports commuting university college students. In addition, a number of restaurants and bookstores were located in the area. Because the area is oriented towards students, there were few opportunities for likely offenders to reside in the area, but provide plenty of targets for theft.

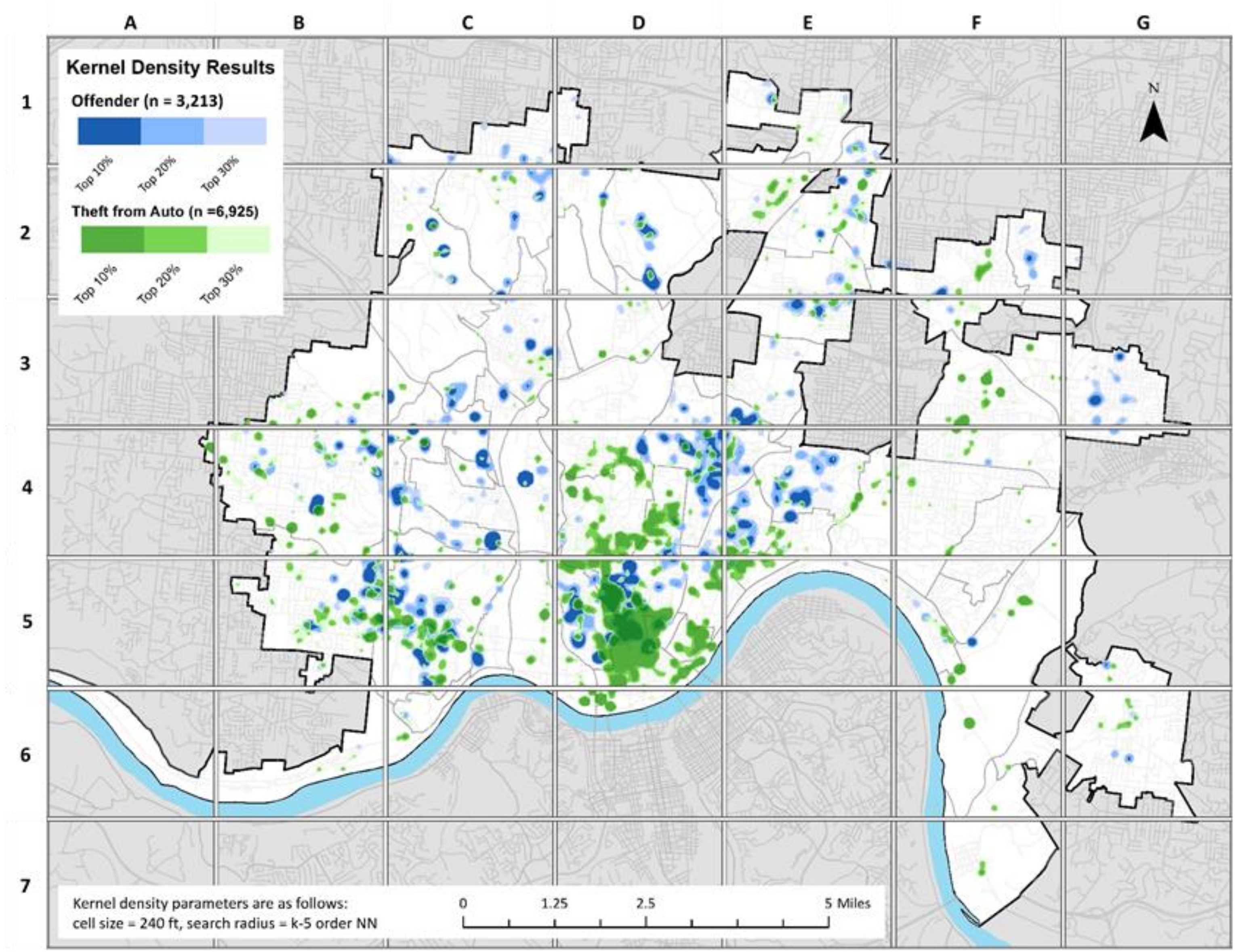

Figure 13. Distribution of Formally Incarcerated Persons and Theft from Auto Hot Spots, Cincinnati, Ohio

Research Question 3: Multivariate Analyses

Research Question 3 examines which variables were significantly associated with crime counts on Cincinnati street blocks. Two methods were used to assess which count distribution was appropriate for both robbery and theft from auto. First each crime's distribution was plotted with a simulated Poisson and negative binomial distribution to assess which visually fit better. Second, Likelihood Ratio Tests performed on both models. It assumes the data fits a Poisson distribution, therefore, rejecting the null hypothesis (the data fits a Poisson distribution), suggests the negative binomial distribution fits better. After the count distribution was established, regression models were presented for robbery and auto-related offenses. In addition to providing information about the main effects of variable types, this step will establish which facility will be included as an interaction term with offender measures.

Assessing Count Distributions

Robbery. Robbery counts among Cincinnati street blocks were over-dispersed and better fit a negative binomial distribution than a Poisson distribution. Figure 14 displays the distribution of robbery (n = 2,437) among Cincinnati streets (n = 10,940). As shown in Figure 14, over 85% of street blocks had no robbery incidents between 2016 and 2017, while most of the remaining street blocks (11.0%) had one or two robberies. The observed distribution was positively skewed because of a small number of streets with many robberies (i.e. nine streets had ten or more robberies). When visually examining the totality of the simulated and observed distributions, the observed distribution's tail and skew more closely match that of the negative binomial than the Poisson distribution. Like the observed data, the simulated negative binomial distribution included nine streets with ten or more robberies, while the Poisson distribution had no streets with more than four robberies. Furthermore, the likelihood ratio test confirmed the distribution better fit a negative binomial distribution than a Poisson distribution.

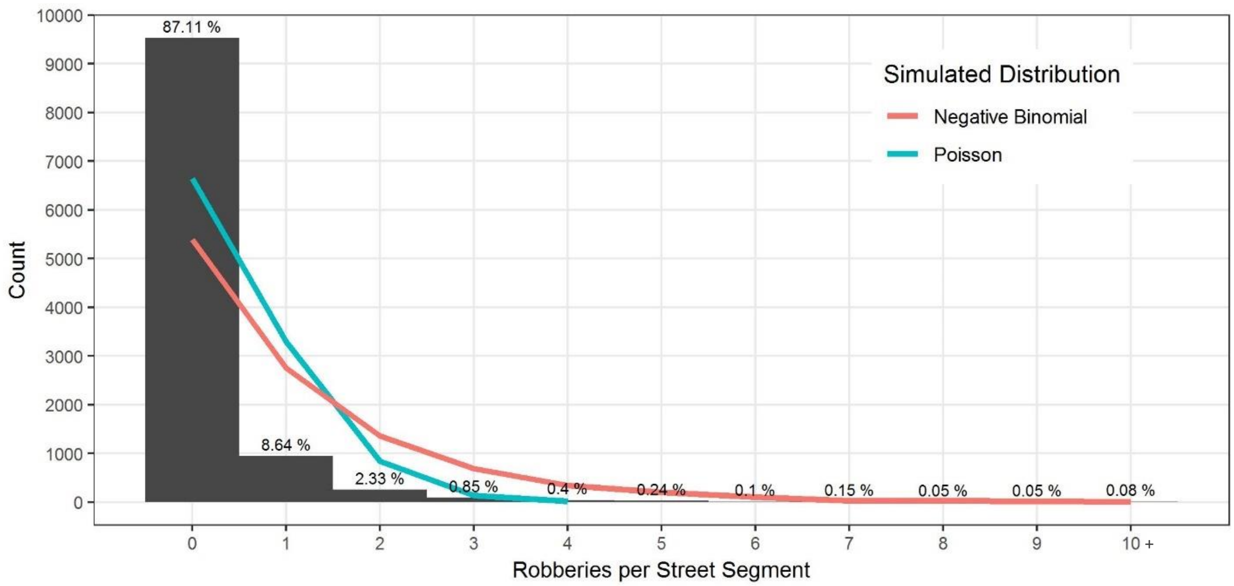

Figure 14. Distribution of Robbery among Cincinnati Street Blocks, 2016 - 2017

Thefts from Auto. Theft from auto counts were also over-dispersed and better fit a negative binomial distribution. Figure 15 displays the distribution of thefts from auto (n = 6,915) among Cincinnati street blocks (n = 10,940). A large proportion of streets had no offenses (70%), but there were a number of streets with disproportionately large quantities of thefts (e.g. nine streets had 20 or more offenses). Overall, the observed distribution more closely resembled a negative binomial distribution, particularly the non-zero distribution. When examining the distribution of non-zero streets, the observed counts were more skewed with a longer tail than the Poisson distribution. The likelihood-ratio test of the full model supports this notion, suggesting the null hypothesis assuming a Poisson distribution was rejected.

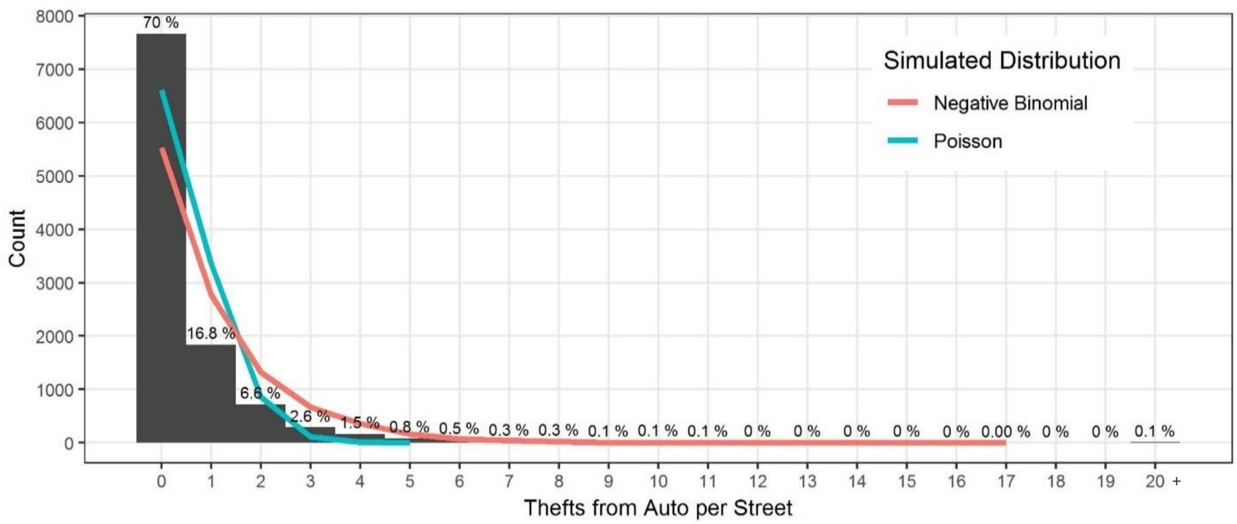

Figure 15. Distribution of Thefts from Auto among Cincinnati Street Blocks, 2016 - 2017

Diagnostics and Sensitivity Checks

Diagnostic testing did not identify any problematic multicollinearity, which was measured using variance inflation factors (VIF). According to Fox and Weisberg (2011), the square root of VIF values represent the how much of the confidence interval is expanded by each respective variable relative to uncorrelated data. Values greater than 2.0 indicated multicollinearity was likely present (Fox, 1991). Between robbery and theft from auto models, the average VIF value was 1.17 and the maximum value was 1.52. To assess the effect of outliers, I used Cook's Distance (Cook's D), which represent the "influence" of outliers, or the effect of removing each observation from the model (Fox and Weisberg, 2011). Values greater than four times the mean of the model's cooks distances indicate outliers and warrant inspection (Fox and Weisberg, 2011). Full models were re-run after removing these outliers, but the results of the robbery and theft from auto models remained consistent with the original models. The theft from auto models had

411 “outlier” cases removed and had six discrepancies among significant factors.[25] The robbery models had 462 “outlier” cases removed and had three discrepancies among significant factors.[26] Most of the discrepancies among spatial lag facility variables. All discrepancies occurred in the same direction (e.g. both positively related to crime) and existed among relationships with lower p-values.

In addition to diagnostic testing, three sensitivity tests were performed.[27] First, the current models including a likely offender IDW measure, using a distance band of 2,500 feet were compared with models using a distance band of 4,000 feet (the approximate distance of the offenders’ average nearest facility within this sample). For each outcome, there were no discrepancies among significant predictors and no major deviations in direction or strength of the relationships. Second, the model results were compared using different coding schemes related to the offender IDW measures. The original operationalization used only each person’s most recent known address was compared to a new measure using their current and prior

[25] Retail stores were positively and significantly associated with theft from auto counts ($p < 0.01$). Public housing communities were no longer associated with theft from auto counts. In addition, the spatial lags of bars and entertainment facilities were no longer significant, while drug treatment facilities were positively and negatively associated with theft from auto counts.

[26] Retail stores were positively and significantly associated with robbery counts ($p < 0.05$). In addition, the spatial lag of parking facility and prostitution markets were no longer significantly associated with robbery.

[27] The first sensitivity check that was performed resulted in disaggregating all auto-related offenses into motor vehicle thefts and thefts from auto. After comparing multivariate models of each disaggregated crime type, there were 11 discrepancies among which variables were significantly related to the dependent variable (30% of the variables). Furthermore, the influence of outliers were much stronger when the two offense types were aggregated as the original plan. There were large discrepancies in models with and without outliers. For that reason, the property crime dependent variable was changed from its original coding (all auto-related offenses) to only one auto-related crime type (theft from auto).

addresses.[28] There were no major differences in significance, direction, or strength of relationships between any variables and the dependent variables.

Third, likely offenders were disaggregated by into violent, property, and drug preferences (Chamberlain and Boggess, 2018). Chamberlain and Boggess (2018) found that concentrations of violent, property, and drug offenders had different effects (strength and direction) on the distribution of different crime types. When the three measures were run in the same model (as per Chamberlain and Boggess, 2018), the models produced VIF values among the offender variables ranging between 8.1 and 11.7, indicating the existence of multicollinearity. Despite results consistent with Chamberlain and Boggess (2018), the VIF values suggested the three offender specialties should be run in separate models. After doing this, the effect sizes and directions of the different specialties were no longer consistent with Chamberlain and Boggess (2018). Instead, the presence of violent, property, and drug offenders had significant positive effects on robbery and theft counts. Appendix A presents and outlines these findings, including how results relate to the main findings.

Robbery Count Models

Recall, Research Question Three sought to understand the relationships among offender and facility measures and crime net of other factors. Table 6 presents the negative binomial count regression models predicting robbery counts among Cincinnati street blocks. Model A included

[28] Offenders were asked for addresses upon entering Ohio Department of Correction, and after every release. Some offenders were released and readmitted for probation or parole violations (known in the data as a "stint"). Each stint also included an address on entry and another upon release related that particular stint. Most offender only had one stint, but some had as many as six stints. If an offender reported the same address among different stints, that address was counted only once. These addresses ranged between 2010 and 2015.

the Exposure to Likely Offender variable. Model B used the Cumulative Offender Risk variable (which weighted the first variable by ORAS Reentry score). Both offender measures (Exposure to Likely Offenders and Cumulative Offender Risk) obtained statistical significance, after controlling for other factors. Robbery counts increased with both IDW offender measures. Robbery counts among street blocks increased by 1.05% for every unit increase in the IDW Exposure to Likely Offender measure (Model A) and 0.65% for every unit increase in the IDW Cumulative Offender Risk measure (Model B). For a standard deviation increase in exposure to likely offenders (SD = 15.9), a street block's expected robbery count increases by 16.7% holding other variables constant. Similarly, a standard deviation increase in the cumulative offender risk (SD = 20.8) resulted in a street block's robbery count increasing by 13.5%.

A number of criminogenic facilities were statistically significant net of the other variables in the models. There were ten of the fifteen criminogenic facilities that had significant associations with robbery counts in both Model A and Model B. Five of these variables were dichotomously coded, meaning their coefficients described changes in robbery for streets with and without the respective facility (Model A: bus stops = 101.3%, drug treatment facilities = 81.8%, public housing communities = 82.5%, parking structures = 41.4%, and gang territories = 90.4%). Three of the significant facilities were measured as counts, meaning the IRR presented the increase in robbery for an additional facility per street (Model A: bars = 57.4%, everyday stores = 187.6%, and restaurants = 14.8%). Lastly, prostitution and drug markets, both of which were measured as a sum of calls for police service (CFS), were also significantly associated with robbery at street blocks. Robbery counts increased by roughly 12.7% with each additional drug CFS and 23.3% with each additional prostitution CFS in both models. In addition to the focal effects, five of the fifteen facility spatial lag controls were significant (everyday store, bus stop, gang territory, parking structure, and prostitution market). For example, street blocks adjacent to gang territories (even those without territories on the respective focal block) had higher robbery counts than those with no nearby gang territories (IRR = 1.39 in Model A and Model B).

Six control variables also achieved significance in the robbery models (Table 6, Model A and Model B). All structural factors were positively and significantly associated with street block robbery counts. For example, a standard deviation increase in the disadvantage index (SD = 3.6) was associated with 27.4% increase in street blocks' expected robbery counts. Next, major streets and longer streets were significantly associated with higher expected robbery counts, but street blocks near interstate highways were not significantly different from other street blocks in the city.

Overall, the results in Table 6 support the hypotheses associated with Research Question 2. Both offender variables and a number of criminogenic facilities were significantly associated with more robberies on Cincinnati street blocks. Overall, there were few differences between Model A and Model B, suggesting the two were capturing the same effect. This consistent with the high correlation between the two offender variables (Pearson's Correlation = 0.986).

Table 6. Results of a Negative Binomial Regression - Robbery Counts 2016 - 2017

Variable	Model A: Likely Offender Exposure β	(SE)	IRR	Model B: Cumulative Offender Risk β	(SE)	IRR
IDW Offender Count	0.010***	(0.00)	1.01	--	--	--
IDW Cumulative Offender Risk	--	--	--	0.006***	(0.00)	1.01
Bar/Club	0.453***	(0.13)	1.57	0.460***	(0.13)	1.58
Entertainment Facility	0.194	(0.25)	1.21	0.200	(0.25)	1.22
Fringe-Banking Store	0.287	(0.35)	1.33	0.275	(0.35)	1.32
Grocery Store	0.293	(0.36)	1.34	0.297	(0.36)	1.35
Everyday Store	1.056***	(0.08)	2.88	1.056***	(0.08)	2.88
Restaurant	0.138**	(0.05)	1.15	0.139**	(0.05)	1.15
Retail Store	0.030	(0.04)	1.03	0.030	(0.04)	1.03
Bus Stop	0.700***	(0.09)	2.01	0.711***	(0.09)	2.04
High School	0.169	(0.23)	1.18	0.170	(0.23)	1.19
Drug Treatment Facility	0.598*	(0.27)	1.82	0.594*	(0.27)	1.81
Public Housing	0.602**	(0.20)	1.83	0.620**	(0.20)	1.86
Parking Lot	0.347***	(0.06)	1.41	0.347***	(0.06)	1.41
Gang Territory	0.644***	(0.07)	1.90	0.650***	(0.07)	1.92
Prostitution Market	0.209**	(0.08)	1.23	0.207**	(0.08)	1.23
Drug Market	0.119***	(0.01)	1.13	0.119***	(0.01)	1.13
Bar/Club SL	-0.010	(0.08)	0.99	-0.004	(0.08)	1.00
Entertainment Facility SL	0.068	(0.13)	1.07	0.072	(0.13)	1.07
Fringe-Banking Store SL	-0.005	(0.19)	0.99	-0.006	(0.19)	0.99
Grocery Store SL	-0.015	(0.20)	0.99	-0.018	(0.20)	0.98
Everyday Store SL	0.157***	(0.05)	1.17	0.156***	(0.05)	1.17
Restaurant SL	0.008	(0.03)	1.01	0.009	(0.03)	1.01
Retail Store SL	0.030	(0.02)	1.03	0.029	(0.02)	1.03
Bus Stop SL	0.243**	(0.08)	1.28	0.247**	(0.08)	1.28
High School SL	0.167	(0.17)	1.18	0.170	(0.17)	1.18
Drug Treatment Facility SL	0.103	(0.14)	1.11	0.101	(0.14)	1.11
Public Housing SL	0.092	(0.20)	1.10	0.102	(0.20)	1.11
Parking Lot SL	0.728*	(0.32)	2.07	0.730*	(0.32)	2.08
Gang Territory SL	0.331***	(0.09)	1.39	0.331***	(0.09)	1.39
Prostitution Market SL	0.055**	(0.02)	1.06	0.056**	(0.02)	1.06
Drug Market SL	0.002	(0.00)	1.00	0.003	(0.00)	1.00
Total Population/100	0.035***	(0.01)	1.04	0.035***	(0.01)	1.04
Concentrated Disadvantage	0.072***	(0.01)	1.08	0.075***	(0.01)	1.08
Residential Stability	0.129***	(0.02)	1.14	0.131***	(0.02)	1.14
Racial Segregation	0.459*	(0.19)	1.58	0.477*	(0.19)	1.61
Length of Street/100	0.048***	(0.00)	1.05	0.048***	(0.00)	1.05
Major Street	0.279***	(0.08)	1.32	0.271**	(0.08)	1.31
Access to Highway	-0.041	(0.20)	0.96	-0.046	(0.20)	0.96
Intercept	-4.751***	(0.33)	0.01	-4.732***	(0.33)	0.01

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Theft from Auto Count Models

Table 7 displays the results of a negative binomial count regression predicting theft from auto counts among Cincinnati street blocks. Model C included the Exposure to Likely Offenders variable. Model D used the Cumulative Offender Risk variable (the previous variable weighted by ORAS Reentry score). Similar to the robbery models, both offender measures obtained significance after controlling for other factors. For a standard deviation increase in the Offender Exposure or the Cumulative Offender Risk variables (Model C and Model D, respectively), a street block's expected robbery count per street block is roughly 19% or 15% higher after holding other variables constant. These results support the hypothesis that offender proximity is associated with higher street block thefts from auto counts.

In Table 7, ten of the fifteen criminogenic facilities were significantly associated with theft from auto in both models. Street blocks with a grocery store, bus stop, high school, public housing community, or parking structure had higher expected theft from auto counts than those without (Model C: grocery = 207.0%, bus stop = 28.8%, high school = 46.7%, public housing = 97.6%, parking structure = 36.5%). Five of the significant facilities were counts of each respective facility per street block (bar/clubs, entertainment facilities, grocery stores, everyday stores, and restaurants). For every additional facility per street block, facilities measured as counts had increased counts of theft from auto (Model C: bars = 99.0%, entertainment facility = 170.3%, everyday store = 22.4%, restaurants = 13.7%). In addition, for every additional drug-related call for service, which was used to represent drug markets, theft from auto increased by 10.1% per street block. The direction, magnitude, and significance of the criminogenic facilities remained consistent between Model C and D.

There were four facility spatial lag variables that achieved significance in Model C, Table 7. Street blocks adjacent to those with bars, entertainment facilities, or parking structures were associated with higher expected theft from auto counts. Streets adjacent to street blocks with everyday stores, however, had fewer thefts from auto (11.6% reduction per additional facility). In addition to the significant facility spatial lags in Model C, the drug market spatial lag was positively and significantly associated with theft from auto counts in Model D. For every additional drug-related CFS, theft from auto increased by only 0.4% among street blocks.

In addition, a number of control variables retained significance in Table 7. All of the structural census and street network controls had significant association with theft from auto counts, with the exception of proximity to a highway. Concentrated disadvantage was negatively associated with thefts from auto. As concentrated disadvantage increases by one standard deviation (SD = 3.6), expected theft from auto counts decreased by 2.8% among street blocks. The other backcloth factors (total population, residential instability, and racial heterogeneity) were all associated with more thefts from auto, consistent with prior literature.

While there were slightly different findings between theft from auto and robbery models, the results from Table 7 also support the hypothesis of Research Question 3. Both the offender and facility measures were statistically associated with more thefts from auto among street blocks net of control variables. Unexpectedly, concentrated disadvantage and spatially-lagged everyday stores had negative relationship with theft from auto counts. Thefts from auto were less likely to occur on street blocks in disadvantaged areas and streets with an everyday store nearby.

Table 7. Results of a Negative Binomial Regression – Theft from Auto Counts 2016 - 2017

	Model C: Likely Offender Exposure			Model D: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
Likely Offender Exposure	0.012***	(0.00)	1.01	--	--	--
IDW Cumulative Offender Risk	--	--	--	0.007***	(0.00)	1.01
Bar/Club	0.688***	(0.11)	1.99	0.693***	(0.11)	2.00
Entertainment Facility	0.994***	(0.17)	2.70	0.996***	(0.17)	2.71
Fringe-Banking Store	-0.269	(0.37)	0.76	-0.280	(0.37)	0.76
Grocery Store	1.122***	(0.32)	3.07	1.123***	(0.32)	3.07
Everyday Store	0.202*	(0.08)	1.22	0.202*	(0.08)	1.22
Restaurant	0.128**	(0.05)	1.14	0.130**	(0.05)	1.14
Retail Store	0.037	(0.04)	1.04	0.038	(0.04)	1.04
Bus Stop	0.253***	(0.06)	1.29	0.265***	(0.06)	1.30
High School	0.383*	(0.17)	1.47	0.379*	(0.17)	1.46
Drug Treatment Facility	0.358	(0.25)	1.43	0.358	(0.25)	1.43
Public Housing	0.681***	(0.18)	1.98	0.697***	(0.18)	2.01
Parking Lot	0.311***	(0.04)	1.36	0.312***	(0.04)	1.37
Gang Territory	-0.083	(0.05)	0.92	-0.074	(0.05)	0.93
Prostitution Market	0.039	(0.08)	1.04	0.038	(0.08)	1.04
Drug Market	0.096***	(0.01)	1.10	0.095***	(0.01)	1.10
Bar/Club SL	0.137**	(0.05)	1.15	0.143**	(0.05)	1.15
Entertainment Facility SL	0.244**	(0.09)	1.28	0.253**	(0.09)	1.29
Fringe-Banking Store SL	0.094	(0.18)	1.10	0.086	(0.18)	1.09
Grocery Store SL	0.087	(0.17)	1.09	0.080	(0.17)	1.08
Everyday Store SL	-0.123**	(0.04)	0.88	-0.124**	(0.04)	0.88
Restaurant SL	-0.014	(0.02)	0.99	-0.013	(0.02)	0.99
Retail Store SL	0.015	(0.02)	1.02	0.014	(0.02)	1.01
Bus Stop SL	-0.025	(0.05)	0.98	-0.019	(0.05)	0.98
High School SL	0.086	(0.13)	1.09	0.086	(0.13)	1.09
Drug Treatment Facility SL	-0.144	(0.13)	0.87	-0.149	(0.13)	0.86
Public Housing SL	0.036	(0.18)	1.04	0.045	(0.18)	1.05
Parking Lot SL	0.313**	(0.12)	1.37	0.311**	(0.12)	1.36
Gang Territory SL	-0.066	(0.06)	0.94	-0.062	(0.06)	0.94
Prostitution Market SL	0.009	(0.02)	1.01	0.010	(0.02)	1.01
Drug Market SL	0.002	(0.00)	1.00	0.004**	(0.00)	1.00
Total Population/100	0.025***	(0.00)	1.03	0.024***	(0.00)	1.02
Concentrated Disadvantage	-0.045***	(0.01)	0.96	-0.043***	(0.01)	0.96
Residential Stability	0.157***	(0.01)	1.17	0.158***	(0.01)	1.17
Racial Segregation	0.443***	(0.12)	1.56	0.457***	(0.12)	1.58
Length of Street/100	0.104***	(0.00)	1.11	0.102***	(0.00)	1.11
Major Street	0.154*	(0.06)	1.17	0.146*	(0.06)	1.16
Access to Highway	-0.011	(0.14)	0.99	-0.013	(0.14)	0.99
Intercept	-2.501***	(0.14)	0.08	-2.472***	(0.14)	0.08

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Research Question 4: Multivariate Analyses with Interaction Terms

The last portion of this dissertation tested whether crime among street blocks were predicted by the interaction between exposure to likely offenders and select criminogenic facilities. Recall, an interactive effect on a dependent variable involves two independent variables acting *together* in such a way to produce a unique effect on the dependent variable *beyond* the effect of each independent variable acting alone (Fox, 1991). A model with significant interaction effects can allow both the intercept and the effect (slope) of offender variables on crime to be different for streets with and without specific criminogenic facilities (Karaca-Mandic, Norton, and Dowd, 2012). Research Question 4 is designed to understand whether some criminogenic facilities were more "risky", or crime-prone, than others of the same type because they were proximal to more likely offenders. Therefore, the effect of criminogenic facilities on crime are hypothesized to be moderated by the differing degrees of exposure to likely offenders. These multiplicative effects are different from the individual main effects or the sum of the main effects of facility and offender measures.

For each crime type, interactive effects were examined between criminogenic facilities with significant main effects and each offender variable on robbery and theft from auto counts. Model I used the Exposure to Likely Offenders measure, while Model J used the Cumulative Offender Risk measure. Interpretation of the interaction terms varies depending on the coding schema of the facility variable. When interaction terms included dichotomously coded facilities (e.g. bus stop, public housing, and gang territory), the interaction effect captures the change in slope or effect of the facility per unit increase of the offender measure. These effects were visualized with interaction plots (using jtools r package; Long, 2019). With all other variables being held constant at their mean, the predicted crime counts were calculated and plotted for streets with (and without) the facility by the degree of offender exposure.

When interaction terms included count or continuously coded facility measures (bar/club, everyday store, restaurant, prostitution and drug markets), coefficients still represent the change in slope for every unit increase in the second variable. The interaction effect is more difficult to assess because it involves applying unit changes in two different continuous variables. For facilities with a count per street, interaction plots show how predicted crime counts changed among different degrees of likely offenders. For continuous facilities (those using calls for service), Johnson-Neyman plots were used to show how the slope of continuously coded facilities change at different degrees of exposure to likely offenders (using jtools package; Long, 2019).

Robbery

Table 8 presents the full interaction models, predicting robbery counts among Cincinnati street blocks. There were ten facility variables with significant main effects on robbery counts, which populated the facility portion of the interaction between criminogenic facilities and likely offenders. These included bar/club, everyday store, restaurant, bus stop, drug treatment facility, public housing, parking structure, gang territory, prostitution market, and drug market. Interactions between these facilities and offender variables were captured by multiplying these facility measures with the Exposure to Likely Offenders measure (Model E and Model G) and Cumulative Offender Risk (Model F and Model I). Recall, the coefficients of interaction terms capture the change in slope of one variable for every unit increase in the second variable. There were only three interaction effects that were significant in Table 8. The effect of bus stops on expected robbery counts increased as the street was exposed to more likely offenders, while the effect of parking structures and gang territories were weakened as streets became exposed to more likely offenders.

Table 8. Negative Binomial Regression Results with Offender x Facility Interactions - Robbery, Cincinnati Ohio, 2016 - 2017

	Model E: Likely Offender Exposure			Model F: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
IDW Likely Offender Exposure	0.019***	(0.00)	1.02	--	--	--
IDW Cumulative Offender Risk	--	--	--	0.013***	(0.00)	1.01
Offender x Bar/Club	0.001	(0.01)	1.00	0.002	(0.00)	1.00
Offender x Everyday Store	0.002	(0.00)	1.00	0.001	(0.00)	1.00
Offender x Restaurant	0.001	(0.00)	1.00	0.001	(0.00)	1.00
Offender x Bus Stop	0.007**	(0.00)	1.01	0.005**	(0.00)	1.01
Offender x Drug Facility	-0.018	(0.01)	0.98	-0.013	(0.01)	0.99
Offender x Public Housing	0.027	(0.02)	1.03	0.016	(0.02)	1.02
Offender x Parking Lot	-0.007*	(0.00)	0.99	-0.006**	(0.00)	0.99
Offender x Gang Territory	-0.014***	(0.00)	0.99	-0.010***	(0.00)	0.99
Offender x Prostitution CFS	-0.004	(0.00)	1.00	-0.003	(0.00)	1.00
Offender x Drug Market	-0.001	(0.00)	1.00	-0.0005	(0.00)	1.00
Bar/Club	0.416*	(0.16)	1.52	0.390*	(0.16)	1.48
Entertainment Facility	0.204	(0.25)	1.23	0.207	(0.25)	1.23
Fringe-Banking Store	0.286	(0.34)	1.33	0.267	(0.35)	1.31
Grocery Store	0.313	(0.35)	1.37	0.305	(0.35)	1.36
Everyday Store	1.022***	(0.10)	2.78	1.023***	(0.10)	2.78
Restaurant	0.124*	(0.06)	1.13	0.118*	(0.06)	1.13
Retail Store	0.034	(0.04)	1.03	0.036	(0.04)	1.04
Bus Stop	0.543***	(0.10)	1.72	0.568***	(0.10)	1.76
High School	0.145	(0.23)	1.16	0.153	(0.23)	1.17
Drug Treatment Facility	0.953*	(0.38)	2.59	0.906*	(0.36)	2.48
Public Housing	0.086	(0.42)	1.09	0.273	(0.39)	1.31
Gang Territory	0.908***	(0.09)	2.48	0.873***	(0.09)	2.39
Parking Lot	0.471***	(0.08)	1.60	0.474***	(0.08)	1.61
Prostitution Market	0.299**	(0.11)	1.35	0.276**	(0.11)	1.32
Drug Market	0.129***	(0.01)	1.14	0.128***	(0.01)	1.14

Table 8 Continued…

Variable	β	(SE)	IRR	β	(SE)	IRR
Bar/Club SL	-0.022	(0.08)	0.98	-0.011	(0.08)	0.99
Entertainment Facility SL	0.077	(0.12)	1.08	0.085	(0.12)	1.09
Fringe-Banking Store SL	-0.005	(0.19)	0.99	-0.007	(0.19)	0.99
Grocery Store SL	-0.009	(0.20)	0.99	-0.021	(0.20)	0.98
Everyday Store SL	0.152***	(0.05)	1.16	0.152***	(0.05)	1.16
Restaurant SL	0.015	(0.03)	1.02	0.015	(0.03)	1.01
Retail Store SL	0.030	(0.02)	1.03	0.029	(0.02)	1.03
Bus Stop SL	0.242**	(0.08)	1.27	0.246**	(0.08)	1.28
High School SL	0.154	(0.17)	1.17	0.161	(0.17)	1.17
Drug Treatment Facility SL	0.099	(0.14)	1.10	0.098	(0.14)	1.10
Public Housing SL	0.091	(0.20)	1.10	0.100	(0.20)	1.11
Gang Territory SL	0.281**	(0.09)	1.32	0.285**	(0.09)	1.33
Parking Lot SL	0.644*	(0.32)	1.90	0.651*	(0.32)	1.92
Prostitution Market SL	0.051**	(0.02)	1.05	0.051**	(0.02)	1.05
Drug Market SL	0.003	(0.00)	1.00	0.004*	(0.00)	1.00
Total Population/100	0.037***	(0.01)	1.04	0.036***	(0.01)	1.04
Concentrated Disadvantage	0.074***	(0.01)	1.08	0.075***	(0.01)	1.08
Residential Stability	0.124***	(0.02)	1.13	0.126***	(0.02)	1.13
Racial Segregation	0.450*	(0.19)	1.57	0.454*	(0.19)	1.57
Length of Street/100	0.05***	(0.00)	1.05	0.049***	(0.00)	1.05
Major Street	0.301***	(0.08)	1.35	0.294***	(0.08)	1.34
Access to Highway	-0.004	(0.20)	1.00	-0.020	(0.20)	0.98
Intercept	-4.801***	(0.33)	0.01	-4.769***	(0.33)	0.01

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Figure 16 displays the predicted robbery counts (and 95% confidence intervals) of streets with and without a bus stop by the Exposure to Likely Offender variable, holding all other variables constant at their mean. With the orange line (streets with a bus stop) consistently predicting more robberies than the green line (streets without a bus stop), Figure 16 shows the significant main effect of bus stops. Regardless of the exposure to likely offenders, streets with bus stops have higher expected robbery counts than streets without a bus stop. The figure also shows the change in slopes among streets with and without a bus stop, as exposure to likely offenders changed (moderating effect). As offender exposure increases, streets with bus stops were associated with greater increases (slope) in robbery than those without bus stops. The moderating effect appears to be greatest with higher degrees of offender exposure (IDW Offender Exposure > 60), when the predicted values and their confidence intervals begin to increase at a steeper rate.

These findings suggest that streets with bus stops are generally more robbery-prone than streets without them, but the criminogenic effects of bus stops are stronger with higher exposure to likely offenders. The findings are consistent with the patron hypothesis, in that the nearby offenders condition the effect of bus stops, but assuming the offenders in the area are patrons of the bus stops may not be appropriate. In fact, it may increase the risk associated with offending to victimize another patron of the same bus stop. Offenders in the area may be actively targeting bus stops because of the reputation of having victims or targets, or they may be passively exploiting bus stop patrons while operating in the nearby area.

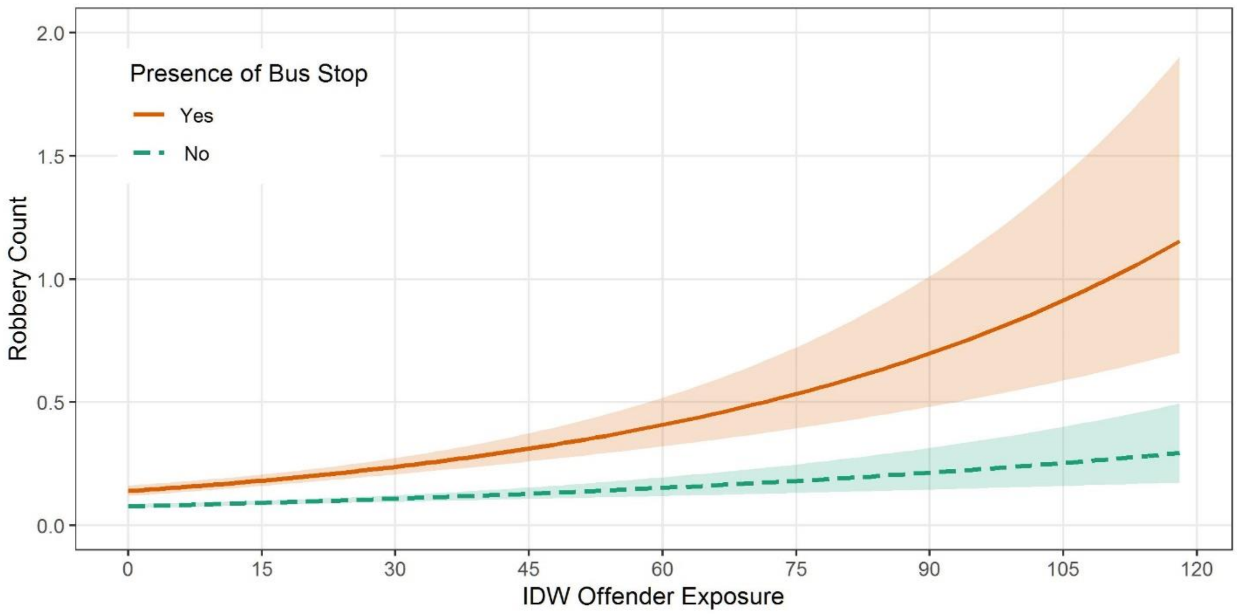

Figure 16. Exposure to Likely Offenders x Bus Stop Interaction Plot Predicting Robbery Counts

The second significant conditioned effect in the robbery models existed among parking structures and likely offenders (Figure 17). When exposure to likely offenders is held at zero or its mean (12.3), streets with parking structures have significantly higher expected robbery counts than streets without a parking structure. As exposure to likely offenders increases, the criminogenic effects of parking structures were no longer significantly associated with robbery counts. The larger confidence intervals suggest the lack of statistical power among streets with large exposure to likely offenders. The mechanism behind this conditional effect is hard to explain, but perhaps a result of the natural segregation of residential and commercial areas. More specifically, areas with large amounts of offender exposure are likely residential and do not include large parking facilities, especially when compared to streets in business or entertainment districts.

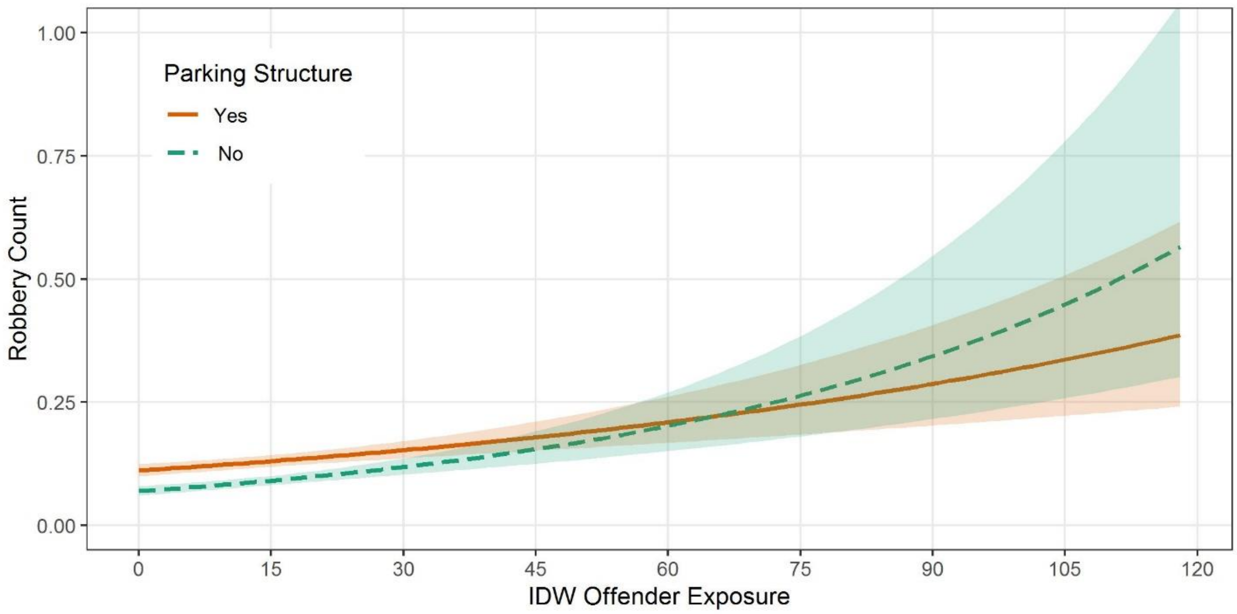

Figure 17. Exposure to Likely Offenders x Parking Structure Interaction Plot, Predicting Robbery Counts

The last significant interaction effect in robbery models existed among gang territories and likely offenders. Unlike the moderating effect on bus stops, greater exposure to likely offenders resulted in a reduction or weakened relationship between gang territories and robbery (β = -0.01; $p < 0.001$). Figure 18 displays the interaction plot of gang territories and the exposure to likely offender measure. The positive main effects of gang territories are seen as the orange line (streets with a gang territory) is above the green line (streets without a gang territory); this is true when offender exposure is zero and held constant at its mean ($Mean_{\text{Exposure to Offender}}$ = 12.3). As the values of exposure to likely offenders exceed 45, the criminogenic effects of gang territories are no longer associated with robbery counts among street blocks. Instead, there is little difference between streets with and without gang territories when in streets with a high exposure to likely offenders.

This finding appears to be counter intuitive; however, this might be explained by what each "measure". Originally, gang territories were included as a criminogenic facility because it facilitates the convergence of people who deal with drugs, guns, cash, and/or gang feuds. In streets with a large degree of exposure to likely offenders, gang territories might not introduce likely offenders in the street that are not already there. Essentially, gang territories may represent a possible offender node, which captures locations with exposure to motivated or likely offenders.

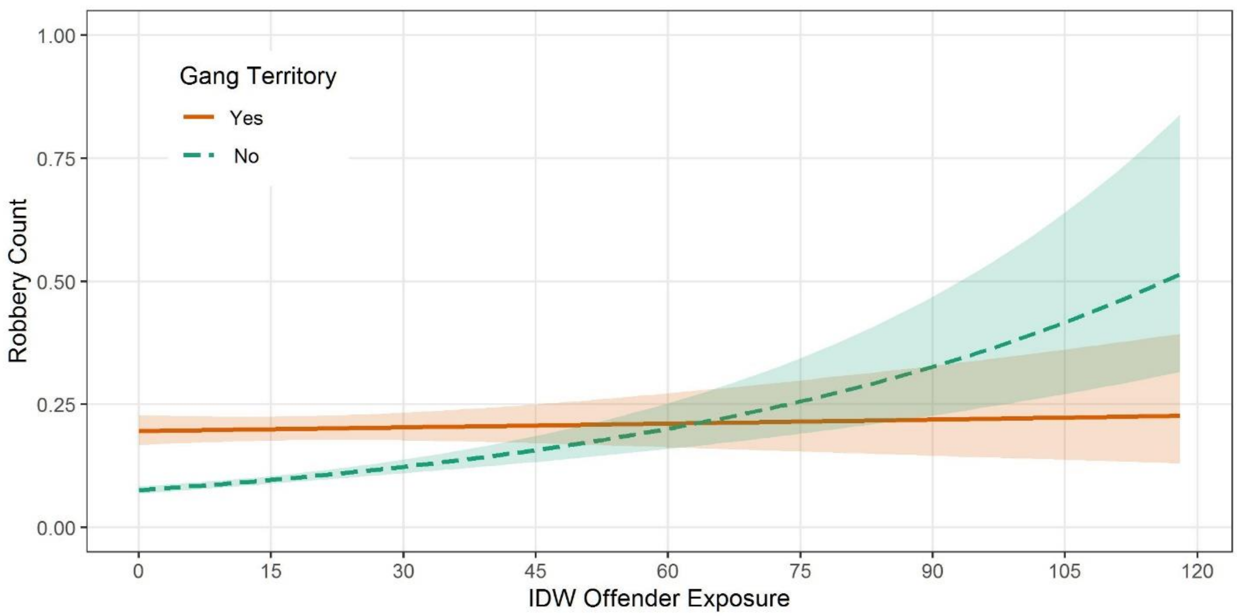

Figure 18. Exposure to Likely Offenders x Gang Territory Interaction Plot, Predicting Robbery Counts

Theft from Auto

There were eight facility variables with significant main effects on theft from auto counts. These included bar/club, entertainment facility, grocery store, everyday store, restaurant, bus stop, public housing, and drug market. Facilities were multiplied by Exposure to Likely Offenders (Model G) and Cumulative Offender Risk (Model H). The interaction terms using dichotomously coded facilities represent the change in slope for streets with the respective facility. While those with count or continuously coded facilities represent change in slope per unit increase in the offender variable, plots provide context. Table 9 shows the offender measures moderated the relationship between three criminogenic facilities (restaurants, bus stops, and drug markets) and theft from auto.

Table 9. Negative Binomial Regression Results with Offender X Facility Interactions - Theft from Auto, Cincinnati Ohio, 2016 – 2017

	Model G: Likely Offender Exposure			Model H: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
IDW Likely Offender Exposure	0.010***	(0.00)	1.01	--	--	--
IDW Cumulative Offender Risk	--	--	--	0.006**	(0.00)	1.01
Offender x Bar/Club	0.0005	(0.01)	1.00	0.002	(0.00)	1.00
Offender x Entertainment	-0.002	(0.01)	1.00	-0.001	(0.01)	1.00
Offender x Grocery Store	-0.014	(0.02)	0.99	-0.016	(0.02)	0.98
Offender x Everyday Store	-0.005	(0.00)	1.00	-0.003	(0.00)	1.00
Offender x Restaurant	0.011***	(0.00)	1.01	0.010***	(0.00)	1.01
Offender x Bus Stop	0.006**	(0.00)	1.01	0.004**	(0.00)	1.00
Offender x High School	-0.011	(0.01)	0.99	-0.008	(0.01)	0.99
Offender x Public Housing	0.029	(0.02)	1.03	0.019	(0.02)	1.02
Offender x Parking Lot	-0.001	(0.00)	1.00	-0.001	(0.00)	1.00
Offender x Drug Market	-0.001***	(0.00)	1.00	-0.001***	(0.00)	1.00
Bar/Club	0.650***	(0.13)	1.92	0.629***	(0.13)	1.88
Entertainment Facility	1.002***	(0.22)	2.72	0.987***	(0.22)	2.68
Fringe-Banking Store	-0.253	(0.37)	0.78	-0.280	(0.37)	0.76
Grocery Store	1.337***	(0.39)	3.81	1.365***	(0.39)	3.91
Everyday Store	0.244*	(0.10)	1.28	0.229*	(0.10)	1.26
Restaurant	0.0002	(0.06)	1.00	-0.006	(0.06)	0.99
Retail Store	0.050	(0.04)	1.05	0.053	(0.04)	1.05
Bus Stop	0.164*	(0.07)	1.18	0.182**	(0.07)	1.20
High School	0.561*	(0.24)	1.75	0.537*	(0.25)	1.71
Drug Treatment Facility	0.427	(0.25)	1.53	0.416	(0.25)	1.52
Public Housing	0.142	(0.39)	1.15	0.302	(0.36)	1.35
Parking Lot	0.331***	(0.05)	1.39	0.330***	(0.05)	1.39
Gang Territory	-0.084	(0.06)	0.92	-0.072	(0.06)	0.93
Prostitution Market	0.050	(0.08)	1.05	0.045	(0.08)	1.05
Drug Market	0.121***	(0.01)	1.13	0.118***	(0.01)	1.13
Bar/Club SL	0.131*	(0.05)	1.14	0.139**	(0.05)	1.15
Entertainment Facility SL	0.241**	(0.09)	1.27	0.253**	(0.09)	1.29

Table 9 Continued….

Variable	β	(SE)	IRR	β	(SE)	IRR
Fringe-Banking Store SL	0.069	(0.18)	1.07	0.055	(0.18)	1.06
Grocery Store SL	0.026	(0.17)	1.03	0.009	(0.17)	1.01
Everyday Store SL	-0.129**	(0.04)	0.88	-0.127**	(0.04)	0.88
Restaurant SL	-0.013	(0.02)	0.99	-0.012	(0.02)	0.99
Retail Store SL	0.018	(0.02)	1.02	0.017	(0.02)	1.02
Bus Stop SL	-0.014	(0.05)	0.99	-0.009	(0.05)	0.99
High School SL	0.102	(0.13)	1.11	0.101	(0.13)	1.11
Drug Treatment Facility SL	-0.151	(0.13)	0.86	-0.156	(0.13)	0.86
Public Housing SL	0.025	(0.18)	1.03	0.033	(0.18)	1.03
Parking Lot SL	0.313**	(0.12)	1.37	0.312**	(0.12)	1.37
Gang Territory SL	-0.077	(0.06)	0.93	-0.071	(0.06)	0.93
Prostitution Market SL	0.010	(0.02)	1.01	0.012	(0.02)	1.01
Drug Market SL	0.003*	(0.00)	1.00	0.004**	(0.00)	1.00
Total Population/100	0.025***	(0.00)	1.03	0.024***	(0.00)	1.02
Concentrated Disadvantage	-0.043***	(0.01)	0.96	-0.041***	(0.01)	0.96
Residential Stability	0.155***	(0.01)	1.17	0.157***	(0.01)	1.17
Racial Segregation	0.427***	(0.12)	1.53	0.439***	(0.12)	1.55
Length of Street/100	0.103***	(0.00)	1.11	0.102***	(0.00)	1.11
Major Street	0.170**	(0.06)	1.18	0.163*	(0.06)	1.18
Access to Highway	-0.005	(0.14)	0.99	-0.006	(0.14)	0.99
Intercept	-2.490***	(0.14)	0.08	-2.460***	(0.14)	0.09

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** p < 0.001 ** p < 0.01 * p < 0.05

The first significant interaction predicting theft from auto counts is among likely offenders and restaurants. While the number of restaurants per street ranged from 0 to 15, most streets (99.0%) had one or no restaurants. For that reason, Figure 19 shows the fitted theft from auto counts among streets with one, two or no restaurants by the Exposure to Likely Offenders measure.[29] Figure 20 shows the effect size of restaurants on crime at varying degrees of exposure to likely offenders. All other variables were held constant at their mean. When there is little or no exposure to likely offenders (Exposure to Likely Offenders < 15), there was no difference in

[29] Because there were so few streets with two or more restaurants, the model poorly predicted the effect of clusters of restaurants. Recall, the observed range of thefts from auto among this sample ranged from 0 to 36. This occurs when the model predicted and then values are extrapolated among variable values with little representation.

thefts from auto among streets with one and without a restaurant. As the streets were exposed to more offenders or offender risk, the effect of restaurants also grows. This suggests restaurants were primarily criminogenic when they exist on streets with a large amount of offenders in the area, consistent with the patron hypothesis.

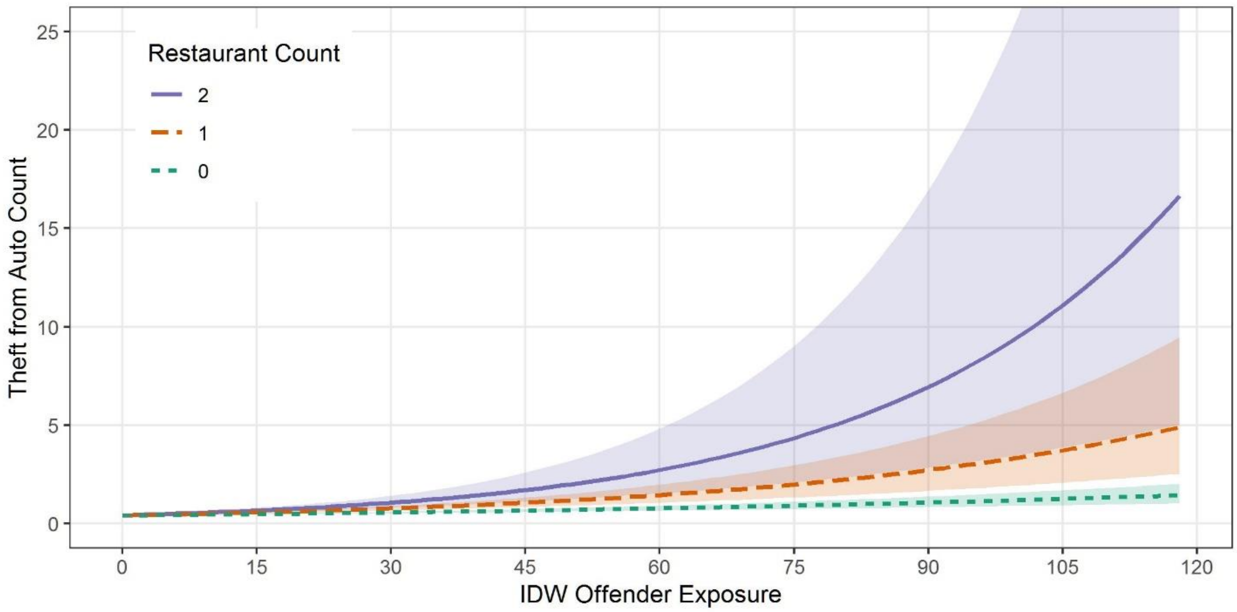

Figure 19. Exposure to Likely Offenders x Restaurant Interaction Plot, Predicting Theft from Auto Counts

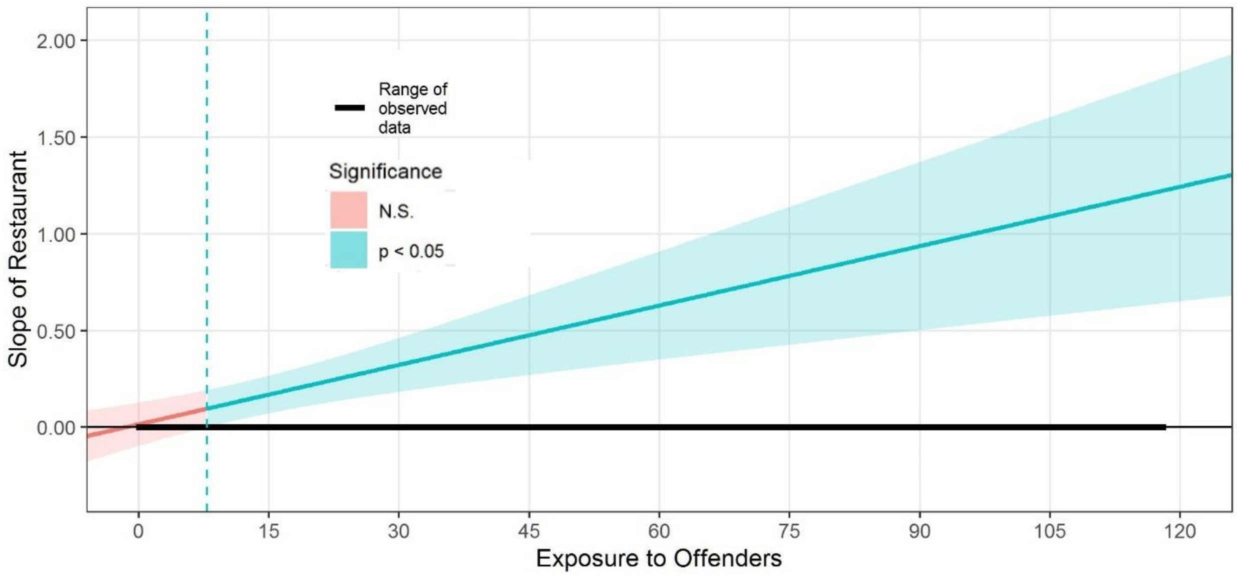

Figure 20. Johnson-Neyman Plot, Likely Offender x Restaurant Interaction, Predicting Thefts from Auto Counts

The second significant interaction in Table 9 exists among bus stops and the offender measures. As streets were exposed to more likely offenders, the criminogenic effect of a bus stop becomes stronger ($\beta = 0.01$; $p < 0.05$). Figure 21 shows that streets with a bus stop have more thefts from auto than those without, on average, but the effect of having a bus stop was conditioned by the presence of likely offenders. As streets became exposed to more likely offenders, the predicted thefts from auto increased at a steeper rate among streets bus stop than those without a bus stop. This finding supports the patron hypothesis, but like the findings among robbery models, these likely do not represent the actual patrons of bus stops. Rather, the people who commit thefts from auto are likely those who passively exploit opportunity while doing non-criminal things, or actively target known criminal opportunity at bus stops.

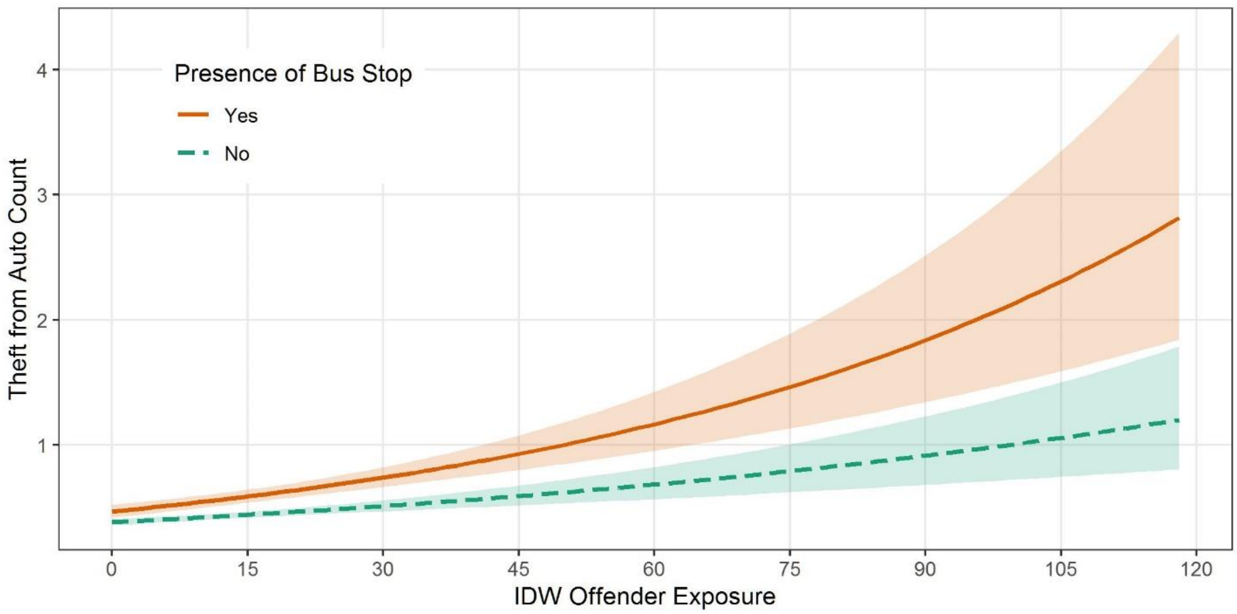

Figure 21. Likely Offender x Bus Stop Interaction Plot, Predicting Theft from Auto Counts

The last significant interaction exists between drug markets (drug-related calls for service) and the offender measures. With a negative coefficicent, the effect of drug markets diminshed among streets with higher exposure to likely offenders (β = -0.002; $p < 0.001$). As a continous measure (range = 0 – 63), interpretation of the coefficient is difficult. Instead, Figure 22 and Figure 23 display the moderating effect in different ways. Figure 22 shows a disordinal effect. When holding the offender measure at zero or its mean, streets with more drug-related calls for service tend to have more thefts from auto; however, this effect is dampened as streets become more exposed to likely offenders. Figure 23 shows the Johnson-Neyman plot shows how the slope of drug market changes with increasing values of the offender exposure variable. Recall, the mean value of exposure to likely offender is approximately 12.3 and the standard deviation is approximately 15 (represented by the x-axis griidlines). The slope and effect of drug markets slowly reduced as offender exposure increased, and dropped to insiginficant at extreme values of offender exposure (> 4 SD).

The mechanism describing this conditioned effect was more complicated than the patron hypothesis. Unlike the conditioned effect of restaurants and bus stops, the effect of drug markets decreased as exposure to likely offenders increased until it was no longer significnatly assoicated with theft from auto counts. There are two possible explanations. First, drug markets could also represent an offender node. Similar to gang territories, drug markets introduce likely offenders or possbile targets to an area, but the effect is not present in areas that laready have higher levels of offender expsoure. Second, the operationalization of drug markets might be representing the conditioned effect of social control or social cohesion. Recall, drug markets were captured as the sum of calls for police service, which requires a citizen to call the police. Some scholars have argued that calling the police is an indication of citizens' willingness to engage in crime prevention via the police and/or trust in police (see Black, 1980). The opposite is also true, in that the lack of calls for service can indicate the lack of trust in the police or unwillingess to engage in crime prevention via the police. Therefore, this conditioned effect may suggest that social control or the willingess to engage the police is greatly reduced in streets with higher degrees of likely offenders.

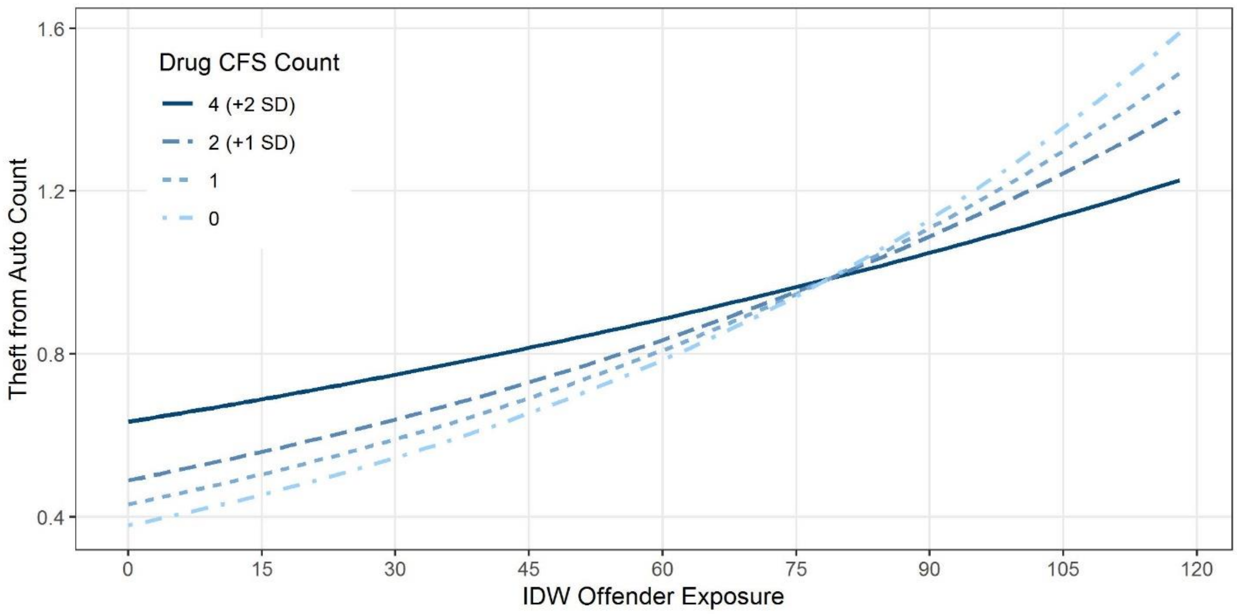

Figure 22. Likely Offender x Drug Market Interaction Plot, Predicting Theft from Auto Counts

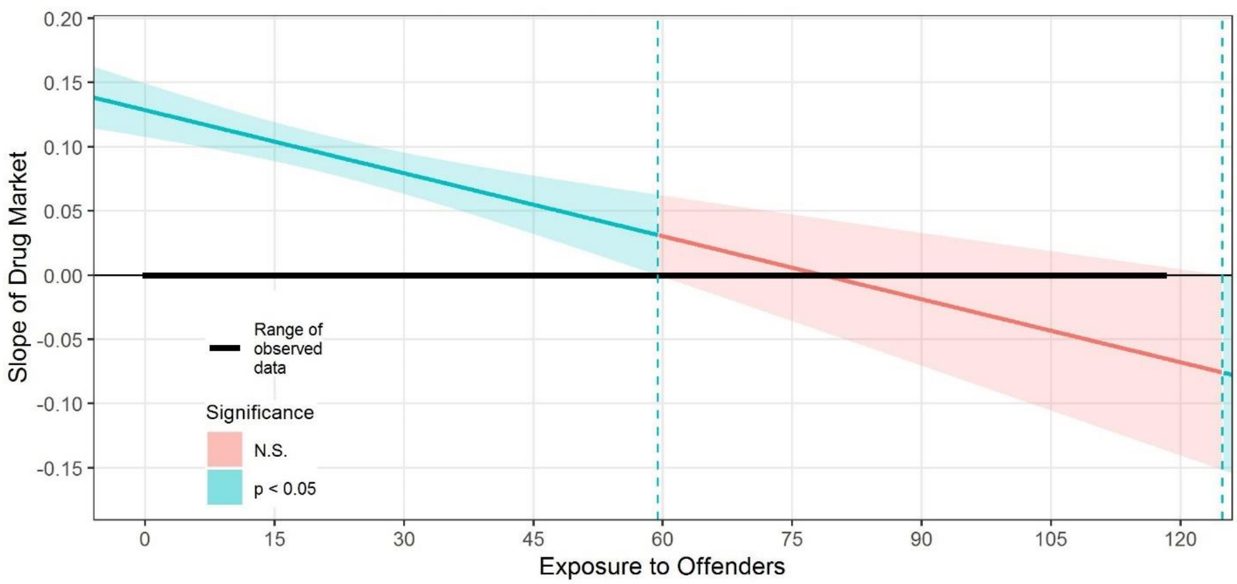

Figure 23. Johnson-Neyman Plot, Exposure to Likely Offenders x Drug Market Interaction, Predicting Thefts from Auto Counts

Summary of Findings

Overall, the analyses built on each other to show the complex relationship likely offenders have with their environment. Consistent with the hypotheses, recently released offenders concentrated in small number of streets. Their home addresses concentrate in a similar way to crime, both degrees of concentration and location of concentrations. As expected, the home addresses of recently released offenders coincide with crime hot spots. However, there were a number of areas in the city that have only a crime hot spot or likely offender hot spot, and are consistent with Brantingham and Brantingham (1990) place characteristics.

The more advanced analyses showed that both the distribution of likely offenders and criminogenic facilities, and other control factors have significant main effects on robbery and theft from auto counts. Brantingham and Brantingham (1990) propose crime concentrations are the result of overlapping hot spot layers, which they argue represent the interaction of likely offenders and their environment. Similar to this notion, Madensen and Eck (2008) proposed concentrations within homogenous groups of facility might be the result of the patronage. Essentially, crime prone facilities are used more frequently by likely offenders than crime-free facilities. While there were a number of interactions that support the patron hypothesis (bus stops and restaurants), a number of interactions were more complex. Some effects were weakened to non-significance as exposure to likely offenders increased; furthermore, many of the facilities were not conditioned by exposure to likely offenders. The mix of findings suggest the patron hypothesis might be an oversimplification of how likely offenders can condition the criminogenic effects of facilities.

CHAPTER 6: DISCUSSION

Chapter 5 presented the results designed to answer four research questions. (1) Do likely offenders geographically concentrate in a small number of places? (2) Do offender hot spots coincide with crime hot spots? (3) How do offender factors and facility factors explain crime across street blocks, net of other factors? (4) Is there an interactive effect between offender and facility factors that explain crime across street blocks, net of other factors? These research questions were examined using one property crime type, theft from auto, and one violent crime type, robbery. The current chapter contextualizes the findings in light of empirical and theoretical literature presented in Chapter 2. It begins by presenting the research questions, hypotheses, and findings. Next, the theoretical and practical implications of the findings are presented. The chapter ends by presenting the limitations and conclusions of the dissertation.

Research Question 1

Research Question 1 focused on the univariate spatial distribution of likely offenders. Previous correctional literature has shown likely offenders geographically concentrate within a city (Clear, 2007; Hesseling, 1992; La Vigne et al., 2003; La Vigne et al., 2003; La Vigne et al., 2003; Rose & Clear, 1998; Travis et al., 2003). This guided the hypothesis that likely offenders would concentrate tightly in a small number of Cincinnati street blocks, while most street blocks would have little or no likely offenders. In this sample, likely offenders were highly concentrated; all formally incarcerated persons lived in just 16.5% of Cincinnati street blocks. In addition, Ripley's K analysis showed that likely offenders were significantly more clustered than we would expect if they were randomly distributed. Lastly, kernel density showed that likely offenders concentrated among the city in one of three different hot spot types (dispersed, clustered, or hot point) (Ratcliffe, 2004). Offender hot spots were located throughout the city, but most of the city was not covered by a hot spot.

Research Question 2

Research Question 2 examined the spatial relationship between likely offenders and crime. Prior literature and theory suggests that likely offenders concentrate within a city and coincide with crime hot spots. Correctional literature not only found likely offenders geographically concentrate, but found the volume of likely offenders are positively associated with the area's crime levels (Drakulich et al., 2012; Hipp & Yates, 2009; Kovandzic et al., 2004; Raphael et al., 2004; Rosenfeld et al., 2005). These findings were consistent with community and crime literature, which used measures to proxy the effects of offenders among other variables common in environmental criminology (Bellair, 1997; Bursik & Grasmick, 1993; Krivo & Peterson, 1996; Lowenkamp et al., 2003; Mazerolle et al., 2010b; Slocum et al., 2013; Sun et al., 2004; Taylor & Covington, 1993; Veysey & Messner, 1999; Weisburd et al., 2014). In light of theory and literature, I hypothesized offender hot spots would coincide with robbery and theft from auto hot spots.

Both Ripley's Cross-K and kernel density analyses showed likely offenders closely coincided with robbery and theft from auto. First, Ripley's Cross-K analyses likely offenders and each crime type were attracted to each other, or "hung together", across different spatial extents. Second, kernel density analyses showed that offender, robbery, and theft from auto hot spot were located in similar areas of the city. Each analysis produced different types of hot spots (dispersed, clustered, and hot point) (Ratcliffe, 2004). There were three areas of the city that contained large dispersed or clustered offender, robbery, and theft from auto hot spots. These areas tended to be mixed-use, including residential housing and commercial facilities. Theoretically, this included motivated offenders and bountiful targets via criminogenic facilities (Cohen & Felson, 1979; Clarke & Cornish, 1978; Brantingham, Paul J. & Brantingham, 1995). Furthermore, there were a handful of offender hot points located near crime hot points, suggesting likely offenders concentrated at a single address and may be attracted to a single address to commit crime.

There were a number of areas with offender and crime hot spots that were not overlapping. These areas often supported criminal opportunity or residential homes, but rarely both. For instance, robbery and theft from auto were concentrated in the business district and riverfront area, but likely offenders did not concentrate in this area. Business offices, parking garages, restaurants, and sporting stadiums were located in this area. There were a handful of riverfront housing options, but all were "luxury" apartments with expensive rent. This pattern suggests that crime occurred in places where criminal opportunity was available, despite a lack of proximal offender housing. Crime Pattern Theory and supporting empirical studies established that likely offenders engage in search behaviors, which span outside of their living area and non-delinquent routines (see Groff & McEwen, 2006:7-8 for an overview). Brantingham and Brantingham (1981, 1991, 1993) also argued that some places carry a reputation for criminal opportunity (crime attractors), which likely offenders will travel farther because of bountiful opportunity these places possess. The non-overlapping crime hot spots may be attracting offender searches by hosting a larger amount of criminogenic facilities, suitable targets, and/or poor guardianship.

The non-overlapping portion of offender hot spots tell a slightly different story. These areas contained concentrations of likely offenders, but did not contain robbery or theft from auto hot spots. The non-overlapping offender hot spots tended to be less frequent and smaller than non-overlapping crime hot spots. They appeared to mimic "crime neutral areas" (Brantingham, Paul J. and Brantingham, 1995). These areas had little crime and few criminogenic facilities. According to Brantingham and Brantingham (1995), the sporadic crimes are the result of local residents or "insiders" occasionally exploiting criminal opportunities. Reid and colleagues (2014) simulated offender movement using offender home addresses, crime attractors and generators, and street network data. Their "crime neutral areas" closely mirrored the spatial patterns of this data. In Reid and colleagues' study (2014), these streets were rarely used to travel to and from major nodes and were located outside of likely offenders' awareness spaces (exceeding distances established in distance decay literature). Similar to their findings and principles of Crime Pattern Theory, the non-overlapping portion of offender hot spots contained few criminogenic facilities or large commercial areas and likely had less foot traffic or heavily-used parking facilities. Crime still occurred in this area, but were not concentrated enough to create a crime hot spot.

Research Question 3

Research Question 3 examined the multivariate relationship among likely offenders, criminogenic facilities, and crime among control variables. Crime Pattern Theory served as the theoretic framework of this dissertation. It suggests that crime is spatially patterned around the distribution and movement of offenders and targets around certain facilities in a city (Brantingham, Patricia L. & Brantingham, 1981; Brantingham, Patricia L. & Brantingham, 1995; Brantingham, Paul J. & Brantingham, 1993). Prior crime and place literature has identified certain facilities, street properties, neighborhood context that are associated with the spatial distribution of crime (Agnew, 2018; Beavon, et al., 1994; Bernasco & Block, 2011; Browning et al., 2010; Groff & Lockwood, 2014; Groff et al., 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Johnson & Bowers, 2010; Kinney et al., 2008; McCord et al., 2007; Steenbeek, et al.2012; Stucky & Ottensmann, 2009; Summers & Johnson, 2017; White, 1990; Wo, 2016). There are no studies to date that assess the effect of criminogenic facilities, street network characteristics, and offenders on the spatial distribution of crime. However, Crime Pattern Theory and research on the movement of offenders suggested areas near offenders are most likely to be the settings targeted and used by offenders (Bernasco, 2010; Block, Galary, & Brice, 2007; Groff & McEwen, 2006; Lu, 2003; Pizarro, Corsaro, & Yu, 2007; Townsley & Sidebottom, 2010; Van Koppen & Jansen, 1998). I hypothesized that offender measures and criminogenic facilities will maintain significance in predicting crime at street blocks.

In the full model, exposure to likely offenders was significantly associated with robbery and theft from auto, even among sociodemographic controls, street network controls, and criminogenic facilities. In each model, an increase in one standard deviation of the offender measure was associated with approximately a 15-20% increase in robbery and theft from auto counts among street blocks. This is consistent with studies that have found likely offenders tend to commit crime near familiar places, like their homes or family member’s homes (Bernasco & Block, 2009; Bernasco & Kooistra, 2010; Block et al, 2007; Johnson & Summers, 2015; Menting et al., 2016). Regardless of their proximity to facilities, streets nearby home addresses are well known and more likely to be used in travel to and from other major nodes (Brantingham & Brantingham, 1981, 1991, 1995).

Furthermore, exposure to likely offenders was captured in two different ways. The first weighted all formally incarcerated persons by their distance to the focal street and the second was then weighted by their likelihood to recidivate, or the variation in criminal inclinations. Theoretically, offenders with higher likelihood to recidivate are more likely to contribute to crime in the area than those with little motivation (Brantingham & Brantingham, 1981; 1991; 1995). Despite the different coding schemas, there were few differences in their relationship with robbery and theft from auto. This may be the result of data limitations (e.g. missing ORAS scores), evidence of the difficulty in conceptualizing and operationalizing offender "motivation", or a result of mis-specifying individual-level processes to a population.

In addition to the likely offender variables, a number of criminogenic facilities remained significantly associated with robbery and theft from auto counts among street blocks. This is consistent with both theory and empirical literature (Agnew, 2018; Beavon et al., 1994; Bernasco & Block, 2011; Browning et al., 2010; Groff & Lockwood, 2014; Groff et al., 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Johnson, S. D. & Bowers, 2010; Kinney et al., 2008; McCord et al., 2007; Steenbeek, et al.2012; Stucky & Ottensmann, 2009; Summers & Johnson, 2017; White, 1990; Wo, 2016). Bars, everyday stores, restaurants, bus stops, drug treatment facilities, public housing communities, gang territories, prostitution markets, and drug markets were significantly associated with higher robbery counts among street blocks. Bars, entertainment facilities, grocery stores, everyday stores, restaurants, bus stops, high schools, public housing communities, and drug markets were significantly associated with higher theft from auto counts among street blocks. The effect sizes varied, but all were positively associated with the respective crime type.

A number of control variables were also associated with robbery and theft from auto in Cincinnati streets. Socioeconomic and street network controls behaved in ways consistent with other crime and place literature (Agnew, 2018; Beavon, et al., 1994; Bernasco & Block, 2011; Browning et al., 2010; Groff & Lockwood, 2014; Groff et al., 2014; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Johnson, S. D. & Bowers, 2010; Kinney et al., 2008; McCord et al., 2007; Steenbeek, et al.2012; Stucky & Ottensmann, 2009; Summers & Johnson, 2017; White, 1990; Wo, 2016), suggesting strong external validity of the dissertation's models. For instance, concentrated disadvantage was associated with higher crime counts among streets, as were streets with larger population or major streets. The spatially lagged facilities were also included and exerted main effects on street block crime counts. Groff and a number of colleagues have found criminogenic effect of facilities can radiate and negatively affect streets nearby (Bernasco & Block, 2011; Bowers, 2014; Groff, 2011; Groff & Lockwood, 2014). With the exception of one facility type, facilities with significant spatial lags increased crime counts among adjacent street blocks. Everyday stores, being the exception, was associated with fewer thefts from auto among adjacent street blocks.

Research Question 4

Research Question 4 assessed the patron hypothesis, one explanation as to why some facilities have more crime than those of the same facility type (Clarke & Eck, 2007; Eck et al., 2007; Madensen, 2007; Madensen & Eck, 2008; Wilcox & Eck, 2011). The patron hypothesis stated that "risky", crime-prone facilities attract more motivated offenders than those with little or no crime (Eck and Madensen, 2008). The patron hypothesis guided the fourth research question and hypothesis, which posited that the degree of exposure to likely offenders moderates the relationship between criminogenic facilities and crime among street blocks. Interaction terms between facilities and likely offender measures captured the conditioning effect "patrons" may have on the relationship between the presence of criminogenic facilities and crime.

There were three facilities whose relationship with robbery was conditioned by likely offender variables, including bus stops, gang territories, and drug markets. Among streets with bus stops, robbery counts increased by about 16% when the exposure to likely offenders increased by one standard deviation. This finding provides some support for the patron hypothesis, in that bus stops are more likely to be associated with robbery when located in streets that are exposed to more likely offenders. However, streets with bus stops had higher robbery counts than those without bus stops, at every value of the offender measures, meaning the criminogenic effect of bus stops was not fully explained by offender presence. The two remaining significant interaction effects both exerted a negative moderating effect. The effect of gang territories and drug markets on robbery decreased as exposure to likely offenders increased. These two facilities, gang territories and drug markets, are both facilities that attract criminal patrons (drug users/dealers and gang members) due to the nature of their business. This finding suggests the criminogenic effects of these facilities is less important when located in streets that already have an extreme degree of exposure to likely offenders.

There were also three facilities whose relationships with theft from auto was moderated by exposure to likely offenders. The effect of restaurants and bus stops were increased with higher degrees of offender exposure. The effect of bus stops on theft from auto counts was partially moderated by exposure to likely offenders, providing some support for the patron hypothesis. The effect of restaurants on theft from auto counts did not become significant *until* streets became exposed to likely offenders. Once exposed, the relationship between restaurants and theft from auto counts increased more steeply than streets without a restaurant. Lastly, the effect of drug markets on theft from auto was negatively moderated by offender exposure. As streets became exposed to extreme amounts of likely offenders (IDW score > 60), drug markets were no longer significantly associated with thefts from auto in streets. Similar to the conceptualization presented with robbery, this may suggest that streets with few likely offenders are exposed to more likely offenders through drug markets, but the effect is reduced when the streets are already exposed to likely offenders.

Assuming likely offenders used and were attracted to facilities near their homes, the findings provided some support for the patron hypothesis (Madensen & Eck, 2008). For a handful of facilities, the presence of likely offenders strengthened the relationship they had with robbery or theft from auto counts among streets. On the other hand, there were relationships that were negatively moderated by the exposure to likely offenders. For instance, the effect of drug markets on both crime types decreased as exposure to likely offenders increased. Counter to some crime and place literature, this suggests proximity to likely offenders may play a stronger role in explaining crime patterns than the presence of criminogenic facilities.

Limitations

Limitations of the current dissertation are broken into three main sections. First, general methodological limitations are presented. For instance, the data is largely cross sectional and uses official crime data. These two limitations are common in tests of criminological research, but warrant discussion. In addition, the dissertation tests the interaction of likely offenders and opportunity to commit crime, but the residential and commercial zoning area often naturally segregated. Generally speaking, home addresses are not always located within a close proximity to opportunity to commit crime. This is discussed in the methodological limitations. Next, limitations of the two major variables are presented. Because the addition of offender data is key to the dissertation, its limitations are important to understand and build on through future research. Furthermore, the facility data fails to provide other variables to test Madensen and Eck's (2008) other hypotheses used to explain the Risky Facility Phenomenon.

Methodological Limitations

The main research question in this study is inherently temporal: do offenders and opportunity lead to more crime? There are two major issues related to the causal nature of the questions. First, the current data is cross-sectional. This limits the claims we can make about causality because we cannot establish strict temporal ordering and rule out all extraneous variables causing trends related to likely offenders, opportunity, and crime. In addition, the data did not contain information on whether or not released offenders recidivated or were removed from the population if they were re-arrested after release. To mitigate the limitation the values for the independent variables were recorded before the outcome occurred. Even though the study can establish an association and time ordering, it cannot establish causality without ruling out spuriousness.

Second, this dissertation used official crime and data on formally incarcerated adults, which has filtered out a large amount of crime and potential offenders throughout the criminal justice process. Crime incidents are one of the first “checkpoints” of the criminal justice system. Unfortunately, it is well documented that not all crimes are detected and recorded (Biderman & Reiss, 1967; Skogan, 1977). It does not require a suspect to be known, but still envelops errors related to under-reporting. The crime incident moves forward if a suspect is identified and arrested, case built and charged by the local attorney’s office, and involved a guilty plea or conviction. At that point, the convicted offenders likely only represent less than 10% of the originally reported crime (Ratcliffe, 2016). Practically speaking, this means the crime and offenders in this study reflect only a small portion of crime and likely offenders in Cincinnati. This clear limitation of the current dissertation. In the future, data from other government agencies (Department of Youth Services, Cincinnati Police Department) can provide other data on offenders, but will still suffer from the “Dark Figure of Crime”.

Lastly, the research questions are set up to understand the role offenders play in crime near their residences. However, residential areas in general are often not located near potential targets or victims (such as those common among commercial areas). For instance, there are multiple hot point-patterned offender hot spots that were located in isolated communities. They were not near many criminogenic facilities, with the exception of bus stops and parking structures. Because the offender data does not include other nodal points, this naturally biases the study in the direction of weakening the influence of likely offenders and the interaction effect with facilities. However, this is less problematic for two reasons. Most simply, reality is structured in this way. While offenders move around the city, the study findings still suggest exposure to their home addresses still influence the distribution of certain crime types. This limitation, however, does require the reader to be cognizant of what the offender data is not measuring, offender activity space. Second, the two crime types chosen (robbery and theft from auto) did not require certain facility types. I did not limit robberies to “commercial” robberies for instance. Residents of the apartment can be victimized by likely offenders they live near, regardless of their proximity to commercial establishments. Future research should consider incorporating police data, which might capture other commonly used nodes or places likely offenders are stopped by the police.

Offender Data Limitations

Capturing motivated or “likely” offenders is difficult and required the dissertation to attempt to proxy this group of people. Using data on formally incarcerated persons assumes these individuals have a higher likelihood to offend, which is not always true, nor is it confirmed in this data. Furthermore, Cohen and Felson (1979) argued that all persons have the ability to commit crime given the right circumstances, but formally incarcerated persons provided a more precise measure who the potential offending population compared to census measures survey measures (used in other studies). The nature of the data limits our ability to fully capture the full activity space of likely offenders and all “active” offenders.

In addition to ignoring other potential offenders, these data do not provide common nodes, like work or family homes, other than their reported home location. The likely offender’s single address likely represents only a small portion of their activity space. In addition, the offender data does not include youth offenders or those who have evaded the law, nor does it provide verification as to whether offenders were active upon returning. The lack of youthful offenders could be addressed in the future using Department of Youth Services (DYS), who supervise youth offenders and use risk assessments (known as Ohio Youth Assessment System or OYAS). Recidivism studies have shown most offenders in the current data set are likely to offend, showing that nearly 75 percent of offenders will be rearrested within five years in the United States (Alper, Durose, Marksman, & United States Bureau of Justice Statistics, 2018). In addition, this was mitigated by accounting for the ORAS score, which assigned a score capturing the likelihood of reoffending. For example, Childs and colleagues (2013) found that low-risk probationers had a 3.7% revocation rate, moderate-risk had a 17% revocation rate, and high-risk had 41.2% revocation rate.

In addition, the accuracy of self-reported offender addresses threatens the validity of the offender measures. The current study assumes the address given by likely offenders is valid. The Ohio Department of Rehabilitation and Correction (ODRC) cannot assert all the offender addresses are valid, simply because of the large variation in expectations and requirements of likely offenders after release. Furthermore, some likely offenders are not required to give an address, some are required but never verified, and some are admittedly homeless. Beyond the validity of the address, I must make a number of assumptions about whether the given address represents their “home”. Does the word “home” represent a permanent address where the offender has spent numerous years? On the other hand, does it represent where the offender can be most easily accessed like a family member’s home or a work place? Furthermore, what address is listed if the offender does not have a permanent home, and instead lives with family members, significant others, or friends? The questions above are important issues to consider and address with future work. Future research should examine the consistency of the addresses provided by likely offenders, which is included in the current data set.

Facility Data Limitations

Criminogenic facilities represent groups of facility types that are more crime-prone than others (Brantingham, Patricia L. & Brantingham, 1995). As presented in Chapter 2, Eck and colleagues (2007) present that a few establishments, even within facility type, are responsible for a majority of its crime. Some have used this finding to suggest it is inappropriate to apply opportunity-level mechanisms to all facilities of a specific type, suggesting the micro-patterns of opportunity structures are to blame (Eck et al, 2008). The current state of the facility data does not identify "risky facilities" in each facility type. It is important to note, however, hypotheses related to the "risky facility phenomenon" are still tested in the study.

The facility data does not account for protective factors that can reduce opportunity or increase social control at a street segment, including certain facilities types or place managers. Place Management theorists argue that the business owners and/or employees have a great deal of control over behavior at their respective place (Eck & Madensen, 2018). Therefore, good place managers can control offending inside and outside their facility (Linning, Forthcoming; Jacobs, 1961). Crime Pattern theory does not explicitly discuss *protective* places, but other opportunity theories would suggest places with a small amount of targets, and/or a large amount of guardianship may reduce the number of motivated offenders in areas around protected places (Clarke & Cornish, 1985; Cohen & Felson, 1979). Some theorists have found that loose connections among residents, community groups, and community-police partnerships can protect areas (Bellair, 1997; Bellair & Browning, 2010; Sampson & Groves, 1989). The current study does not control for any of these effects. It points to the clear limitations of using only Crime Pattern theory as representative of opportunity data.

Implications

The role offenders play in local crime patterns are often misunderstood; while most people would agree that offenders are required for a crime to occur, there is relatively little evidence about how they interact with their environment. Arguing offenders are linked to crime, often invokes the "so what…" argument from academics and practitioners alike. In addition, data and analytic limitations have stopped criminologists from testing the role offenders play among a myriad of crime and place variables. However, the current study sheds light on concepts central to environmental criminology theory, which can provide practical advice as to environmental risks of returning offenders.

Theoretical Implications

Brantingham and Brantingham (1981; 1991; 1995; 1993) argued crime concentrations were the result of the travel patterns of humans among crime-prone facilities (criminogenic facilities). Both likely offenders and facilities are positioned in the greater community backcloth, which includes large-level structural, social, cultural, and political processes. They influence the placement as well as the movement around the major nodes. Tests of Crime Pattern Theory have been limited to crime-prone facilities, major pathways, environmental backcloth, and temporal nature of crime and opportunity. These concepts have not been tested in the same model due to the difficulty in obtaining, preparing and analyzing such data.

The current study found that likely offenders and select criminogenic facilities both influence the distribution of robbery and theft from auto among city streets. The findings provided evidence that streets with greater exposure to likely offender home addresses, as an important node, have higher crime counts. This was true even after accounting for control variables and criminogenic facilities common in crime and place literature. Brantingham and Brantingham (1981) argued offender motivation varies in strength and character, but does not elaborate on how that may change the spatial distribution of crime. There was no evidence that offender risk scores or offense specialty changed the criminogenic influence of likely offenders. The dissertation's offender data, particularly among ORAS scores, was limited by non-random missing data, which likely biases the results in the direction of not finding a relationship. However, models accounting for differences in offense type (property, violent, or drug), showed little difference among strength of offender variables.

Furthermore, Eck and colleagues (2007) argued that small numbers of establishments within groupings of facilities account for most of its associated crime. In attempting to explain these trends, Madensen and Eck (2008) present the possibility that crime-prone establishments are the result of the patrons attracted to that respective facility. A number of studies have examined the potential role of community factors and situational characteristics (at the control of place management), but none have directly tested their patron hypothesis (Madensen & Eck, 2008).

The current dissertation found that the degree of offender exposure moderated only a few of the criminogenic facilities' relationship with crime. Some facilities were fully moderated, others were partially moderated (continuing to exert main effects), and many had no significant moderation effect. These findings provided mixed evidence for the patron hypothesis. When combined with research on the neighborhood and place management hypothesis, this evidence more likely supports the behavior setting hypothesis. It suggests risky facilities are the result of a combination of neighborhood, patron, and place management factors. Without including place management variables, the dissertation cannot assert the veracity of hypotheses outlined by Madensen and Eck (2008).

Practical Implications

The current study explored the relationship between crime-prone people, places, and crime, which is often the key component to crime reduction strategies. Policing scholars have identified the most efficient and effective method of controlling crime is to control the places and people that account for the most of the crime (National Research Council, 2004). Offender-focused strategies (e.g. focused deterrence) tend to remove crime-prone offenders from the population, while place-based strategies (problem-oriented policing) alter assessments of targets or guardianship of criminogenic or "risky" facilities. The strategies rarely intersect. This current study's findings gave us more insight into the relationship between crime-prone people and places. For instance, bus stops continued to exert a positive main effect on robbery and theft from auto, suggesting bus stop in general are criminogenic. From a problem-oriented policing perspective, bus stops may need to be redesigned throughout the city. However, the criminogenic effects of restaurants only existed in streets with large degrees of offender exposure. Restaurants in these areas may need a more classic problem-solving approach (place-specific response).

Correctional research, particularly surrounding the Ohio Risk Assessment System (ORAS), has stressed the importance in offender variation. In a number of studies, researchers found rehabilitative treatment should not be uniformly applied to all offenders, due to its risk of negatively impacting an offender (Latessa, Listwan, & Koetzle, 2014; Lowenkamp & Latessa, 2004; Lowenkamp, Latessa, & Holsinger, 2006). Instead, different offenders require different types of treatments that focus on their unique needs. This process is mirrored in place-based interventions (see Cozens & Love, 2015 for review of CPTED principles), but the same process is not used in offender-focused strategies. This study's results are different than Chamberlain and Boggess (2018) who found variation in offender influence after disaggregating offense specialization (property, violent, or drug-related). The current findings, while limited by offender data issues, suggested that offenders do not vary dramatically in terms of their influence on street-level crime patterns. This relationship should be assessed further by accounting for offenders' other nodes, or further specifications of offender differences (age, substance abuse status, etc.).

Conclusions

Environmental criminology has been relatively consistent about the theoretical role of offenders and the distribution of criminal opportunity, but empirical tests have rarely tested the relationship. The offenders' interaction with their environment is particularly clear in Crime Pattern Theory (Brantingham & Brantingham, 1981; 1991; 1993). A handful of literature has found pieces of evidence to support their assertions, but none tested the concepts in the same model. The current study sought to fill this gap. It included measures of offender exposure, criminogenic facilities, street network controls, and sociodemographic controls. Furthermore, using street blocks as the unit of analysis, better modeled the movement of offenders among facilities.

Generally, the dissertation found that both offenders and criminogenic facilities play important roles in explaining the spatial distribution of robbery and theft from auto among streets. There was little difference between models after accounting for variation in offenders' likelihood to reoffend, but this may be the result of non-random missing data among offender data. Furthermore, this dissertation found the criminogenic effect of some facilities was moderated by the presence of likely offenders. A handful exerted a positive interaction effect, meaning the facility became more crime-prone near more likely offenders. Others exerted a negative interaction effect, meaning the strength of facilities' influence decreased as the exposure to likely offenders increased. These findings suggested the relationship between offenders and criminogenic facility may be more complex than theorized by the patron hypothesis (Madensen & Eck, 2008).

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Appendix A – Models with Offender Specialties

Chamberlain and Boggess (2018) presented a novel study that tested the affect of parolee concentrations on violent crime rates at the Census block group-level. It should be noted the authors controlled for common structural factors, but did not include measures of criminogenic facilities or street network characteristics. In the study, Chamberlain and Boggess created percentages of returning parolees by race, supervision level, and prior conviction type. These relationships were then assessed in a series of interaction variables. Generally, they found more parolees were associated with higher rates of violent crime. The most interesting finding was that three offender conceptualizations were associated with lower violent crime rates (percent of parolees with a prior drug conviction, percent of parolees with average supervision, and percent of parolees with high supervision). The authors suggested drug offenders (and those with average or high supervision) were more likely to be supervised or monitored closely, and thus drug offenders were less involved in criminal activity. While this explanation explains why those concepts would not have a positive relationship with crime, it does not explain the negative relationship (protective factor) with crime.

In attempt to reproduce Chamberlain and Boggess' (2018) findings and check the consistency of the current data, models were run by separating out offenders with prior violent, property, and drug offenses. The models included offender, facility, facility spatial lags, structural factors, and street network characteristics as was used in the other models in this dissertation. Offender measures were calculated using the same inverse distance weighting method, and did not replicate Chamberlain and Boggess' (2018) percent of offenders per block group nor did it restrict variables to only structural factors. Table A1 and Table A2 present the findings for the models, predicting robbery counts and theft from auto counts among Cincinnati street blocks. The results are generally consistent with Chamberlain and Boggess (2018), showing negative associations between offenders with prior drug offenses and both crime types (not reaching statistical significance in three of the four models). These models, however, presented large VIF values (ranging from 4.33 to 11.66), which suggested multicollinearity among the disaggregated offender variables. Multicollinearity indicates two or more of these variables were closely related and biasing the full model results.

To address the problem, a series of models were run with only one offense type (seen in Table A3 – Table A8). Counter to the findings in Table A1 and Table A2 and those of Chamberlain and Boggess (2018), all offender conceptualizations were positive and significantly related with robbery and theft from auto counts. These are consistent with the main findings of the current dissertation. The discrepancy between the current study and Chamberlain and Boggess (2018) could be the result of different study sites or the previous study may have had undetected multicollinearity among the offender measures. Chamberlain and Boggess (2018) did not provide VIF or other diagnostic testing results. In addition, the current study's results appear to be more consistent with crime and place literature, which does not theorize a "protective" factor from the presence of offenders.

Table A1. Results of a Negative Binomial Regression with All Offender Specialties - Robbery Counts

Variable	Model I: Likely Offender Exposure β	(SE)	IRR	Model J: Cumulative Offender Risk β	(SE)	IRR
IDW Offender Count - Violent	0.095***	(0.02)	1.10	---	---	---
IDW Offender Count - Property	0.071***	(0.02)	1.07	---	---	---
IDW Offender Count - Drug	-0.073***	(0.02)	0.93	---	---	---
IDW Offender Risk - Violent	---	---	---	-0.001	(0.01)	1.00
IDW Offender Risk - Property	---	---	---	0.066***	(0.01)	1.07
IDW Offender Risk - Drug	---	---	---	-0.001	(0.01)	1.00
Bar/Club	0.447***	(0.13)	1.56	0.471***	(0.13)	1.60
Entertainment Facility	0.219	(0.25)	1.25	0.185	(0.25)	1.20
Fringe-Banking Store	0.338	(0.34)	1.40	0.246	(0.34)	1.28
Grocery Store	0.365	(0.35)	1.44	0.382	(0.35)	1.47
Everyday Store	1.054***	(0.08)	2.87	1.070***	(0.08)	2.92
Restaurant	0.129*	(0.05)	1.14	0.133**	(0.05)	1.14
Retail Store	0.031	(0.04)	1.03	0.025	(0.04)	1.03
Bus Stop	0.652***	(0.09)	1.92	0.677***	(0.09)	1.97
High School	0.194	(0.22)	1.21	0.175	(0.23)	1.19
Drug Treatment Facility	0.613*	(0.27)	1.85	0.601*	(0.27)	1.82
Public Housing	0.607**	(0.19)	1.84	0.587**	(0.19)	1.80
Gang Territory	0.641***	(0.07)	1.90	0.594***	(0.07)	1.81
Parking Lot	0.341***	(0.06)	1.41	0.351***	(0.06)	1.42
Prostitution Market	0.204**	(0.07)	1.23	0.197**	(0.08)	1.22
Drug Market	0.116***	(0.01)	1.12	0.117***	(0.01)	1.12
Bar/Club SL	-0.014	(0.08)	0.99	0.014	(0.08)	1.01
Entertainment Facility SL	0.074	(0.12)	1.08	0.059	(0.13)	1.06
Fringe-Banking Store SL	-0.072	(0.19)	0.93	-0.065	(0.19)	0.94
Grocery Store SL	0.066	(0.20)	1.07	0.043	(0.20)	1.04
Everyday Store SL	0.153***	(0.05)	1.16	0.163***	(0.05)	1.18
Restaurant SL	0.003	(0.03)	1.00	0.003	(0.03)	1.00
Retail Store SL	0.030	(0.02)	1.03	0.029	(0.02)	1.03
Bus Stop SL	0.200*	(0.08)	1.22	0.219**	(0.08)	1.25
High School SL	0.178	(0.17)	1.19	0.174	(0.17)	1.19
Drug Treatment Facility SL	0.102	(0.14)	1.11	0.077	(0.14)	1.08
Public Housing SL	0.071	(0.20)	1.07	0.080	(0.20)	1.08
Gang Territory SL	0.298***	(0.09)	1.35	0.284**	(0.09)	1.33
Parking Lot SL	0.749*	(0.32)	2.11	0.682*	(0.32)	1.98
Prostitution Market SL	0.063**	(0.02)	1.06	0.046*	(0.02)	1.05
Drug Market SL	-0.0003	(0.00)	1.00	0.002	(0.00)	1.00

Table A1 Continued…

Variable	β	(SE)	IRR	β	(SE)	IRR
Total Population/100	0.032***	(0.01)	1.03	0.035***	(0.01)	1.04
Concentrated Disadvantage	0.08***	(0.01)	1.08	0.076***	(0.01)	1.08
Residential Stability	0.104***	(0.02)	1.11	0.114***	(0.02)	1.12
Racial Segregation	0.361	(0.19)	1.43	0.479*	(0.19)	1.61
Length of Street/100	0.049***	(0.00)	1.05	0.050***	(0.00)	1.05
Major Street	0.252**	(0.08)	1.29	0.257**	(0.08)	1.29
Access to Highway	-0.086	(0.20)	0.92	-0.102	(0.20)	0.90
Intercept	-4.670***	(0.33)	0.01	-4.756***	(0.33)	0.01

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag

Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table A2. Results of Negative Binomial Regression with All Offender Specialties - Theft from Auto Counts

Variable	Model K: Likely Offender Exposure β	(SE)	IRR	Model L: Cumulative Offender Risk β	(SE)	IRR
IDW Offender Count - Violent	0.041*	(0.02)	1.04	---	---	---
IDW Offender Count - Property	0.054***	(0.01)	1.06	---	---	---
IDW Offender Count - Drug	-0.022	(0.01)	0.98	---	---	---
IDW Offender Risk - Violent	---	---	---	0.040***	(0.01)	1.04
IDW Offender Risk - Property	---	---	---	0.018	(0.01)	1.02
IDW Offender Risk - Drug	---	---	---	-0.015	(0.01)	0.98
Bar/Club	0.698***	(0.11)	2.01	0.703***	(0.11)	2.02
Entertainment Facility	0.993***	(0.17)	2.70	0.998***	(0.17)	2.71
Fringe-Banking Store	-0.289	(0.37)	0.75	-0.297	(0.37)	0.74
Grocery Store	1.135***	(0.32)	3.11	1.135***	(0.32)	3.11
Everyday Store	0.196*	(0.08)	1.22	0.200*	(0.08)	1.22
Restaurant	0.121**	(0.05)	1.13	0.124**	(0.05)	1.13
Retail Store	0.040	(0.04)	1.04	0.038	(0.04)	1.04
Bus Stop	0.234***	(0.06)	1.26	0.255***	(0.06)	1.29
High School	0.384*	(0.17)	1.47	0.373*	(0.17)	1.45
Drug Treatment Facility	0.358	(0.25)	1.43	0.346	(0.25)	1.41
Public Housing	0.691***	(0.18)	1.99	0.686***	(0.18)	1.99
Gang Territory	-0.075	(0.06)	0.93	-0.092	(0.06)	0.91
Parking Lot	0.316***	(0.04)	1.37	0.309***	(0.04)	1.36
Prostitution Market	0.031	(0.08)	1.03	0.039	(0.08)	1.04
Drug Market	0.096***	(0.01)	1.10	0.094***	(0.01)	1.10
Bar/Club SL	0.129*	(0.05)	1.14	0.143**	(0.05)	1.15
Entertainment Facility SL	0.227**	(0.09)	1.25	0.241**	(0.09)	1.27
Fringe-Banking Store SL	0.069	(0.18)	1.07	0.052	(0.18)	1.05
Grocery Store SL	0.124	(0.16)	1.13	0.118	(0.17)	1.13
Everyday Store SL	-0.127**	(0.04)	0.88	-0.124**	(0.04)	0.88
Restaurant SL	-0.018	(0.02)	0.98	-0.017	(0.02)	0.98
Retail Store SL	0.015	(0.02)	1.02	0.016	(0.02)	1.02
Bus Stop SL	-0.043	(0.05)	0.96	-0.027	(0.05)	0.97
High School SL	0.083	(0.13)	1.09	0.070	(0.13)	1.07
Drug Treatment Facility SL	-0.147	(0.13)	0.86	-0.149	(0.13)	0.86
Public Housing SL	0.038	(0.18)	1.04	0.047	(0.18)	1.05
Gang Territory SL	-0.073	(0.06)	0.93	-0.074	(0.06)	0.93
Parking Lot SL	0.310**	(0.12)	1.36	0.300*	(0.12)	1.35
Prostitution Market SL	0.017	(0.02)	1.02	0.017	(0.02)	1.02
Drug Market SL	0.001	(0.00)	1.00	0.003	(0.00)	1.00

Table A2 Continued…

Variable	β	(SE)	IRR	β	(SE)	IRR
Total Population/100	0.023***	(0.00)	1.02	0.023***	(0.00)	1.02
Concentrated Disadvantage	-0.043***	(0.01)	0.96	-0.043***	(0.01)	0.96
Residential Stability	0.147***	(0.01)	1.16	0.151***	(0.01)	1.16
Racial Segregation	0.396**	(0.13)	1.49	0.451***	(0.12)	1.57
Length of Street/100	0.104***	(0.00)	1.11	0.104***	(0.00)	1.11
Major Street	0.146*	(0.06)	1.16	0.145*	(0.06)	1.16
Access to Highway	-0.030	(0.14)	0.97	-0.029	(0.14)	0.97
Intercept	-2.474***	(0.14)	0.08	-2.475***	(0.14)	0.08

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table A3. Results of Negative Binomial Regression with Prior Violent Offense – Robbery Counts

	Model M: Likely Offender Exposure			Model N: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
IDW Offender Count - Violent	0.076***	(0.01)	1.08	---	---	---
IDW Offender Risk - Violent	---	---	---	0.033***	(0.01)	1.03
Bar/Club	0.447***	(0.13)	1.56	0.45***	(0.13)	1.57
Entertainment Facility	0.195	(0.25)	1.22	0.201	(0.25)	1.22
Fringe-Banking Store	0.292	(0.34)	1.34	0.284	(0.35)	1.33
Grocery Store	0.335	(0.35)	1.40	0.309	(0.36)	1.36
Everyday Store	1.059***	(0.08)	2.88	1.056***	(0.08)	2.88
Restaurant	0.140**	(0.05)	1.15	0.138**	(0.05)	1.15
Retail Store	0.029	(0.04)	1.03	0.030	(0.04)	1.03
Bus Stop	0.671***	(0.09)	1.96	0.705***	(0.09)	2.02
High School	0.168	(0.22)	1.18	0.178	(0.22)	1.19
Drug Treatment Facility	0.601*	(0.27)	1.82	0.599*	(0.27)	1.82
Public Housing	0.585**	(0.19)	1.79	0.599**	(0.19)	1.82
Gang Territory	0.620***	(0.07)	1.86	0.623***	(0.07)	1.86
Parking Lot	0.338***	(0.06)	1.40	0.342***	(0.06)	1.41
Prostitution Market	0.219**	(0.08)	1.24	0.213**	(0.08)	1.24
Drug Market	0.118***	(0.01)	1.13	0.119***	(0.01)	1.13
Bar/Club SL	-0.010	(0.08)	0.99	-0.008	(0.08)	0.99
Entertainment Facility SL	0.074	(0.12)	1.08	0.070	(0.13)	1.07
Fringe-Banking Store SL	-0.057	(0.19)	0.94	-0.032	(0.19)	0.97
Grocery Store SL	0.015	(0.20)	1.02	0.001	(0.20)	1.00
Everyday Store SL	0.157***	(0.05)	1.17	0.158***	(0.05)	1.17
Restaurant SL	0.009	(0.03)	1.01	0.008	(0.03)	1.01
Retail Store SL	0.030	(0.02)	1.03	0.031	(0.02)	1.03
Bus Stop SL	0.227**	(0.08)	1.25	0.246**	(0.08)	1.28
High School SL	0.155	(0.17)	1.17	0.161	(0.17)	1.17
Drug Treatment Facility SL	0.115	(0.14)	1.12	0.123	(0.14)	1.13
Public Housing SL	0.058	(0.20)	1.06	0.087	(0.20)	1.09
Gang Territory SL	0.308***	(0.09)	1.36	0.316***	(0.09)	1.37
Parking Lot SL	0.737*	(0.32)	2.09	0.725*	(0.32)	2.06
Prostitution Market SL	0.061**	(0.02)	1.06	0.063***	(0.02)	1.07
Drug Market SL	-0.001	(0.00)	1.00	0.002	(0.00)	1.00
Total Population/100	0.036***	(0.01)	1.04	0.034***	(0.01)	1.03
Concentrated Disadvantage	0.068***	(0.01)	1.07	0.073***	(0.01)	1.08
Residential Stability	0.117***	(0.02)	1.12	0.126***	(0.02)	1.13
Racial Segregation	0.489**	(0.19)	1.63	0.460*	(0.19)	1.58
Length of Street/100	0.050***	(0.00)	1.05	0.048***	(0.00)	1.05
Major Street	0.277***	(0.08)	1.32	0.274***	(0.08)	1.32
Access to Highway	-0.079	(0.20)	0.92	-0.077	(0.20)	0.93
Intercept	-4.816***	(0.33)	0.01	-4.732***	(0.33)	0.01

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table A4. Results of Negative Binomial Regression with Prior Violent Offense - Theft from Auto Counts

	Model O: Likely Offender Exposure			Model P: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
IDW Offender Count - Violent	0.064***	(0.01)	1.07	---	---	---
IDW Offender Risk - Violent	---	---	---	0.038***	(0.00)	1.04
Bar/Club	0.704***	(0.11)	2.02	0.698***	(0.11)	2.01
Entertainment Facility	1.002***	(0.17)	2.72	0.998***	(0.17)	2.71
Fringe-Banking Store	-0.310	(0.37)	0.73	-0.292	(0.37)	0.75
Grocery Store	1.133***	(0.32)	3.10	1.126***	(0.32)	3.08
Everyday Store	0.202*	(0.08)	1.22	0.203*	(0.08)	1.22
Restaurant	0.127**	(0.05)	1.14	0.127**	(0.05)	1.13
Retail Store	0.037	(0.04)	1.04	0.037	(0.04)	1.04
Bus Stop	0.247***	(0.06)	1.28	0.259***	(0.06)	1.30
High School	0.367*	(0.17)	1.44	0.368*	(0.17)	1.45
Drug Treatment Facility	0.353	(0.25)	1.42	0.349	(0.25)	1.42
Public Housing	0.676***	(0.18)	1.97	0.681***	(0.18)	1.98
Gang Territory	-0.084	(0.06)	0.92	-0.092	(0.06)	0.91
Parking Lot	0.307***	(0.04)	1.36	0.306***	(0.04)	1.36
Prostitution Market	0.041	(0.08)	1.04	0.041	(0.08)	1.04
Drug Market	0.095***	(0.01)	1.10	0.095***	(0.01)	1.10
Bar/Club SL	0.139**	(0.05)	1.15	0.142**	(0.05)	1.15
Entertainment Facility SL	0.241**	(0.09)	1.27	0.243**	(0.09)	1.28
Fringe-Banking Store SL	0.072	(0.18)	1.07	0.068	(0.18)	1.07
Grocery Store SL	0.103	(0.17)	1.11	0.098	(0.17)	1.10
Everyday Store SL	-0.126**	(0.04)	0.88	-0.122**	(0.04)	0.89
Restaurant SL	-0.015	(0.02)	0.99	-0.015	(0.02)	0.99
Retail Store SL	0.016	(0.02)	1.02	0.017	(0.02)	1.02
Bus Stop SL	-0.031	(0.05)	0.97	-0.021	(0.05)	0.98
High School SL	0.067	(0.13)	1.07	0.067	(0.13)	1.07
Drug Treatment Facility SL	-0.143	(0.13)	0.87	-0.139	(0.13)	0.87
Public Housing SL	0.022	(0.18)	1.02	0.039	(0.18)	1.04
Gang Territory SL	-0.070	(0.06)	0.93	-0.072	(0.06)	0.93
Parking Lot SL	0.316**	(0.12)	1.37	0.310**	(0.12)	1.36
Prostitution Market SL	0.019	(0.02)	1.02	0.019	(0.02)	1.02
Drug Market SL	0.002	(0.00)	1.00	0.002	(0.00)	1.00
Total Population/100	0.024***	(0.00)	1.02	0.023***	(0.00)	1.02
Concentrated Disadvantage	-0.047***	(0.01)	0.95	-0.046***	(0.01)	0.95
Residential Stability	0.152***	(0.01)	1.16	0.154***	(0.01)	1.17
Racial Segregation	0.457***	(0.12)	1.58	0.454***	(0.12)	1.57
Length of Street/100	0.104***	(0.00)	1.11	0.104***	(0.00)	1.11
Major Street	0.143*	(0.06)	1.15	0.150*	(0.06)	1.16
Access to Highway	-0.030	(0.14)	0.97	-0.037	(0.14)	0.96
Intercept	-2.517***	(0.14)	0.08	-2.495***	(0.14)	0.08

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table A5. Results of Negative Binomial Regression with Prior Property Offense – Robbery Counts

	Model Q: Likely Offender Exposure			Model R: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
IDW Offender Count - Property	0.072***	(0.01)	1.07			
IDW Offender Risk - Property				0.064***	(0.01)	1.07
Bar/Club	0.441***	(0.13)	1.55	0.470***	(0.13)	1.60
Entertainment Facility	0.177	(0.25)	1.19	0.185	(0.25)	1.20
Fringe-Banking Store	0.311	(0.34)	1.36	0.246	(0.34)	1.28
Grocery Store	0.319	(0.36)	1.38	0.382	(0.35)	1.47
Everyday Store	1.062***	(0.08)	2.89	1.07***	(0.08)	2.92
Restaurant	0.130*	(0.05)	1.14	0.133**	(0.05)	1.14
Retail Store	0.031	(0.04)	1.03	0.025	(0.04)	1.03
Bus Stop	0.665***	(0.09)	1.94	0.677***	(0.09)	1.97
High School	0.192	(0.23)	1.21	0.174	(0.23)	1.19
Drug Treatment Facility	0.628*	(0.27)	1.87	0.602*	(0.27)	1.82
Public Housing	0.579**	(0.19)	1.78	0.587**	(0.19)	1.80
Gang Territory	0.617***	(0.07)	1.85	0.593***	(0.07)	1.81
Parking Lot	0.349***	(0.06)	1.42	0.350***	(0.06)	1.42
Prostitution Market	0.202**	(0.08)	1.22	0.198**	(0.08)	1.22
Drug Market	0.120***	(0.01)	1.13	0.117***	(0.01)	1.12
Bar/Club SL	-0.019	(0.08)	0.98	0.013	(0.08)	1.01
Entertainment Facility SL	0.051	(0.12)	1.05	0.059	(0.13)	1.06
Fringe-Banking Store SL	-0.027	(0.19)	0.97	-0.065	(0.19)	0.94
Grocery Store SL	0.035	(0.20)	1.04	0.042	(0.20)	1.04
Everyday Store SL	0.161***	(0.05)	1.17	0.163***	(0.05)	1.18
Restaurant SL	0.004	(0.03)	1.00	0.003	(0.03)	1.00
Retail Store SL	0.030	(0.02)	1.03	0.029	(0.02)	1.03
Bus Stop SL	0.218**	(0.08)	1.24	0.220**	(0.08)	1.25
High School SL	0.185	(0.17)	1.20	0.174	(0.17)	1.19
Drug Treatment Facility SL	0.115	(0.14)	1.12	0.079	(0.14)	1.08
Public Housing SL	0.092	(0.20)	1.10	0.079	(0.20)	1.08
Gang Territory SL	0.313***	(0.09)	1.37	0.284**	(0.09)	1.33
Parking Lot SL	0.712*	(0.32)	2.04	0.683*	(0.32)	1.98
Prostitution Market SL	0.055**	(0.02)	1.06	0.046*	(0.02)	1.05
Drug Market SL	-0.001	(0.00)	1.00	0.002	(0.00)	1.00
Total Population/100	0.036***	(0.01)	1.04	0.035***	(0.01)	1.04
Concentrated Disadvantage	0.074***	(0.01)	1.08	0.075***	(0.01)	1.08
Residential Stability	0.116***	(0.02)	1.12	0.114***	(0.02)	1.12
Racial Segregation	0.344	(0.19)	1.41	0.479*	(0.19)	1.61
Length of Street/100	0.05***	(0.00)	1.05	0.050***	(0.00)	1.05
Major Street	0.283***	(0.08)	1.33	0.258**	(0.08)	1.29
Access to Highway	-0.076	(0.20)	0.93	-0.104	(0.20)	0.90
Intercept	-4.727***	(0.33)	0.01	-4.759***	(0.33)	0.01

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag

Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table A6. Results of Negative Binomial Regression with Prior Property Offense - Theft from Auto Counts

	Model S: Likely Offender Exposure			Model T: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
IDW Offender Count - Property	0.063***	(0.01)	1.06	---	---	---
IDW Offender Risk - Property	---	---	---	0.041***	(0.01)	1.04
Bar/Club	0.692***	(0.11)	2.00	0.715***	(0.11)	2.04
Entertainment Facility	0.985***	(0.17)	2.68	0.994***	(0.17)	2.70
Fringe-Banking Store	-0.261	(0.37)	0.77	-0.299	(0.37)	0.74
Grocery Store	1.124***	(0.32)	3.08	1.137***	(0.32)	3.12
Everyday Store	0.197*	(0.08)	1.22	0.200*	(0.08)	1.22
Restaurant	0.120*	(0.05)	1.13	0.126**	(0.05)	1.13
Retail Store	0.041	(0.04)	1.04	0.041	(0.04)	1.04
Bus Stop	0.238***	(0.06)	1.27	0.262***	(0.06)	1.30
High School	0.391*	(0.17)	1.48	0.374*	(0.17)	1.45
Drug Treatment Facility	0.362	(0.25)	1.44	0.347	(0.25)	1.42
Public Housing	0.676***	(0.18)	1.97	0.676***	(0.18)	1.97
Gang Territory	-0.087	(0.05)	0.92	-0.092	(0.06)	0.91
Parking Lot	0.319***	(0.04)	1.38	0.321***	(0.04)	1.38
Prostitution Market	0.027	(0.08)	1.03	0.028	(0.08)	1.03
Drug Market	0.097***	(0.01)	1.10	0.093***	(0.01)	1.10
Bar/Club SL	0.127*	(0.05)	1.14	0.150**	(0.05)	1.16
Entertainment Facility SL	0.218*	(0.09)	1.24	0.246**	(0.09)	1.28
Fringe-Banking Store SL	0.084	(0.18)	1.09	0.058	(0.18)	1.06
Grocery Store SL	0.113	(0.16)	1.12	0.107	(0.17)	1.11
Everyday Store SL	-0.123**	(0.04)	0.88	-0.125**	(0.04)	0.88
Restaurant SL	-0.019	(0.02)	0.98	-0.017	(0.02)	0.98
Retail Store SL	0.015	(0.02)	1.02	0.012	(0.02)	1.01
Bus Stop SL	-0.041	(0.05)	0.96	-0.030	(0.05)	0.97
High School SL	0.095	(0.13)	1.10	0.081	(0.13)	1.08
Drug Treatment Facility SL	-0.140	(0.13)	0.87	-0.170	(0.13)	0.84
Public Housing SL	0.038	(0.18)	1.04	0.025	(0.18)	1.03
Gang Territory SL	-0.073	(0.06)	0.93	-0.077	(0.06)	0.93
Parking Lot SL	0.303*	(0.12)	1.35	0.284*	(0.12)	1.33
Prostitution Market SL	0.014	(0.02)	1.01	0.011	(0.02)	1.01
Drug Market SL	0.001	(0.00)	1.00	0.005***	(0.00)	1.00
Total Population/100	0.024***	(0.00)	1.02	0.022***	(0.00)	1.02
Concentrated Disadvantage	-0.042***	(0.01)	0.96	-0.038***	(0.01)	0.96
Residential Stability	0.151***	(0.01)	1.16	0.156***	(0.01)	1.17
Racial Segregation	0.377**	(0.12)	1.46	0.437***	(0.12)	1.55
Length of Street/100	0.104***	(0.00)	1.11	0.102***	(0.00)	1.11
Major Street	0.152*	(0.06)	1.16	0.129*	(0.06)	1.14
Access to Highway	-0.026	(0.14)	0.97	-0.025	(0.14)	0.97
Intercept	-2.474***	(0.14)	0.08	-2.438***	(0.14)	0.09

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table A7. Results of Negative Binomial Regression with Prior Drug Offense – Robbery Counts

Variable	Model U: Likely Offender Exposure β	(SE)	IRR	Model V: Cumulative Offender Risk β	(SE)	IRR
IDW Offender Count - Drug	0.034***	(0.01)	1.03	---	---	---
IDW Offender Risk - Drug	---	---	---	0.038***	(0.01)	1.04
Bar/Club	0.457***	(0.13)	1.58	0.459***	(0.13)	1.58
Entertainment Facility	0.180	(0.25)	1.20	0.188	(0.25)	1.21
Fringe-Banking Store	0.282	(0.35)	1.33	0.245	(0.35)	1.28
Grocery Store	0.277	(0.36)	1.32	0.315	(0.36)	1.37
Everyday Store	1.060***	(0.08)	2.89	1.066***	(0.08)	2.90
Restaurant	0.139**	(0.05)	1.15	0.142**	(0.05)	1.15
Retail Store	0.031	(0.04)	1.03	0.028	(0.04)	1.03
Bus Stop	0.713***	(0.09)	2.04	0.704***	(0.09)	2.02
High School	0.162	(0.23)	1.18	0.143	(0.23)	1.15
Drug Treatment Facility	0.605*	(0.27)	1.83	0.611*	(0.27)	1.84
Public Housing	0.584**	(0.20)	1.79	0.594**	(0.19)	1.81
Gang Territory	0.631***	(0.07)	1.88	0.615***	(0.07)	1.85
Parking Lot	0.347***	(0.06)	1.41	0.342***	(0.06)	1.41
Prostitution Market	0.207**	(0.08)	1.23	0.202**	(0.08)	1.22
Drug Market	0.119***	(0.01)	1.13	0.119***	(0.01)	1.13
Bar/Club SL	-0.008	(0.08)	0.99	0.004	(0.08)	1.00
Entertainment Facility SL	0.059	(0.13)	1.06	0.075	(0.12)	1.08
Fringe-Banking Store SL	-0.001	(0.19)	1.00	-0.029	(0.19)	0.97
Grocery Store SL	-0.031	(0.20)	0.97	-0.033	(0.20)	0.97
Everyday Store SL	0.157***	(0.05)	1.17	0.164***	(0.05)	1.18
Restaurant SL	0.007	(0.03)	1.01	0.011	(0.03)	1.01
Retail Store SL	0.031	(0.02)	1.03	0.030	(0.02)	1.03
Bus Stop SL	0.252**	(0.08)	1.29	0.249**	(0.08)	1.28
High School SL	0.158	(0.17)	1.17	0.155	(0.17)	1.17
Drug Treatment Facility SL	0.108	(0.14)	1.11	0.101	(0.14)	1.11
Public Housing SL	0.081	(0.20)	1.08	0.064	(0.20)	1.07
Gang Territory SL	0.33***	(0.09)	1.39	0.307***	(0.09)	1.36
Parking Lot SL	0.711*	(0.32)	2.04	0.727*	(0.32)	2.07
Prostitution Market SL	0.060**	(0.02)	1.06	0.059**	(0.02)	1.06
Drug Market SL	0.002	(0.00)	1.00	0.002	(0.00)	1.00
Total Population/100	0.036***	(0.01)	1.04	0.037***	(0.01)	1.04
Concentrated Disadvantage	0.072***	(0.01)	1.07	0.067***	(0.01)	1.07
Residential Stability	0.135***	(0.02)	1.14	0.130***	(0.02)	1.14
Racial Segregation	0.474*	(0.19)	1.61	0.483*	(0.19)	1.62
Length of Street/100	0.049***	(0.00)	1.05	0.049***	(0.00)	1.05
Major Street	0.279***	(0.08)	1.32	0.280***	(0.08)	1.32
Access to Highway	-0.040	(0.20)	0.96	-0.105	(0.20)	0.90
Intercept	-4.767***	(0.33)	0.01	-4.809***	(0.33)	0.01

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table A8. Results of Negative Binomial Regression with Prior Drug Offense - Theft from Auto Counts

	Model W: Likely Offender Exposure			Model X: Cumulative Offender Risk		
Variable	**β**	**(SE)**	**IRR**	**β**	**(SE)**	**IRR**
IDW Offender Count - Drug	0.039***	(0.01)	1.04	---	---	---
IDW Offender Risk - Drug	---	---	---	0.028***	(0.00)	1.03
Bar/Club	0.694***	(0.11)	2.00	0.701***	(0.11)	2.02
Entertainment Facility	0.989***	(0.17)	2.69	0.994***	(0.17)	2.70
Fringe-Banking Store	-0.267	(0.37)	0.77	-0.286	(0.37)	0.75
Grocery Store	1.111***	(0.32)	3.04	1.116***	(0.32)	3.05
Everyday Store	0.205**	(0.08)	1.23	0.206**	(0.08)	1.23
Restaurant	0.127**	(0.05)	1.14	0.132**	(0.05)	1.14
Retail Store	0.038	(0.04)	1.04	0.039	(0.04)	1.04
Bus Stop	0.262***	(0.06)	1.30	0.273***	(0.06)	1.31
High School	0.375*	(0.17)	1.45	0.363*	(0.17)	1.44
Drug Treatment Facility	0.357	(0.25)	1.43	0.353	(0.25)	1.42
Public Housing	0.652***	(0.18)	1.92	0.666***	(0.18)	1.95
Gang Territory	-0.102	(0.06)	0.90	-0.089	(0.06)	0.91
Parking Lot	0.310***	(0.04)	1.36	0.313***	(0.04)	1.37
Prostitution Market	0.036	(0.08)	1.04	0.033	(0.08)	1.03
Drug Market	0.096***	(0.01)	1.10	0.094***	(0.01)	1.10
Bar/Club SL	0.140**	(0.05)	1.15	0.147**	(0.05)	1.16
Entertainment Facility SL	0.233**	(0.09)	1.26	0.250**	(0.09)	1.28
Fringe-Banking Store SL	0.10	(0.18)	1.10	0.094	(0.18)	1.10
Grocery Store SL	0.075	(0.16)	1.08	0.064	(0.17)	1.07
Everyday Store SL	-0.12**	(0.04)	0.89	-0.121**	(0.04)	0.89
Restaurant SL	-0.015	(0.02)	0.98	-0.013	(0.02)	0.99
Retail Store SL	0.016	(0.02)	1.02	0.015	(0.02)	1.02
Bus Stop SL	-0.021	(0.05)	0.98	-0.017	(0.05)	0.98
High School SL	0.082	(0.13)	1.09	0.074	(0.13)	1.08
Drug Treatment Facility SL	-0.132	(0.13)	0.88	-0.147	(0.13)	0.86
Public Housing SL	0.018	(0.18)	1.02	0.013	(0.18)	1.01
Gang Territory SL	-0.067	(0.06)	0.94	-0.069	(0.06)	0.93
Parking Lot SL	0.304*	(0.12)	1.35	0.306*	(0.12)	1.36
Prostitution Market SL	0.015	(0.02)	1.02	0.018	(0.02)	1.02
Drug Market SL	0.003	(0.00)	1.00	0.004**	(0.00)	1.00
Total Population/100	0.025***	(0.00)	1.03	0.024***	(0.00)	1.02
Concentrated Disadvantage	-0.046***	(0.01)	0.95	-0.045***	(0.01)	0.96
Residential Stability	0.161***	(0.01)	1.17	0.163***	(0.01)	1.18
Racial Segregation	0.439***	(0.12)	1.55	0.442***	(0.12)	1.56
Length of Street/100	0.104***	(0.00)	1.11	0.102***	(0.00)	1.11
Major Street	0.149*	(0.06)	1.16	0.138*	(0.06)	1.15
Access to Highway	-0.022	(0.14)	0.98	-0.040	(0.14)	0.96
Intercept	-2.512***	(0.14)	0.08	-2.472***	(0.14)	0.08

N = 10,940 street blocks; β = Coefficient, IRR = Incident Rate Ratio, SE = Standard Error, SL = Spatial Lag
Significance values are as follows: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$