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I, Samantha M. Henderson, hereby submit this original work as part of the requirements for the degree of Doctor of Philosophy in Criminal Justice.

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Proposing and Assessing Facility Risk Measures for Place Based Studies of Crime

Student's name: **Samantha M. Henderson**

This work and its defense approved by:

Committee chair: Cory Haberman, Ph.D.

Committee member: Martin Andresen, Ph.D.

Committee member: John Eck, Ph.D.

Committee member: Pamela Wilcox, Ph.D.

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Proposing and Assessing Facility Risk Measures for Place Based Studies of Crime

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by

Samantha M. Henderson

B.A., Wilfrid Laurier University, 2009
M.A., University of Waterloo, 2011

Dissertation Committee:

Cory P. Haberman, Ph.D. (Chair)

John E. Eck, Ph.D.

Pamela Wilcox, Ph.D.

Martin A. Andresen, Ph.D.

ABSTRACT

Objectives. This study addresses a shortcoming in the facility measurement approach used in some studies of crime and place. That is, researchers tend to treat facilities as though they have a homogenous crime risk despite research indicating there is significant variation in crime across facilities. In this study, I propose and examine a series of eight empirically rooted alternative measures of risky facilities. I assess what, if any, impact each has on the outcomes of models of robbery and theft at street blocks in Cincinnati, Ohio, as compared to the more commonly used homogenous risk measure.

Methods. To compare facility risk measures, I use a series of nearly identical negative binomial regressions to model the effects of sixteen facility types on robbery and theft at street blocks. Models vary only in their operationalization of facility risk. I use model comparison statistics (AIC, BIC) to determine if any of the proposed facility risk variables offer an improved model fit over the homogenous facility crime risk approach. For those that result in an improved fit, I assess model coefficients and significance to determine if the conclusions differ meaningfully from those derived from the homogenous facility crime risk approach.

Results. Of the eight proposed measures, only the continuous measure created using calls for service within a 500ft buffer area offered an improved model fit, and only for robbery. The conclusions drawn from the proposed measure regression results largely mirrored those of the homogenous facility count regression results. A number of other models that did not have an improved fit were impacted by multicollinearity, possibly due to the presence of co-located facilities with shared addresses.

Conclusion. A continuous crime risk variable created using calls for service data within an approximately one block buffer area of facilities may act as an acceptable alternative measure of facility robbery risk in future studies of crime and place. However, this measure is limited by its less intuitive coefficient interpretation and the possibility of biased results in study areas with a high number of facilities with shared addresses. Measuring facilities using simple counts remains a viable operationalization according to the results of this study.

KEYWORDS

Environmental Criminology; Geography of crime; Criminology of place; Risky facilities

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CHAPTER 1: INTRODUCTION

This dissertation is about the crime risk of places and, specifically, how to effectively operationalize this risk in models of crime and place. As the definition of place has varied across prior studies, I will explain here exactly what I mean by place. Broadly, the term *place* refers to a microgeographic unit, such as individual businesses, street addresses, street segments or blocks, or clusters of street segments (Weisburd et al., 2016). Madensen and Eck (2012) further break places down into a three-part classification scheme: proprietary places, pooled places, and proximal places. *A proprietary place* is "a small area reserved for a narrow range of functions, often controlled by a single owner, and separated from the surrounding area" (Eck, 2002, p. 241). For example, individual buildings would be considered proprietary places. These types of places are often operationalized in research as individual addresses (e.g. Sherman, Gartin, & Buerger, 1989), although it is not always a perfect translation (e.g. some buildings contain multiple addresses and some addresses contain multiple proprietary places).

Proprietary places of the same type are called *facilities* (Eck, Clarke, & Guerette, 2007). A facility may be "located adjacent to others in its set, but typically members of the set are dispersed" (Madensen & Eck, 2012, p.573). Common examples of facilities include bars, libraries, and convenience stores[1]. Like moose, however, facility has the somewhat confusing characteristic of being used as a plural of itself. So, while some use facility to refer to group of places of the same type, such as bars, other times facility is used to refer to a single bar within that group. For example, Eck, Clarke, and Guerette (2007) use the noun in the singular sense when they say "[p]lace characteristics are under the control of people who own and manage the facility" (p. 239), while Wilcox and Eck (2011) use the noun in its collective sense, saying "only a few places within

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[1] Note that this differs from Felson's (1987) use of the term facility, which refers to groupings of businesses clustered together in a single complex, such as shopping malls or office parks.

any category of busy facility are really troublesome" (p. 476) and "[i]f the events being examined are common, then it will be relatively easy to describe the distribution of crimes per facility" (p. 241). To avoid any confusion related to the meaning of facility, in this dissertation I will differentiate by referring to the singular noun as *facility* and the plural noun as *facility sets*. In other words, drawing and expanding on Eck, Clarke, and Guerette (2007) and Madensen and Eck's (2012) definitions, facility sets are homogenous groups of all places with a similar function within a given geographic area. Facilities are individual units within facility sets. In keeping with prior research, facilities expected to impact crime in their area will be called *risky facilities* (Eck et al., 2007).

Proximal places are groups of proprietary places that are located close to one another (Madensen & Eck, 2012). There are usually multiple property owners within each proximal place. This type of place is often operationalized as a street segment or street block. Weisburd, Groff and Yang (2012), for instance, use street segments as their proximal place unit of analysis because they consider them to be representative of behavioral settings (Barker, 1968; Wicker, 1987). Comprehensive studies on the impact of multiple types of risky facilities on crime are often evaluated at this unit of analysis (e.g. Clutter, Henderson, & Haberman, 2019; Duru, 2010; Groff, & Lockwood, 2014; Kelsay & Haberman, 2020; Smith, Frazee, & Davison, 2000). In these studies, researchers aggregate facilities to the proximal place level. This approach is useful as it enables researchers to determine the impact of individual types of risky facilities on crime in their area, while controlling for the presence of other types of risky facilities.

Finally, *pooled places* are groups of proximal places that, when combined, make up a larger geographic area (Madensen & Eck, 2012). Pooled places are typically operationalized as census tracts or neighborhoods but can also include even larger units of analysis, such as cities. In this dissertation, I focus on the crime impact of proprietary places, and the risky facility groups to which they belong. For my analyses, I follow the approach of previous studies of crime and place and aggregate to the proximal place level. Pooled places are not assessed.

One important element of crime opportunity is place (Eck & Guerette, 2012; Madensen & Eck, 2012). There is a large body of research indicating that crime concentrates disproportionately in some places and not others (see for example Sherman et al., 1989; Weisburd et al., 2012). One branch of place-based crime research has focused on the impact of facilities on crime. This research has found that crime is increased by some types of facilities (Bernasco & Block, 2011; Haberman & Ratcliffe, 2015; Roncek & Bell, 1981; Stucky & Ottensmann, 2009), and that some types of facilities impact crime in their surrounding area (Bowers, 2014; Groff & Lockwood, 2014; Haberman, Groff, & Taylor, 2013). However, the strength of this impact also varies within facility sets, with some locations having no impact, or even a crime reduction impact, on the area around them (Haberman et al., 2013; Roncek & Maier, 1991). Taken together, these findings suggest that the riskiness of particular types of places is not constant, and that, despite having a similar purpose, some differences may exist within facility sets that differentiates the levels of crime at each facility. Crime opportunity theories offer a number of complementary explanations for this phenomenon including the convergence of motivated offenders with suitable targets in the absence of capable guardianship (Cohen & Felson, 1979), poor place management (Madensen, 2007; Madensen & Eck, 2008; Madensen & Eck, 2012), and highly traveled nodes and paths (Brantingham, Paul J. & Brantingham, 1993).

One potential limitation of research assessing the impact of proprietary places on crime is that some studies ignore variation in crime both among and around facilities. Many place-based crime studies rely on an *Assumption of Crime Homogeneity*, whereby all places of the same type are assumed to have the same impact on crime. As a result of this assumption, researchers operationalize places of the same type homogenously, either by measuring their presence or absence (e.g. Stucky & Ottensmann, 2009; Stucky & Smith, 2017), counting the number of facilities of each type present in each unit (e.g. Bernasco & Block, 2011; Haberman & Ratcliffe, 2015), measuring the percentage of each unit covered by a particular facility type (e.g. Stucky & Ottensmann, 2009; Weisburd et al., 2012), or measuring the distance to the nearest facility of each type (e.g. Clutter et al., 2019; Dario, Morrow, Wooditch, & Vickovic, 2015; Irvin-Erickson, 2014; Kennedy, Caplan, Piza, & Buccine-Schraeder, 2016). Variations in factors that impact criminogenic risk, including the criminal history of each location, are rarely considered in the operationalization of places in these studies. One notable exception is Bowers' (2014) treatment of risky facilities based on theft levels. Her study draws on an empirically supported *Assumption of Crime Concentration*, whereby places of the same type are expected to have differential impacts on crime as a result of their individual criminogenic risk factors.

It is unclear what the effects are of relying on an *Assumption of Crime Homogeneity* when operationalizing facilities as no one has compared this approach to an alternative approach based on an *Assumption of Crime Concentration*. It may be that the outcomes of research are insensitive to the distribution of crime among facilities. However, given previous findings about facilities and crime, it is entirely possible that the homogenous operationalization approach is affecting study outcomes. Moreover, it is possible that accounting for crime concentration among and around facilities in the operationalization of potentially criminogenic places may improve the performance of models explaining geographic crime patterns. Determining if this is true is important as study outcomes affect our understanding of the relationship between crime and place, and in turn are used to design place-based strategies to reduce crime and offending (e.g. Eck, 2002; Eck & Guerette, 2012; Welsh & Farrington, 2009).

In this dissertation, I propose and examine eight measures of risky facilities rooted in the empirical distribution of crime within facility sets. These measures vary along three domains, including: (1) the area assumed to be impacted by facility riskiness (at-facility only versus the facility and its surrounding area), (2) the types of crime used to operationalize riskiness (specific crime measures versus general crime measures), and (3) the level of measurement used to operationalize risk (binary versus continuous). Each of these approaches has different strengths and limitations, with no single approach being clearly superior to the others. The purpose of this dissertation is to test the performance of these proposed measures in a model of crime and place to see which measures, if any, offer an improvement in model performance over a commonly used homogenous measure of facilities.

This study is presented in six parts. This chapter provides a brief introduction to the study topic. The next two chapters summarize the background literature related to this study. Chapter 2 overviews relevant theories of criminal opportunity, including the Rational Choice Perspective (Clarke & Cornish, 1985; Cornish & Clarke, 2016), the Routine Activities Approach (Cohen & Felson, 1979), and the Geometry of Crime (Brantingham, Patricia L. & Brantingham, 1981; Brantingham, Patricia L. & Brantingham, 1995; Brantingham, Paul J. & Brantingham, 1993). These three theories combine into a metatheory, Crime Pattern Theory (Andresen, 2014; Andresen, Brantingham, & Kinney, 2010; Brantingham, Patricia L. & Brantingham, 1993), to provide the rationale for expecting crime to concentrate at place, including within places of the same type. Chapter 3 presents a summary of research on the impact of places on crime, crime concentrations within and around facilities, and the measurement approaches used to capture facility risk in studies of crime and place. This includes a discussion of crime concentration in space and the stability of this concentration over time.

Chapter 4 describes the methods I use to answer my research question, which is "Can risky facility measures based on an *Assumption of Crime Concentration* better explain crime counts at micro-places than commonly used *Assumption of Crime Homogeneity* facility measures of all places within each facility type?".

To answer this question, I assess the impact of my proposed risky facility measures on the outcomes of a series of crime and place models by comparing them to a commonly used homogenous facility measure (i.e. counts of facility presence). In these models, 16 facility types are included as predictors of either street block-level street robbery or theft counts in Cincinnati, Ohio. I use the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and a comparison of model coefficient strength and direction to determine what differences and/or benefits the proposed risky facility measures offer over the homogenous facility measure.

Chapter 5 presents the results of my analyses. Of the eight proposed measures, only the continuous measure created using calls for service within a 500ft buffer area offered an improved model fit, and only for the robbery outcome. The conclusions drawn from the proposed measure regression results largely mirrored those of the homogenous measure regression results with only a few small differences. The results of model sensitivity checks and diagnostic tests are also presented in this chapter, including a discussion of the possible impact of multicollinearity on some of the models that did not offer an improved model fit.

Chapter 6 discusses the study results and limitations. The results indicate that a continuous crime risk variable created using calls for service data within an approximately one block buffer area of facilities may act as an acceptable alternative measure of facility robbery risk in future studies of crime and place. However, this measure is limited by its less intuitive coefficient interpretation and the possibility of biased results in study areas with a high number of facilities with shared addresses.

To save space in text, three appendices are included with full results for all regressions and sensitivity checks. Appendix C contains the full regression results for each of the 16 robbery and theft models. Appendix D contains the distance sensitivity check regression results. Appendix E contains the multi-facility address sensitivity check regression results.

CHAPTER 2: THEORETICAL BACKGROUND

To provide context and justification for my research question, in the following two chapters I overview theoretical explanations for the spatial distribution of crime and research findings related to facilities and the concentration of crime across places. The current chapter is presented in four parts. I begin by broadly discussing some of the opportunity theories of crime. I provide background on four theories: the Rational Choice Perspective, the Routine Activities Approach, the Geometry of Crime, and Crime Pattern Theory. I conclude by discussing the spatial extent of the theories. Taken together, these complementary theories are useful for understanding and explaining differences in crime across small units of analysis, such as street blocks. They are particularly relevant for explaining the non-random distribution of crime among and around similar types of proprietary places, which is the focus of this dissertation.

Theoretical Explanations of Crime

Historically, theories of crime have focused on offenders and their dispositions (Clarke, 1980). These theories have tended to attribute crime to individual and societal afflictions, such as poor social bonds (Hirschi, 1969), low self-control (Gottfredson & Hirschi, 1990), strain (Agnew, 1992; Merton, 1938), labeling (Braithwaite, 1989), deviant peers and family members (Sutherland, 1947), and subcultures of crime (Anderson, 1999). More recently, this trend has begun to shift as theorists have recognized that crime concentrates nonrandomly across space and time (e.g. Haberman & Ratcliffe, 2015; Sherman et al., 1989; Weisburd et al., 2012; Weisburd, 2015), bringing forth a recognition of the importance of crime incidents and the situations and places in which they occur (Eck & Weisburd, 1995). Principally, this shift has led to a focus on place, and the explanation and understanding of the unequal distribution of crime across places. Although they vary in their concepts, theories that are used to explain the unequal distribution of crime at place are united in putting forth that crime events are directly related to the availability of criminal opportunities (Wilcox, Gialopsos, & Land, 2012).

Rational Choice Perspective

Regardless of their specific arguments, theories of crime opportunity are predicated on the notion that criminals *choose* to engage in illegal acts (Clarke & Cornish, 1985). The Rational Choice Perspective (Cornish & Clarke, 2016) argues that criminal behavior is both purposeful and rational. Importantly, this perspective does not argue for perfect rationality. Instead, offenders are thought to have limited or bounded rationality, marked by an incomplete understanding of the possible outcomes of their actions (Clarke & Cornish, 1985; Jones, 1999; Simon, 1982). Their decision making is also impacted by their previous experiences, their intelligence, and their preferences (Cornish & Clarke, 2016; Jacobs, B. A. & Wright, 2010). Thus, offenders make decisions which are adequate rather than optimal[2] (Simon, 1957), and the rational choices related to committing crime differ among offenders (Carroll & Weaver, 1986; Weaver & Carroll, 1985).

Offenders engage in both long-term involvement decisions and short-term event decisions. Involvement decisions include those surrounding initial involvement in crime (i.e. initiation), continued involvement in crime (i.e. habituation), and the ceasing of involvement in crime (i.e. desistance) (Clarke & Cornish, 1985). These are all crime specific, meaning that offenders might choose to be involved in one type of crime, such as burglary, but not others, such as robbery or murder. Event decisions have a short time horizon and occur directly before and during a crime incident. They also typically follow a set pattern or script (Cornish, 1994).

When encountering a criminal opportunity, offenders weigh the potential risks and benefits of committing a crime. If the potential of getting caught is too high or the payoff is too low, they

[2] Though not optimized, these decisions can be considered to be “satisficing”, or both satisfying and sufficient (Simon, 1957).

will not take advantage of that particular opportunity. Engagement in crime is thus largely guided by the decisions made during the situation directly preceding the criminal act (Cornish & Clarke, 2003; Wortley, 2001; Wortley, 2002). Although some individuals may be predisposed to crime, it is situational cues that are more proximate to the crime event, and thus more salient to the decision to commit crime (Clarke, 2005) than any particular criminal disposition. Crime can be prevented by modifying these situational cues (Clarke, 1980).

Routine Activities Approach

One theory which draws on the Rational Choice Perspective is the Routine Activities Approach. Proposed by Cohen and Felson (1979), the Routine Activities Approach puts forth that, in order for a crime to occur, three things must converge in both space and time: a *motivated offender* must encounter a *suitable target* that *lacks capable guardianship*. As it was originally presented (Cohen & Felson, 1979), the Routine Activities Approach was a macro-level theory of crime, explaining an increase in aggregate rates of direct contact predatory crimes[3] (e.g. robbery, theft) across the USA following World War II (Wilcox & Cullen, 2018).

Since then, the Routine Activities Approach has been expanded and applied as a theory of crime events at micro-level units of analysis, including individuals and places (Haberman & Ratcliffe, 2015; LaGrange, 1999; Smith et al., 2000; Stucky & Ottensmann, 2009). The expanded theory now includes offender handlers and place managers. Offender handlers are people who are tied to an offender and have an interest in keeping them out of trouble (Felson, 1986). Place managers are owners and other individuals instructed by owners to govern over the functioning of places (Eck, 1994). Thus, the theory now postulates that in order for a crime to occur a suitable target must meet a motivated offender in a poorly managed place which lacks capable guardians[4]

[3] Defined as any incident where "someone definitely and intentionally takes or damages the person or property of another" (Glaser 1971:4 as cited in Cohen & Felson, 1979).
[4] See Eck and Madensen-Herold (2018) for a summary of five sources of guardianship.

and offender handlers. Broadly speaking, this is expected to happen more often in busy places where more people come together, as there is a greater likelihood of these requirements co-occurring there.

Place Management Theory is an extension of the Routine Activities Approach (Cohen & Felson, 1979), which puts forth that the decisions and actions made by place managers impact crime levels at places (Eck, 1994; Eck & Madensen-Herold, 2018). Place managers are owners and other individuals instructed by owners to govern over the functioning of places. They make decisions with respect to the physical organization of their place, who can access their place, the regulation of conduct within their place, and the acquisition of resources for their place[5] (Eck & Madensen-Herold, 2018; Madensen, 2007). Though these actions are not necessarily intended to affect crime, they directly impact several elements of criminal opportunity (Madensen, 2007; Madensen & Eck, 2012).

Good place management can prevent crimes by decreasing offenders' perceptions of criminal opportunities, and bad place management can enable or even encourage crime by increasing offenders' perceptions of criminal opportunities (Madensen & Eck, 2012). Poor place managers are thus responsible for negative crime externalities, the costs of which are largely borne by crime victims and the criminal justice system (Eck & Eck, 2012).

Eck and Madensen-Herold (2018) break down place managers into four types[6]: reactors, enablers, promoters and suppressors. *Suppressors* proactively engage in crime prevention

[5] Place manager tasks can thus be summarized using the acronym ORCA: *organization* of space, *regulation* of conduct, *control* of access, and *acquisition* of resources (Madensen & Eck, 2012)

[6] Felson (1995) also discusses four types of place managers that can have an impact on crime. In decreasing order of responsibility, these include: those with personal responsibility for a place, such as owners and those closely related to them; those with assigned responsibility for a place, such as employees tasked with monitoring the place; those with diffuse job responsibility at a place, such as those employees who work at the place but are not assigned any job-related monitoring tasks; and those with general responsibility for a place, such as visitors to a place who discourage crime simply by being present. Current applications of Place Management Theory, with their emphasis on the impact of place-related decision making (e.g. Madensen & Eck, 2008) tend to focus on the former three types of managers.

behaviors and are least likely to experience crime at their locations. *Reactors* do not invest much effort in preventing crime initially but react once a crime happens in order to prevent future crimes, thus keeping their overall crime rate low. In contrast, *promoters* encourage crime by failing to prevent, and even strengthening, criminal opportunities at their location for their own gain. Finally, *enablers*, for a variety of reasons, do not address criminal opportunities at their location. Through their passivity, they allow crime to occur. Thus, suppressors and reactors are expected to have low or no crime at their locations, while enablers and promoters are expected to have higher concentrations of crime.

For instance, a bar manager might allow their staff to overserve patrons to make more money, while also removing security staff from outside to cut costs. This would decrease the number of guardians in the area surrounding the bar, while also increasing the number of suitable (i.e. inebriated) targets for robbery as patrons head home. Likewise, a convenience store manager might decide to layout their store in a way that impedes their employees' views of certain products. This would make it difficult for employees to guard those products from theft, thus increasing opportunities for theft in the store. In contrast, if the store manager ensured small, valuable products were easily monitored by employees, they would block theft opportunities (Clarke & Petrossian, 2013). Place manager decisions thus actively contribute to places and their surrounding environment becoming criminogenic via their impact on criminal opportunity (Madensen & Eck, 2012).

Geometry of Crime

The Geometry of Crime is also important for understanding crime at places as it provides a more concrete spatial context for the concepts presented in the Routine Activities Approach and Place Management Theory. The Geometry of Crime is premised on the notion that crime opportunities occur as a result of behavioral patterns which bring together offenders and their victims in space and time (Brantingham & Brantingham, 1981). Specifically, it suggests human behaviors (including criminal behaviors) are patterned, and these patterns are influenced by the physical environment. Criminals search for targets around the paths they travel and at the nodes in which they conduct their usual activities. Further, they tend to follow a template when assessing situations and deciding to commit a crime (Brantingham, Paul J. & Brantingham, 1978).

All of this occurs in the context of an environmental backcloth. That is, the offender operates in a particular social, economic, and physical context, which includes both criminals and non-criminals, and which can vary from place to place and over time (Brantingham & Brantingham, 1981). Throughout the course of their day, offenders predominantly engage in legitimate legal activities. In these activity spaces, they search for crime opportunities similar to how they search for opportunities to engage in legitimate activities. For example, they would look for a purse to snatch much the same way they would look for a restaurant to eat lunch at. Additionally, offenders rarely go out of their way to explore unknown places, and instead spend their time in places that they are familiar with, also known as their awareness space (Brantingham, Paul J. & Brantingham, 1993; Kinney, Brantingham, Kirk, & Brantingham, 2008).

Spatial concentration of crime occurs because offenders and victims tend to travel the same paths and congregate at the same nodes. As a result, crime, particularly at the aggregate level, is "highly patterned and frequently localized" (Brantingham, Paul J. & Brantingham, 1993, p.5) along busy paths and nodes. High traffic places are thus expected to have more crime than those with less traffic as they increase the likelihood that offenders and victims come together. Crime is also expected to concentrate along edges where two or more unique areas meet, creating a distinctive noticeable change between them (Brantingham, Paul J. & Brantingham, 1993).

The Geometry of Crime classifies places as crime generators, crime attractors, crime neutral (Brantingham & Brantingham, 1995) and crime enablers (Clarke & Eck, 2005). *Crime generators* are those places where offenders and targets come together for non-criminal reasons and offenders take advantage of the abundance of targets, such as shopping malls. In contrast, *crime attractors* are places where known crime opportunities exist and as such offenders are drawn to those areas to take advantage of the criminal opportunities, such as street corners known for drug dealing. *Crime enablers* are those places with few to no controls, which facilitate criminal behavior (Clarke & Eck, 2005). Finally, *crime neutral* places are those that are crime-free.

Crime Pattern Theory

Crime Pattern Theory (Brantingham, Patricia L. & Brantingham, 1993) pulls together the Geometry of Crime, the Routine Activities Approach, and the Rational Choice Perspective, among other environmental criminology theories, to form a meta-theory merging the concepts of each (Andresen, 2014; Andresen, Brantingham, & Kinney, 2010). This theory explains the lead up to crime events as a dynamic process impacted by several interconnected systems.

The theory argues that, while engaged in their routine activities in their activity and awareness spaces, potential offenders encounter triggering events which initiate their willingness to commit a crime (Andresen, 2014; Andresen, Brantingham, & Kinney, 2010; Brantingham, Patricia L. & Brantingham, 1993). This process is guided by crime templates, which vary by individual and by crime. These templates guide the assessments of criminal opportunities and the rational choices to commit a crime – they help the offender decide what a good opportunity is, and in what circumstances to take advantage of that opportunity. This template is continually updated and impacted by an offender's routine activities and by the environmental backcloth. Likewise, templates are updated after each crime attempt, and this can also impact the offender's future behaviors, including their routine activities. Patterns of crime emerge because there is overlap in the routine activities of offenders and their targets, in the distribution of criminal opportunities, and in the process decisions made by offenders (Andresen, 2014; Andresen, Brantingham, & Kinney, 2010; Brantingham, Patricia L. & Brantingham, 1993).

The Spatial Extent of Criminal Opportunity Theories

Taken together, opportunity theories predict that particular types of places can impact crime both at their location and in their surrounding area as a result of the spatial overlap of victim and offender travel. The impact of places on crime at their location should be relatively obvious – as described above, particular types of places tend to attract both potential victims and potential offenders. Some of these places are poorly managed and offer a larger number of criminal opportunities. Offenders take advantage of these opportunities, thus increasing the crime rate at those particular locations.

Places can also have an impact on surrounding area crime in at least three ways. First, some types of crime generators have characteristics which increase the likelihood of particular types of crime around them rather than at them. Transit stations, for instance, are robbery crime generators because they bring together many people. However, because they attract a large number of people, and as such many potential guardians, it is not until riders walk away from their station and into areas with less guardianship that the opportunity for robbery arises (Block & Davis, 1996). Similarly, bars can act as assault generators because they contain a lot of drunk customers. But because many bar managers do not tolerate fighting within their bars, fights can spill outside leading to higher street block assault levels (Scott, 2001).

Second, crime attractors bring together offenders who are interested in taking advantage of the available opportunities in the area (Brantingham & Brantingham, 1995). The concentration of motivated offenders in the areas surrounding crime attractors is hypothesized to lead to higher street level crime as a result of the increased number of criminal opportunities being taken advantage of by these offenders. In other words, all else being equal, a crime attractor is expected to have more crime in its surrounding area than an identical area without a crime attractor because of the influx of motivated offenders in the area that would not otherwise be there and able to notice and take advantage of criminal opportunities on their route to and from the crime attractor. This effect is furthered in areas with a high density of crime attractors and generators as a result of spatial clustering (Bowers, 2014; Deryol, Wilcox, Logan, & Wooldredge, 2016). Research findings that particular types of busy places (e.g. bars, restaurants) correlate with higher levels of crime in their area offer support for this mechanism (Wilcox & Cullen, 2018).

Third, and closely related to the scenario outlined above, is the idea of near-repeat victimization (Morgan, 2001). Once a target has been victimized, those near it spatially are at a higher risk of victimization for a short period of time thereafter (Bowers & Johnson, 2004; Haberman & Ratcliffe, 2015; Johnson et al., 2007; Townsley, Homel, & Chaseling, 2003). This is especially true for those that are similar targets (e.g. nearby houses that are similar in design to those that have been burgled). This is likely because offenders become more aware of their surroundings in a particular area the more time they spend there. The risk of victimization for surrounding places is thus 'boosted' as offenders become more aware of available criminal opportunities (Bowers & Johnson, 2004; Pease, 1998), and decide to take advantage of them because they require less effort than finding alternative opportunities (Townsley, Johnson, & Ratcliffe, 2008). For this mechanism, as well as the two others outlined above, the effect of places are expected to be strongest in the areas directly adjacent to them and to dissipate as one moves farther away.

Overall, the criminal opportunity theories discussed in this chapter provide a useful framework for understanding and studying crime at proprietary and proximal places. They are particularly useful for explaining crime variation among and around facilities (Eck et al., 2007), a central concept in this dissertation.

CHAPTER 3: RESEARCH ON PLACES AND CRIME

Two bodies of crime and place research are directly relevant to this dissertation. The first looks at the impact of facilities on crime. The second looks at the concentration of crime across places. This dissertation ties together and builds on these two lines of enquiry, particularly looking at their implications for the measurement of risky facilities. Together, the study findings presented in this chapter provide empirical support for operationalizing risky facilities in studies of crime and place based on an *Assumption of Crime Concentration*, whereby places of the same type are expected to have differential impacts on crime as a result of their individual criminogenic risk factors.

I begin this chapter by overviewing research estimating the impact of facilities on crime. Thereafter I discuss research that assesses how crime concentrates across space, including within facilities of the same type. Next, I highlight the inconsistencies between crime concentration research and the *Assumption of Crime Homogeneity* approach often taken to study the impact of facilities on crime. I conclude the chapter by overviewing research on crime stability which suggests one potentially fruitful alternative avenue for capturing facility crime risk is via historic crime data.

Research on the Impact of Facilities on Crime

There is an extensive body of research that assesses the impact of particular types of places on crime at their location and in their surrounding area. These studies have contributed to the now common understanding that a wide breadth of facility sets can increase crime. Some of the first studies estimating the impact of individual types of facilities on crime were conducted by Dennis W. Roncek and his colleagues. Roncek argued that "isolating the associations between specific land uses and crime is important for understanding how much, if at all, each type of land use is linked with different types and amounts of criminal activity" (Roncek & Maier, 1991, p. 727). To this end, he conducted a series of studies on various facility sets to estimate their impact on crime in their surrounding area. First, Roncek and Bell (1981) studied the effects of Cleveland, Ohio bars on street block level violent and index crime. They found that the number of bars on each residential street block was significantly and positively correlated with both types of crime. The same year, Roncek, Bell, and Francik (1981) assessed the impact of public housing projects on crime in adjacent residential city blocks in Cleveland, Ohio. They found that closer proximity to public housing resulted in significant increases in violent crime. Likewise, Roncek and LoBosco (1983) conducted a study of the effects of adjacency to high schools in San Diego, and found that public high schools, but not private ones, had significantly higher crime in their area. Later, Roncek and his colleagues replicated the initial studies of bars and high schools and found similar results (Roncek & Faggiani, 1985; Roncek & Pravatiner, 1989; Roncek & Maier, 1991).

Many have followed Roncek's approach, and there is now a wide breadth of research indicating that a variety of facility types are criminogenic, with higher crime at their location or in their area. Criminogenic facilities identified in these studies include ATMs, alcohol/liquor stores, apartments and other high density residential housing, banks, bars and taverns, check cashing stores, corner or convenience stores, drug treatment centers, fast-food restaurants, pawn shops, playgrounds and parks, police/fire stations, public facilities, public housing, public transit stations, schools, sit-down restaurants, slaughterhouses, and surf spots (e.g. Block & Davis, 1996; Block & Block, 2000; Fitzgerald, Kalof, & Dietz, 2009; Haberman & Ratcliffe, 2015; Kelsay & Haberman, 2020; Kennedy et al., 2016; McCord, Eric S. & Ratcliffe, 2007; Stucky & Ottensmann, 2009; Weisburd et al., 2012; White & Muldoon, 2015; Xu & Griffiths, 2017).

The general approach taken by most of these studies is to assess the impact of a single facility on crime by aggregating the presence of the facility to some proximal place unit of analysis, either by counting the number of facilities, dichotomously indicating the presence of any facility in each unit, measuring the proportion of each unit covered by a particular facility type, or measuring the distance from each unit to the closest facility of the studied type. Then, a statistical model, usually a regression or location quotient, is used to compare crime at proximal places with and without the studied facility. These studies all rely on an *Assumption of Crime Homogeneity*, whereby all places of the same type are assumed to have the same riskiness and thus the same impact on crime in their area. This assumption results in an operationalization of facilities that treats all places the same, regardless of how much crime actually occurs at or around them.

More recently, this approach has been expanded and used to assess the impact of multiple facilities simultaneously. These comprehensive studies of crime and place incorporate numerous facilities into multivariate models to isolate the effects of each facility type on crime while controlling for the presence of other facilities and relevant socioeconomic disadvantage variables. As with the single facility studies overviewed above, most multi-facility studies of crime and place tend to measure facilities either as dichotomous indicators, counts, proportions of area covered, distance to nearest facility, or some combination thereof (e.g. Bernasco & Block, 2011; Boessen & Hipp, 2015; Bowers, 2014; Haberman & Ratcliffe, 2015; Kelsay & Haberman, 2020; Kennedy et al., 2016; McCord & Ratcliffe, 2007; Smith et al., 2000; Stucky & Ottensmann, 2009; Xu & Griffiths, 2017). As such, all places of each studied facility type tend to be treated as equally risky. A selection of single and multi-facility studies and their underlying facility measurement assumptions are summarized below in Table 1.

Table 1. Assumptions Underlying Facility Measurement in a Selection of Studies of Crime and Place

Study (Year)	City	Number of Facilities Studied	Type(s) of Facilities Studied	Facility Operationalization	Crime(s) Studied	Analysis Method	Assumption(s) Underlying Facility Operationalization
Single Facility Studies							
Dario, Morrow, Wooditch & Vickovic (2015)	Ventura, California	1	Surf spots	Euclidean distance to surf spot	Police incident reports	Negative binomial regression of street segments	Crime Homogeneity
Groff (2011)	Seattle, Washington	1	Bars	Buffers measured around all bars using Euclidean and street network distance	Crime incidents	Location quotient; ANOVA	Crime Homogeneity
Groff (2013)	Seattle, Washington	1	Drinking places	Simple count of facilities, inverse distance weighted count of facilities, and distance weighted activity	Crime incidents	Bivariate local indicator of spatial association	Crime Homogeneity *and* Crime Concentration (Distance Weighted Activity measures assume differential impact of bars on crime via varying activity potential of each place)
Groff (2014)	Seattle, Washington	1	Drinking places	Count of facilities and inverse distance weighted count of facilities	Violent crime incidents	Negative binomial regression of street segments	Crime Homogeneity
Groff & McCord (2012)	Philadelphia, Pennsylvania	1	Parks	Park environs; presence of particular facility characteristics	Violent crime, property crime, disorder	Location quotient of park environs compared to rest of city	Crime Homogeneity *and* Crime Concentration (parks assessed for differential impact on crime via the presence of particular park characteristics)
Haberman, Clutter & Henderson (2018)	Cincinnati, Ohio	1	Bike-sharing stations	Facility presence	Street robbery	Multi-level logistic regression of street intersection centered Thiessen polygons	Crime Homogeneity
Kubrin, Squires, Graves & Ousey (2011)	Seattle, Washington	1	Payday lenders	Number of facilities divided by the population	Violent crime rates; property crime rates	Ordinary least-squares and two-stage least-squares regressions of census tracts	Crime Homogeneity

Study (Year)	City	Number of Facilities Studied	Type(s) of Facilities Studied	Facility Operationalization	Crime(s) Studied	Analysis Method	Assumption(s) Underlying Facility Operationalization
McCord & Houser (2017)	Philadelphia, Pennsylvania and Louisville, Kentucky	1	Parks	Park environs	Outdoor violent crime; outdoor property crime; outdoor disorder crime	Location quotient of park environs compared to rest of city and ANOVA of park characteristics	Crime Homogeneity *and* Crime Concentration (parks assessed for differential impact on crime via the presence of particular characteristics)
McCord & Ratcliffe (2009)	Philadelphia, Pennsylvania	1	Subway stations	Crime around subway stations	Street Robbery	Location quotients and t-tests of subway stations compared to a random sample of street corners	Crime Homogeneity *and* Crime Concentration (Intensity Value Analysis calculated for individual facilities acts as a continuous measure of facility risk)
Roncek & Bell (1981)	Cleveland, Ohio	1	Bars	Count of bars	Murder, rape, assault, robbery, burglary, grand theft, auto theft, total violent crime, total index crime	T-tests of all crimes on blocks with and without bars; Multiple linear regression on residential city blocks of only total violent and total index crime	Crime Homogeneity
Roncek, Bell, & Francik (1981)	Cleveland, Ohio	1	Public housing projects	Size of public housing project; distance to public housing projects; adjacency to public housing projects	Total violent crime, total property crime	T-tests of crime on blocks with and without public housing; Multiple linear regression of crime on residential city blocks	Crime Homogeneity
Roncek & Faggiani (1985)	Cleveland, Ohio	1	High schools	Adjacency to high school (high school either in focal block or in block directly adjacent)	Murder, rape, assault, robbery, burglary, grand theft, auto theft, total violent crime, total property crime, total index crime	T-tests of crime on blocks with and without high schools; Multiple linear regression of crime on residential city blocks	Crime Homogeneity
Roncek & LoBosco (1983)	San Diego, California	1	High schools	Adjacency to high school (high school either in focal block or in block directly adjacent)	Murder, rape, assault, robbery, burglary, grand theft, auto theft, total violent crime, total property crime, total index crime	T-tests of crime on blocks with and without high schools; Multiple linear regression of crime on residential city blocks	Crime Homogeneity

Study (Year)	City	Number of Facilities Studied	Type(s) of Facilities Studied	Facility Operationalization	Crime(s) Studied	Analysis Method	Assumption(s) Underlying Facility Operationalization
Roncek & Maier (1991)	Cleveland, Ohio	1	Taverns/cocktail lounges	Count of facilities in each unit	Murder, rape, robbery, aggravated assault, burglary, grand theft, auto theft, total violent crime, total property crime, total index crime	T-tests of crime on blocks with and without taverns or cocktail lounges; Multiple linear regression of crime on residential city blocks; Tobit models	Crime Homogeneity
Roncek & Pravatiner (1989)	San Diego, California	1	Taverns/bars	Count of facilities in each unit	Murder, rape, robbery, aggravated assault, burglary, grand theft, auto theft, total violent crime, total property crime, total index crime	Multiple regression analysis of residential city blocks	Crime Homogeneity
Multiple Facility Studies							
Barnum, Caplan, Kennedy & Piza (2017)	Chicago, Illinois; Newark, New Jersey; Kansas City, Missouri	14	Bars, bus stops, drug markets, foreclosures, gas stations, grocery stores, health centers and gyms, laundromats, liquor stores, parking stations, parks, pawn shops, schools, variety stores	Density of facilities and proximity to facilities	Robbery	Risk terrain modelling	Crime Homogeneity *and* Crime Concentration (facilities expected to have homogenous impact within each city, but to differ across cities)
Bernasco & Block (2011)	Chicago, Illinois	10	Bars/clubs, restaurants/fast food outlets/food stands, barbershops/beauty salons, elevated train stations, liquor stores, grocery stores, general merchandise shops, gas stations, laundromats, pawn shops/currency exchange/check-cashing	Count or indicator of the presence of all facilities (a subset of facilities - bars, clubs, fast food restaurants, barbers, and beauty salons – were included only if they had 10 or fewer employees, presumably as a result of data availability, though no explanation was offered for this choice)	Street robbery	Negative binomial regression of census blocks	Crime Homogeneity

Study (Year)	City	Number of Facilities Studied	Type(s) of Facilities Studied	Facility Operationalization	Crime(s) Studied	Analysis Method	Assumption(s) Underlying Facility Operationalization
Bowers (2014)	Large metropolitan area, United Kingdom	4	Retail, recreational, service, other commercial use	Facility counts; risky facilities identified by increasing threshold of thefts (2+, 3+, 4+)	Theft from person	Spatial regression of 50m x 50m grid cells	Crime Homogeneity *and* Crime Concentration (some models done with homogenous measures of all parcel types, other models included variable representing the number of risky facilities with 2+, 3+, or 4+ thefts only)
Brantingham & Brantingham (1982)	New Westminster, British Columbia	5	Fast food restaurants, department stores, grocery store, pubs, regular restaurants	Random sample of the population was asked to identify the three best known locations of each facility type (except for pubs), in order to capture the facilities within the awareness space of individuals (all pubs were included)	Commercial burglary	Burglary rates for blocks surrounding studied facilities	Crime Concentration *and* Crime Homogeneity (only pubs assumed to have homogenous effect)
Clutter, Henderson, & Haberman (2019)	Cincinnati, Ohio	20	Body art parlors, bus stops, business improvement districts, check cashing and pawn stores, drinking places, drug treatment centers, eating places, entertainment places, everyday stores, grocery stores, high schools, higher education, hotels, laundry, parks, public housing, public libraries, recreation centers, retail stores, salons/barbers	Count of facilities, street network distance to facilities, and presence of facilities	Street robbery	Negative binomial regression of street blocks	Crime Homogeneity
Drawve & Barnum (2017)	Little Rock, Arkansas	14	Banks, big box retail stores, bus stops, check-cashing stores, convenience marts, fast food restaurants, grocery stores, hotels/motels, liquor stores, lottery retailers, pawn shops, public high schools, restaurants/bars, tattoo/piercing parlors	Density of facilities and proximity to facilities	Aggravated assault	Risk terrain modelling	Crime Homogeneity *and* Crime Concentration (facilities expected to have homogenous impact within each police division, but to differ across police divisions)
Duru (2010)	Bursa, Turkey	5	High schools, mosques, on-premise alcohol outlets, points of interest, Turkish coffeehouses	Count of facilities	Burglary, theft, auto-theft, theft from auto, violent crime, total crime	Multi-level multivariate Poisson modeling of street blocks nested within neighbourhoods	Crime Homogeneity
Groff & Lockwood (2014)	Philadelphia, Pennsylvania	5	Bars, drug treatment centers, halfway houses, schools, subway stops	Facility exposure (measured using inverse distance weighting)	Violent crime, property crime, disorder	Negative binomial regression of street segments	Crime Homogeneity

Study (Year)	City	Number of Facilities Studied	Type(s) of Facilities Studied	Facility Operationalization	Crime(s) Studied	Analysis Method	Assumption(s) Underlying Facility Operationalization
Haberman, Groff & Taylor (2013)	Philadelphia, Pennsylvania	10	Beer establishments, check-cashing businesses, drug treatment centers, halfway houses, high schools, homeless shelters, parks, pawn brokers, public housing communities, subway stations	Proximity	Robbery	Multi-level count models of public housing communities nested within the buffer areas surrounding them	Crime Homogeneity *and* Crime Concentration (public housing communities assessed for differential impact on crime via the presence of particular characteristics)
Haberman & Ratcliffe (2015)	Philadelphia, Pennsylvania	12	ATMS and banks, alcohol stores, bars, check-cashing stores, corner stores, drug-treatment centers, high schools, parks, subway stops, fast-food restaurants, pawn shops, public housing	Count of facilities	Street robbery	Negative binomial regression of census blocks	Crime Homogeneity
Houser, McCord, & Nicholson (2018)	Philadelphia, Pennsylvania	5	Beer bars/outlets, churches, drug treatment centers, liquor stores, restaurants	Count and presence of facilities	Parolee recidivism	Logistic regression and linear regression of parolee living area (measured using the .25 miles surrounding each parolee residence)	Crime Homogeneity
Irvin-Erickson (2014)	Newark, New Jersey	21	At-risk housing, auto repair shops, banks, bars, car dealers, car washes, cemeteries/crematories, churches, gas stations, grocery stores, hair/nail salons, laundries/drycleaners, libraries, light rail stops, liquor stores, pawn shops, post offices, retail stores, schools, sit-down restaurants, take-out restaurants	Distance to facility	Street robbery	Negative binomial regressions of 100ft by 100ft grid cells; Risk terrain models	Crime Homogeneity
Kennedy, Caplan, Piza, & Buccine-Schraeder (2016)	Chicago, Illinois	18	Apartment complexes, automatic teller machines, bars, bus stops, foreclosures, gas stations, gas stations with convenience stores, grocery stores, healthcare centers/gymnasiums, homeless shelters, laundromats, liquor stores, nightclubs, post offices, recreation centers/rental halls, retail shops, schools, variety stores	Distance to facility and density of facilities	Aggravated assault	Risk terrain models of 426ft by 426ft grid cells	Crime Homogeneity *and* Crime Concentration (facilities measured homogenously, but additional variable representing problem buildings identified by police was included in the analyses)
LaGrange (1999)	Edmonton, Alberta	2	High schools, large shopping malls	Facility presence	Mischief and vandalism incidents	Ordinary least square regression of census enumeration areas	Crime Homogeneity

Study (Year)	City	Number of Facilities Studied	Type(s) of Facilities Studied	Facility Operationalization	Crime(s) Studied	Analysis Method	Assumption(s) Underlying Facility Operationalization
Miller, Caplan, & Osterman (2016)	Newark, New Jersey	9	Bars/clubs, bus stops, light rail stops, liquor stores, parks, retail stores, schools, sit-down restaurants, take-out restaurants	Counts of facilities and indicators of facility presence	Parolee failure	Cox proportional hazards survival models of parolee home nodes (measured using the 1240 ft surrounding each parolee residence)	Crime Homogeneity *and* Crime Concentration (facilities measured homogenously, but additional variable representing crime prone housing identified by police was included in the analysis)
Smith, Frazee, and Davison (2000)	Midsized southeastern U.S. city	8	Bars/restaurants/gas stations, commercial places/businesses/industries/warehouses, hotels/motels, owner occupied places, multifamily residential buildings, stores, vacant/parking lots, youth related places	Count of facilities	Street robbery	Two-stage least-squares regression of street blocks	Crime Homogeneity *and* Crime Concentration (facilities measured homogenously, but variables representing potential interactions between facilities and social disorganization variables were included)
Stucky & Ottensmann (2009)	Indianapolis, Indiana	6	Cemeteries, schools, hospitals, parks, vacant buildings, high-density residential buildings	Dichotomous indicators of presence; percentage of land within each grid cell occupied by a facility	Murder, nonnegligent manslaughter, rape, robbery, aggravated assault, total violent crime	Negative binomial regression of 1000ft square grid cells	Crime Homogeneity
Weisburd, Groff, & Yang (2012)	Seattle, Washington	5	Bus stops, police/fire stations, public facilities (including community centers, parks, libraries, middle/high schools, hospitals), public housing, vacant land	Count of facilities or percentage of land covered	All crime incidents	Multinomial logistic regression of the odds of being in a chronic crime trajectory street segment versus a no crime street segment	Crime Homogeneity
Xu & Griffiths (2017)	Newark, New Jersey	8	Bus stops, fast food/take out eateries, foreclosures, gas stations, grocery stores, laundry/dry-cleaning stores, liquor stores, middle/high schools	Presence of facilities	Gun shootings	Network Cross K-function test of facility and crime points	Crime Homogeneity

Groff (2014) introduced a more complex measure of facility risk based on an inverse street network distance weighted count. In this approach, proximal place units are assigned an exposure value based on the number of facilities in each area, with nearer establishments given higher weight than those farther away. Groff (2014) found that the inverse distance measure strongly outperformed simple count measures of facilities. Groff and Lockwood (2014) used this approach to study the effect of facilities on crime in Philadelphia, Pennsylvania. Notably however, this approach still represents a homogenous risk measure of facilities, as all places of a particular type are included in facility operationalization, they are just expected to have less of an impact the farther away one travels from them.

The *Assumption of Crime Homogeneity* also guides facility measurement in some predictive crime modeling when facilities are incorporated into analyses, often as part of risk terrain models (see for example Barnum et al., 2017; Caplan, Kennedy, & Miller, 2011; Drawve, Moak, & Berthelot, 2016; Groff, Elizabeth R. & LaVigne, 2001; Kennedy, Caplan, & Piza, 2011). Kennedy, Caplan and Piza (2011) for instance incorporated homogenous measures of bars, social clubs, liquor stores, dance halls, and take-out restaurants in their risk terrain models of gun violence in Newark, New Jersey. Likewise, in their comparison of the effectiveness of risk terrain models and retrospective hotspot mapping for predicting future shootings in Irvington, New Jersey, Caplan, Kennedy, and Miller (2011) controlled for retail businesses, including bars, strip clubs, bus stops, check cashing stores, pawn shops, fast food restaurants, and liquor stores, collectively rather than including only criminogenic locations. This approach has also been incorporated into some predictive policing software. For example, CivicScape (2017) incorporates relevant vacant building data when available and includes all reported vacant buildings rather than just criminogenic ones.

Studies that diverge from this *Assumption of Crime Homogeneity* approach are few, and do not tend to be consistent in their measurement of facilities. However, underlying most of these studies is an *Assumption of Crime Concentration*, whereby places of the same type are expected to have differential impacts on crime as a result of their individual criminogenic risk factors. For instance, Brantingham and Brantingham (1982) surveyed respondents and had them identify the three most well-known locations of each place type studied, including fast food restaurants, department stores, grocery stores, regular restaurants, and pubs, while Bichler, Malm and Enriquez (2014) used social network statistics to identify convergence settings where delinquent and/or criminal juveniles interact. Likewise, in their study of the impact of criminogenic places on parole success, Miller, Caplan, and Osterman (2016) operationalized residential places by including only crime prone locations identified through police intelligence. However, the remainder of their facility variables were measured homogenously akin to the *Assumption of Crime Homogeneity* studies discussed above.

Bernasco and Block (2011) used an approach similar to the other multi-facility studies discussed above (e.g. Haberman & Ratcliffe, 2015; Stucky & Ottensmann, 2009) to assess the effects of ten different facilities on street robbery across census blocks in Chicago. However, for three of their facility types (bars/clubs, restaurants/fast food outlets/food stands, barbershops/beauty salons) they excluded businesses with 11 or more employees from their analysis, leaving them with only a subset of each facility. Though the assumption underlying this operationalization decision was not explained in their paper, it seems likely it was result of data availability rather than a belief that stores with less than 11 employees are particularly risky, as the remaining seven facilities included in their study were measured homogenously.

Notably, Bowers (2014) operationalized facility riskiness by using an *Assumption of Crime Concentration*, at least in part, in her study of the impact of at-facility crime on crime in the surrounding area in a large city in the UK. Specifically, she ran a series of models with risky facilities defined as those experiencing increasingly higher levels of theft (i.e. number of facilities with two or more, three or more, or four or more thefts).

One approach for quantifying facility risk based on an *Assumption of Crime Concentration* has been proposed by McCord and Ratcliffe (2009). Like Groff's (2014) approach, discussed above, McCord and Ratcliffe (2009) also suggest using an inverse weighted approach to quantify the criminogenic risk of facilities. They propose intensity value analysis (IVA), which can be used to create a single global measure of crime clustering in a specified buffer area around each facility set. Similar to inverse distance weighting, intensity value analysis ascribes higher values to crimes occurring closer to the studied facility sets, and lower values to those occurring farther away. Like Groff's (2014) measure, this global measure of crime clustering relies on an *Assumption of Crime Homogeneity,* as it incorporates all facilities of a given type into its calculation. However, this measure can also be used to create individual IVA values for each facility, as McCord and Ratcliffe (2009) demonstrate in their example application of the IVA approach to the assessment of crime at 22 subway stations and 500 street corners in Philadelphia, Pennsylvania. Here, they showed that though the intensity values calculated for subway stations tended to be significantly higher than random streets corners, there was still a large amount of variation in the individual values calculated for each subway station. When used in this manner, this approach represents a facility risk operationalization based on an *Assumption of Crime Concentration*.

Interestingly, though the approach to studying crime around facilities has been mostly uniform, the results of such research have not been. Many facilities have been found to have different impacts on crime across studies. For instance, Haberman and Ratcliffe (2015) found no spatially immediate effect of alcohol stores and bars on robbery across census blocks in Philadelphia, while Bernasco and Block (2011) found an effect for both in Chicago. Likewise, Ridgeway and MacDonald (2017) found no effect for transit stations on crime, while Hart and Miethe (2014), Bernasco and Block (2011), and Haberman and Ratcliffe (2015) did.

These differences extend to direct comparisons of models across and within cities. Barnum et al (2017) used risk terrain modelling to compare risk factors for robbery across three cities – Chicago, Newark, and Kansas City. They found that facility risk factors were not consistent across cities. Specifically, of the 14 places tested[7], 12 were risk factors in Chicago, 10 were in Newark and eight were in Kansas City. Six places including (1) bus stops, (2) drug markets, (3) foreclosures, (4) gas stations, (5) grocery stores, and (6) liquor stores, were risk factors in all three cities but varied in their intensity. Further, Drawve and Barnum (2017) found the impact of facilities on aggravated assault to vary across Little Rock, Arkansas police divisions, including (1) convenience stores, (2) grocery stores, (3) fast food restaurants, (4) hotels and motels, (5) lottery retailers, and (6) public high schools. The only consistent predictors across all police divisions were bus stops and liquor stores.

The fact that the results of facility research are not consistent across studies can be at least partially understood through the lens of the second body of crime and place research relevant to this dissertation[8] – that which looks at the concentration of crime across places, and in particular across places of the same type. Findings from this body of research suggest that crime concentrates non-randomly in space and that this concentration is relatively stable over time. They further

[7] Including (1) bars, (2) bus stops, (3) drug markets, (4) foreclosures, (5) gas stations, (6) grocery stores, (7) health centers and gyms, (8) laundromats, (9) liquor stores, (10) parking stations, (11) parks, (12) pawn shops, (13) schools, and (14) variety stores

[8] An alternative explanation for these disparate findings is that the locations the studies were conducted in have differing urban mosaics resulting in different crime patterns (Kinney et al., 2008).

suggest that high-crime and low-crime locations are located near one another, possibly as a result of micro-place differences in opportunity theory concepts such as highly trafficked nodes, the convergence of offenders and targets, and place manager decision making. Particularly relevant to this dissertation is the fact that, despite the findings presented earlier in this chapter which showed that some facilities significantly impact crime in their area, research has found that *even within and around similar types of places there is variation in crime*. This is consistent with the expectations of criminal opportunity theories.

Crime Concentrates in Space

Rather than assess the relationship between place type and crime, another body of research assesses the spatial distribution of crime across broad geographic areas and has consistently found that crime is non-randomly distributed in space. First, Pierce, Spaar, and Briggs (1988) found that 18% of street addresses produced 75% of calls for police assistance in Boston, Massachusetts, while less than 1% accounted for almost a quarter of calls. This finding that a small number of places was responsible for a disproportionately large amount of crime also held true at the blockface, street intersection, and neighborhood levels of analysis. Another early study examined 323,979 calls for service made to the Minneapolis, Minnesota police over a one-year period (Sherman et al., 1989). This too found that crime concentrated, with 50% of crimes occurring at a mere 3% of the city's roughly 115,000 addresses and intersections. Further, 95% of places experienced no predatory crime at all. More recently, Weisburd, Groff and Yang (2012) found that less than 6% of street segments contained 50% of crime incidents in Seattle, Washington between 1989 and 2004, and that all crimes occurred on 60% to 66% of streets segments each year. This high level of crime concentration persisted even after a city-wide crime decline of over 20% (also see Gill, Wooditch, & Weisburd, 2017; Groff, Weisburd, & Morris, 2009; Groff, Weisburd, &

Yang, 2010; Weisburd et al., 1993; Weisburd & Green, 1995; Weisburd, Bushway, Lum, & Yang, 2004; Weisburd, 2015).

Spatial concentrations of crime have also been found in research outside the United States. For instance, several studies have found that both violent and property crime concentrate across multiple units of analysis in Canadian cities (Andresen & Malleson, 2011; Andresen & Linning, 2012; Andresen, Linning, & Malleson, 2017; Wuschke, 2016). Likewise, geographic concentrations of crime have been noted at street segments in Tel Aviv-Jaffa, Israel (Weisburd & Amram, 2014), Campinas, Brazil (de Melo, Matias, & Andresen, 2015), and Milan, Italy (Favarin, 2018), across grid cells in police districts in Jaipur, India (Mazeika & Kumar, 2016), and in self-reported burglaries in Malawi (Sidebottom, 2012).

Crime concentrations have been noted in both qualitative (St. Jean, 2007) and quantitative studies, including both urban (Braga, Papachristos, & Hureau, 2010; Sherman et al., 1989) and rural areas (Gill et al., 2017). They have been observed across different temporal scales (Haberman, Sorg, & Ratcliffe, 2017) and across a variety of crime types. This includes crime aggregates (Sherman et al., 1989; Weisburd et al., 2012) and individual crimes, such as burglary (Polvi, Looman, Humphries, & Pease, 1991), sexual assault (Sherman et al., 1989), shootings (Braga et al., 2010; Sherman & Rogan, 1995), robberies (Braga, Hureau, & Papachristos, 2011), and domestic disturbances (Sherman et al., 1989). Finally, crime concentration findings also persist across a variety of data types, including police incident data (e.g. Braga et al., 2010; Braga et al., 2011; Dario et al., 2015; Gill et al., 2017), police calls for service data (e.g. O’Brien & Winship, 2017), self-report survey data (e.g. Hope, 1982; Madensen, 2007; Nelson, 1980; Sidebottom, 2012), and emergency services data (e.g. Hibdon, Telep, & Groff, 2017).

The remarkable consistency of findings across this extensive body of crime concentration research has led Weisburd, Groff, and Yang (2012) and Weisburd (2015) to put forth that a law of crime concentration exists. The law of crime concentration states that a large proportion of crime will always concentrate within a narrow percentage range of places. Weisburd (2015) supported this hypothesis by conducting a comparison of crime incident concentrations at street segments in eight cities including Redlands, Ventura, and Sacramento, California; Brooklyn Park, Minnesota; Cincinnati, Ohio; Seattle, Washington; New York, New York; and Tel Aviv-Jaffa, Israel[9]. He found that even though the cities had different populations, crime rates, social characteristics, and average street segment lengths, 50% of crime concentrated in 2.1-6.0% of street segments while 25% concentrated in 0.4-1.6% of street segments in each place.

Recent research suggests these crime concentration bands may be too narrow and that findings related to the concentration of crime can vary as a result of measurement, unit of analysis, study location, and crimes studied (Hibdon et al., 2017; Hipp & Kim, 2017; Lee, Eck, O, & Martinez, 2017). Further, crime concentration appears to increase at smaller units of analysis (Andresen & Malleson, 2011). Nevertheless, the overarching theme remains - a small number of places are consistently responsible for a disproportionately large amount of crime, regardless of unit of analysis used or location observed. Importantly, these findings are exactly what opportunity theories of crime would predict. Places with an abundance of criminal opportunities are expected to have disproportionately high crime levels, while places with few opportunities are expected to have few or no crimes.

[9] Referred to as the Hebrew Tel Aviv-Yafo in Weisburd (2015), here translated to the English Tel Aviv-Jaffa to highlight that the city is the same as that studied in Weisburd & Amran (2014), discussed above

The Concentration of Crime Within Facility Sets

As noted earlier in the chapter, findings about the impact of facilities on crime sometimes differ across studies. The inconsistency in facility research results may be partially explained by the fact that crime, and the influence of places on crime, has also been found to concentrate *within* facility sets. For instance, though Roncek and Maier (1991) are often cited as an example of bars increasing crime in their area, the authors actually found that only *some* bars increased crime (Payne, 2010). Indeed, their findings indicated that over a quarter of blocks with taverns and cocktails lounges fell *below* the city's median number of violent crimes. This is echoed by Grubesic and Pridemore's (2011) finding that only some clusters of alcohol serving outlets in Cincinnati, Ohio increased assault in their area, while others did not.

This concentration finding extends to other types of facility sets, and other types of crimes, as well. For instance, Sidebottom and Bowers (2010) found that within a single chain of London, UK bars bag theft widely varied, from 2 to 221 thefts over two years. This variation persisted even after controlling for bar seating capacity. Likewise, Matthews, Pease, and Pease (2001) showed that robbery concentrated among bank branches in the Metropolitan Police District in the United Kingdom, and Kinney et al (2008) found that crime concentrated within a variety of land uses in Burnaby, British Columbia.

Haberman, Groff, and Taylor (2013) investigated the effects of public housing communities on street robberies in their surrounding area in Philadelphia, Pennsylvania. Buffers of 50 feet, 450 feet, and 850 feet were used to assess the spatial spread of violence. The authors accounted for compositional differences across buffers by controlling for the presence of nine facility types. Using multi-level models, they found that crime significantly decreased by 34% for each additional buffer distance traveled away from a public housing community. Importantly however, they also found significant variation in robbery levels across communities, with some communities having lower crime levels than their surrounding buffers, rather than higher. As such they concluded that "painting all public housing communities with the same brush, as comparably powerful generators of robbery for spaces in and immediately around them, is misleading" (p. 178) and that "researchers should use caution before labeling a particular facility type as criminogenic" (p. 179).

Further, even within a small population of a known problematic group of facilities, such as the motels of Chula Vista, California, wide variations in crime have been found. Specifically, the calls for service rate at motels was found to range from 0.11 to 2.77 calls per room (Schmerler, Hunter, Eisenberg, & Jones, 2009). Differences in calls for service across motels could not be accounted for by room rates or neighborhood levels of crime. In fact, the highest and lowest calls for service locations were located directly across the street from one another.

Troublesome Places

The above findings suggest that the riskiness of places within facility sets is not constant, and that some differences may exist between facilities of the same type to differentiate their levels of crime. Eck, Clark, and Guerette (2007) examined this idea by assessing the distribution of crime across a wide breadth of facility sets. Their analysis included 37 studies with a variety of outcome variables (e.g. crime incidents, calls for service, self-report surveys), and 17 different facility types, including (1) bars, (2) retail stores, (3) apartment complexes, (4) non-chain and (5) national chain motels, (6) sports facilities, (7) telephone booths, (8) young offender institutions, (9) parking lots, (10) schools, (11) healthcare facilities, (12) convenience stores, (13) fast-food establishments, (14) gas stations, (15) construction sites, (16) bus stop shelters, and (17) banks. Though their analysis did not represent a hypothesis test as the included studies were purposively sampled to illustrate a particular point, their findings did suggest that crime is highly concentrated within facility sets, with a small number of risky facilities accounting for most crime, while the majority of facilities have either low or no crime.

Subsequent research on facility crime concentration has supported Eck, Clark, and Guerette's (2007) assertions (see for example Blair, Wilcox, & Eck, 2017; Eck et al., 2009; Haberman et al., 2013; Payne, 2010). A facility type that defies this distribution has yet to be identified – indeed this skewed distribution of crime at facilities is so pervasive that Wilcox and Eck (2011) called it the "Iron Law of Troublesome Places". This has led some researchers to raise the potential benefit of controlling for varying risk levels within facilities or land uses, rather than controlling for them as a uniform group (Blair et al., 2017, p. 79; Kennedy et al., 2011, p. 347).

Wilcox and Eck (2011) have argued that it may be "the busy nature of facilities in general and the busy context in which facilities are often situated, rather than the facility type itself, that generates crime" (p. 476). This busyness hypothesis is consistent with the predictions of crime opportunity theory. As described earlier in Chapter 2, from the Geometry of Crime, busy places are those paths and nodes that are highly trafficked (Brantingham, Paul J. & Brantingham, 1993). As per the Routine Activities Approach, these places are expected to have more crime than those with less traffic as they increase the likelihood that offenders and victims come together in a poorly managed place which lacks capable guardians and offender handlers (Cohen & Felson, 1979; Eck, 1994; Felson, 1986).

Research on busyness and crime has been historically limited by a lack of good micro-level ambient population proxy measures (Andresen & Jenion, 2010; Malleson & Andresen, 2016). Some recent research however does support the hypothesis that busy places generate crime. Specifically, Askey, Taylor, Groff, and Fingerhut (2018) assessed the impact of fast food restaurant and convenience store revenue (a proxy for busyness) on street block crime levels in

Seattle using longitudinal multilevel models. They found that street blocks with higher sales also had significantly higher crime counts, even after controlling for the presence of surrounding retailers and local socio-economic status. A full model, including retail sales for all surrounding retailers as well as fast food restaurants and convenience stores, found that sales from all businesses also significantly correlated with yearly crime counts.

Importantly however busyness does not appear to be the sole predictor of crime concentration (Eck et al., 2007). Bowers (2014) found that theft risk varied across retail facilities in a UK metropolitan area even after controlling for ambient population using a proxy variable measuring the through-movement potential of each street segment. Likewise, Sidebottom and Bowers (2010) used a count of seats in bars as a proxy for busyness and found no relationship between that measure and the level of bag theft in 26 London, UK bars.

Risky Facilities as Crime Radiators

Research has also found that risky facilities can increase crime in their area by acting as crime radiators (Bowers, 2014). As discussed in the previous chapter, criminal opportunity theories would predict that criminogenic places can have an impact on crime levels at their immediate location as well as in their area. Differences in crime radiating effects across places are thought to be a result of differences in place characteristics that impact the convergence of motivated offenders, suitable targets, and inadequate guardianship and offender handling (Brantingham, Paul J. & Brantingham, 1993; Cohen & Felson, 1979; Madensen, 2007; Madensen & Eck, 2008; Madensen & Eck, 2012).

Bowers (2014) investigated the relationship between internal and external levels of crime at micro-places by studying theft across 50x50 m grid cells in a United Kingdom metropolitan area. She assessed a variety of facilities in her study, including bars, restaurants, retail stores, and banks, among others. Crime was highly concentrated, with 20% of facilities accounting for 80%

of thefts. Bowers found a significant relationship between internal and external crime. Specifically, she found that the internal theft levels of places significantly correlated with the external theft levels of focal cells as well as the external theft levels of adjacent cells. Further, she found that theft times peaked internally prior to peaking externally. She thus concluded that risky facilities have a crime radiating effect, whereby internal levels of crime spill over and affect external levels of crime.

Moreover, she also found that increased numbers of risky facilities in close proximity led to higher levels of external theft, even after controlling for internal theft levels. Model fit improved as Bowers increased the inclusion threshold for risky facilities (i.e. shifting from a cut-off of one or more thefts, to two or more thefts, to three or more thefts, etc.). These findings persisted across sensitivity analyses, including tests of 100x100m grid cells and negative binomial models in addition to the original 50x50m grid cells and ordinary least squares regression models.

Further, research on offender crime location choices suggests that high-crime places act as crime attractors. For instance, Hanayama, Haginoya, Kuraishi, and Kobayashi (2018) used a discrete choice model to examine characteristics impacting neighborhood level residential burglary attractiveness in 500m by 500m grid cells in Sendai City, Japan. They found that both the raw number of past residential burglaries and the past residential burglary rate significantly increased the likelihood of a grid cell being chosen for future residential burglaries. Likewise, studies of burglary and robbery also suggest that a place's risk of victimization increases after it experiences a crime (Matthews et al., 2001; Polvi, Looman, Humphries, & Pease, 1990; Polvi et al., 1991). Johnson et al (2007) found that this risk extends to nearby locations as well (see also Johnson, 2008). This is consistent with the concept of crime attractors in the Geometry of Crime, as well as near-repeat victimization, which were discussed in Chapter 2.

Stability of Crime at Place

The above findings suggest two important points, both of which are consistent with criminal opportunity theories. First, higher crime facilities have a greater impact on crime in their surroundings than facilities with some, but not much, crime. And second, the concentration of these high crime locations may be a better predictor of micro-level crime than the concentration of particular types of facilities. Indeed, Bowers (2014) put forth that the "clustering in particular of the heavy weight high theft facilities appears to create riper conditions for crime in nearby locations" (p. 409). These study findings lend empirical support for operationalizing facilities in studies of crime and place based on an *Assumption of Crime Concentration*, whereby places of the same type are operationalized differently depending on their individual criminogenic risk factors.

But how to effectively operationalize facilities based on this assumption? In addition to Bowers' (2014) study discussed above, studies on the stability of crime at place offer some guidance. A number of studies have now examined whether high crime locations tend to remain as such and found that crime tends to remain stable at the proprietary and proximal place level over time. The findings of these studies suggest that one way to capture facility crime risk is using historic crime data.

To investigate the stability of crime over time, researchers have generally relied on two types of tests: group-based trajectory analysis and spatial point pattern tests. Originally used to model the criminal careers of offenders (Nagin & Land, 1993; Nagin & Odgers, 2010), group-based trajectory analysis (GBTA) is now also used to assess the stability of crime at place. GBTA approximates the number and pattern of unique latent groups using nonparametric maximum likelihood estimation (Nagin & Land, 1993; Nagin & Tremblay, 2005). While the resultant models are not an exact depiction of reality, this method simplifies complex longitudinal data by allowing for the segmentation of a continuous distribution that maximizes the similarity within groups and the differences between groups (Nagin & Tremblay, 2005; Piquero, 2008). This allows researchers to compare the relative ranking and contribution of crime patterns at micro-spatial units to city levels of crime over time.

This approach was first used by Weisburd, Bushway, Lum, and Yang (2004) to study crime and place when they assessed the crime trajectories of approximately 30,000 street segments over 14 years in Seattle, Washington. The authors identified 18 distinct trajectories. Many of these - eight of the 18 identified trajectories representing a full 84% of street segments - had stable crime levels over time. The remaining trajectories had either increasing or decreasing levels of crime and made up 2% and 14% of the studied street segments, respectively. This observation of general stability remained when the analysis was limited to juvenile crimes over the same time period (Groff et al., 2009; Weisburd, Morris, & Groff, 2009).

Weisburd, Groff and Yang (2012) later expanded on these analyses and examined crime in Seattle over a 16-year period, from 1989 to 2004. They too found that crime tended to be both highly concentrated and stable, with 1% of street segments falling into a chronically high crime trajectory responsible for 23% of the Seattle's total crime during the study time frame.

In the first study to use GBTA outside of Seattle, Curman, Andresen, and Brantingham (2015) assessed the developmental trajectories of Vancouver, British Columbia street segments between 1991 and 2006 for 22 categories of crime[10]. As with Seattle, very few Vancouver street segments had changes in crime levels over time. Indeed, most segments were stable, with a small number of segments being chronically high crime over each of the years studied. The authors supplemented their GBTA analysis with a k-means non-parametric cluster analysis, which also

[10] Including (1) arson, (2) assault, (3) assault in progress, (4) attempted break and enter, (5) attempted theft, (6) break and enter, (7) break and enter in progress, (8) drug arrest, (9) fight, (10) alarm, (11) holdup, (12) homicide, (13) purse snatching, (14) robbery, (15) robbery in progress, (16) shoplifting, (17) stabbing, (18) stolen vehicle, (19) sexual assault, (20) theft from vehicle, (21) theft, (22) theft in progress

groups places into trajectories but has less stringent assumptions than GBTA. The results of this analysis were largely the same as the GBTA analysis, suggesting that crime stability findings are not merely a by-product of the GBTA approach.

Wheeler, Worden, and McLean (2016) expanded the use of GBTA beyond the Pacific-Northwest to Albany, NY to determine if crime remained similarly stable in a smaller city situated in a different social and geographic context. Additionally, the authors broadened their unit of analysis to include street intersections in addition to street segments. Their findings were similar to those above, as were Gill et al's (2017) findings when they tested crime stability in a suburban area adjacent to Minneapolis, Minnesota.

Though the majority of group-based trajectory analysis studies of crime and place have focused on street segments, Payne and Gallagher (2016) used this approach to study the trajectories of individual addresses in Cincinnati, Ohio over a 15-year period. They too found that crime could be classified as mostly stable, with 60.8% of addresses falling into either low-crime stable (58.3%) or high-crime stable (2.5%) trajectories, the latter of which accounted for approximately 33% of crime over the study period.

The second method used to study the stability of crime at place is the spatial point pattern test (SPPT). Developed by Andresen (2009), the SPPT is a nonparametric area-based Monte Carlo test that compares spatial point patterns from two time periods to determine if statistically significant changes have occurred. The test produces a similarity measure ranging from 0, representing no similarity, to 1, representing complete similarity.

Andresen and Malleson (2011) used SPPT to compare calls for service data from 1991, 1996, and 2001 for several crimes across three units of analysis in Vancouver, British Columbia. They found that street segments, dissemination areas (akin to US census blocks), and census tracts all had somewhat stable point patterns over time for (1) assault, (2) burglary, (3) robbery, (4) sexual assault, (5) theft, (6) theft of vehicle, and (7) theft from vehicle. Additionally, stability was found to increase as the unit of analysis got smaller. This finding also held true when assessing only those units with a minimum of 1 crime, though the level of stability decreased when compared to the analysis of all units.

Similarly, in their study of the spatial stability of property crime at the street segment and intersection level in Vancouver, British Columbia, Andresen, Linning and Malleson (2017) found that crime remained fairly stable across 12 years of analysis (2003-2014), despite a large drop in city-wide crime throughout the same time frame. As with Andresen and Malleson (2011), above, Andresen et al (2017) found that when limiting their analyses to those street segments and intersections with at least one reported crime, stability decreased (also see Hibdon et al., 2017 for further evidence that low and no-crime street segments drive stability findings). The authors thus concluded that "generally speaking spatial stability in the locations that actually have crime has a shorter time horizon" (p. 19).

These findings suggest that estimations of future criminogenic places can be guided by recent crime data. However, it is important to note that this consensus is not universal, and Gill, Wooditch, and Weisburd's (2017) findings led them to conclude the opposite – after their research results suggested that there were some short-term fluctuations in high-crime locations (also see Levin, Rosenfeld, & Deckard, 2017), the authors put forth that "the identification of hot spots for research or intervention should be based on longitudinal trends and trajectories rather than short-term data" (p. 534). Likewise, O'Brien and Winship (2017) found that 16% of Boston addresses had calls for service in only one of three years studied, suggesting the potential for short-term, nonpersistent flare-ups of crime. Despite this disagreement, the finding that crime at place is mostly stable over time is persistent across multiple analytic methods, units of analysis, and social contexts, particularly when no and low-crime units are included in analyses.

Current Study

To summarize, researchers conducting place-based studies of crime have tended to rely on an *Assumption of Crime Homogeneity*, incorporating and controlling for potentially criminogenic places by accounting for *all* places of each included facility set. Some predictive crime modellers have taken a similar approach when incorporating criminogenic places into their forecasts of future crime locations (see for example Caplan et al., 2011; Groff & LaVigne, 2001). Importantly, places are included in these studies regardless of whether or not any individual location has criminogenic risk factors. This method is inconsistent with research findings related to the distribution of crime within facility sets, as most places within any given facility type have little to no crime, while a very small proportion are responsible for the vast majority of crime incidents (Eck et al., 2007). Further, this method is inconsistent with findings suggesting that particularly criminogenic places act as crime radiators increasing crime in their surrounding area, and that clusters of the most criminogenic places have effects not otherwise accounted for when measuring all facilities (Bowers, 2014).

The inconsistency between research findings on facilities and the widespread use of homogenous operationalizations of criminogenic places have implications not just theoretically but practically as well. Crime and place research findings are often used to guide the development of crime prevention interventions, such as those using problem-oriented policing (Goldstein, 1979) or situational crime prevention approaches (Clarke, 1980). Likewise, the burgeoning field of predictive policing and its related tools, such as risk terrain modeling, sometimes rely on theoretically guided variables to predict and prevent future criminal events at places (for example Caplan et al., 2011; Groff & LaVigne, 2001). Operationalizations of relevant variables that are inconsistent with the empirical findings related to the distribution of crime across facilities may lead to weakened or inaccurate research findings and predictions about crime, which in turn may affect crime prevention policies and policing strategies.

Findings related to the stability of crime at place – specifically that high crime places tend to remain as such, with little variation year to year (Weisburd, Bernasco, & Bruinsma, 2009; Weisburd et al., 2012) - suggest that one possible substitute method for operationalizing criminogenic places is via historic crime counts. An alternate method for controlling for the presence of criminogenic places thus might be to differentiate places within facility sets by examining recent historic levels of crime and controlling for only criminogenic places. This method could feasibly improve on the shortcomings of the *Assumption of Crime Homogeneity* approach as it is not much more complicated than controlling for all places within each facility set but may allow for more specificity and accuracy in identifying criminogenic places. However, the usefulness of this type of measure has yet to be determined. It is unclear if using a measure rooted in historic crime would actually improve model performance as compared to the homogenous measure of all places within each potentially criminogenic facility set. The current study investigates these issues by proposing and examining the usefulness of a series of eight empirically rooted alternative measures of risky facilities.

CHAPTER 4: STUDY METHODS

This chapter overviews my research question and the analyses I used to answer it.

Research Question

The previous chapters highlighted that researchers often operationalize facility sets as though they have a homogenous crime risk despite research indicating there is variation in crime across facilities of the same type. In this dissertation, I address this need by investigating the following research question:

- Can risky facility measures based on an *Assumption of Crime Concentration* better explain crime counts at micro-places than commonly used *Assumption of Crime Homogeneity* facility measures of all places within each facility type?

Study Site

Cincinnati, Ohio is the study site for this research. Cincinnati is a Midwestern city located in Hamilton County. Comprised of 52 neighborhoods, Cincinnati is geographically unique in that its southern border is demarcated by the Ohio River, and it is connected to neighboring Kentucky via a series of nine automobile, train, and pedestrian bridges. In 2016, Cincinnati had a population of approximately 300,000 people, and a median household income of $34,629 (US Census Bureau, 2019), which was lower than both the national ($59,039) and Midwestern ($58,305) medians (Semega, Fontenot, & Kollar, 2017). Further, Cincinnati's poverty rate is over twice that of the national average (31% versus 14%). Racially, Cincinnati is diverse, with 50% of residents identifying as White, 43% as Black, and 7% as Asian, mixed race, or other (US Census Bureau, 2019).

Unit of Analysis

The finding that crime concentrates more at smaller units of analysis (Lee et al., 2017), and that criminogenic micro-places often border non-criminogenic ones (e.g. Groff et al., 2010) has lead a number of scholars to advocate for the use of smaller units of analysis in crime and place research to prevent the loss of important variation resulting from aggregation (Andresen et al., 2017; Brantingham, Patricia L., Brantingham, Vajihollahi, & Wuschke, 2009; Groff et al., 2009; Oberwittler & Wikström, 2009). This dissertation uses one such small unit, street blocks, for its unit of analysis. Street blocks include both sides of a street between two intersections (Taylor, 1997; Taylor, 1998; Weisburd et al., 2012).

Street blocks are a useful unit of analysis for this dissertation for several reasons. First, there is a greater amount of variability in crime across street blocks than in larger units of analysis, such a neighborhoods or community areas (Schnell, Braga, & Piza, 2017; Steenbeek & Weisburd, 2016). Second, entry and exit points of facilities face street blocks, and the routes to and from these places tend to be organized around street blocks and the larger street network to which they belong (Okabe, Yomono, & Kitamura, 1995). Third, it is important that the spatial unit I use is consistent with the theoretical concepts being modelled (Askey et al., 2018). The crime opportunity theories outlined above are consistent with a micro-level of analysis. Fourth, research suggests that criminogenic places can act as crime radiators in their environment, with their effects spilling over into the surrounding micro-geographic environment (Bowers, 2014). This effect is compounded when there are multiple criminogenic places in close proximity. Smaller units of analysis, such as addresses, would be insufficient to model this crime radiating effect. Fifth, streets and sidewalks act as behavioral settings (Barker & Barker, 1961, p. 144; Barker & Schoggen, 1973, p. 8), and street blocks can be a useful unit for capturing human activity rhythms (Jacobs, J., 1961; Jacobs, J., 1968) that create the local social contexts which impact various elements of the Routine Activity

Approach (Taylor, 1997). Finally, as I am seeking to replicate existing crime and place research approaches to determine the impact of the proposed risky facility measures on study outcomes, it is useful to use street blocks as my unit of analysis as street blocks have become the de facto unit of analysis in recent crime and place research (e.g. Clutter et al., 2019; Dario et al., 2015; Duru, 2010; Groff, 2014; Groff & Lockwood, 2014; Kelsay & Haberman, 2020; Smith et al., 2000).

Cincinnati street data comes from a Hamilton County street centreline data set (N = 32,734) made available by the Cincinnati Area Geographic Information System (CAGIS). The data have been cleaned to remove any street blocks outside of city limits or without valid addresses (e.g. highways, on and off ramps), to fix streets incorrectly documented as having two centrelines (see Schnell et al., 2017, footnote 6; Weisburd, Telep, & Lawton, 2014, footnote 9), and to remove locations for which crime data is unavailable (e.g. intrauniversity streets, enclaves of Norwood and Saint Bernard; see Kelsay & Haberman, 2020, Note 4, for a further description of the cleaning process). After cleaning, there were 10,940 street blocks in the data set, with an average street block length of approximately 480 ft (see Table 23).

Outcome Variables

This dissertation uses two crime outcome variables, one violent crime and one property crime. Specifically, I use street block level incident counts of 2016 robbery and theft. Research has suggested that aggregating across multiple crime types is inadvisable given the differing spatial patterns and opportunity structures between, and even within, different types of crime (see for example Andresen et al., 2017; Haberman, 2017; Haberman, Clutter, & Lee, forthcoming). The use of two outcome variables is thus necessary to see if the study's findings are consistent across crimes types.

I use robbery and theft for their breadth and utility in studying the impact of crime and place measures. First, street robbery is a particularly useful crime to include in this study, as it is often the subject of studies of crime and place, particularly those which measure facilities homogenously (e.g. Bernasco & Block, 2011; Clutter et al., 2019; Haberman et al., 2013; Haberman & Ratcliffe, 2015; Haberman et al., 2018; Irvin-Erickson, 2014; Smith et al., 2000; Stucky & Ottensmann, 2009). It is also a predatory crime which occurs in public places, consistent with the predictions of the Routine Activities Approach. Finally, robbery has a higher reporting rate than many other crimes (Truman & Morgan, 2016), and thus suffers less potential measurement error than other types of crime.

Theft is also useful for examining the impact of facilities on crime as it is prevalent in areas with high levels of pedestrian traffic, such as bars (Johnson, Bowers, Gamman, Mamerow, & Warne, 2010), particularly in areas with high concentrations of businesses (Bowers, 2014). Further, the opportunity structure for theft differs from street robbery, and the hotspots for each crime do not tend to overlap (Haberman, 2017).

I obtained Cincinnati Police Department (CPD) incident data for these two crimes from January 1st, 2015 to December 31st, 2016. Theft and robbery data from 2016 were used to create the crime outcome variables. These data are summarized below in Table 2. Data from 2015 were used to create facility risk variables, discussed below.

Table 2. Street Block Level Descriptive Statistics of Crime Outcome Variables (n=10,940)

	N	Min	Max	Mean	Standard Deviation
Robbery 2016	921	0	9	0.08	0.37
Theft 2016	11399	0	304	1.04	5.66

Robbery data came from an existing data set that was obtained from CPD and then cleaned and qualitatively coded to include only similar street robbery incidents[11]. The coding includes

[11] Referred to as opportunistic robberies by Clutter (2019) and foraging robberies by Haberman et al (forthcoming)

robbery incidents where property was taken by force or threat of force in a public location and excludes extraneous incidents likely to result from differing opportunity structures. Specifically, it excludes residential and commercial robberies, robberies between individuals who know each other, robberies set up over the internet (e.g. Craigslist sales), and robberies of delivery drivers. Addresses and/or coordinates were available for each incident and I geocoded the robbery data (and all other crime and facility data used in this dissertation) with ArcGIS 10.7.1 for Desktop.

Theft data came directly from the CPD and includes motor vehicle theft, pocket picking, purse snatching, shoplifting, theft from building, theft from motor vehicle, theft of motor vehicle parts or accessories, theft of license plate, theft from coin-operated machine or device, and all other larceny. These data I cleaned myself. I began with 23,610 theft incidents for 2015 and 2016. I removed all incident addresses that occurred outside the study area, that were missing a location, or that were without a decipherable address (N = 156). I was left with 23,454 theft incidents. This represents a successful geocoding rate of 99.6%[12], which is typically considered acceptable for analysis (Ratcliffe, 2004).

Creating Risky Facility Variables

Recall my research question asks: Can risky facility measures based on an *Assumption of Crime Concentration* better explain crime counts at micro-places than commonly used *Assumption of Crime Homogeneity* facility measures of all places within each facility type? Two types of risky facility measures are needed to assess this research question. First, a homogenous measure of all potentially criminogenic places in each spatial unit is needed to act as an A*ssumption of Crime Homogeneity* facility risk measure. This is operationalized using count variables of all facilities of a particular type on each street block.

[12] The denominator for this successful geocoding measure includes only those incidents occurring within the study area and those that were missing a location or had indecipherable addresses. Incidents occurring outside the study area were not included here, as they could be geocoded but they were not within the scope of this study.

Second, risky facility measures created using temporally lagged crime data are needed to act as *Assumption of Crime Concentration* facility risk measures. As these measures have not been tested before, there is no clear guidance on how they should be operationalized. Thus, I test a series of measures that capture three potential contingencies: (1) the area assumed to be impacted by facility riskiness (at-facility only versus a buffer area around each facility), (2) the types of crime used to operationalize riskiness (specific crime measures vs general crime measures), and (3) the level of measurement used to operationalize risk (binary versus continuous).

Area of Impact

As was discussed in the previous chapter, research has shown that some facilities have higher levels of crime but also that facilities can impact crime in their surrounding area and high crime locations can radiate crime outwards (Bowers, 2014). Facility risk can thus be quantified using only those incidents occurring at each facility or by using incidents occurring within a buffer area around each facility. In this dissertation, buffer area facility risk is captured using Intensity Value Analysis (IVA) (McCord & Ratcliffe, 2009). IVA is useful because it accounts for crime that occurs both at the facility and in the area surrounding a place, but weights crimes based on how close they occur to the facility. The IVA formula (taken from McCord & Ratcliffe, 2009) is as follows:

$$\lambda_\tau(r) = \sum_{d_i \leq \tau} (1 - \frac{d_i}{\tau})$$

In this formula, $\lambda_\tau(r)$ is the intensity value for a facility. The intensity value is calculated via a sum of all crime points (i) occurring within a predetermined buffer area (τ) of each facility, which are weighted based on their distance (*d*) from each facility, with a linear reduction the farther the crime occurs from the facility and the closer it occurs to the edge of the buffer area $(1 - \frac{d_i}{\tau})$.

The IVA scores are based on a 500ft street network distance buffer surrounding each facility (roughly equivalent to the average street block length in Cincinnati). Prior research has found that a variety of places impact crime at this distance (e.g. Groff & Lockwood, 2014; Ratcliffe, 2012). I use street network distance in this dissertation, rather than Manhattan or Euclidean distance, as it more closely represents the paths and routes people travel between nodes, including the facilities they patronize (Okabe et al., 1995; Xu & Griffiths, 2017).

However, it is possible that basing risk measures on incidents occurring in a buffer area around each facility might overestimate the riskiness of low-risk facilities located in close proximity to high-risk ones. Measures that rely on only at-facility incidents or calls for service provide a facility specific measure of risk. This measurement approach has the converse limitation that some facilities may affect crime in their vicinity in a way that cannot be quantified by assessing at-facility crime alone. For instance, bars might impact street robbery in their surrounding area as inebriated customers walk home. Using only at-facility incidents might underestimate the riskiness of some facilities. Further, this approach is limited in that it cannot be used to assess some types of crime. The aforementioned street robbery is an apt example as it, by definition, occurs on the street rather than in a facility.

Type of Crime Used to Operationalize Risk

Assumption of Crime Concentration measures can be developed using different types of crime. One way to operationalize the riskiness of facilities for robbery and theft is to use prior robbery and theft incidents. This represents a crime specific measure of risk, as a particular crime is used to estimate future incidents of the same type of crime. Operationalizing risk this way is consistent with research showing that crime tends to remain fairly stable year to year. It is also consistent with the idea that if the situational characteristics leading to opportunities for particular types of crime remain unchanged, crime of that type will continue to occur at the locations it has before. In this dissertation, I use 2015 robbery and theft data to create crime specific measures of facility risk that are used to estimate 2016 robbery and theft levels. As was discussed above, this robbery and theft data was acquired from the CPD.

The potential shortcoming of using crime specific facility risk measures is that they may be too narrow in scope. Further, there is a potential tautology in using counts of specific crimes at each location to develop riskiness measures for the same type of crime incidents the following year. Calls for service data provide a more general proxy for capturing facility risk. In Cincinnati, calls for service data include any time a member of the public calls the police emergency services line (911) or police initiate a response to an incident without being prompted by a call. The benefit of these data is that they capture a broad array of crime and disorder, so they provide a more general representation of facility risk than do the theft and robbery incidents used in the crime specific measures of risk. However, calls for service data also have limitations. They may be too broad to develop risky facility measures that are useful for estimating specific crimes in models of crime and place. For example, a facility receiving a high-risk score as a result of numerous calls for service for auto thefts may not be high risk for assault incidents. For this reason, I test both crime specific and crime general measures of risk in this dissertation.

I use 2015 calls for service data to create the crime general measures of facility risk that are used to model 2016 robbery and theft street block counts. I obtained calls for service data from the CPD for January 1st, 2015 to December 31st, 2015. I began with 357,398 calls for service for 2015. I removed all calls for service categories that were not related to risk, including police checkins for directed patrols and reporting for court attendance. Likewise, I removed calls for service categories related to providing support on university campuses, as these areas are excluded from this study. Next, I removed all calls for service addresses that occurred outside the study area and several addresses within the study area that had artificially inflated calls for service numbers (e.g. police stations, sheriff's office, courthouse). This reduced the total number of calls for service to 276,378. I then removed incidents that were missing a location or that were without a decipherable address (N = 5176). I was left with N = 271,202 calls for service. This represents a successful geocoding rate of 98.1%[13].

Binary versus Continuous Operationalization of Risk

The next issue related to operationalizing facility risk is whether to represent risk as a binary of risky and non-risky places, or to use a continuous measure of risk that allows for more variation. The Iron Law of Troublesome Places, discussed in the previous chapter, was derived from the 80/20 rule (Clarke & Eck, 2005), alternatively called the Pareto principle (Juran, 1975; Pareto, 1906; Pareto, 2014). This principle dictates that a small proportion of cases are responsible for the majority of outcomes. The rule of thumb associated with this principle is that about 20% of cases cause about 80% of outcomes (thus the 80/20 rule moniker). In reality this distribution often differs, though the general principle still applies. With crime, a small minority of individuals commit the vast majority of criminal offences (Wolfgang, Figlio, & Sellin, 1972), a small number of individuals experience far larger than their fair share of repeat victimization (Hindelang, Gottfredson, & Garofalo, 1978; Nelson, 1980; O, Martinez, Lee, & Eck, 2017), and a small number of items and products are targeted for theft more often than others (Clarke, 1999).

[13] As with the successful geocoding percentage for robbery and theft, the denominator for this successful geocoding measure includes only those incidents occurring within the study area and those that were missing a location or had indecipherable addresses.

Interestingly, this disproportionate concentration of events and outcomes has also been noted in a wide breadth of fields outside of criminology and appears to be applicable in many facets of life (Eck et al., 2007). For instance, approximately 20% of programming bugs are responsible for causing 80% of errors in Microsoft code (Ballmer, 2002), the wealthiest 20% of Americans own approximately 90% of household wealth (Wolff, 2016), and around 3% of total infected people were responsible for spreading almost two-thirds of Ebola cases in the West African epidemic of 2014 and 2015 (Lau et al., 2017). Thus, the concentration of crime at place is unsurprising, and is in keeping with concentrations observed in many other social and natural phenomena (Eck, Lee, O, & Martinez, 2017).

I use the 80/20 rule as a guide to create binary measures of facility riskiness in this dissertation. Using this approach, I coded those facilities with the top 20% highest crime count or IVA values within each facility set as risky facilities ("1"), while the remaining facilities were as coded as not risky ("0"). This process was repeated for each facility set, for each crime. In cases where there were tied riskiness values that straddled the 20% cut-off, all facilities with the cut-off value were counted as risky. Thus, some facility measures have slightly more than 20% of places designated as risky facilities. A summary of the percentage of crime occurring within the top 20% of facilities in each facility set is presented below in Table 3. Additional J-curve charts displaying crime concentration at and around facilities are presented in Appendix B.

When aggregated to the street block level for regression analyses, the binary operationalization of risky facilities results in a count of the number of *risky* facilities of each type on each street block. This parallels the standard homogenous risk approach which uses a count of *all* facilities of each type on each street block. The benefit of this approach is that resultant coefficient interpretations are similar to the homogenous risk measures people tend to use and they are able to answer the same types of research questions (e.g. what effect does the presence of each type of risky facility have on the risk of crimes occurring in a street block?).

However, binary measures are simplistic, and though they may provide a useful means of identifying the riskiest facilities, it may be that crime risk is better represented using a continuous scale. As such, I test continuous measures of risk too. I created continuous measures of risk by leaving crime counts and IVA values as-is (i.e. not converting them to binary measures based on

Table 3. Percent of Facility-Level Crime Occurring Within the Top 20% of Facilities in Each Facility Set in 2015

	Theft			Calls for Service		
	Total N for Facility Set	N at Top 20%	% Theft in Top 20% of Facilities	Total N for Facility Set	N at Top 20%	% CFS in Top 20% of Facilities
Bars	173	136	78.6%	1810	1192	65.9%
Consumer Electronics Stores	153	140	91.5%	1485	1071	72.1%
Convenience Stores	226	204	90.3%	2698	1914	70.9%
Discount and Dollar Stores	217	155	71.4%	1116	616	55.2%
Drug Treatment Centers	71	55	77.5%	1603	1229	76.7%
Entertainment Venues	120	88	73.3%	1772	1329	75.0%
Fast Food Restaurants	373	296	79.4%	5503	3761	68.3%
Gas Stations	375	237	63.2%	3865	2229	57.7%
Grocery Stores	497	344	69.2%	2379	1442	60.6%
Home Décor and Furniture Stores	204	196	96.1%	727	607	83.5%
Hotels	70	43	61.4%	1192	610	51.2%
Pharmacies	327	290	88.7%	1102	837	76.0%
Recreation Centers	53	34	64.2%	824	497	60.3%
Recreation Retails Stores	232	218	94.0%	1077	924	85.8%
Salons and Barber Shops	120	119	99.2%	1504	1249	83.0%
Sit-Down Restaurants	428	389	90.9%	3243	2602	80.2%

Note: Robbery is excluded from this chart as street robberies do not occur at facilities

the 80/20 rule). Notably, when aggregated to the street block level for regression analyses, the continuous facility risk measures result in a count of the number of *crimes* related to each facility type on each street block (either a raw count or an IVA weighted count). So, though the benefit of this approach is that it allows for greater variation in risk, the limitation of this approach is that, once aggregated, the underlying facility composition is masked. For instance, two street blocks might have the same number of crime incidents at bars. One of the blocks may have a single high-risk location, while the other has several bars with a few incidents each. This approach precludes determining what, if any, differences these two compositions have on subsequent crime. Likewise, the interpretation of the regression coefficients related to these measures become less intuitively understandable. Notably, when combined with a buffer-area inverse distance weighted based count of crimes and aggregated to the street block level this approach also results in individual crime incidents or calls for service being counted multiple times, which may inflate riskiness estimates.

Facility Data

To test the proposed risky facility measures, I use 16 facility sets. Facility data came from a dataset that was collected, coded, and checked for inter-rater reliability in 2016 by University of Cincinnati researchers (including myself) led by Dr. Cory Haberman. The data came from various departments within the City of Cincinnati and the State of Ohio.

Since there is no standard established for a minimum acceptable level of facility geocoding, here I have opted to follow the approach used elsewhere (Askey et al., 2018) and included only those facilities that meet or exceed the standard minimum level of 85% geocoding for crimes (Ratcliffe, 2004). The facility variables included in my analyses are overviewed in Table 4, below, and also summarized here.

First, five types of commonly used "everyday" facilities were included. Specifically, *Convenience Stores* (N = 156) include all small stores selling items of convenience that do not have gas pumps. *Fast Food Restaurants* (N = 340) are quick service food locations where people get their food either via a drive-thru or at a counter. *Gas Stations* (N = 89) are places where people go to purchase gas for their motor vehicles, and also sometimes to buy items of convenience when there is an attached convenience store. *Grocery Stores* (N = 26) are larger stores selling groceries which patrons typically drive to and from in order to shop for large quantities of food (e.g. Kroger). *Pharmacies* (N = 32) are places to purchase medical supplies and have prescriptions filled.

Second, five entertainment related facilities were included. *Sit Down Restaurants* (N = 235) are those places where people order off of a menu and a server brings them their meal to a table at which they sit to eat. *Bars and Clubs* (N = 153) are places whose primary function is the sale of alcohol for entertainment, and which are open later than midnight on weekends. These places can include live music and/or a dance floor and exclude venues which are rented out for private functions only. *Entertainment Venues* (N = 76) include amusement parks, arenas, casinos, escape rooms, movie theatres, miniature golf, bowling alleys, landmarks, and live performance theatres. *Hotels* (N = 27) are places offering overnight accommodation. Lastly, *Recreation Centers* (N = 38) include indoor recreation centers and public pools used for exercise and fitness.

Two facilities offering services to the public were also included. *Drug Treatment Centers* (N = 42) are places to receive counselling or treatment for drug addiction. *Salons and Barber Shops* (N = 179) are places people go to get a haircut or receive other beauty treatments. These include hair salons, barber shops, nail salons, estheticians, wax bars, and massage parlors, and exclude stores that mostly sell beauty supplies, such as Ulta or Sephora.

Finally, four retail facilities were included. *Consumer Electronic Stores* (N = 114) include all stores selling electronic goods such as televisions, audio-visual equipment, video games, and cell phones (e.g. Best Buy). *Discount and Dollar Stores* (N = 26) include all stores selling inexpensive items (e.g. Dollar General). *Home Décor and Furniture Stores* (N = 76) are those which sell home furniture and decoration items (e.g. Lay-Z-Boy Furniture Galleries). Finally, *Recreation Retail Stores* (N = 85) sell a variety of recreational products, including books, toys, instruments, sports and hunting equipment, records, hobby supplies, and gifts.

Table 4. Operationalization of Facility Variables and their Data Sources

Facility Type	N	Operationalization	Source
Bars and Clubs	153	Places whose primary function is the sale of alcohol and which are open later than midnight on weekends; may include live music and/or dancefloor, excludes venues rented out for private functions only	Ohio Department of Taxation
Consumer Electronic Stores	114	Stores selling TVs, audio-visual equipment, video games, cell phones, etc (e.g. Best Buy)	Ohio Department of Taxation
Convenience Stores	156	Small stores selling items of convenience; excludes locations with gas pumps	Ohio Department of Taxation
Discount and Dollar Stores	26	Stores that sell inexpensive things (e.g. Dollar General, Dollar Tree, Family Dollar)	Ohio Department of Taxation
Drug Treatment Centers	42	Places to receive counselling or treatment for drug addiction	Ohio Mental Health and Addiction Services
Entertainment Venues	76	Places people go to for entertainment. Amusement parks (e.g. Cincinnati Zoo), arenas (e.g. US Bank Arena), casinos, entertainment centers (e.g. escape rooms, laser tag, movie theatres, mini golf, bowling alleys), landmarks (e.g. Fountain Square), and live performance theaters (e.g. Cincinnati Playhouse in the Park, Cincinnati Music Hall)	Ohio Department of Taxation
Fast Food Restaurants	340	Quick-service food locations, served via drive-thru or at a counter (e.g. McDonald's, Chinese food take out)	Ohio Department of Taxation
Gas Stations	89	Gas stations (including those with convenience stores)	Ohio Department of Taxation
Grocery Stores	26	Larger grocery stores which patrons typically drive to and from in order to shop for larger quantities of food (e.g. Kroger, Meijer)	Ohio Department of Taxation
Home Décor and Furniture Stores	76	Furniture stores and home decoration stores (e.g. Bed Bath Beyond, Lay-Z-Boy Furniture Galleries)	Ohio Department of Taxation
Hotels	27	Establishments offering overnight accommodation (e.g. 21c Museum Hotel, Gaslight Bed and Breakfast, Millennium Hotel)	Ohio Department of Taxation
Pharmacies	32	Places to purchase medical supplies and have prescriptions filled (e.g. CVS, Walgreens)	Ohio Department of Taxation
Recreation Centers	38	Indoor recreation centers and public pools (e.g. Bond Hill Pool, North Avondale Recreation Center, YMCA of Greater Cincinnati)	Cincinnati Recreation Commission
Recreation Retail Stores	85	Sports equipment, bike shops, hunting/fishing supplies, art supplies, toy stores, record stores, bookstores, instrument stores, hobby stores, gift stores	Ohio Department of Taxation
Salons and Barber Shops	179	Hair salons, barber shops, nail salons, estheticians, wax bars, and massage parlors; excludes stores that strictly sell beauty supplies	Ohio Department of Taxation
Sit-Down Restaurants	235	Places people sit down to eat; where they order off of a menu and a server brings their meal	Ohio Department of Taxation

Spatial lags were included for each of the place variables and represent a sum of risky facility values of adjacent units. Spatial lag variables are useful for accounting for the crime radiating effects of places into their nearby areas (Bernasco & Block, 2011; Bowers, 2014; Groff, 2011; Haberman & Ratcliffe, 2015; Ratcliffe, 2012). They are also useful for accounting for the spatial relationships inherent in place-based units. In other words, because near places are more likely to be similar than those farther away (Tobler, 1970), it is necessary to measure and control For this similarity in order to properly specify models of crime and place (Anselin, 1988; Cliff & Ord, 1970; LeSage, 2008; LeSage & Pace, 2009). Spatial lag facility variables were generated using a queen-contiguity first-order spatial weights matrix. Queen-contiguity first-order spatial weights matrices treat units as contiguous if they share any vertices or edges (Anselin, 2018). For street blocks, this includes any streets that intersect with one another.

Risky Facility Operationalization

The combinations of the above possible operationalizations of concentrated risk (at-facility versus buffer area crime, crime specific versus crime general, and binary versus continuous), and the two different outcome variables, results in fourteen different risky facility operationalizations to be tested in this dissertation. Eight of these measures capture theft risk. Six capture street robbery risk (recall that it is not possible to calculate street robbery risk using the at-facility crime specific approach).

These measures are tested against an additional two homogenous facility risk measures that replicate the common homogenous count operationalization of the *Assumption of Crime Homogeneity.* The 6 robbery and 8 theft *Assumption of Crime Concentration* based facility risk measures are overviewed below. The benefits and limitations of each of these approaches are summarized in Table 5. Street block level descriptive statistics for each measure are presented in Table 7 through Table 22, separated by facility set.

The correlations between each of these measures at the street block level, and broken down by facility type, ranges from -0.005 to 0.9488 for robbery and 0.1683 to 0.9778 for theft. This suggests there is some overlap between measures, but that they are not simply a measure of the exact same thing. The range of correlations for the measures, separated by facility set, are presented in

Table **6**.

Binary Robbery Risk Using Buffer-Area Street Robbery Incidents

The Binary Robbery Risk Using Buffer-Area Street Robbery Incidents measure used an IVA weighted sum of all 2015 street robbery incidents occurring within a 500ft street network distance of each facility. The IVA sum values were converted into a binary measure of risk within each of the 16 facility sets included in the dissertation. The top 20% of values in each facility set were coded as risky (assigned a value of 1) while the lowest 80% were coded as non-risky (assigned a value of 0).

Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents

The Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents measure used an IVA weighted sum of all 2015 street robbery incidents occurring within a 500ft street network distance of each facility.

Binary Robbery Risk Using At-Facility Calls for Service

The Binary Robbery Risk Using At-Facility Calls for Service measure used a count of 2015 calls for service incidents occurring at each facility. The at-facility count values were converted into a binary measure of risk within each of the 16 facility sets included in the dissertation. The top 20% of values in each facility set were coded as risky (assigned a value of 1) while the lowest 80% were coded as non-risky (assigned a value of 0).

Continuous Robbery Risk Using At-Facility Calls for Service

The Continuous Robbery Risk Using At-Facility Calls for Service measure used a count of 2015 calls for service occurring at each facility.

Binary Robbery Risk Using Buffer-Area Calls for Service

The Binary Robbery Risk Using Buffer-Area Calls for Service measure used an IVA weighted sum of all 2015 calls for service occurring within a 500ft street network distance of each facility. The IVA sum values were converted into a binary measure of risk within each of the 16 facility sets included in the dissertation. The top 20% of values in each facility set were coded as risky (assigned a value of 1) while the lowest 80% were coded as non-risky (assigned a value of 0).

Continuous Robbery Risk Using Buffer-Area Calls for Service

The Continuous Robbery Risk Using Buffer-Area Calls for Service measure used an IVA weighted sum of all 2015 calls for service incidents occurring within a 500ft street network distance of each facility.

Binary Theft Risk Using At-Facility Theft Incidents

The Binary Theft Risk Using At-Facility Theft Incidents measure used a count of 2015 theft incidents occurring at each facility. The at-facility count values were converted into a binary measure of risk within each of the 16 facility sets included in the dissertation. The top 20% of values in each facility category were coded as risky (assigned a value of 1) while the lowest 80% were coded as non-risky (assigned a value of 0).

Continuous Theft Risk Using At-Facility Theft Incidents

The Continuous Theft Risk Using At-Facility Theft Incidents measure used a count of 2015 theft incidents occurring at each facility.

Table 5. Benefits and Limitations of Proposed Risky Facility Measures

	Benefits				Limitations					
	Specific representation of risk	General representation of risk	Once aggregated, is a count of risky facilities on each block	Allows for variations in risk beyond risky/not-risky dichotomy	Overestimates riskiness for low-crime facilities located near high-crime facilities	Underestimates riskiness for facilities that impact crime in their area more than at their location	Masks facility composition once aggregated	Potentially Tautological	Potentially too broad to be useful for estimation of specific crime types	Inflated riskiness estimates for high crime areas
Binary Robbery Risk Using Buffer-Area Incidents	X		X		X			X		X
Binary Robbery Risk Using At-Facility CFS		X	X			X			X	
Binary Robbery Risk Using Buffer-Area CFS		X	X		X				X	X
Continuous Robbery Risk Using Buffer-Area Incidents	X			X	X		X	X		X
Continuous Robbery Risk Using At-Facility CFS		X		X		X	X		X	
Continuous Robbery Risk Using Buffer-Area CFS		X		X	X		X		X	X
Binary Theft Risk Using At-Facility Incidents	X		X			X		X		
Binary Theft Risk Using Buffer-Area Incidents	X		X		X			X		X
Binary Theft Risk Using At-Facility CFS		X	X			X			X	
Binary Theft Risk Using Buffer-Area CFS		X	X		X				X	X
Continuous Theft Risk Using At-Facility Incidents	X			X		X	X	X		
Continuous Theft Risk Using Buffer-Area Incidents	X			X	X		X	X		X
Continuous Theft Risk Using At-Facility CFS		X		X		X	X		X	
Continuous Theft Risk Using Buffer-Area CFS		X		X	X		X		X	X

Binary Theft Risk Using Buffer-Area Theft Incidents

The Binary Theft Risk Using Buffer-Area Theft Incidents measure used an IVA weighted sum of all 2015 theft incidents occurring within a 500ft street network distance of each facility. The IVA values were converted into a binary measure of risk within each of the 16 facility sets included in the dissertation. The top 20% of values in each facility set were coded as risky (assigned a value of 1) while the lowest 80% were coded as non-risky (assigned a value of 0).

Continuous Theft Risk Using Buffer-Area Theft Incidents

The Continuous Theft Risk Using Buffer-Area Theft Incidents measure used an IVA weighted sum of all 2015 theft incidents occurring within a 500ft street network distance of each facility.

Binary Theft Risk Using At-Facility Calls for Service

The Binary Theft Risk Using At-Facility Calls for Service measure used a count of 2015 calls for service incidents occurring at each facility. The at-facility count values were converted into a binary measure of risk within each of the 16 facility sets included in the dissertation. The top 20% of values in each facility set were coded as risky (assigned a value of 1) while the lowest 80% were coded as non-risky (assigned a value of 0).

Continuous Theft Risk Using At-Facility Calls for Service

The Continuous Theft Risk Using At-Facility Calls for Service measure used a count of 2015 calls for service occurring at each facility.

Binary Theft Risk Using Buffer-Area Calls for Service

The Binary Theft Risk Using Buffer-Area Calls for Service measure used an IVA weighted sum of all 2015 calls for service incidents within a 500ft street network distance of each facility. The IVA sum values were converted into a binary measure of risk within each of the 16 facility sets included in the dissertation. The top 20% of values in each facility set were coded as risky (assigned a value of 1) while the lowest 80% were coded as non-risky (assigned a value of 0).

Continuous Theft Risk Using Buffer-Area Calls for Service

The Continuous Theft Risk Using Buffer-Area Calls for Service used an IVA weighted sum of all 2015 calls for service occurring within a 500ft street network distance of each facility.

Table 6. Correlation Range for Facility Risk Variables, by Facility Type

	Robbery Risk Measure Correlation Range		**Theft Risk Measure Correlation Range**	
	Low	High	Low	High
Bars and Clubs	0.4516	0.8305	0.3809	0.8708
Consumer Electronic Stores	0.3234	0.8857	0.3867	0.9021
Convenience Stores	0.3806	0.8644	0.3128	0.8676
Discount and Dollar Stores	0.5161	0.9488	0.4327	0.9204
Drug Treatment Centers	0.3328	0.9190	0.4211	0.8424
Entertainment Venues	0.1863	0.9053	0.1863	0.8940
Fast Food Restaurants	0.2440	0.8648	0.2039	0.8418
Gas Stations	0.4270	0.8831	0.4270	0.8831
Grocery Stores	0.4877	0.8910	0.3885	0.9018
Home Décor and Furniture Stores	0.1012	0.8856	0.1946	0.9778
Hotels	-0.0005	0.8862	0.2883	0.9121
Pharmacies	0.1250	0.8956	0.4282	0.9402
Recreation Centers	0.3745	0.8477	0.2125	0.8649
Recreation Retail Stores	0.1152	0.8614	0.1903	0.8322
Salons and Barber Shops	0.2330	0.8356	0.1683	0.8193
Sit-Down Restaurants	0.2574	0.8729	0.2009	0.8661

Note: Correlations were calculated for all seven types of robbery risk measures and all nine types of theft risk measures within each facility type, including the homogenous count measure.

Additional Variables

Crime at the street block level is also affected by environmental backcloth variables (Brantingham, Paul J. & Brantingham, 1993), such as socio-demographics used to measure social disorganization (Smith et al., 2000; Weisburd et al., 2012; Wilcox, Quisenberry, & Jones, 2003;

Wilcox, Quisenberry, Cabrera, & Jones, 2004). Many studies of crime and place that rely on an *Assumption of Crime Homogeneity* to operationalize their facilities also include social disorganization control variables. It is important to include these here to get a more accurate understanding of the relationship between facilities and crime. I incorporated four control variables to account for these potential contributors to crime concentration. Specifically, I included measures of street block-level socioeconomic disadvantage, residential population, residential mobility, and racial heterogeneity. These were calculated using 2015 American Community Survey 5-year Census Block Group estimates. In order to estimate street block level data with the census block group data, the data for all census blocks overlapping a particular street block were averaged (called the simple average approach by Kim, 2018). I chose this operationalization approach for several reasons. First, it considers the micro-community context within which each street block is situated. Second, this approach has been shown to highly correlate with street block-level data, and thus provides a feasible alternative when no street block level data is available (Kim, 2018). Finally, this approach provides a simple, yet just as effective, alternative to more complex approaches like street block weighted averaging (Kim, 2018).

Within this simple average approach, the sociodemographic variables were measured as follows: *Residential population* is represented with the number of residents living in the area. *Socioeconomic status* is represented with the percentage of residents living under the poverty line. *Residential mobility* is captured using the percentage of residents reporting to have lived in another location in the prior year. Finally, drawing on an approach used in previous studies of crime and place (Chainey & Ratcliffe, 2005; Haberman & Ratcliffe, 2015), and developed by Gibbs and Martin (1962), *racial heterogeneity* was calculated by subtracting the squared proportion of five race groups (white only, African-American only, Hispanic only, Asian only, all other races) from

Table 7. Street Block Level Descriptive Statistics for Bar and Club Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	4.00	0.01	0.14
Binary Risk Using Buffer-Area Robbery Incidents	0.00	3.00	0.00	0.06
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	10.38	0.01	0.20
Binary Risk Using At-Facility Theft Incidents	0.00	2.00	0.00	0.06
Continuous Risk Using At-Facility Theft Incidents	0.00	23.00	0.02	0.35
Binary Risk Using Buffer-Area Theft Incidents	0.00	3.00	0.00	0.07
Continuous Risk Using Buffer-Area Theft Incidents	0.00	85.85	0.13	1.82
Binary Risk Using At-Facility CFS	0.00	2.00	0.00	0.06
Continuous Risk Using At-Facility CFS	0.00	168.00	0.17	2.91
Binary Risk Using Buffer-Area CFS	0.00	3.00	0.00	0.06
Continuous Risk Using Buffer-Area CFS	0.00	1126.68	2.44	31.57
SL Homogenous Count	0.00	8.00	0.08	0.39
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	4.00	0.02	0.18
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	19.19	0.07	0.58
SL Binary Risk Using At-Facility Theft Incidents	0.00	4.00	0.02	0.16
SL Continuous Risk Using At-Facility Theft Incidents	0.00	32.00	0.09	0.89
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	4.00	0.02	0.17
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	122.42	0.73	4.98
SL Binary Risk Using At-Facility CFS	0.00	3.00	0.02	0.16
SL Continuous Risk Using At-Facility CFS	0.00	256.00	0.98	8.01
SL Binary Risk Using Buffer-Area CFS	0.00	4.00	0.02	0.17
SL Continuous Risk Using Buffer-Area CFS	0.00	1769.94	14.31	87.35

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 8. Street Block Level Descriptive Statistics for Consumer Electronic Store Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	3.00	0.01	0.12
Binary Risk Using Buffer-Area Robbery Incidents	0.00	3.00	0.00	0.06
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	7.59	0.01	0.18
Binary Risk Using At-Facility Theft Incidents	0.00	3.00	0.00	0.07
Continuous Risk Using At-Facility Theft Incidents	0.00	47.00	0.01	0.57
Binary Risk Using Buffer-Area Theft Incidents	0.00	3.00	0.00	0.06
Continuous Risk Using Buffer-Area Theft Incidents	0.00	262.36	0.16	3.93
Binary Risk Using At-Facility CFS	0.00	3.00	0.00	0.06
Continuous Risk Using At-Facility CFS	0.00	363.00	0.14	4.05
Binary Risk Using Buffer-Area CFS	0.00	3.00	0.00	0.06
Continuous Risk Using Buffer-Area CFS	0.00	1254.87	2.25	32.61
SL Homogenous Count	0.00	6.00	0.06	0.31
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	4.00	0.01	0.16
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	11.73	0.06	0.48
SL Binary Risk Using At-Facility Theft Incidents	0.00	4.00	0.02	0.17
SL Continuous Risk Using At-Facility Theft Incidents	0.00	56.00	0.08	1.39
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	6.00	0.01	0.16
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	498.33	0.89	10.91
SL Binary Risk Using At-Facility CFS	0.00	4.00	0.01	0.15
SL Continuous Risk Using At-Facility CFS	0.00	451.00	0.80	10.24
SL Binary Risk Using Buffer-Area CFS	0.00	3.00	0.01	0.15
SL Continuous Risk Using Buffer-Area CFS	0.00	1883.77	13.38	89.35

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 9. Street Block Level Descriptive Statistics for Convenience Store Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	3.00	0.01	0.13
Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.06
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	5.27	0.01	0.16
Binary Risk Using At-Facility Theft Incidents	0.00	3.00	0.01	0.08
Continuous Risk Using At-Facility Theft Incidents	0.00	34.00	0.02	0.56
Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.00	0.06
Continuous Risk Using Buffer-Area Theft Incidents	0.00	41.91	0.09	1.19
Binary Risk Using At-Facility CFS	0.00	2.00	0.00	0.06
Continuous Risk Using At-Facility CFS	0.00	283.00	0.25	4.57
Binary Risk Using Buffer-Area CFS	0.00	2.00	0.00	0.06
Continuous Risk Using Buffer-Area CFS	0.00	900.25	2.34	25.53
SL Homogenous Count	0.00	4.00	0.09	0.32
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	3.00	0.02	0.15
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	8.94	0.07	0.43
SL Binary Risk Using At-Facility Theft Incidents	0.00	4.00	0.03	0.19
SL Continuous Risk Using At-Facility Theft Incidents	0.00	42.00	0.12	1.31
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	3.00	0.02	0.15
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	61.41	0.54	3.00
SL Binary Risk Using At-Facility CFS	0.00	3.00	0.02	0.14
SL Continuous Risk Using At-Facility CFS	0.00	357.00	1.41	10.81
SL Binary Risk Using Buffer-Area CFS	0.00	3.00	0.02	0.15
SL Continuous Risk Using Buffer-Area CFS	0.00	1220.46	14.21	66.87

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 10. Street Block Level Descriptive Statistics for Discount and Dollar Store Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	2.00	0.00	0.05
Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.03
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	11.35	0.00	0.15
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.02
Continuous Risk Using At-Facility Theft Incidents	0.00	41.00	0.02	0.67
Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.00	0.03
Continuous Risk Using Buffer-Area Theft Incidents	0.00	97.02	0.05	1.43
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.02
Continuous Risk Using At-Facility CFS	0.00	183.00	0.10	3.05
Binary Risk Using Buffer-Area CFS	0.00	2.00	0.00	0.03
Continuous Risk Using Buffer-Area CFS	0.00	1303.19	0.54	16.53
SL Homogenous Count	0.00	2.00	0.01	0.13
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.07
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	11.35	0.02	0.35
SL Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.06
SL Continuous Risk Using At-Facility Theft Incidents	0.00	41.00	0.12	1.61
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.00	0.07
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	97.02	0.27	3.47
SL Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.06
SL Continuous Risk Using At-Facility CFS	0.00	183.00	0.61	7.51
SL Binary Risk Using Buffer-Area CFS	0.00	2.00	0.00	0.07
SL Continuous Risk Using Buffer-Area CFS	0.00	1303.19	3.20	40.63

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 11. Street Block Level Descriptive Statistics for Drug Treatment Center Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	1.00	0.00	0.06
Binary Risk Using Buffer-Area Robbery Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	2.64	0.00	0.06
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using At-Facility Theft Incidents	0.00	14.00	0.01	0.22
Binary Risk Using Buffer-Area Theft Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area Theft Incidents	0.00	44.78	0.03	0.71
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.03
Continuous Risk Using At-Facility CFS	0.00	464.00	0.15	5.58
Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area CFS	0.00	601.16	0.60	12.76
SL Homogenous Count	0.00	3.00	0.02	0.16
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.01	0.08
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.63	0.01	0.16
SL Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.01	0.08
SL Continuous Risk Using At-Facility Theft Incidents	0.00	14.00	0.04	0.52
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.01	0.08
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	59.19	0.16	1.80
SL Binary Risk Using At-Facility CFS	0.00	1.00	0.01	0.07
SL Continuous Risk Using At-Facility CFS	0.00	464.00	0.88	13.58
SL Binary Risk Using Buffer-Area CFS	0.00	2.00	0.01	0.08
SL Continuous Risk Using Buffer-Area CFS	0.00	1082.35	3.57	35.02

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 12. Street Block Level Descriptive Statistics for Entertainment Venue Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	2.00	0.01	0.08
Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.04
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	2.66	0.00	0.06
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.05
Continuous Risk Using At-Facility Theft Incidents	0.00	23.00	0.01	0.29
Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.00	0.04
Continuous Risk Using Buffer-Area Theft Incidents	0.00	81.55	0.06	1.30
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.04
Continuous Risk Using At-Facility CFS	0.00	580.00	0.16	5.91
Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.04
Continuous Risk Using Buffer-Area CFS	0.00	749.17	0.95	17.51
SL Homogenous Count	0.00	4.00	0.04	0.22
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	3.00	0.01	0.11
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	5.35	0.02	0.17
SL Binary Risk Using At-Facility Theft Incidents	0.00	3.00	0.01	0.12
SL Continuous Risk Using At-Facility Theft Incidents	0.00	23.00	0.06	0.73
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	3.00	0.01	0.11
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	185.67	0.33	4.01
SL Binary Risk Using At-Facility CFS	0.00	2.00	0.01	0.10
SL Continuous Risk Using At-Facility CFS	0.00	580.00	0.98	15.53
SL Binary Risk Using Buffer-Area CFS	0.00	4.00	0.01	0.11
SL Continuous Risk Using Buffer-Area CFS	0.00	2085.92	5.84	52.44

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 13. Street Block Level Descriptive Statistics for Fast Food Restaurant Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	10.00	0.03	0.27
Binary Risk Using Buffer-Area Robbery Incidents	0.00	4.00	0.01	0.11
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	10.44	0.02	0.28
Binary Risk Using At-Facility Theft Incidents	0.00	5.00	0.01	0.10
Continuous Risk Using At-Facility Theft Incidents	0.00	60.00	0.03	0.72
Binary Risk Using Buffer-Area Theft Incidents	0.00	10.00	0.01	0.14
Continuous Risk Using Buffer-Area Theft Incidents	0.00	376.55	0.38	5.69
Binary Risk Using At-Facility CFS	0.00	2.00	0.01	0.09
Continuous Risk Using At-Facility CFS	0.00	357.00	0.50	6.89
Binary Risk Using Buffer-Area CFS	0.00	8.00	0.01	0.13
Continuous Risk Using Buffer-Area CFS	0.00	3343.99	6.28	68.20
SL Homogenous Count	0.00	15.00	0.18	0.82
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	9.00	0.04	0.31
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	19.59	0.14	0.87
SL Binary Risk Using At-Facility Theft Incidents	0.00	8.00	0.04	0.28
SL Continuous Risk Using At-Facility Theft Incidents	0.00	63.00	0.19	1.79
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	10.00	0.04	0.38
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	662.65	2.15	17.12
SL Binary Risk Using At-Facility CFS	0.00	4.00	0.04	0.24
SL Continuous Risk Using At-Facility CFS	0.00	575.00	3.00	20.12
SL Binary Risk Using Buffer-Area CFS	0.00	13.00	0.04	0.44
SL Continuous Risk Using Buffer-Area CFS	0.00	6039.14	37.40	234.42

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 14. Street Block Level Descriptive Statistics for Gas Station Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	2.00	0.01	0.09
Binary Risk Using Buffer-Area Robbery Incidents	0.00	1.00	0.00	0.04
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	8.00	0.01	0.14
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.04
Continuous Risk Using At-Facility Theft Incidents	0.00	46.00	0.03	0.68
Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.00	0.04
Continuous Risk Using Buffer-Area Theft Incidents	0.00	67.36	0.07	1.28
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.04
Continuous Risk Using At-Facility CFS	0.00	403.00	0.35	6.41
Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.04
Continuous Risk Using Buffer-Area CFS	0.00	785.51	1.37	19.99
SL Homogenous Count	0.00	4.00	0.05	0.24
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.01	0.10
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	9.84	0.04	0.36
SL Binary Risk Using At-Facility Theft Incidents	0.00	2.00	0.01	0.11
SL Continuous Risk Using At-Facility Theft Incidents	0.00	47.00	0.21	1.74
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.01	0.11
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	67.36	0.46	3.33
SL Binary Risk Using At-Facility CFS	0.00	2.00	0.01	0.11
SL Continuous Risk Using At-Facility CFS	0.00	403.00	2.20	16.45
SL Binary Risk Using Buffer-Area CFS	0.00	2.00	0.01	0.11
SL Continuous Risk Using Buffer-Area CFS	0.00	915.39	8.40	52.35

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 15. Street Block Level Descriptive Statistics for Grocery Store Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	1.00	0.00	0.05
Binary Risk Using Buffer-Area Robbery Incidents	0.00	1.00	0.00	0.02
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.20	0.00	0.06
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.02
Continuous Risk Using At-Facility Theft Incidents	0.00	128.00	0.05	1.65
Binary Risk Using Buffer-Area Theft Incidents	0.00	1.00	0.00	0.02
Continuous Risk Using Buffer-Area Theft Incidents	0.00	311.35	0.09	3.61
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.02
Continuous Risk Using At-Facility CFS	0.00	379.00	0.22	6.57
Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.02
Continuous Risk Using Buffer-Area CFS	0.00	690.76	0.55	15.08
SL Homogenous Count	0.00	3.00	0.01	0.12
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	1.00	0.00	0.06
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.20	0.01	0.14
SL Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.06
SL Continuous Risk Using At-Facility Theft Incidents	0.00	141.00	0.27	4.30
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	1.00	0.00	0.06
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	311.35	0.51	8.89
SL Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.06
SL Continuous Risk Using At-Facility CFS	0.00	379.00	1.27	16.53
SL Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.06
SL Continuous Risk Using Buffer-Area CFS	0.00	690.76	3.15	36.77

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 16. Street Block Level Descriptive Statistics for Home Decor and Furniture Store Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	3.00	0.01	0.10
Binary Risk Using Buffer-Area Robbery Incidents	0.00	3.00	0.00	0.05
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	9.11	0.00	0.12
Binary Risk Using At-Facility Theft Incidents	0.00	3.00	0.00	0.06
Continuous Risk Using At-Facility Theft Incidents	0.00	128.00	0.02	1.27
Binary Risk Using Buffer-Area Theft Incidents	0.00	3.00	0.00	0.06
Continuous Risk Using Buffer-Area Theft Incidents	0.00	265.48	0.09	3.16
Binary Risk Using At-Facility CFS	0.00	2.00	0.00	0.04
Continuous Risk Using At-Facility CFS	0.00	291.00	0.07	3.02
Binary Risk Using Buffer-Area CFS	0.00	3.00	0.00	0.05
Continuous Risk Using Buffer-Area CFS	0.00	1275.38	1.05	22.79
SL Homogenous Count	0.00	7.00	0.04	0.27
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	4.00	0.01	0.13
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	9.11	0.03	0.30
SL Binary Risk Using At-Facility Theft Incidents	0.00	6.00	0.01	0.16
SL Continuous Risk Using At-Facility Theft Incidents	0.00	128.00	0.12	3.37
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	4.00	0.01	0.15
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	357.41	0.52	8.64
SL Binary Risk Using At-Facility CFS	0.00	4.00	0.01	0.11
SL Continuous Risk Using At-Facility CFS	0.00	291.00	0.40	7.99
SL Binary Risk Using Buffer-Area CFS	0.00	4.00	0.01	0.13
SL Continuous Risk Using Buffer-Area CFS	0.00	1497.26	6.19	60.10

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 17. Street Block Level Descriptive Statistics for Hotel Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	2.00	0.00	0.05
Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.03
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	4.81	0.00	0.06
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.02
Continuous Risk Using At-Facility Theft Incidents	0.00	15.00	0.01	0.22
Binary Risk Using Buffer-Area Theft Incidents	0.00	2.00	0.00	0.03
Continuous Risk Using Buffer-Area Theft Incidents	0.00	104.21	0.04	1.60
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.02
Continuous Risk Using At-Facility CFS	0.00	201.00	0.11	3.20
Binary Risk Using Buffer-Area CFS	0.00	2.00	0.00	0.03
Continuous Risk Using Buffer-Area CFS	0.00	975.12	0.58	18.23
SL Homogenous Count	0.00	4.00	0.01	0.14
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.07
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	4.81	0.01	0.16
SL Binary Risk Using At-Facility Theft Incidents	0.00	3.00	0.00	0.07
SL Continuous Risk Using At-Facility Theft Incidents	0.00	30.00	0.04	0.69
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	4.00	0.00	0.09
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	245.97	0.27	5.39
SL Binary Risk Using At-Facility CFS	0.00	3.00	0.00	0.07
SL Continuous Risk Using At-Facility CFS	0.00	394.00	0.68	9.72
SL Binary Risk Using Buffer-Area CFS	0.00	2.00	0.00	0.07
SL Continuous Risk Using Buffer-Area CFS	0.00	2126.92	3.75	55.34

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 18. Street Block Level Descriptive Statistics for Pharmacy Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	2.00	0.00	0.06
Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.03
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.29	0.00	0.06
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using At-Facility Theft Incidents	0.00	128.00	0.03	1.51
Binary Risk Using Buffer-Area Theft Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area Theft Incidents	0.00	131.40	0.06	1.98
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.03
Continuous Risk Using At-Facility CFS	0.00	291.00	0.10	3.88
Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area CFS	0.00	442.47	0.57	12.62
SL Homogenous Count	0.00	2.00	0.02	0.14
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.08
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.29	0.01	0.16
SL Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.06
SL Continuous Risk Using At-Facility Theft Incidents	0.00	128.00	0.17	3.71
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	1.00	0.00	0.06
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	131.40	0.32	4.65
SL Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.06
SL Continuous Risk Using At-Facility CFS	0.00	291.00	0.57	9.27
SL Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.06
SL Continuous Risk Using Buffer-Area CFS	0.00	442.47	3.40	30.71

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 19. Street Block Level Descriptive Statistics for Recreation Center Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	1.00	0.00	0.06
Binary Risk Using Buffer-Area Robbery Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.43	0.00	0.05
Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using At-Facility Theft Incidents	0.00	10.00	0.00	0.14
Binary Risk Using Buffer-Area Theft Incidents	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area Theft Incidents	0.00	20.36	0.01	0.36
Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.03
Continuous Risk Using At-Facility CFS	0.00	104.00	0.08	1.94
Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.03
Continuous Risk Using Buffer-Area CFS	0.00	216.00	0.29	6.26
SL Homogenous Count	0.00	1.00	0.02	0.14
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	1.00	0.00	0.07
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.43	0.01	0.13
SL Binary Risk Using At-Facility Theft Incidents	0.00	1.00	0.01	0.08
SL Continuous Risk Using At-Facility Theft Incidents	0.00	10.00	0.03	0.34
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	1.00	0.00	0.07
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	20.36	0.08	0.88
SL Binary Risk Using At-Facility CFS	0.00	1.00	0.00	0.06
SL Continuous Risk Using At-Facility CFS	0.00	104.00	0.43	4.66
SL Binary Risk Using Buffer-Area CFS	0.00	1.00	0.00	0.07
SL Continuous Risk Using Buffer-Area CFS	0.00	216.00	1.71	15.22

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 20. Street Block Level Descriptive Statistics for Recreation Retail Store Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	3.00	0.01	0.10
Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.04
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	3.98	0.00	0.08
Binary Risk Using At-Facility Theft Incidents	0.00	2.00	0.00	0.05
Continuous Risk Using At-Facility Theft Incidents	0.00	103.00	0.02	1.16
Binary Risk Using Buffer-Area Theft Incidents	0.00	3.00	0.00	0.05
Continuous Risk Using Buffer-Area Theft Incidents	0.00	140.22	0.08	1.94
Binary Risk Using At-Facility CFS	0.00	2.00	0.00	0.05
Continuous Risk Using At-Facility CFS	0.00	357.00	0.10	4.31
Binary Risk Using Buffer-Area CFS	0.00	2.00	0.00	0.04
Continuous Risk Using Buffer-Area CFS	0.00	948.82	1.17	20.13
SL Homogenous Count	0.00	6.00	0.04	0.27
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	4.00	0.01	0.14
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	5.12	0.02	0.21
SL Binary Risk Using At-Facility Theft Incidents	0.00	3.00	0.01	0.11
SL Continuous Risk Using At-Facility Theft Incidents	0.00	103.00	0.12	2.83
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	3.00	0.01	0.12
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	140.22	0.45	4.84
SL Binary Risk Using At-Facility CFS	0.00	3.00	0.01	0.11
SL Continuous Risk Using At-Facility CFS	0.00	357.00	0.52	9.95
SL Binary Risk Using Buffer-Area CFS	0.00	3.00	0.01	0.11
SL Continuous Risk Using Buffer-Area CFS	0.00	1172.41	6.50	51.76

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 21. Street Block Level Descriptive Statistics for Sit-Down Restaurant Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	5.00	0.02	0.20
Binary Risk Using Buffer-Area Robbery Incidents	0.00	4.00	0.00	0.09
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	5.81	0.01	0.19
Binary Risk Using At-Facility Theft Incidents	0.00	4.00	0.01	0.11
Continuous Risk Using At-Facility Theft Incidents	0.00	128.00	0.04	1.63
Binary Risk Using Buffer-Area Theft Incidents	0.00	5.00	0.00	0.11
Continuous Risk Using Buffer-Area Theft Incidents	0.00	448.97	0.30	6.06
Binary Risk Using At-Facility CFS	0.00	4.00	0.00	0.08
Continuous Risk Using At-Facility CFS	0.00	580.00	0.30	7.54
Binary Risk Using Buffer-Area CFS	0.00	5.00	0.00	0.10
Continuous Risk Using Buffer-Area CFS	0.00	2543.93	4.24	56.00
SL Homogenous Count	0.00	9.00	0.13	0.59
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	6.00	0.03	0.25
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	12.03	0.08	0.55
SL Binary Risk Using At-Facility Theft Incidents	0.00	7.00	0.05	0.31
SL Continuous Risk Using At-Facility Theft Incidents	0.00	128.00	0.25	4.36
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	9.00	0.02	0.29
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	503.25	1.72	16.49
SL Binary Risk Using At-Facility CFS	0.00	5.00	0.03	0.22
SL Continuous Risk Using At-Facility CFS	0.00	580.00	1.85	21.49
SL Binary Risk Using Buffer-Area CFS	0.00	9.00	0.03	0.31
SL Continuous Risk Using Buffer-Area CFS	0.00	4976.20	25.55	180.07

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Table 22. Street Block Level Descriptive Statistics for Salon and Barber Shop Risk Variables (n=10,940)

	Min	Max	Mean	Standard Deviation
Homogenous Count	0.00	7.00	0.02	0.17
Binary Risk Using Buffer-Area Robbery Incidents	0.00	2.00	0.00	0.06
Continuous Risk Using Buffer-Area Robbery Incidents	0.00	5.63	0.01	0.13
Binary Risk Using At-Facility Theft Incidents	0.00	2.00	0.00	0.06
Continuous Risk Using At-Facility Theft Incidents	0.00	30.00	0.01	0.39
Binary Risk Using Buffer-Area Theft Incidents	0.00	7.00	0.00	0.10
Continuous Risk Using Buffer-Area Theft Incidents	0.00	404.46	0.19	4.70
Binary Risk Using At-Facility CFS	0.00	2.00	0.00	0.06
Continuous Risk Using At-Facility CFS	0.00	201.00	0.14	3.29
Binary Risk Using Buffer-Area CFS	0.00	3.00	0.00	0.06
Continuous Risk Using Buffer-Area CFS	0.00	1175.82	2.43	30.51
SL Homogenous Count	0.00	8.00	0.10	0.45
SL Binary Risk Using Buffer-Area Robbery Incidents	0.00	4.00	0.02	0.17
SL Continuous Risk Using Buffer-Area Robbery Incidents	0.00	5.65	0.05	0.35
SL Binary Risk Using At-Facility Theft Incidents	0.00	2.00	0.02	0.16
SL Continuous Risk Using At-Facility Theft Incidents	0.00	30.00	0.06	0.93
SL Binary Risk Using Buffer-Area Theft Incidents	0.00	7.00	0.02	0.23
SL Continuous Risk Using Buffer-Area Theft Incidents	0.00	551.43	1.06	11.72
SL Binary Risk Using At-Facility CFS	0.00	2.00	0.02	0.16
SL Continuous Risk Using At-Facility CFS	0.00	244.00	0.83	8.73
SL Binary Risk Using Buffer-Area CFS	0.00	5.00	0.02	0.17
SL Continuous Risk Using Buffer-Area CFS	0.00	1852.39	14.60	83.27

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

one. This created a variable ranging from 0 (complete racial homogeneity) to 0.8 (complete racial heterogeneity). Descriptive statistics for each of the control variables are presented below in Table 23.

Finally, research has found that major or permeable roads (Beavon, Brantingham, & Brantingham, 1994; Brantingham & Brantingham, 1981) tend to have more crime. As such, two street block control variables were included in each model. Street type was measured with a dichotomous indicator of major (1) or minor roads (0). Following Groff and Lockwood (2014), major roads include major arterials and minor arterials. Minor roads include collector roads, local roads, alleys, and pedestrian walks[14]. Data for this measure was contained in the CAGIS Hamilton County street centreline data set. An additional control variable representing street block length in feet, easily computed within a geographic information system, was included.

Table 23. Street Block Level Descriptive Statistics for Control Variables (n=10,940)

	Min	**Max**	**Mean**	**Standard Deviation**
Residential Population	157.00	3655.00	1081.09	473.17
Socioeconomic Status	0.00	93.84	30.86	20.11
Residential Mobility	0.00	78.34	22.09	12.71
Racial Heterogeneity	0.03	0.67	0.38	0.16
Street Type	0.00	1.00	0.23	0.42
Street Block Length (ft)	12.63	18808.05	478.94	501.44

Note: Min = Minimum, Max = Maximum, SL = Spatially Lagged

Analysis Plan

In order to answer my research question, I ran a series of count regression models and obtained model fit statistics, which I overview below. Prior to completing these analyses, I had to determine which count regression model was most appropriate for my data. Poisson regression is typically used to model equidispersed count-based outcome variables, whose variances are equal

[14] Groff and Lockwood's (2014) coding slightly differs from mine as the CAGIS road class categories do not match exactly to the U.S. Census TIGER/Line categories they used. They included interstates, freeways and expressways (which were all excluded from this study), principal arterials, and minor arterials as major roads, and major collectors, minor collectors, and local roads not eligible for federal aid as minor roads.

to their means (Long & Freese, 2014). Negative binomial regression is an extension of Poisson regression that accounts for overdispersed outcome variables with variances that exceed their means (Long & Freese, 2014). I determined the appropriate count-based model for my data via a number of tests.

First, following Long and Freese (2014) and Hilbe's (2012; 2014) recommendations, I visually compared charts of observed and predicted outcome variable counts to get a feel for how much the observed theft and robbery values differed from those expected under a Poisson distribution. Both charts indicated that the data were more consistent with the negative binomial distribution.

I followed this informal assessment with a formal test of model fit. For this, I followed Long and Freese (2014) and Hilbe's (2012; 2014) recommendation of using the likelihood-ratio test. The likelihood-ratio test is a goodness of fit test used to determine if two models, one nested within the other, are the same. It does so by comparing the log-likelihoods of both models, with the hypothesis that the model with fewer parameters is better than the model with more parameters (Hilbe, 2012). Because the negative binomial regression model is nearly the same as the Poisson regression model when the fitted values and variance are equal (Hilbe, 2012; Long & Freese, 2014), the likelihood-ratio test can be used to determine which form of regression should be used to model a particular data set. As the test result was significant for all models, I proceeded with using negative binomial regression models.

To answer my research question, I ran a series of 16 count regression models. The first model used a simple count operationalization of facility sets, representing a commonly used operationalization of the *Assumption of Crime Homogeneity*. This model used robbery as its outcome variable. The second model mirrors the first but used theft as its outcome variable. These two models formed the basis to which I compared models using the series of risky facility variables I proposed based on an *Assumption of Crime Concentration*. Both of these models include 16 count-based facility risk variables, 16 spatially lagged count-based facility risk variables, and the six socio-demographic and street control variables outlined above.

The remaining 14 count regression models each incorporated one of the *Assumption of Crime Concentration* operationalizations of risky facilities. These models also incorporated 16 facility risk variables, 16 spatially lagged facility risk variables, and six control variables. All sixteen count regression models were thus identical with the exception of the operationalization of the facility variables.

To answer my research question, I used two model fit statistics, the Akaike Information Criterion (AIC) (Akaike, 1973) and the Bayesian Information Criterion (BIC) (Schwarz, 1978). These two statistics were designed to compare model fit in non-nested models with the same number of observations (Cameron & Trivedi, 2013; Fox, 2015; Hilbe, 2012; Hilbe, 2014; Long & Freese, 2014). Both are also penalized fit statistics which punish for the inclusion of additional variables. However, the BIC penalizes more aggressively (Long & Freese, 2014). Though the magnitude of their values can typically not be interpreted individually, they are particularly useful for comparing and selecting across similar models (Fox, 2015). For both tests, values that are lower are considered to have a better model fit.

For the AIC test, Hilbe (2009) suggests using the following criteria for assessing model differences: if AIC values differ between 0 and 2.5, there is no difference in models; if AIC values differ between 2.5 and 6, the lower AIC model is preferred only if the sample size is greater than 256; if AIC values differ between 6 and 9.9, the lower AIC model is preferred only if the sample size is greater than 64; and finally, if AIC values differ by 10 or more, the lower AIC model is preferred for any sample size.

For the BIC test, Fox (Fox, 2015; also see Raftery, 1995) suggests that differences of 6 or more represent strong evidence for the model with the lower BIC value. Long and Freese (2014) draw on Raftery (1995) to further differentiate BIC values. They suggest that differences of 0 to 2 should be interpreted as weak evidence in favour of the lower model; differences of 2 to 6 should be interpreted as positive evidence in favour of the lower model; difference of 6 to 10 should be interpreted as strong evidence in favour of the lower model; and differences of over 10 should be interpreted as very strong evidence in favour of the lower model.

Running both and comparing their results is useful because it acts as a check for consistency. It is possible for the two tests to disagree, namely, to get a non-meaningful difference for BIC but a meaningful one for AIC. This is in part because AIC values are affected by large sample sizes more so than BIC values are, and the BIC test is designed in a way that makes it less likely to lead to a Type I error (i.e. false positive) than the AIC test (Dziak, Coffman, Lanza, & Li, 2012). If the AIC value change indicates an improved model but the BIC value does not, it is suggestive of nonzero but small effects (Dziak et al., 2012). Thus, both AIC and BIC were used to compare the *Assumption of Crime Concentration* measure models and the *Assumption of Crime Homogeneity* measure models for robbery and theft to determine if the results were consistent.

I also compared the substantive conclusions of facility coefficients in each of the improved models to determine if there is any impact on model outcomes as a result of the *Assumption of Crime Concentration* based risky facility measures. This includes calculating and inspecting variance inflation factors (VIF) for each variable in the final models to check for multicollinearity that might be impacting coefficient estimates (Zuur, Ieno, & Elphick, 2010). It is possible that, even with an improved model fit, the tested measures might lead to the same overall conclusions as the model incorporating the homogenous facility measures. Thus, it was important to assess what, if any, differing conclusions the *Assumption of Crime Concentration* measures have on models of robbery and theft at street blocks aside from model fit.

Next, I ran a series of sensitivity checks to ensure the results have not been impacted solely by my choice of operationalization. One potential issue with the at-facility measures is the fact that some facilities share the same address. Specifically, 274 (16%) of the total 1710 included facilities had shared addresses. There were 113 addresses with multiple facilities, ranging from 2 to 8 facilities at a single address. As both the theft incident and calls for service data were only available at the street address level, it is impossible to differentiate which unit/facility within the street address a particular call or incident occurred at. In the operationalizations overviewed above, these incidents and calls were included in the counts for each facility at an address. This operationalization thus accounted for risk at each place with the maximum possible number of incidents that might have occurred there.

The distribution of co-located facilities by facility set is broken down below in Table 24. Additional information about the co-located facilities in this data set is included in Appendix A. An assessment of this table shows that the extent of co-located facilities varies by facility type from 0% of recreation centers sharing addresses with other facilities to 28.9% of consumer electronic stores sharing addresses with other facilities. There are also large variations in the amount of crime occurring at co-located facilities by facility type. For instance, only 2.8% of thefts and 1.3% of calls for service at drug treatment centers were at centers that share addresses with other facilities. This is contrasted by home décor and furniture stores which had 92.6% of thefts and 74.1% of calls for service occurring at locations that share addresses with other facilities. It is likely that some facility sets are having their crime counts inflated by sharing addresses with high crime locations of other facility types.

Table 24. Crime at Co-Located Facilities

Facility Type	Total Number of Facilities	Number of Co-Located Facilities (%)	Total Thefts at Facility Set in 2015	Thefts at Co-Located Facilities in 2015 (%)	Total Calls for Service at Facility Set in 2015	Calls for Service at Co-Located Facilities in 2015 (%)
Bars and Clubs	153	14 (9.2%)	173	48 (27.7%)	1810	413 (22.8%)
Consumer Electronic Stores	114	33 (28.9%)	153	128 (83.7%)	1485	993 (66.9%)
Convenience Stores	156	10 (6.4%)	226	46 (20.4%)	2698	428 (15.9%)
Discount and Dollar Stores	26	6 (23.1%)	217	22 (10.1%)	1116	315 (28.2%)
Drug Treatment Centers	42	2 (3.4%)	71	2 (2.8%)	1603	21 (1.3%)
Entertainment Venues	76	10 (13.2%)	120	41 (34.2%)	1772	760 (42.9%)
Fast Food Restaurants	340	79 (23.2%)	373	203 (54.4%)	5503	2244 (40.8%)
Gas Stations	89	4 (4.5%)	375	10 (2.7%)	3865	141 (3.6%)
Grocery Stores	26	5 (19.2%)	497	180 (36.2%)	2379	641 (26.9%)
Home Décor and Furniture Stores	76	16 (21.1%)	204	189 (92.6%)	727	539 (74.1%)
Hotels	27	1 (3.7%)	70	5 (7.1%)	1192	201 (16.9%)
Pharmacies	32	4 (12.5%)	327	170 (52.0%)	1102	507 (46.0%)
Recreation Centers	38	0 (0.0%)	--	--	--	--
Recreation Retail Stores	85	24 (28.2%)	232	204 (87.9%)	1077	891 (82.7%)
Salons and Barber Shops	179	30 (16.8%)	120	91 (75.8%)	1504	924 (61.4%)
Sit-Down Restaurants	235	36 (15.3%)	428	322 (75.2%)	3243	1883 (58.1%)

An alternative way to operationalize risk at multi-facility addresses is to create an average rate of thefts and incidents across the facilities at any particular address by dividing the total number of crimes at an address by the total number of facilities there. This approach tempers the inflating effects of using the total crime at each address for any facility at that address, but it also has the potential to underestimate crimes at high crime locations. As a sensitivity check, I reran all of the at-facility based regression models with a rate operationalization to see if it had any impact on the results. Likewise, to make sure my selection of a 500ft street network distance for the buffer area operationalizations did not impact results, I reran all of the buffer area regressions using a 1000ft street network distance buffer.

Finally, as an improved AIC or BIC value is no guarantee that a model is actually a good one, it merely shows which is better out of the options assessed (Raftery, 1995), I ran a series of model diagnostics to assess model performance for those *Assumption of Crime Concentration* models that had an improved model fit compared to the *Assumption of Crime Homogeneity* base models. First, plots of residual and predicted values were used to determine if the model fit varied at different levels of the dependent variable, such as for very small or very large values (Cameron & Trivedi, 2013). Next, a Global Moran's I test (Moran, 1950) was used to confirm that any spatial autocorrelation was sufficiently accounted for by the incorporation of the spatial lag facility variables. This test was calculated using GeoDa 1.14.0.4 (Anselin, Syabri, & Kho, 2006) and model residuals were used to check for remaining spatial dependencies. Thereafter, the influence of outlier cases with large residuals was assessed by running a series of models, each identical to the original model with the exception of the exclusion of one outlier case (Long & Freese, 2014). The new model coefficients were compared to the original model coefficients to ensure that the outlier cases were not overly influential on the estimated model parameters.

CHAPTER 5: RESULTS

This chapter presents the results of the analyses overviewed in Chapter 4. The results are presented in several sections. I start by presenting the results as they relate to my research question, which asked “Can risky facility measures based on an *Assumption of Crime Concentration* better explain crime counts at micro-places than commonly used *Assumption of Crime Homogeneity* facility measures of all places within each facility type?”. To answer this question, I first compare the AIC and BIC values of each model. Recall that this is necessary to determine which model(s) have the best fit. There was only one model that had an improved fit over the homogenous count base models – the one that used the Continuous Robbery Risk Using Buffer-Area Calls For Service measures.

Second, to see if any of the measures led to modeling problems, I assess variance inflation factor values to determine if multicollinearity is an issue in any of the models. This assessment shows that some models are impacted by multicollinearity, but that this issue does not extend to the Continuous Robbery Risk Using Buffer-Area Calls For Service model that has an improved model fit over the homogenous count base model.

Third, I assess and compare model coefficients. Specifically, I compare the results of the model found to improve on the base model to the base model results to determine if the conclusions drawn from each model differ. The results of this comparison suggest that the models lead to mostly the same conclusions, with only some small differences in the impact of a few spatial lag variables.

Finally, I present the results of my sensitivity analyses and model diagnostic checks. These indicate that a using larger distance to create the buffer area risk variables (1000ft) and that using a rate to account for crime at multi-facility addresses lead to the same substantive conclusions as using a 500ft buffer area and ascribing the full incident count from each address to each facility at that address. They also suggest that the base and improved robbery models have similar model fit at high and low values of the dependent variable, that spatial correlation was not an issue in either model, and that substantive conclusions do not differ after removing outlier cases from each model.

Comparison of Robbery Model AIC and BIC Values

In the next two sections, I focus on comparing and interpreting the model fit statistics. The parameter estimates for the individual robbery models are shown in Appendix C. Robbery model fit statistics and their interpretation are presented below in Table 25. Recall seven robbery models were estimated, one for each of the different operationalizations of facilities described above, with the exception of the at-facility incident measures since street robbery cannot occur in facilities. The base model, measuring robbery risk using a homogenous count of facilities, had AIC and BIC values of 5662.629 and 5954.636, respectively.

Recall that lower AIC and BIC values indicate improved model fit, with a BIC reduction of zero to two interpreted as weak evidence in favor of the lower model, a reduction of two to six interpreted as positive evidence, a reduction of six to 10 interpreted as strong evidence, and a reduction of 10 or more interpreted as very strong evidence in favour of the lower model. With a sample of 10,940, AIC differences of greater than 2.5 are interpreted as favourable evidence for the lower model (Hilbe, 2009).

Only one robbery model had an AIC and BIC value reduction compared to the base model. The Continuous Robbery Risk Using Buffer-Area Calls for Service model had an AIC value of 5624.984 and a BIC value of 5916.991, both a reduction of 37.645. This suggests that this model is very strongly favored over the homogenous count of facilities model.

Table 25. Robbery Model Fit Statistics and Interpretation

Model	AIC Value (Difference from Base Model)	AIC Difference Interpretation	BIC Value (Difference from Base Model)	BIC Difference Interpretation
Base Model: Robbery Risk Using Homogenous Count of Facilities	5662.629		5954.636	
Binary Robbery Risk Using Buffer-Area Street Robbery Incidents	5700.247 (+37.618)	Base Model Favored	5992.254 (+37.618)	Base Model Very Strongly Favored
Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents	5671.251 (+8.622)	Base Model Favored	5963.258 (+8.622)	Base Model Strongly Favored
Binary Robbery Risk Using At-Facility Calls for Service	5721.449 (+58.820)	Base Model Favored	6013.457 (+58.820)	Base Model Very Strongly Favored
Continuous Robbery Risk Using At-Facility Calls for Service	5701.836 (+39.207)	Base Model Favored	5993.843 (+39.207)	Base Model Very Strongly Favored
Binary Robbery Risk Using Buffer-Area Calls for Service	5697.418 (+34.789)	Base Model Favored	5989.425 (+34.789)	Base Model Very Strongly Favored
Continuous Robbery Risk Using Buffer-Area Calls for Service	5624.984 (-37.645)	Alternate Model Favored	5916.991 (-37.645)	Alternate Model Very Strongly Favored

Notes: AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion

Comparison of Theft Model AIC and BIC Values

Next, I compare model fit statistics for the theft models. Nine theft models were estimated, one for each of the different operationalizations of facilities discussed in Chapter 4. Theft model fit statistics and their interpretation are presented below in Table 26. The parameter estimates for the individual theft models are shown in Appendix C.

The base model, measuring theft risk using a Homogenous Count of Facilities, had AIC and BIC values of 24712.360 and 25004.367, respectively. None of the risky facility models using measures based on an *Assumption of Crime Concentration* improved on these values. The closest two models were the Continuous Theft Risk Using Buffer-Area Theft Incidents and the Continuous Theft Risk Using Buffer-Area Calls for Service models. These had increased AIC and BIC values of 55.803 and 56.048, respectively, suggesting that the homogenous count of facilities model is very strongly favored.

Table 26. Theft Model Fit Statistics and Interpretation

Model	AIC Value (Difference from Base Model)	AIC Difference Interpretation	BIC Value (Difference from Base Model)	BIC Difference Interpretation
Base Model: Theft Risk Using Homogenous Count of Facilities	24712.360	--	25004.367	--
Binary Theft Risk Using At-Facility Theft Incidents	24995.193 (+282.833)	Base Model Favored	25287.200 (+282.833)	Base Model Very Strongly Favored
Continuous Theft Risk Using At-Facility Theft Incidents	24901.045 (+188.685)	Base Model Favored	25193.052 (+188.685)	Base Model Very Strongly Favored
Binary Theft Risk Using Buffer-Area Theft Incidents	25074.460 (+362.100)	Base Model Favored	25366.467 (+362.100)	Base Model Very Strongly Favored
Continuous Theft Risk Using Buffer-Area Theft Incidents	24768.163 (+55.803)	Base Model Favored	25060.170 (+55.803)	Base Model Very Strongly Favored
Binary Theft Risk Using At-Facility Calls for Service	25105.016 (+392.656)	Base Model Favored	25397.023 (+392.656)	Base Model Very Strongly Favored
Continuous Theft Risk Using At-Facility Calls for Service	24860.441 (+148.081)	Base Model Favored	25152.448 (+148.081)	Base Model Very Strongly Favored
Binary Theft Risk Using Buffer-Area Calls for Service	25218.861 (+506.501)	Base Model Favored	25510.869 (+506.501)	Base Model Very Strongly Favored
Continuous Theft Risk Using Buffer-Area Calls for Service	24768.408 (+56.048)	Base Model Favored	25060.415 (+56.048)	Base Model Very Strongly Favored

Notes: AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion

Variance Inflation Factors by Model

Because the focus of this study is proposing and testing a series of new facility risk measures, I next checked the variance inflation factors (VIF) for each model to see if they led to multicollinearity, paying particular attention to the robbery model with an improved model fit. The range of VIF scores and the mean for each model are presented below in Table 27. VIF values for all model coefficients are presented in Appendix C.

Table 27. Mean Variance Inflation Factor Score and Range by Model

Robbery Models	Mean VIF	VIF Range	Theft Models	Mean VIF	VIF Range
Base Model: Robbery Risk Using Homogenous Count of Facilities	1.48	1.03 – 2.34	Base Model: Theft Risk Using Homogenous Count of Facilities	1.48	1.03 – 2.34
Binary Robbery Risk Using Buffer-Area Street Robbery Incidents	1.47	1.03 – 2.20	Binary Theft Risk Using At-Facility Theft Incidents	1.40	1.03 – 2.00
Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents	1.57	1.03 – 2.47	Continuous Theft Risk Using At-Facility Theft Incidents	4.03	1.03 – 13.38
Binary Robbery Risk Using At-Facility Calls for Service	1.37	1.03 - 1.89	Binary Theft Risk Using Buffer-Area Theft Incidents	1.90	1.03 – 4.73
Continuous Robbery Risk Using At-Facility Calls for Service	2.18	1.03 – 6.48	Continuous Theft Risk Using Buffer-Area Theft Incidents	3.03	1.03 – 9.78
Binary Robbery Risk Using Buffer-Area Calls for Service	1.58	1.03 – 3.05	Binary Theft Risk Using At-Facility Calls for Service	1.37	1.03 – 1.89
Continuous Robbery Risk Using Buffer-Area Calls for Service*	1.64	1.03 – 3.13	Continuous Theft Risk Using At-Facility Calls for Service	2.18	1.03 – 6.48
			Binary Theft Risk Using Buffer-Area Calls for Service	1.58	1.03 – 3.05
			Continuous Theft Risk Using Buffer-Area Calls for Service	1.64	1.03 – 3.13

Notes: * Models with improved model fit over base model, VIF = Variance Inflation Factor

The first thing I want to point out is that the VIF scores, in some models, have hit ranges that some would find concerning. A series of cut-off values have been suggested for this test, ranging from 3 (Zuur et al., 2010), up to 10 (Montgomery, Peck, & Vining, 2012). The improved robbery model had similar, though slightly higher, VIF values compared to the homogenous count base model. Neither of these models was problematic.

However, a number of the models that did not have an improved model fit over the homogenous count base models had high VIF values, and these warrant some discussion. In this situation, some recommend dropping one or more highly correlated variables to lower the VIF values of the remaining variables in the model (Zuur et al., 2010). However, O’Brien (2007; also see O'Brien, 2017) cautions against dropping high VIF measures solely to lower VIF values as it leads to models that are “not theoretically well motivated” (p. 683). He advises limiting the dropping or combining of variables to instances where they are conceptually similar or are measuring the same underlying construct.

For the purposes of this dissertation, I have opted not to drop the variables and rerun the models. My reasoning for this is that the point of this dissertation is to propose and test a series of facility risk operationalizations rooted in an *Assumption of Crime Concentration* to see if they might serve as alternatives for the more common approach of operationalizing facilities based on an *Assumption of Crime Homogeneity.* Leaving the models as-is and reporting their high VIF values provides valuable information about the usefulness (or lack thereof) of some of the proposed measures.

For instance, an inspection of Table 27 shows that continuous measures of facility theft risk based on at-facility theft incidents and buffer-area theft incidents both lead to unacceptably high VIF values. Likewise, the continuous robbery and theft risk measures using at-facility calls for service also have high VIF values. Multicollinearity can lead to unstable coefficient estimations and inflated standard error estimations (O’Brien, 2007) which can impact the significance and interpretation of regressed variables. Given the high percentage of thefts and calls for service occurring at co-located facilities, as highlighted in Table 24, it is likely these high VIF values are being driven by crime at facilities sharing addresses. This suggests that these measures may be inappropriate for studies of crime and place using data with a large proportion of crime at co-located facilities, particularly if the goal of these studies is to quantify the impact of different facility types on crime. However, if the goal of the study is to predict future observations and researchers are not interested in individual parameter estimates, then these high VIF values may not be an issue as “[t]he fact that some or all predictor variables are correlated among themselves does not, in general, inhibit our ability to obtain a good fit nor does it tend to affect inferences about mean responses or predictions of new observations, provided these inferences are made within the region of observations" (Kutner, Nachtsheim, Neter, & Li, 2005, p. 283).

Finally, in order to drop the problematic variables in the high VIF models, I would have needed to also drop them in all other models to ensure that the only difference across models was the operationalization of facilities and not the actual facility types included. Doing this would have led to a decrease in information about the utility of those operationalizations, as there is no reason to believe that any of the other variables in my models capture the underlying construct that I am attempting to quantify using the high VIF facility types. As such, I've left the measures in the regressions here, but note that their high level of collinearity has increased their standard errors and thus may have led them to be found to not have a statistically significant impact on crime when, in a situation without collinearity, they may have been found to be significant.

Comparison of Robbery Model Coefficients

Next, I assess and compare model coefficients to determine if the conclusions drawn from the homogenous count base model and the improved fit Continuous Robbery Risk Using Buffer-Area Calls For Service model differ. Table 28, below, presents the incident rate ratio values and 95% confidence intervals for all of the robbery models. An inspection of this table shows that, by and large, the homogenous count base model and the improved fit Continuous Robbery Risk Using Buffer-Area Calls For Service model come to the same conclusions. Both find that focal street block convenience stores and gas stations are positively associated with robbery. Likewise, they both find that spatially lagged consumer electronics stores, convenience stores, and recreation centers are positively associated with robbery. In both models, the same five control variables are found to be significantly and positively associated with robbery.

The only differences in the two models are with respect to spatially lagged discount and dollar stores and spatially lagged drug treatment centers. The base model finds a fairly sizable positive association between spatially lagged discount and dollar stores and robbery, which is missing in the Continuous Robbery Risk Using Buffer-Area Calls for Service model. Conversely, the Continuous Robbery Risk Using Buffer-Area Calls for Service model finds that spatially lagged drug treatment centers are linked to a small but significant increase in robbery, whereas the base model does not.

Comparison of Theft Model Coefficients

The incident rate ratio values and 95% confidence intervals for each of the theft models are presented below, in Table 29. Recall that none of the *Assumption of Crime Concentration* facility risk models resulted in an improved model fit for the theft outcome. As such there are no improved models to compare the homogenous count theft model coefficients to in order to see if there is any difference in the conclusions drawn from each model. It is interesting to note, however, that there is a large amount of disagreement across theft models. This may be partially attributable to the collinearity discussed above. The models are in agreement on the relationship between six different focal street block facilities and theft. However, the remaining nine facilities vary in their links to street block level theft, with home décor and furniture stores even flipping from a significant positive relationship with theft in the *Binary Theft Risk Using At-Facility Calls for Service* model to a significant negative relationship in the *Continuous Theft Risk Using At-Facility Theft Incidents* model.

Sensitivity Checks

As described in the “Analysis Plan” section in the previous Chapter, I ran a series of sensitivity checks to ensure my results were not solely a result of my operationalization choices. First, I reran all of the models that incorporated an IVA based facility risk measure using a street

Table 28. Incident Rate Ratios and Confidence Intervals of Robbery Risk Measure Models

	Base Model: Robbery Risk Using Homogenous Count of Facilities			Binary Robbery Risk Using Buffer-Area Street Robbery Incidents			Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents			Binary Robbery Risk Using At-Facility Calls for Service			Continuous Robbery Risk Using At-Facility Calls for Service			Binary Robbery Risk Using Buffer-Area Calls for Service			Continuous Robbery Risk Using Buffer-Area Calls for Service		
	IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval	
Bars	1.529	0.922	2.537	1.779	0.655	4.835	1.371	0.963	1.953	1.891	0.738	4.848	1.022	0.995	1.051	2.018	0.778	5.234	1.001	0.999	1.003
Consumer Electronics Stores	1.091	0.638	1.867	0.778	0.257	2.355	0.941	0.652	1.359	1.259	0.386	4.107	0.985	0.959	1.012	0.628	0.234	1.684	1.000	0.998	1.002
Convenience Stores	2.307	1.480	3.598	4.540	1.684	12.243	1.570	1.085	2.272	3.143	1.200	8.230	1.016	0.998	1.035	1.909	0.766	4.762	1.003	1.001	1.006
Discount and Dollar Stores	0.916	0.334	2.514	1.595	0.323	7.867	1.029	0.705	1.503	1.558	0.241	10.084	1.002	0.986	1.017	2.630	0.551	12.551	1.001	0.998	1.003
Drug Treatment Centers	1.196	0.444	3.221	0.750	0.118	4.774	0.847	0.360	1.989	4.362	0.603	31.532	1.004	0.992	1.016	1.089	0.179	6.633	1.000	0.996	1.005
Entertainment Venues	1.104	0.456	2.673	1.064	0.238	4.756	0.801	0.280	2.290	1.461	0.162	13.167	0.996	0.975	1.017	0.895	0.129	6.193	1.000	0.996	1.004
Fast Food Restaurants	1.123	0.839	1.504	0.945	0.506	1.765	1.040	0.811	1.333	1.427	0.707	2.881	1.002	0.991	1.012	0.737	0.372	1.460	1.000	0.999	1.002
Gas Stations	2.125	1.122	4.025	3.906	1.142	13.359	1.481	0.957	2.294	2.188	0.730	6.561	1.009	1.001	1.018	2.858	0.843	9.687	1.003	1.000	1.006
Grocery Stores	2.263	0.639	8.015	1.531	0.163	14.384	1.499	0.571	3.936	3.870	0.461	32.512	1.006	0.998	1.013	3.042	0.387	23.912	1.003	1.000	1.006
Home Décor and Furniture Stores	1.732	0.863	3.474	1.798	0.568	5.693	1.110	0.680	1.814	2.266	0.378	13.566	0.969	0.930	1.009	2.316	0.621	8.641	1.001	0.998	1.004
Hotels	2.100	0.671	6.578	1.866	0.318	10.948	1.715	0.711	4.137	2.041	0.171	24.405	1.013	0.992	1.035	5.082	0.804	32.138	1.003	1.000	1.005
Pharmacies	1.600	0.455	5.623	0.280	0.007	10.993	0.841	0.220	3.210	9.691	0.722	130.042	1.032	1.001	1.064	1.047	0.070	15.634	1.001	0.995	1.006
Recreation Centers	2.076	0.782	5.510	3.502	0.560	21.908	1.792	0.508	6.318	2.420	0.379	15.464	1.019	0.991	1.049	1.607	0.240	10.760	1.004	0.996	1.013
Recreation Retails Stores	0.634	0.264	1.519	0.757	0.152	3.770	1.035	0.442	2.423	0.664	0.066	6.729	1.043	1.000	1.088	1.266	0.224	7.148	1.000	0.996	1.003
Salons and Barber Shops	0.890	0.506	1.568	1.909	0.711	5.122	1.007	0.585	1.734	0.850	0.266	2.712	1.022	0.996	1.050	0.869	0.284	2.660	0.999	0.996	1.001
Sit-Down Restaurants	1.118	0.750	1.666	1.268	0.638	2.521	1.174	0.850	1.622	1.612	0.683	3.808	1.002	0.984	1.020	1.485	0.717	3.076	1.001	1.000	1.002
SL Bars	1.102	0.873	1.391	1.279	0.827	1.978	0.993	0.846	1.166	1.459	0.909	2.341	1.005	0.992	1.018	1.540	0.957	2.478	1.001	1.000	1.002
SL Consumer Electronics Stores	1.603	1.263	2.034	1.934	1.224	3.058	1.304	1.109	1.534	0.788	0.446	1.390	0.997	0.985	1.009	2.157	1.375	3.385	1.002	1.001	1.002
SL Convenience Stores	1.612	1.297	2.004	1.089	0.666	1.780	1.222	1.038	1.438	1.469	0.889	2.429	1.007	0.999	1.015	2.577	1.650	4.023	1.003	1.002	1.004
SL Discount and Dollar Stores	1.752	1.083	2.835	0.917	0.389	2.159	1.011	0.828	1.234	2.924	1.252	6.833	1.015	1.007	1.022	1.150	0.498	2.654	1.001	1.000	1.003
SL Drug Treatment Centers	1.490	0.997	2.227	1.497	0.690	3.247	1.316	0.908	1.907	0.760	0.239	2.413	1.001	0.995	1.006	2.017	0.918	4.429	1.002	1.000	1.004
SL Entertainment Venues	1.201	0.829	1.740	1.716	0.872	3.378	1.537	1.009	2.341	0.658	0.244	1.777	0.997	0.988	1.006	0.870	0.410	1.847	1.000	0.998	1.002
SL Fast Food Restaurants	0.943	0.839	1.059	1.075	0.827	1.396	0.990	0.892	1.099	1.360	0.994	1.861	1.006	1.001	1.010	0.899	0.716	1.130	1.000	0.999	1.000
SL Gas Stations	1.029	0.762	1.390	1.181	0.605	2.306	1.022	0.841	1.242	1.917	1.153	3.187	1.005	1.002	1.008	1.238	0.682	2.247	1.000	0.999	1.001
SL Grocery Stores	0.883	0.450	1.733	2.680	0.828	8.672	1.384	0.872	2.196	1.370	0.474	3.961	1.002	0.998	1.007	1.664	0.515	5.376	1.000	0.998	1.002
SL Home Décor & Furniture Stores	0.749	0.512	1.094	0.584	0.276	1.234	0.795	0.588	1.074	0.928	0.386	2.233	1.010	0.985	1.035	0.770	0.387	1.532	0.999	0.998	1.001
SL Hotels	1.395	0.822	2.366	0.956	0.366	2.497	0.980	0.584	1.646	1.316	0.402	4.311	1.007	0.997	1.017	1.942	0.727	5.191	1.001	0.999	1.002
SL Pharmacies	0.822	0.437	1.545	0.200	0.038	1.059	0.651	0.363	1.170	0.530	0.100	2.805	0.982	0.959	1.005	0.423	0.097	1.845	1.000	0.997	1.002
SL Recreation Centers	1.846	1.121	3.039	1.496	0.594	3.767	1.148	0.696	1.892	2.527	0.962	6.635	1.011	0.995	1.027	2.869	1.195	6.885	1.006	1.002	1.010
SL Recreation Retails Stores	1.089	0.752	1.575	1.752	0.925	3.318	1.353	0.918	1.995	0.348	0.113	1.075	0.957	0.917	0.998	0.540	0.229	1.273	1.000	0.998	1.002
SL Salons and Barber Shops	0.924	0.724	1.179	1.268	0.770	2.088	1.040	0.804	1.345	1.208	0.715	2.039	0.983	0.969	0.998	1.100	0.598	2.023	1.000	0.998	1.001
SL Sit-Down Restaurants	1.103	0.933	1.304	1.282	0.955	1.722	1.149	1.002	1.318	1.257	0.882	1.792	1.006	0.998	1.015	1.115	0.849	1.464	1.000	1.000	1.001
Disadvantage	1.032	1.028	1.037	1.033	1.028	1.037	1.032	1.028	1.037	1.032	1.028	1.037	1.032	1.027	1.036	1.032	1.027	1.036	1.031	1.027	1.036
Residential Mobility	0.995	0.988	1.002	0.996	0.989	1.003	0.996	0.989	1.002	0.994	0.987	1.000	0.994	0.987	1.000	0.995	0.988	1.001	0.995	0.988	1.002
Racial Heterogeneity	2.405	1.413	4.093	2.014	1.186	3.421	1.975	1.166	3.346	2.606	1.534	4.426	2.524	1.487	4.286	2.170	1.277	3.688	2.167	1.280	3.669
Population	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Street Length	1.001	1.000	1.001	1.001	1.000	1.001	1.001	1.000	1.001	1.001	1.000	1.001	1.001	1.000	1.001	1.001	1.000	1.001	1.001	1.000	1.001
Street Type	1.641	1.365	1.974	1.997	1.678	2.378	1.918	1.610	2.286	1.934	1.620	2.309	1.856	1.553	2.217	2.015	1.692	2.400	1.739	1.455	2.078
Constant	0.008	0.005	0.011	0.009	0.006	0.012	0.009	0.006	0.012	0.009	0.006	0.012	0.009	0.006	0.012	0.009	0.006	0.013	0.008	0.006	0.012
AIC			5662.629			5700.247			5671.251			5721.449			5701.836			5697.418			5624.984
BIC			5954.636			5992.254			5963.258			6013.457			5993.843			5989.425			5916.991

Notes: IRR = Incident Rate Ratio; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 29. Incident Rate Ratios and Confidence Intervals of Theft Risk Measure Models

	Base Model: Theft Risk Using Homogenous Count of Facilities			Binary Theft Risk Using At-Facility Theft Incidents			Continuous Theft Risk Using At-Facility Theft Incidents			Binary Theft Risk Using Buffer-Area Theft Incidents			Continuous Theft Risk Using Buffer-Area Theft Incidents			Binary Theft Risk Using At-Facility Calls for Service			Continuous Theft Risk Using At-Facility Calls for Service			Binary Theft Risk Using Buffer-Area Calls for Service			Continuous Theft Risk Using Buffer-Area Calls for Service		
	IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval		IRR	95% Confidence Interval	
Bars	1.944	1.503	2.515	4.730	2.727	8.206	1.461	1.251	1.705	2.337	1.308	4.177	1.059	1.036	1.083	3.630	2.048	6.434	1.044	1.027	1.061	1.892	1.043	3.431	1.003	1.001	1.004
Consumer Electronics Stores	1.194	0.877	1.625	1.155	0.642	2.077	0.726	0.594	0.889	4.081	1.540	10.809	1.006	0.983	1.029	2.032	1.052	3.928	0.996	0.979	1.013	1.238	0.527	2.905	1.000	0.999	1.001
Convenience Stores	2.475	1.886	3.248	2.626	1.652	4.172	1.207	1.117	1.305	3.844	2.123	6.961	1.101	1.067	1.136	4.632	2.494	8.601	1.028	1.018	1.038	3.349	1.772	6.328	1.005	1.003	1.006
Discount and Dollar Stores	5.574	3.025	10.274	7.307	1.968	27.130	1.211	1.096	1.337	4.894	1.258	19.042	1.083	1.047	1.121	5.323	1.380	20.528	1.040	1.023	1.058	1.967	0.601	6.442	1.008	1.005	1.011
Drug Treatment Centers	3.024	1.738	5.262	5.115	1.799	14.538	1.272	1.072	1.510	6.187	1.856	20.623	1.100	1.034	1.170	4.296	1.370	13.469	1.010	1.002	1.017	4.502	1.298	15.613	1.005	1.002	1.008
Entertainment Venues	2.579	1.753	3.796	3.690	1.889	7.206	1.397	1.191	1.639	3.644	1.484	8.947	1.090	1.049	1.133	4.933	2.114	11.513	1.028	1.015	1.041	5.777	2.246	14.861	1.005	1.003	1.008
Fast Food Restaurants	1.339	1.147	1.564	1.599	1.070	2.390	1.228	1.089	1.384	0.844	0.552	1.288	1.012	0.999	1.025	1.407	0.938	2.110	1.009	1.002	1.015	0.902	0.635	1.282	1.001	1.000	1.002
Gas Stations	3.259	2.294	4.630	6.206	3.004	12.821	1.172	1.101	1.247	2.993	1.380	6.491	1.091	1.056	1.128	6.516	3.006	14.124	1.017	1.011	1.023	2.773	1.218	6.309	1.005	1.003	1.007
Grocery Stores	21.014	10.492	42.087	28.670	7.242	113.497	1.123	1.090	1.157	30.499	7.616	122.139	1.062	1.036	1.088	9.635	2.486	37.343	1.022	1.016	1.028	46.949	11.504	191.600	1.007	1.005	1.010
Home Décor and Furniture Stores	1.292	0.905	1.845	1.436	0.792	2.604	0.811	0.742	0.887	0.822	0.369	1.831	0.995	0.972	1.019	2.943	1.130	7.669	1.019	0.987	1.053	2.309	0.774	6.894	1.001	0.999	1.003
Hotels	1.742	0.975	3.112	4.667	1.127	19.325	1.233	1.021	1.489	2.971	0.728	12.126	1.028	1.000	1.056	4.552	1.023	20.249	1.013	1.001	1.025	3.053	0.732	12.731	1.002	1.000	1.004
Pharmacies	2.347	1.401	3.933	3.438	0.918	12.876	1.052	0.994	1.113	2.977	0.748	11.842	1.027	0.998	1.056	3.003	0.834	10.818	1.023	1.006	1.040	7.246	1.485	35.363	1.004	1.001	1.006
Recreation Centers	1.633	0.932	2.861	1.382	0.493	3.875	1.114	0.880	1.410	1.738	0.522	5.787	1.066	0.968	1.173	1.460	0.420	5.073	1.015	0.996	1.035	3.364	1.021	11.088	1.004	0.999	1.010
Recreation Retails Stores	1.385	0.945	2.029	0.803	0.340	1.894	0.965	0.895	1.041	1.580	0.666	3.746	1.024	0.994	1.056	2.518	1.122	5.652	0.999	0.988	1.011	2.302	0.949	5.586	1.003	1.001	1.005
Salons and Barber Shops	0.932	0.718	1.210	1.759	1.010	3.064	1.179	0.967	1.436	1.038	0.505	2.133	0.990	0.966	1.014	1.796	1.004	3.212	1.010	0.995	1.025	0.840	0.413	1.707	0.999	0.998	1.001
Sit-Down Restaurants	1.291	1.045	1.596	1.274	0.887	1.831	1.086	1.002	1.177	1.223	0.764	1.960	0.999	0.986	1.012	1.573	0.971	2.548	1.011	1.002	1.020	1.657	1.058	2.596	1.001	1.000	1.001
SL Bars	1.149	1.037	1.273	1.181	0.929	1.501	1.093	1.028	1.161	1.593	1.270	1.996	1.019	1.010	1.027	1.277	1.004	1.623	1.010	1.004	1.016	1.604	1.244	2.067	1.001	1.000	1.001
SL Consumer Electronics Stores	1.077	0.947	1.225	1.091	0.876	1.359	0.937	0.878	1.000	0.666	0.482	0.921	0.989	0.981	0.998	0.938	0.721	1.222	0.998	0.993	1.003	0.982	0.730	1.319	1.000	1.000	1.001
SL Convenience Stores	1.126	0.999	1.268	1.522	1.244	1.863	1.013	0.977	1.050	1.817	1.402	2.354	1.034	1.021	1.047	1.282	0.969	1.695	1.001	0.997	1.005	1.474	1.120	1.939	1.001	1.000	1.001
SL Discount and Dollar Stores	1.471	1.106	1.955	1.880	1.044	3.384	1.038	1.016	1.061	1.492	0.895	2.489	1.022	1.009	1.034	1.708	0.938	3.110	1.007	1.003	1.012	1.061	0.562	2.004	1.001	1.000	1.002
SL Drug Treatment Centers	1.041	0.829	1.307	1.029	0.630	1.680	0.988	0.919	1.062	0.854	0.511	1.428	1.005	0.983	1.028	0.813	0.465	1.421	1.000	0.997	1.003	1.003	0.585	1.720	1.000	0.999	1.001
SL Entertainment Venues	1.251	1.053	1.486	1.498	1.083	2.072	1.068	1.007	1.133	2.353	1.615	3.428	1.015	0.999	1.032	1.202	0.805	1.794	1.002	0.998	1.006	0.737	0.492	1.105	1.000	0.999	1.001
SL Fast Food Restaurants	0.967	0.911	1.026	1.045	0.888	1.228	1.093	1.048	1.139	1.061	0.905	1.245	1.000	0.995	1.005	1.127	0.951	1.334	1.003	1.000	1.005	0.968	0.850	1.102	1.000	1.000	1.000
SL Gas Stations	0.914	0.779	1.072	1.104	0.800	1.526	1.009	0.989	1.029	1.279	0.902	1.813	0.999	0.986	1.011	1.130	0.804	1.588	1.002	1.000	1.004	1.532	1.074	2.187	1.000	1.000	1.001
SL Grocery Stores	0.994	0.716	1.380	1.769	0.824	3.799	1.001	0.987	1.015	1.605	0.762	3.382	1.002	0.997	1.006	1.379	0.729	2.610	1.001	0.998	1.003	0.882	0.434	1.795	1.001	0.999	1.002
SL Home Décor & Furniture Stores	1.003	0.852	1.181	1.401	1.083	1.811	0.998	0.973	1.023	1.205	0.875	1.660	1.002	0.993	1.011	1.295	0.865	1.939	1.002	0.996	1.009	1.167	0.810	1.682	1.000	0.999	1.001
SL Hotels	1.678	1.301	2.164	0.874	0.497	1.536	1.052	0.985	1.123	1.631	0.989	2.690	1.004	0.995	1.014	0.973	0.553	1.711	1.006	1.001	1.011	2.364	1.360	4.110	1.001	1.000	1.002
SL Pharmacies	1.045	0.818	1.335	1.362	0.663	2.799	1.039	1.022	1.057	2.670	1.325	5.377	1.010	0.999	1.021	2.391	1.272	4.494	1.006	1.001	1.012	2.421	1.311	4.471	1.001	1.000	1.003
SL Recreation Centers	1.491	1.155	1.926	1.660	1.058	2.603	1.125	1.012	1.250	1.694	0.997	2.877	1.048	1.005	1.093	1.455	0.820	2.580	1.008	1.000	1.016	1.627	0.937	2.827	1.003	1.001	1.005
SL Recreation Retails Stores	1.033	0.874	1.220	1.205	0.826	1.759	1.011	0.983	1.039	0.709	0.470	1.072	1.002	0.992	1.013	1.338	0.941	1.903	1.001	0.996	1.005	1.054	0.715	1.553	1.000	0.999	1.001
SL Salons and Barber Shops	1.023	0.924	1.132	1.042	0.822	1.320	0.986	0.894	1.087	1.112	0.847	1.459	0.996	0.987	1.006	1.325	1.045	1.680	0.998	0.992	1.005	1.145	0.835	1.570	1.000	0.999	1.001
SL Sit-Down Restaurants	1.100	1.012	1.195	1.529	1.322	1.768	0.975	0.950	0.999	0.880	0.741	1.045	1.001	0.996	1.006	1.286	1.066	1.551	0.998	0.995	1.002	0.945	0.798	1.120	1.000	1.000	1.000
Disadvantage	1.010	1.008	1.012	1.009	1.007	1.011	1.008	1.006	1.010	1.008	1.006	1.010	1.009	1.007	1.011	1.009	1.007	1.011	1.009	1.007	1.011	1.008	1.006	1.010	1.008	1.006	1.010
Residential Mobility	1.006	1.003	1.009	1.006	1.003	1.009	1.006	1.003	1.009	1.006	1.003	1.009	1.006	1.003	1.009	1.005	1.001	1.008	1.006	1.003	1.009	1.008	1.005	1.011	1.007	1.004	1.010
Racial Heterogeneity	2.173	1.728	2.733	2.012	1.594	2.540	2.127	1.688	2.681	2.059	1.627	2.606	2.031	1.615	2.554	2.268	1.786	2.881	2.117	1.680	2.668	2.223	1.753	2.818	2.086	1.660	2.623
Population	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Street Length	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001
Street Type	1.642	1.507	1.788	2.046	1.882	2.225	1.936	1.781	2.105	2.283	2.103	2.478	1.896	1.744	2.060	2.239	2.058	2.434	1.860	1.711	2.023	2.332	2.145	2.535	1.772	1.629	1.927
Constant	0.106	0.092	0.124	0.120	0.103	0.139	0.120	0.104	0.140	0.118	0.101	0.137	0.114	0.098	0.132	0.114	0.098	0.134	0.117	0.101	0.136	0.112	0.096	0.131	0.111	0.096	0.129
AIC			24712.360			24995.193			24901.045			25074.460			24768.163			25105.016			24860.441			25218.861			24768.408
BIC			25004.367			25287.200			25193.052			25366.467			25060.170			25397.023			25152.448			25510.869			25060.415

Notes: IRR = Incident Rate Ratio; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion network distance buffer of 1000ft instead of my original 500ft. Full regression models for the distance sensitivity checks are presented in Appendix D. Second, I reran all of the models that incorporated at-facility crime counts using a crime rate for the addresses with multiple facilities instead of my original operationalization of assigning all facilities at each shared address with the full crime count for that address. Full models for the multi-facility sensitivity checks are presented in Appendix E.

A condensed presentation of the incident rate ratios and significance of the sensitivity checks are presented in the tables below. Table 30 and Table 31 present the buffer distance sensitivity check of 1000ft instead of 500ft. Distance sensitivity check model fit statistics and interpretation are presented in Table 32. Table 33 and Table 34 present the multi-facility sensitivity check of rates instead of counts. Multi-facility sensitivity check model fit statistics and interpretation are presented in Table 35.

The results of the sensitivity checks mostly mirror the main findings presented above. For robbery, the Continuous Robbery Risk Using Buffer-Area Calls For Service model outperformed the homogenous count base model in both the 500ft buffer area and 1000ft buffer area models. Interestingly, in the sensitivity check model of a 1000ft buffer area, the Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents model also outperformed the homogenous count base model, with AIC and BIC values 21.928 points lower than the base model AIC and BIC values. Again, there is very little difference in the conclusions drawn from the base model and the Continuous Robbery Risk Using 1000ft Buffer-Area Robbery Incidents model.

As with the original at-facility count regressions, none of the at-facility rate robbery models outperformed the base model. For theft, no sensitivity check theft measures had a lower AIC or BIC value than the homogenous count base model.

Table 30. 1000ft Buffer Area Distance Sensitivity Checks - Robbery

	Count of All Facilities	Binary Robbery Risk Using Buffer Area Street Robbery Incidents	Continuous Robbery Risk Using Buffer Area Street Robbery Incidents	Binary Robbery Risk Using Buffer Area Calls for Service	Continuous Robbery Risk Using Buffer Area Calls for Service
Bars	1.5290	2.2560	1.1181	1.8787	1.0006
Consumer Electronics Stores	1.0914	1.2890	1.0172	0.9444	1.0001
Convenience Stores	2.3074***	3.3996**	1.2457*	2.9993*	1.0015***
Discount and Dollar Stores	0.9162	0.9432	0.9712	0.8888	1.0000
Drug Treatment Centers	1.1959	0.3791	0.8932	0.3388	0.9998
Entertainment Venues	1.1040	1.3565	0.9518	0.5516	1.0000
Fast Food Restaurants	1.1230	1.0262	1.0405	0.7919	1.0002
Gas Stations	2.1251*	5.7111**	1.3807*	4.4839*	1.0019*
Grocery Stores	2.2631	0.4724	1.1707	2.7094	1.0015
Home Décor and Furniture Stores	1.7316	2.0408	1.0523	1.8036	1.0006
Hotels	2.1002	5.5664	1.2492	4.7590	1.0012
Pharmacies	1.5996	0.9621	0.9758	0.6378	1.0004
Recreation Centers	2.0760	1.1001	1.1929	1.6618	1.0014
Recreation Retails Stores	0.6338	0.8902	0.9476	0.3452	0.9996
Salons and Barber Shops	0.8904	2.7475	1.0492	1.5106	0.9996
Sit-Down Restaurants	1.1175	1.2003	1.0497	1.4006	1.0003
SL Bars	1.1020	1.5389*	1.0255	1.4937	1.0003***
SL Consumer Electronics Stores	1.6026***	1.9299**	1.1583***	1.9805**	1.0008***
SL Convenience Stores	1.6119***	2.0939**	1.1393***	2.1612***	1.0011**
SL Discount and Dollar Stores	1.7522*	1.7296	1.0529	2.2382	1.0011**
SL Drug Treatment Centers	1.4901	2.1990*	1.1788*	2.3920*	1.0011
SL Entertainment Venues	1.2012	1.0391	1.0523	0.9925	0.9999**
SL Fast Food Restaurants	0.9425	0.8890	0.9854	0.8140	0.9998
SL Gas Stations	1.0291	1.0690	0.9762	1.2511	0.9999
SL Grocery Stores	0.8829	1.6947	1.0205	1.2536	0.9998
SL Home Décor and Furniture Stores	0.7485	0.4760	0.9000	0.8214	0.9996
SL Hotels	1.3948	1.6483	1.1082	2.4241	1.0002
SL Pharmacies	0.8217	0.3056	0.9389	1.4125	0.9998
SL Recreation Centers	1.8456*	2.3226*	1.2014	3.4142**	1.0017**
SL Recreation Retails Stores	1.0885	1.5365	1.1118	1.2618	1.0001
SL Salons and Barber Shops	0.9240	0.8996	1.0153	0.9471	0.9999
SL Sit-Down Restaurants	1.1029	1.2336	1.0286	1.1448	1.0001
Disadvantage	1.0320***	1.0317***	1.0314***	1.0309***	1.0308***
Residential Mobility	0.9950	0.9956	0.9957	0.9941	0.9946
Racial Heterogeneity	2.4049**	1.9143*	1.8874*	2.2360**	2.0915**
Population	1.0002***	1.0003***	1.0003***	1.0003***	1.0003***
Street Length	1.0005***	1.0006***	1.0005***	1.0006***	1.0005***
Street Type	1.6412***	2.0275***	1.8618***	2.0881***	1.7418***
Constant	0.0077***	0.0085***	0.0084***	0.0086***	0.0083***
AIC	5662.629	5669.046	5640.701	5700.378	5615.755
BIC	5954.636	5961.053	5932.709	5992.385	5907.762

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

Table 31. 1000ft Buffer Area Distance Sensitivity Checks - Theft

	Count of All Facilities	Binary Theft Risk Using Buffer Area Street Robbery Incidents	Continuous Theft Risk Using Buffer Area Street Robbery Incidents	Binary Theft Risk Using Buffer Area Calls for Service	Continuous Theft Risk Using Buffer Area Calls for Service
Bars	1.9442***	2.4308**	1.0229***	2.4500*	1.0010***
Consumer Electronics Stores	1.1935	1.3811	1.0073	1.2304	1.0001
Convenience Stores	2.4751***	3.0493***	1.0491***	2.8289**	1.0020***
Discount and Dollar Stores	5.5744***	5.5774*	1.0546***	1.8036	1.0039***
Drug Treatment Centers	3.0240***	4.5671*	1.0564***	4.6230*	1.0023***
Entertainment Venues	2.5793***	4.6296**	1.0320***	4.7166***	1.0016**
Fast Food Restaurants	1.3394***	1.1995	1.0055*	0.9977	1.0004***
Gas Stations	3.2590***	3.6673**	1.0582***	3.0797**	1.0027***
Grocery Stores	21.0136***	19.4244***	1.0375***	49.0017***	1.0055*
Home Décor and Furniture Stores	1.2921	1.1862	0.9985	1.5044	1.0010*
Hotels	1.7420	4.0593*	1.0122**	2.8700	1.0009**
Pharmacies	2.3471**	1.5050	1.0111	1.5177	1.0018
Recreation Centers	1.6332	2.8121	1.0286	1.8325	1.0012
Recreation Retails Stores	1.3849	1.4166	1.0087	2.0989	1.0008
Salons and Barber Shops	0.9321	2.3028**	0.9967	1.1195	0.9999
Sit-Down Restaurants	1.2912*	1.3050	1.0034	1.4712	1.0003*
SL Bars	1.1487**	1.5969***	1.0076***	1.5810***	1.0004***
SL Consumer Electronics Stores	1.0772	0.9215	0.9978	1.0151	1.0001
SL Convenience Stores	1.1255	1.9973***	1.0114***	1.3052	1.0003**
SL Discount and Dollar Stores	1.4708**	1.6980	1.0105*	1.1191	1.0005
SL Drug Treatment Centers	1.0409	0.8688	1.0006	0.8379	1.0000
SL Entertainment Venues	1.2509*	1.6461*	1.0065*	1.1552	1.0001
SL Fast Food Restaurants	0.9665	0.8000*	0.9974**	0.8959	0.9998***
SL Gas Stations	0.9141	1.3182	1.0014	1.7630**	1.0002
SL Grocery Stores	0.9942	2.0125	1.0019	0.7592	1.0003
SL Home Décor and Furniture Stores	1.0026	0.7946	1.0010	1.3057	1.0000
SL Hotels	1.6782***	1.1430	1.0019	2.0874*	1.0004**
SL Pharmacies	1.0450	1.3639	1.0044	1.5125	1.0004
SL Recreation Centers	1.4914**	0.9420	1.0172*	1.8926*	1.0011**
SL Recreation Retails Stores	1.0325	1.1090	1.0041	1.0024	1.0001
SL Salons and Barber Shops	1.0226	1.1989	0.9990	1.5232**	1.0001
SL Sit-Down Restaurants	1.0997*	1.1064	1.0006	0.9270	1.0000
Disadvantage	1.0098***	1.0088***	1.0088***	1.0057***	1.0081***
Residential Mobility	1.0057***	1.0066***	1.0061***	1.0082***	1.0069***
Racial Heterogeneity	2.1730***	1.8827***	1.9263***	2.3723***	2.0319***
Population	1.0003***	1.0003***	1.0003***	1.0002***	1.0003***
Street Length	1.0014***	1.0012***	1.0011***	1.0013***	1.0011***
Street Type	1.6415***	2.3586***	1.9006***	2.2727***	1.7861***
Constant	0.1064***	0.1146***	0.1140***	0.1152***	0.1106***
AIC	24712.360	25127.729	24787.350	25403.990	24772.491
BIC	25004.367	25419.736	25079.357	25695.998	25064.498

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

Table 32. Buffer Area Distance Sensitivity Check Model Fit Statistics and Interpretation

Measure	AIC Value (Difference from Base Model)	AIC Difference Interpretation	BIC Value (Difference from Base Model)	BIC Difference Interpretation
Base Model: Robbery Risk Using Homogenous Count of Facilities	5662.629	--	5954.636	--
Binary Robbery Risk Using Buffer-Area Street Robbery Incidents	5669.046 (+6.417)	Base Model Favored	5961.053 (+6.417)	Base Model Strongly Favored
Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents	5640.701 (-21.928)	Alternate Model Favored	5932.709 (-21.927)	Alternate Model Very Strongly Favored
Binary Robbery Risk Using Buffer-Area Calls for Service	5700.378 (+37.749)	Base Model Favored	5992.385 (+37.749)	Base Model Very Strongly Favored
Continuous Robbery Risk Using Buffer-Area Calls for Service	5615.755 (-46.874)	Alternate Model Favored	5907.762 (-46.874)	Alternate Model Very Strongly Favored
Base Model: Theft Risk Using Homogenous Count of Facilities	24712.360	--	25004.367	--
Binary Theft Risk Using Buffer-Area Theft Incidents	25127.729 (+415.369)	Base Model Favored	25419.736 (+415.369)	Base Model Very Strongly Favored
Continuous Theft Risk Using Buffer-Area Theft Incidents	24787.35 (+74.99)	Base Model Favored	25079.357 (+74.99)	Base Model Very Strongly Favored
Binary Theft Risk Using Buffer-Area Calls for Service	25403.99 (+691.63)	Base Model Favored	25695.998 (+691.63)	Base Model Very Strongly Favored
Continuous Theft Risk Using Buffer-Area Calls for Service	24772.491 (+60.131)	Base Model Favored	25064.498 (+60.131)	Base Model Very Strongly Favored

Table 33. Multi-Facility Sensitivity Checks - Robbery

	Count of All Facilities	Binary Robbery Risk Using At-Facility Calls for Service Rate	Continuous Robbery Risk Using At-Facility Calls for Service Rate
Bars	1.5290	1.8378	1.0242
Consumer Electronics Stores	1.0914	2.2946	1.0230
Convenience Stores	2.3074***	2.8911*	1.0186
Discount and Dollar Stores	0.9162	0.9713	0.9983
Drug Treatment Centers	1.1959	4.5497	1.0034
Entertainment Venues	1.1040	1.4383	0.9976
Fast Food Restaurants	1.1230	1.2948	1.0028
Gas Stations	2.1251*	2.3886	1.0084
Grocery Stores	2.2631	3.7560	1.0041
Home Décor and Furniture Stores	1.7316	0.4603	0.9884
Hotels	2.1002	6.7339	1.0148
Pharmacies	1.5996	16.4360*	1.0466*
Recreation Centers	2.0760	2.5203	1.0192
Recreation Retails Stores	0.6338	2.8506	1.0354
Salons and Barber Shops	0.8904	1.0373	1.0261
Sit-Down Restaurants	1.1175	1.3810	0.9993
SL Bars	1.1020	1.5141	1.0104
SL Consumer Electronics Stores	1.6026***	1.3640	1.0156
SL Convenience Stores	1.6119***	1.4634	1.0094*
SL Discount and Dollar Stores	1.7522*	3.3662**	1.0127**
SL Drug Treatment Centers	1.4901	0.6762	1.0008
SL Entertainment Venues	1.2012	0.8616	0.9990
SL Fast Food Restaurants	0.9425	1.2833	1.0064
SL Gas Stations	1.0291	1.8762*	1.0046**
SL Grocery Stores	0.8829	1.4391	1.0010
SL Home Décor and Furniture Stores	0.7485	1.9712*	1.0201
SL Hotels	1.3948	2.9589*	1.0073
SL Pharmacies	0.8217	0.4173	0.9831
SL Recreation Centers	1.8456*	2.8779*	1.0120
SL Recreation Retails Stores	1.0885	0.6338	0.9626
SL Salons and Barber Shops	0.9240	0.9303	0.9915
SL Sit-Down Restaurants	1.1029	1.1824	1.0070
Disadvantage	1.0320***	1.0323***	1.0321***
Residential Mobility	0.9950	0.9932*	0.9926*
Racial Heterogeneity	2.4049**	2.4470***	2.4291***
Population	1.0002***	1.0002**	1.0003***
Street Length	1.0005***	1.0005***	1.0005***
Street Type	1.6412***	1.8462***	1.7708***
Constant	0.0077***	0.0086***	0.0087***
AIC	5662.629	5693.664	5680.319
BIC	5954.636	5985.672	5972.326

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

Table 34. Multi-Facility Sensitivity Checks - Theft

	Count of All Facilities	Binary Theft Risk Using At-Facility Theft Rate	Continuous Theft Risk Using At-Facility Theft Rate	Binary Theft Risk Using At-Facility Calls for Service Rate	Continuous Theft Risk Using At-Facility Calls for Service Rate
Bars	1.9442***	4.4994***	1.5963***	4.0885***	1.0488***
Consumer Electronics Stores	1.1935	1.2116	0.9637	1.3222	1.0116
Convenience Stores	2.4751***	2.9539***	1.2338***	5.1788***	1.0291***
Discount and Dollar Stores	5.5744***	8.0726**	1.2033***	6.5127**	1.0401***
Drug Treatment Centers	3.0240***	6.2616***	1.2854**	4.9748**	1.0099*
Entertainment Venues	2.5793***	4.1265***	1.4001***	5.1241***	1.0342***
Fast Food Restaurants	1.3394***	1.5442**	1.2284**	1.6353*	1.0123**
Gas Stations	3.2590***	6.5371***	1.1709***	6.8559***	1.0164***
Grocery Stores	21.0136***	43.2882***	1.1231***	45.6932***	1.0244***
Home Décor and Furniture Stores	1.2921	1.5175	0.8332	2.5651**	1.0851**
Hotels	1.7420	2.0673	1.2039	2.1464	1.0117
Pharmacies	2.3471**	4.1882*	1.0728	7.9847***	1.0370**
Recreation Centers	1.6332	1.4290	1.1099	1.7119	1.0161
Recreation Retails Stores	1.3849	1.7763	0.9871	2.6742**	1.0222
Salons and Barber Shops	0.9321	1.3666	1.2710	1.7009	1.0201
Sit-Down Restaurants	1.2912*	1.5204*	1.1941*	1.8653**	1.0186*
SL Bars	1.1487**	1.2707	1.0899*	1.2181	1.0107**
SL Consumer Electronics Stores	1.0772	0.8973	0.9988	1.0748	1.0048
SL Convenience Stores	1.1255	1.3289**	1.0140	1.2417	1.0029
SL Discount and Dollar Stores	1.4708**	1.8978*	1.0349**	1.8707*	1.0070**
SL Drug Treatment Centers	1.0409	0.8360	0.9831	0.7343	0.9997
SL Entertainment Venues	1.2509*	1.5599*	1.1101**	1.1777	1.0008
SL Fast Food Restaurants	0.9665	1.2179**	1.1649***	1.2148*	1.0020
SL Gas Stations	0.9141	1.1136	1.0054	1.1448	1.0019*
SL Grocery Stores	0.9942	1.3845	1.0032	1.1053	1.0005
SL Home Décor and Furniture Stores	1.0026	1.9658***	0.9754	1.5491*	1.0180*
SL Hotels	1.6782***	2.1101*	1.0387	2.3951**	1.0092***
SL Pharmacies	1.0450	1.2766	1.0756***	2.1853**	1.0093
SL Recreation Centers	1.4914**	1.6275*	1.1264*	1.5308	1.0086*
SL Recreation Retails Stores	1.0325	1.0585	1.0233	1.0603	1.0054
SL Salons and Barber Shops	1.0226	1.1692	1.0268	1.1357	1.0064
SL Sit-Down Restaurants	1.0997*	1.4711***	1.0153	1.2542*	1.0021
Disadvantage	1.0098***	1.0089***	1.0086***	1.0083***	1.0089***
Residential Mobility	1.0057***	1.0053**	1.0050**	1.0056***	1.0051**
Racial Heterogeneity	2.1730***	1.9396***	2.1025***	2.0650***	2.0458***
Population	1.0003***	1.0003***	1.0003***	1.0003***	1.0003***
Street Length	1.0014***	1.0010***	1.0010***	1.0011***	1.0010***
Street Type	1.6415***	1.9442***	1.8620***	2.0201***	1.7646***
Constant	0.1064***	0.1211***	0.1212***	0.1224***	1.0488***
AIC	24712.360	24915.284	24825.699	24938.106	24728.020
BIC	25004.367	25207.291	25117.707	25230.113	25020.028

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

Table 35. Multi-Facility Sensitivity Check Model Fit Statistics and Interpretation

Measure	AIC Value (Difference from Base Model)	AIC Difference Interpretation	BIC Value (Difference from Base Model)	BIC Difference Interpretation
Base Model: Robbery Risk Using Homogenous Count of Facilities	5662.629	--	5954.636	--
Binary Robbery Risk Using At-Facility Calls for Service	5693.664 (+31.035)	Base Model Favored	5985.672 (+31.036)	Base Model Very Strongly Favored
Continuous Robbery Risk Using At-Facility Calls for Service	5680.319 (+17.690)	Base Model Favored	5972.326 (+17.690)	Base Model Very Strongly Favored
Base Model: Theft Risk Using Homogenous Count of Facilities	24712.360	--	25004.367	--
Binary Theft Risk Using At-Facility Theft Incidents	24915.284 (+202.924)	Base Model Favored	25207.291 (+202.924)	Base Model Very Strongly Favored
Continuous Theft Risk Using At-Facility Theft Incidents	24825.699 (+113.339)	Base Model Favored	25117.707 (+113.34)	Base Model Very Strongly Favored
Binary Theft Risk Using At-Facility Calls for Service	24938.106 (+225.746)	Base Model Favored	25230.113 (+225.746)	Base Model Very Strongly Favored
Continuous Theft Risk Using At-Facility Calls for Service	24728.02 (+15.660)	Base Model Favored	25020.028 (+15.661)	Base Model Very Strongly Favored

Model Diagnostics

One *Assumption of Crime Concentration* operationalization resulted in an improved model fit over the *Assumption of Crime Homogeneity* base model. This was the Continuous Robbery Risk Using Buffer-Area Calls for Service operationalization. In this section, I move beyond model fit and coefficient comparisons to run a series of model diagnostics to compare this improved model to the base model.

First, I used plots of residual and predicted values to compare model fit at different levels of the dependent variable for the base and improved models (Cameron & Trivedi, 2013). These plots indicated that the models were very similar in their fit, including for very high and very low values.

Next, I used GeoDa 1.14.0.4 (Anselin et al., 2006) to calculate a Global Moran's I (Moran, 1950) statistic on the regression residuals to determine if there was any remaining spatial correlation. Following the approach of Bernasco and Block (2011), Haberman and Ratcliffe (2015), and Clutter et al (2019), I assessed standardized Pearson residuals using a 6-order k-nearest neighbors spatial weights matrix. I conducted this test on both the homogenous count robbery model and the favored Continuous Robbery Risk Using Buffer-Area Calls for Service model. The homogenous count model had a Global Moran's I value 0.0694 (pseudo p-value: 0.001) and the Continuous Robbery Risk Using Buffer-Area Calls for Service model had a value of 0.0688 (pseudo p-value: 0.001). These results suggest there was no issue with spatial autocorrelation in the regression residuals.

I also confirmed that outlier cases did not have an undue impact on the regression results by rerunning each regression several times, each time less one outlier case. I identified outlier cases using plots of hat diagonal values (Long & Freese, 2014). I compared the resultant coefficients to their respective full models to see if the results remained the same. Again, I conducted this examination for both the homogenous count robbery model and the favored Continuous Robbery Risk Using Buffer-Area Calls for Service model. For both models, I removed and tested the impact of the top five outlier cases. A comparison of the resultant coefficients and model fit statistics suggest that the results changed only minimally after removing the outlier cases, and the substantive conclusions were not changed.

CHAPTER 6: DISCUSSION

In the previous chapter, I presented the results of my analyses. Here, I discuss these results. I begin by interpreting the results in the context of my research question. I then overview the limitations of this study. Next, I situate the findings in the context of previous crime and place research and discuss the implications of my findings. I conclude with a summary of this study.

Summary of the Results

My research question asked "can risky facility measures based on an *Assumption of Crime Concentration* better explain crime counts at micro-places than commonly used *Assumption of Crime Homogeneity* facility measures of all places within each facility type?". To answer this question, I tested eight different operationalizations of risky facilities using temporally lagged crime data. These measures were rooted in empirical findings about the distribution of crime across facility sets and the stability of crime at places over time. The measures incorporated all of the possible combinations of two different areas of impact (at-facility only and surrounding buffer area), two categories of crime (general and specific), and two types of measurement (binary and continuous). All eight measures were tested using theft as an outcome variable. Six of the measures were tested using street robbery as an outcome variable (because street robbery, by definition, cannot be measured using an at-facility robbery incident operationalization).

I first compared the model fit statistics of negative binomial regression models using the proposed risky facility operationalizations to two base models that incorporated a commonly used count measure of facilities. In all cases except for one, both the AIC and BIC values suggested that the homogenous count model – or simply counting the number of facilities on a street block without any weighting – was preferred. The exception was the Continuous Robbery Risk Using Buffer-Area Calls for Service measure model, which had AIC and BIC value reductions of approximately 38 points. This indicated that this model was very strongly favored over the homogenous count model for estimating street block level robbery. This finding persisted across the 1000ft distance sensitivity check. A second exception arose during the distance sensitivity checks. The Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents measure model was not favored when using a 500ft buffer area. However, this model had an improved model fit over the based model when the buffer area was extended to 1000ft, with AIC and BIC reductions of approximately 22 points. The AIC and BIC values indicated that no *Assumption of Crime Concentration* measure theft models were preferred over the homogenous count model.

Next, I compared the magnitude and direction of the model coefficients for the improved model fit Continuous Robbery Risk Using Buffer-Area Calls for Service model to the robbery base model that used a homogenous count measure of facilities. The Continuous Robbery Risk Using Buffer-Area Calls for Service model minimally differed from the homogenous count model. For both models, six facility variables significantly impacted robbery – two focal facilities and four spatially lagged facilities. For the two focal facility effects, convenience stores had the largest effect on robbery followed by gas stations in both models. For the spatially lagged facilities, recreation centers, convenience stores, and consumer electronic stores - were the same across models and again mirrored one another in their relative magnitude (i.e. recreation centers had the largest effect, followed by convenience stores, followed by consumer electronic stores). However, two differences emerged. First, there was a fairly sizable effect for discount and dollar stores in the homogenous count model that was not present in the Continuous Robbery Risk Using Buffer-Area Calls for Service model. Second, there was also a significant finding for spatially lagged drug treatment centers that was present in the Continuous Robbery Risk Using Buffer-Area Calls for Service model, but not the homogenous count model.

The answer to my research question is, thus, mixed. There are some small differences between the homogenous count model and the model using the risky facility measures that led to an improved model fit. However, these differences are minimal, and for the most part the models tended to agree on which facility variables significantly impacted robbery, and on the direction and relative magnitude of the relationship between the significant facilities and robbery. It is possible that the small differences across models are reflective of true real-world differences in the impact of risky facilities on crime that are only detected when measuring facilities using an *Assumption of Crime Concentration* measure. It is also possible that the differences are due to the operationalization of facilities with shared addresses (which is discussed in further detail below in the limitations section).

Continuous Robbery Risk Using Buffer-Area Calls for Service *Assumption of Crime Concentration* facility risk measures may be useful in some limited instances for future studies. Specifically, if a study site has a low number of multi-facility addresses *or* good notes associated with their calls for service data that allow for the differentiation of crime across co-located facilities, then using this measure may be more consistent with empirical findings and theoretical predictions about crime at facilities. However, given that the differences in the results of the homogenous count model and the Continuous Robbery Risk Using Buffer-Area Calls for Service model are minimal, and the fact that the interpretation of the model coefficients in the Continuous Robbery Risk Using Buffer-Area Calls for Service model are less intuitive, it seems reasonable for future studies of crime and place to continue using homogenous facility measures to capture facility risk, assuming more direct measures of facility risk are not available.

Limitations of Study

This study has a number of limitations that are important to note. These limitations can be broken down into three categories: (1) data limitations, (2) analysis limitations, and (3) measure limitations.

Data Limitations

First, this dissertation is limited by the use of official crime incident data as an outcome measure. Not all crimes are reported to the police (Biderman & Reiss, 1967; Koss, 1992). More importantly, those that are reported do not follow a random pattern. Instead, reporting rates vary by crime and by victim characteristic (see for example Sinha, 2015; Tarling & Morris, 2010). This limitation is likely to affect models of theft more so than robbery, given that theft is much less likely to be reported to the police (Truman & Morgan, 2016). Thus, the results of the study may be biased towards the types of crimes that are reported to the police, as opposed to all thefts and street robberies.

Next, there are limitations with the facilities used in this dissertation. Though a large number of facility types are measured and accounted for, there are additional facilities that are not included (e.g. schools, ATMs, public transit stations) that may have an impact on the spatial patterning of street robbery and theft. Additionally, because there are a large number of facility variables included in the models (16 focal facility variables and 16 spatially lagged facility variables, for a total of 32 facility variables) there is an increased chance of obtaining a false positive parameter result, otherwise known as making a Type 1 error.

Analysis Limitations

There are also a number of limitations related to the analyses in this study. Because of the sheer number of models that were run in this dissertation, it is possible that those measures observed to have an improved model fit are a result of a Type 1 error. It is necessary to replicate the approach found here in other contexts to make sure the results hold true elsewhere and were not merely obtained by chance. Next, this study is limited by the fact that some of the crimes included in the theft measure can only occur at facilities and not outside of them (e.g. shoplifting, theft from building).

Additionally, this dissertation does not account for potential interactions between neighborhood level characteristics and micro-place level characteristics that increase facility risk. Eck and Madensen-Herold (2018) argue that neighborhoods are important because they influence facility management, which in turn influences crime. Specifically, they put forth that low-income neighborhoods may be more likely to have poor place management because it is more difficult for managers there to acquire resources to improve their businesses and address crime. Further, those neighborhoods with a high proportion of minority residents may have a higher concentration of inadequate place management as a result of historic and current social segregation practices which disincentivize good place management in those areas (Eck & Madensen-Herold, 2018). This study does not assess whether the relationship between risky facilities and crime in their vicinity differs in low SES and racially segregated minority neighborhoods.

Measure Limitations

Next, there are a number of limitations related to the measures I used that are important to note. As a result of the cross-sectional approach used in this dissertation, there is the potential for the misclassification of risky places in each of the *Assumption of Crime Concentration* facility operationalizations. For instance, it is possible that places with high historic levels of crime that receive interventions in the interim period will have been classified as risky when they no longer are. Conversely, it is possible that previously low crime places have an influx of criminal opportunities and thus criminal incidents (perhaps due to a new bad place manager) and would have been classified as not risky when they in fact are. However, results from Weisburd, Groff, and Yang (2012) suggest that this risk should be fairly low (also see Groff et al., 2010). Specifically, they found that over a 16-year period, roughly 16% of Seattle street segments had nonstable levels of crime, while the remaining 84% had stable levels of crime. Further, even within the unstable street segments, large fluctuations of crime year over year were rare.

Though the measures I proposed sounded like valid alternatives to the often relied on *Assumption of Crime Homogeneity* approach used in crime and place research, a number of limitations of these measures came up during my analyses that were not foreseen and are worth noting here. First, the simultaneous presence of multiple facilities at individual addresses (which are further discussed in Appendix A) and a lack of sub-address level differentiating information in much of the crime/calls for service data I used resulted in some facilities receiving the same risk score despite likely differences in their actual real-world crime risk. This likely biased the results to some extent as it inflated the number of crimes occurring at co-located facilities higher than what they actually are. If this problem consistently occurred for some types of facilities, it may have impacted their regression results, including their VIF scores. This seems likely to be the case as several of the facilities with locations at multi-facility addresses had a majority of their crimes occur at those addresses, as is evidenced in Table 24.

Though the availability and geographic precision of crime data has improved over time, it can still be difficult to pinpoint incidents to the sub-address level. It is likely that this limitation is not unique to Cincinnati – I suspect many other cities also have facilities at shared address locations, like strip malls, and that their crime incident data does not reliably specify location beyond the address level. This limitation should be kept in mind for anyone thinking of using any of the *Assumption of Crime Concentration* measures proposed here. Fewer co-located facilities would result in less potential bias, while a higher proportion of co-located facilities relative to the total number of risky facilities studied would result in a greater potential for bias in study results.

Second, the majority of the *Assumption of Crime Concentration* measures had higher VIF values than the base homogenous count models. It is possible that these higher values are a result of the unique nature of the data set I used to test my research question, particularly with respect to the presence of the co-located facilities I discussed above. The high VIF values may also be a by-product of my model specification – I included a fairly wide variety of facilities, some of which have not had their relationship to crime previously tested (or at least not with any regularity). A third possibility is that the high VIF values are a direct result of my operationalization approach. The buffer area operationalizations create facility risk values by drawing on the same pool of incidents. Though they are weighted by distance, this may lead to highly correlated values. This is especially true for theft, given that thefts are often located at commercial places, which tend to be located close to one another.

Implications

The findings of this study were somewhat surprising. Prior research has shown fairly conclusively that crime concentrates within facility sets (Eck et al., 2007). Findings also suggest that spatial crime concentrations are fairly stable over time (e.g. Andresen & Malleson, 2011; Andresen et al., 2017; Curman et al., 2015; Gill et al., 2017; Payne & Gallagher, 2016; Weisburd et al., 2004; Weisburd et al., 2012; Wheeler et al., 2016), and that high crime facilities can radiate crime into their surrounding environment (Bowers, 2014). One would thus expect that models using empirically rooted facility risk operationalizations that account for variations in crime risk would outperform models using facility risk operationalizations that do not account for these variations. The results of this study, however, indicate that was not the case. Indeed, the majority of the measures tested here failed to outperform simple counts of facility presence when incorporated into models of street block-level robbery and theft counts.

Previous crime and place research has produced t1

he seemingly incompatible findings that some types of facility sets increase crime in their area but also that crime, and the impact of facilities on crime, concentrates within facility sets. It is possible that the cooccurrence of these findings is a result of some high crime facilities having such a large impact on crime around them that they are driving the significant regression results for their entire facility sets. However, if this were the case, you'd expect that operationalizing facilities based on an *Assumption of Crime Concentration* rather than an *Assumption of Crime Homogeneity* would result in an improved model fit and better model performance. Here that was not the case - the results of this study suggest that a homogenous count measure of facility sets outperforms most of the proposed *Assumption of Crime Concentration* measures. Indeed, only one crime risk concentration measures outperformed the homogenous count measure, and even then only for one type of crime.

So, it seems that simply swapping a concentrated crime risk measure for a homogenous facility count measure will not necessarily lead to a better specified model. This raises further questions about the nature of facility risk. What exactly makes a facility risky and how do we best capture this riskiness? One possible explanation for the findings of this dissertation is that there are two separate riskiness processes occurring– one involving factors that tend to vary within facility sets and another involving factors that tend to vary across facility sets. The former would account for findings that crime concentrates within facilities of the same type. Variation of this type is expected theoretically as a result of differences in place management, facility busyness, and an overlap in victim and offender routine activity spaces that lead to different levels of criminal opportunities. The latter would suggest facilities of the same type tend to function in a similar way and may be designed in a similar manner. Sit-down restaurants, for instance, tend to have tables that people sit and spend time at, while grocery stores are marked by aisles of products for purchase and a centralized check out area. If these differences in function are stronger between facility sets than they are within facility sets, and if the types of functional differences across facility sets have an impact on the availability of criminal opportunities, then opportunity theories of crime would predict that this would also lead to differences in facility-level criminogenic risk.

Perhaps then what is needed to properly capture facility risk is two different types of measures representing these two mechanisms. An *Assumption of Crime Concentration* based measure could be used to capture the first mechanism of within facility set differences in risk. The commonly used *Assumption of Crime Homogeneity* measures would capture the second mechanism of between facility set differences in risk. If this were the case, the finding here that most *Assumption of Crime Concentration* measures do not outperform the tested *Assumption of Crime Homogeneity* measure would not be surprising. It would be expected that these two types of measures would pick up on different elements of risk and would explain different parts of the variation in crime at facilities, without one necessarily outperforming the other in models of crime and place.

Conclusion

Many studies of crime and place rely on an *Assumption of Crime Homogeneity* when operationalizing facilities and examples of the use of homogenous facility measures to estimate aggregate levels of crime are widespread (see Table 1 in Chapter 3 for a summary of a selection of these studies). This approach treats all facilities of the same type as though they have the same impact on crime. As a result, most of these studies tend to operationalize facilities in a similar manner – either as an indicator of facility presence (e.g. Stucky & Ottensmann, 2009; Stucky & Smith, 2017), a count of facilities in each unit (e.g. Bernasco & Block, 2011; Haberman & Ratcliffe, 2015), a percentage of the unit covered by a particular facility (e.g. Stucky & Ottensmann, 2009; Weisburd et al., 2012), or the distance to the nearest facility of each type (e.g. Clutter et al., 2019; Dario et al., 2015; Irvin-Erickson, 2014; Kennedy et al., 2016).

Studies that draw on an *Assumption of Crime Concentration* and account for facility level variations in criminogenic risk are far fewer and tend to be much more varied in their approach. Thus far, it has been unclear what the effects are of relying on an *Assumption of Crime Homogeneity* when operationalizing facilities as no one has compared this approach to an alternative approach based on an *Assumption of Crime Concentration*.

With this dissertation, I set out to test a series of facility risk measures that account for variations in criminogenic risk using historic crime concentration data. I proposed and examined eight measures of risky facilities rooted in the empirical distribution of crime across facilities from past research. These measures varied along three domains, including: the area assumed to be impacted by facility riskiness (at-facility only versus the facility and its surrounding area), the types of crime used to operationalize riskiness (specific crime measures vs general crime measures), and the level of measurement used to operationalize risk (binary versus continuous).

I tested these measures using a series of near-identical negative binomial regression models, with the only variation across models being the operationalization of risky facilities. The results of these models suggest that operationalizing facilities using historic crime data did not improve model fit for most operationalizations. Further, they also suggest that the conclusions drawn from these models may be largely similar to those derived from models operationalizing facilities as simple homogenous counts based on an *Assumption of Crime Homogeneity*.

My findings may be because the outcomes of crime and place research are insensitive to the distribution of crime among facilities. Or, it may be that the facility measures I proposed are mostly ineffective at capturing differences in facility risk. It also possible that homogenous facility measures account for some aspect of facility risk that is separate from the risk related to prior crime and some combination of the two measure types are necessary to fully account for facility risk. Regardless, this study indicates that further research on the operationalization of places is necessary. Two possible avenues for future research are to investigate whether two facility crime risk mechanisms – one within facility and one between facility – might be at work, and to replicate this investigation of *Assumption of Crime Concentration* facility risk operationalizations in a location with fewer limitations related to co-located facilities.

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APPENDIX A – CO-LOCATED FACILITIES

One issue that arose during my data analyses was that of co-located facilities. Specifically, some facilities included in my analyses shared the same address (e.g. those in the strip mall called Valley Shopping Center at 7617 Reading Rd) with only unit numbers or letters to differentiate them. The crime data provided by the Cincinnati Police Department was also largely only available at the street address level, with no reliable sub-address differentiating information included for most incidents. This meant that it was impossible to differentiate which unit/facility within shared street addresses a particular call or incident occurred at. This issue was discussed briefly in the body of this dissertation, but I provide further information here as I think this is an interesting data limitation that may be present in other crime and place data sets. Some of the information presented here was also presented in the body of the dissertation – I reiterate it here as well to provide a comprehensive description of the co-located facility issue in one place.

Of the 1710 included facilities in my data set, 274 (16%) had shared addresses. There were 113 addresses with multiple facilities, ranging from 2 to 8 facilities at a single address. The frequency of addresses with different numbers of co-located facilities is presented below in Table 36.

Table 36. Frequency of Addresses with Co-Located Facilities

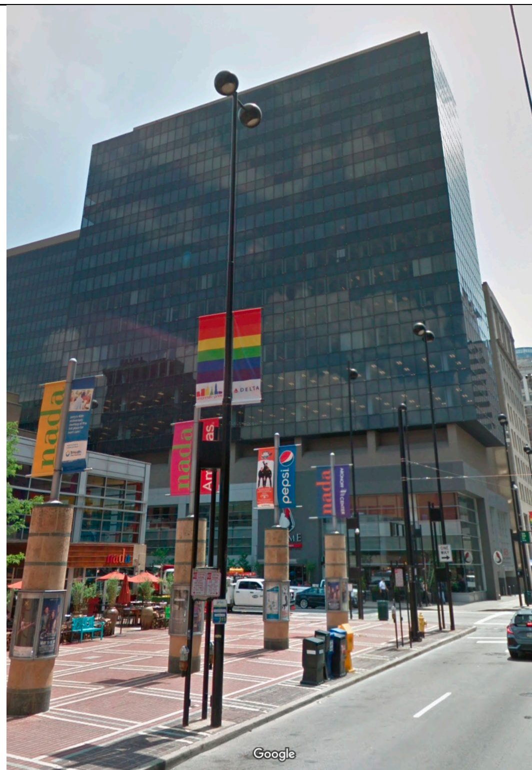
Number of Co-Located Facilities at Address	Frequency of Addresses
2	91
3	11
4	4
5	3
6	1
7	2
8	1
Total	113

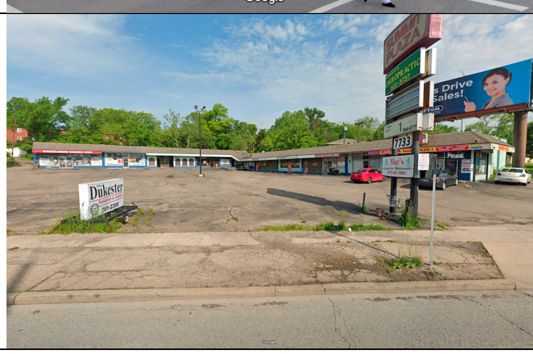
Below, in Table 37, a description of the facility composition at the ten addresses with the highest number of co-located facilities is presented, including an image of each address. The composition of facilities at these addresses varies, but the addresses with the highest number of co-located facilities all tend to be the ground levels of office/condo buildings or shopping plazas.

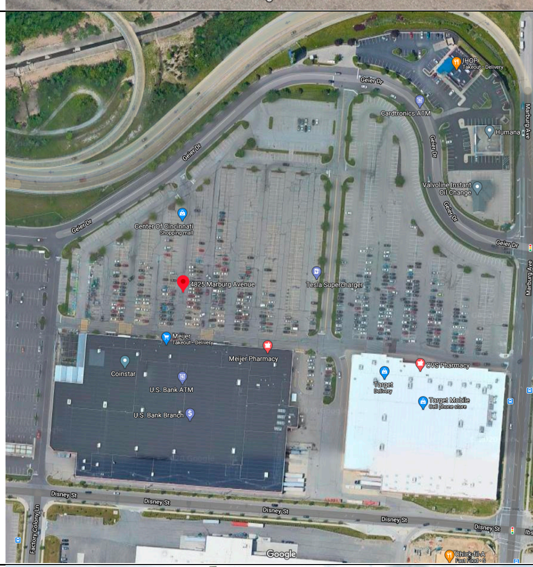
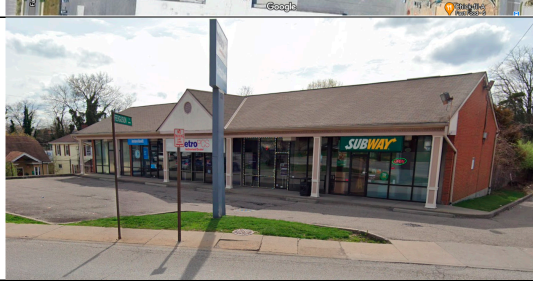
Table 37. Description of Facility Composition at the Ten Addresses with the Highest Number of Co-Located Facilities

Address	Image of Location	Description of Location	# of Facilities at Address	Facility Composition
441 Vine St		Carew Tower - office tower with businesses	8	2 consumer electronics stores 1 entertainment venue 2 fast food restaurants 1 salon and barber shop 2 sit-down restaurants

Address	Image of Location	Description of Location	# of Facilities at Address	Facility Composition
5555 Glenway Av		Western Hills Marketplace - strip mall shopping plaza	7	1 consumer electronics store 2 fast food restaurants 1 home décor and furniture store 2 recreation retail stores 1 salon and barber shop
7617 Reading Rd		Valley Shopping Center - strip mall shopping plaza	7	1 bar 2 consumer electronics stores 1 convenience store 1 fast food restaurant 1 salon and barber shop 1 sit-down restaurant

Address	Image of Location	Description of Location	# of Facilities at Address	Facility Composition
580 Walnut St		AT580 Apartments – residential building with businesses at ground level	6	2 fast food restaurants 4 sit-down restaurants
3880 Paxton Av		One strip of Hyde Park Plaza - strip mall shopping plaza	5	2 fast food restaurants 1 home décor and furniture store 1 recreation retail store 1 salon and barber shop

Address	Image of Location	Description of Location	# of Facilities at Address	Facility Composition
511 Walnut St		Fifth Third Center - office tower with businesses at ground level	5	1 entertainment venue 4 fast food restaurants
7733 Reading Rd		Summit Shopping Center - strip mall shopping plaza	5	1 bar 1 consumer electronics store 2 convenience stores 1 fast food restaurant

Address	Image of Location	Description of Location	# of Facilities at Address	Facility Composition
3500 Reading Rd		Unnamed strip mall shopping plaza	4	1 consumer electronic store 1 discount and dollar store 1 fast food restaurant 1 salon and barber shop
4825 Marburg Av		Part of the Center of Cincinnati shopping plaza	4	1 grocery store 1 home décor and furniture store 1 pharmacy 1 sit-down restaurant
5301 Glenway Av		Unnamed strip mall shopping plaza	4	2 consumer electronics stores 2 fast food restaurants

The proportion of co-located facilities varied by facility set, as did the percent of crimes that could be attributed to co-located facilities. The distribution of co-located facilities by facility set is broken down below in **Error! Not a valid bookmark self-reference.**. An assessment of this table shows that the extent of co-located facilities ranged from 0% of recreation centers sharing addresses with other facilities to 28.9% of consumer electronic stores sharing addresses with other facilities. Likewise, there are large variations in the amount of crime occurring at co-located facilities when broken down by facility type. For instance, only 2.8% of thefts and 1.3% of calls for service were at drug treatment centers that shared addresses with other facilities. This is contrasted by home décor and furniture stores which had 92.6% of thefts and 74.1% of calls for service occurring at locations that share addresses with other facilities.

Table 38. Crime at Co-Located Facilities

Facility Type	Total Number of Facilities	Number of Co-Located Facilities (%)	Total Thefts at Facility Set in 2015	Thefts at Co-Located Facilities in 2015 (%)	Total Calls for Service at Facility Set in 2015	Calls for Service at Co-Located Facilities in 2015 (%)
Bars and Clubs	153	14 (9.2%)	173	48 (27.7%)	1810	413 (22.8%)
Consumer Electronic Stores	114	33 (28.9%)	153	128 (83.7%)	1485	993 (66.9%)
Convenience Stores	156	10 (6.4%)	226	46 (20.4%)	2698	428 (15.9%)
Discount and Dollar Stores	26	6 (23.1%)	217	22 (10.1%)	1116	315 (28.2%)
Drug Treatment Centers	42	2 (3.4%)	71	2 (2.8%)	1603	21 (1.3%)
Entertainment Venues	76	10 (13.2%)	120	41 (34.2%)	1772	760 (42.9%)
Fast Food Restaurants	340	79 (23.2%)	373	203 (54.4%)	5503	2244 (40.8%)
Gas Stations	89	4 (4.5%)	375	10 (2.7%)	3865	141 (3.6%)
Grocery Stores	26	5 (19.2%)	497	180 (36.2%)	2379	641 (26.9%)
Home Décor and Furniture Stores	76	16 (21.1%)	204	189 (92.6%)	727	539 (74.1%)
Hotels	27	1 (3.7%)	70	5 (7.1%)	1192	201 (16.9%)
Pharmacies	32	4 (12.5%)	327	170 (52.0%)	1102	507 (46.0%)
Recreation Centers	38	0 (0.0%)	--	--	--	--
Recreation Retail Stores	85	24 (28.2%)	232	204 (87.9%)	1077	891 (82.7%)
Salons and Barber Shops	179	30 (16.8%)	120	91 (75.8%)	1504	924 (61.4%)
Sit-Down Restaurants	235	36 (15.3%)	428	322 (75.2%)	3243	1883 (58.1%)

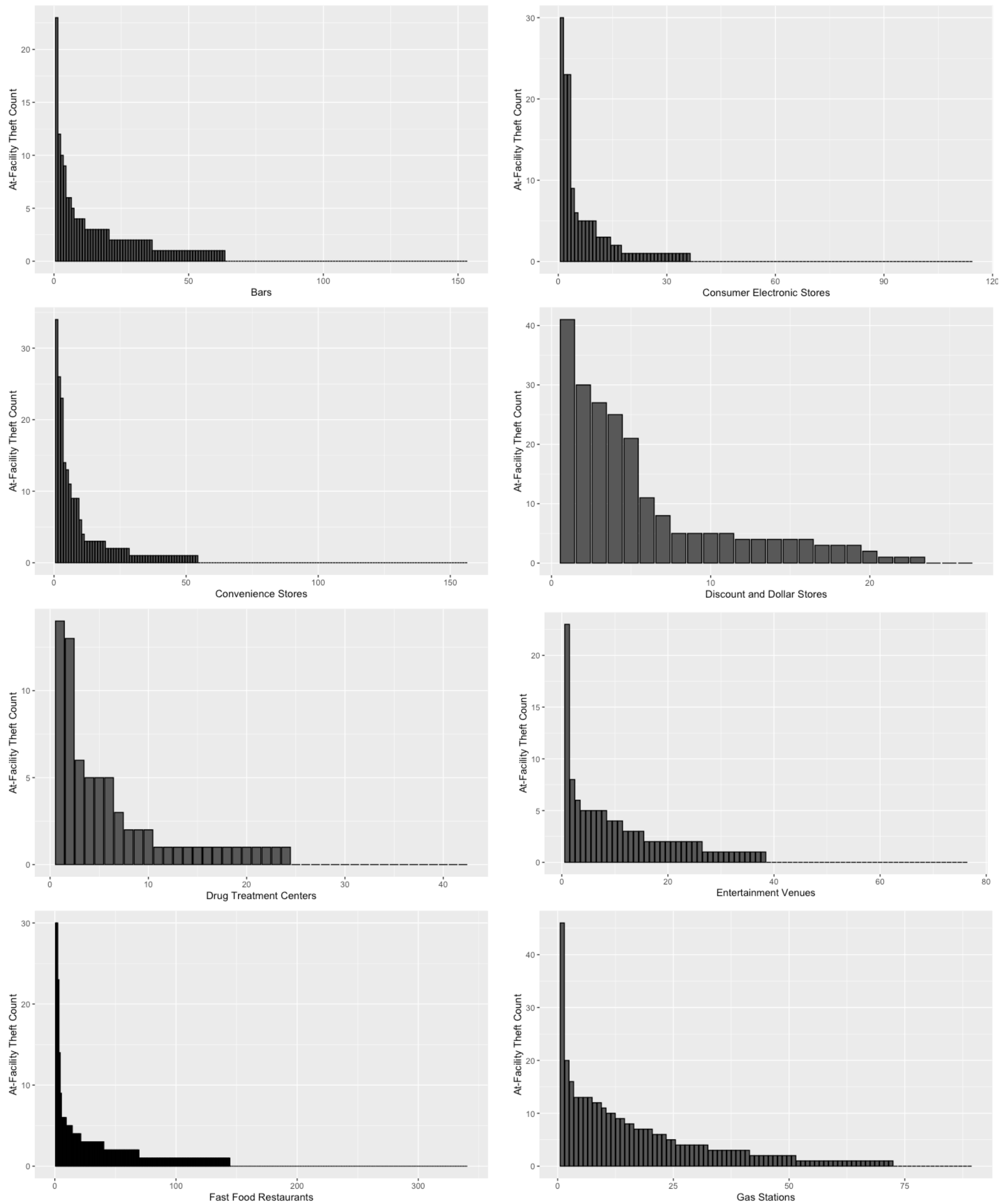
APPENDIX B – CONCENTRATION OF CRIME AT FACILITIES

Below, a series of J-curve charts are presented. These follow the approach used by Eck, Clarke, and Guerette (2007) to depict the concentration of crime in and around facilities. Here, I present charts showing 2015 crime, broken down by facility set. In these bar charts, each facility is represented along the x-axis and the number of crimes is represented along the y-axis (note that the y-axis scales are not equal across plots - their maximum is dictated by the maximum number of crimes in the most criminogenic location of each facility set). The facilities are also ordered in descending order, from the highest number of crimes to the lowest. This ordering results in a chart that forms a reclining J shape in facility sets with a high level of crime concentration (Eck, Clarke, & Guerette, 2007).

Beginning on the next page:

- Table 39 shows counts of at-facility thefts, by facility set
- Table 40 shows 500ft inverse distance weighted buffer area counts of facility thefts, by facility set
- Table 41 shows counts of at-facility calls for service, by facility set
- Table 42 shows 500ft inverse distance weighted buffer area counts of calls for service at and around facilities, by facility set
- Table 43 shows 500ft inverse distance weighted buffer area counts of robberies around facilities, by facility set.

Table 39. J-Curve Charts of 2015 At-Facility Thefts, by Facility Set



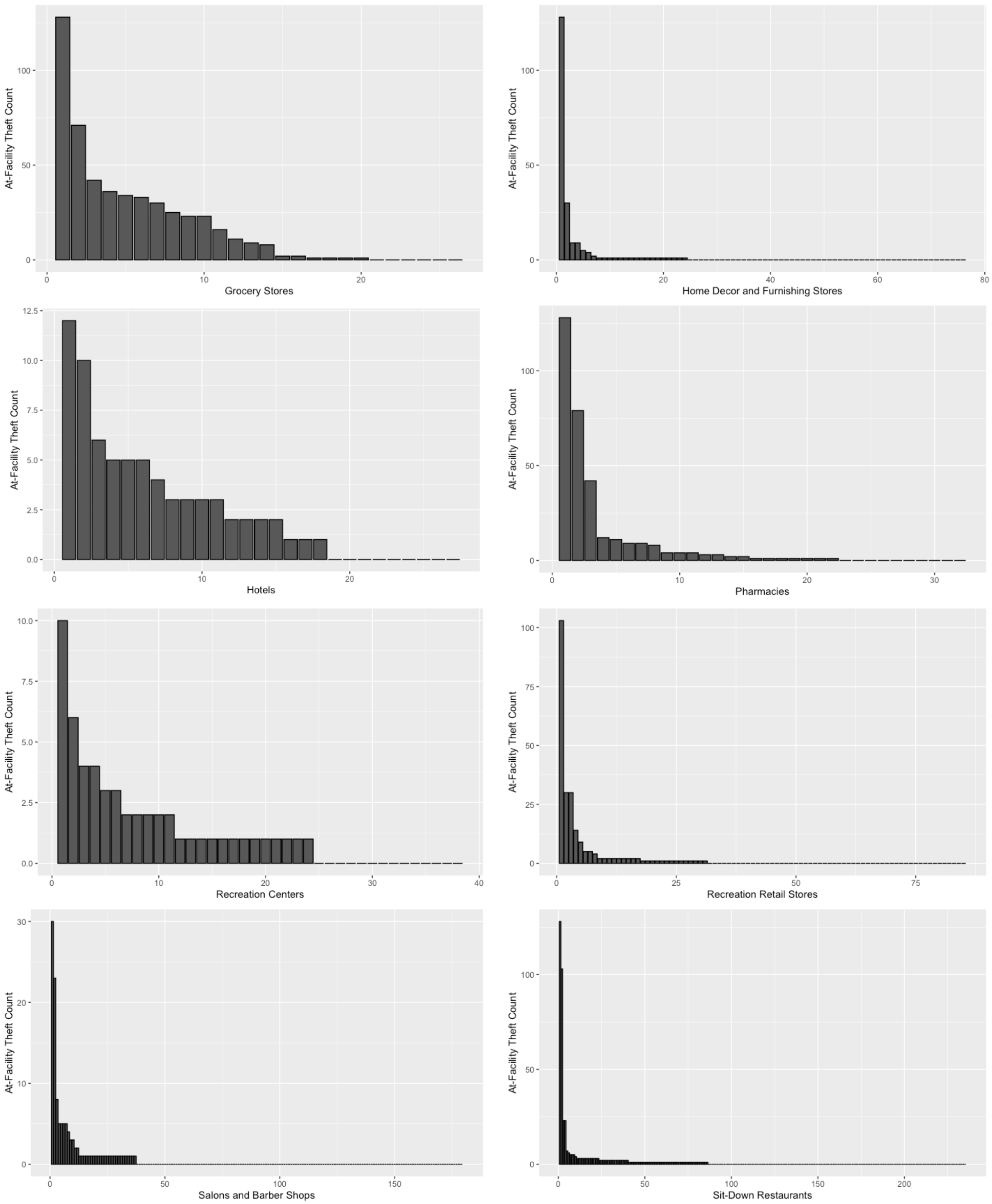
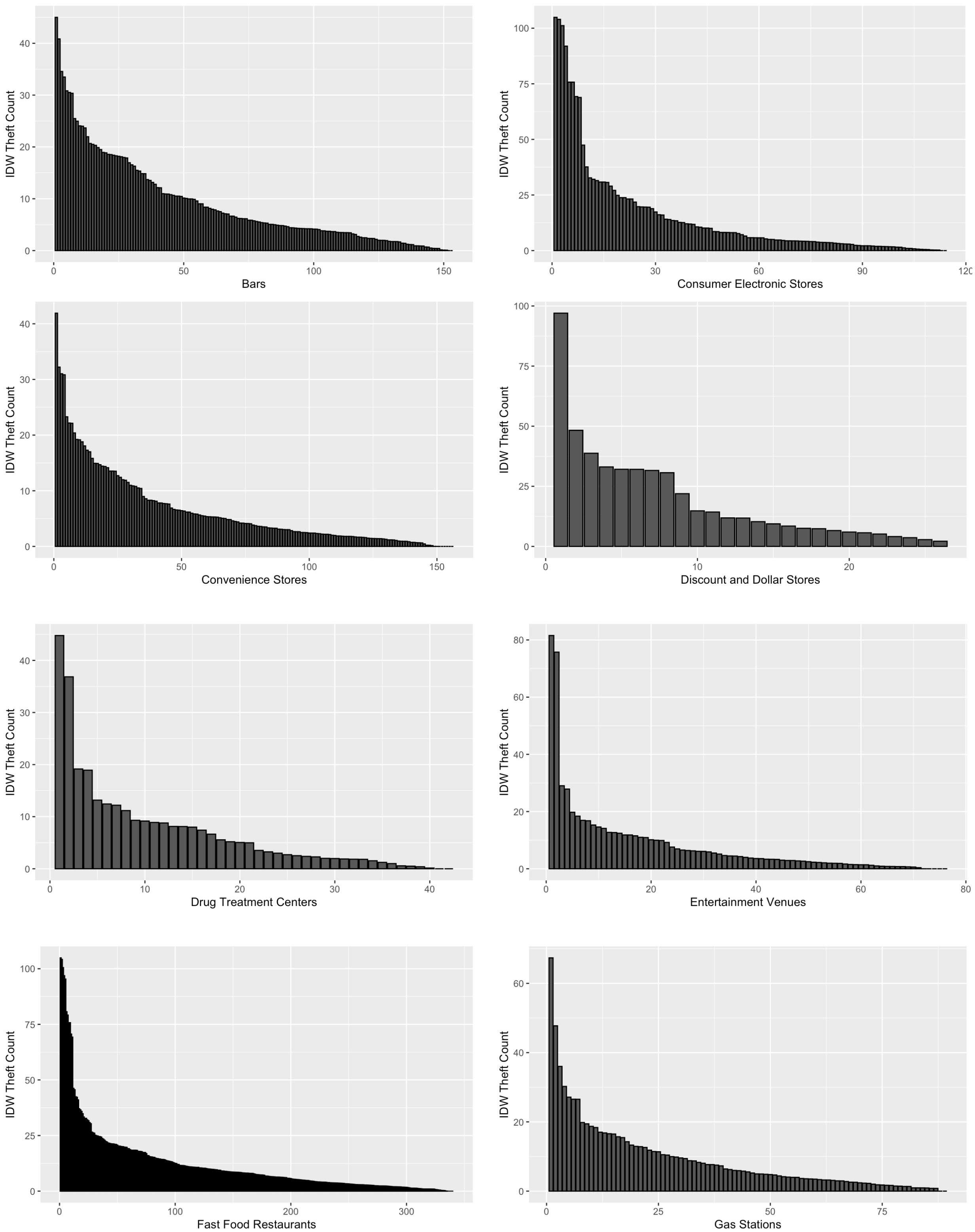
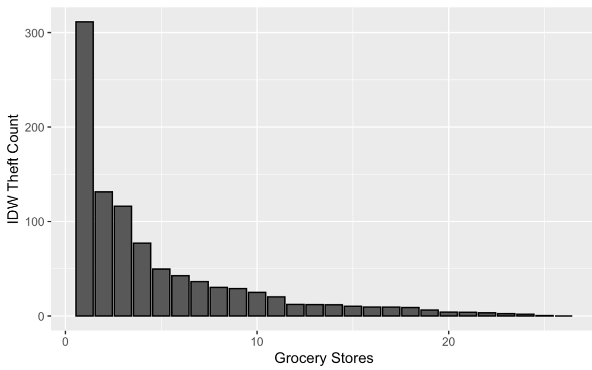
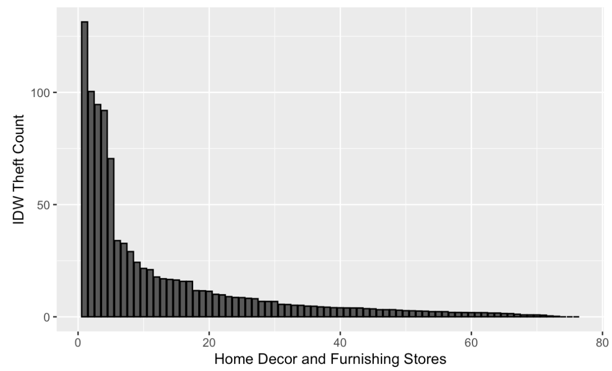
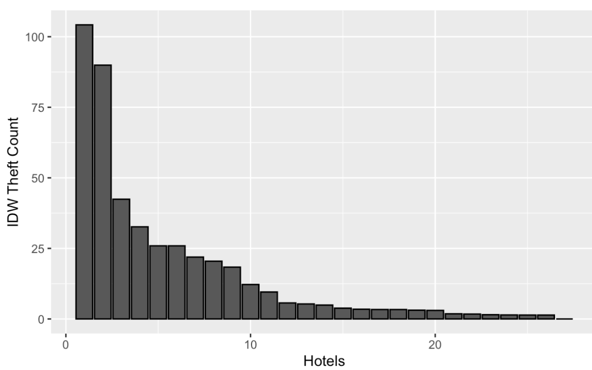

At-Facility Theft Count
Grocery Stores
Home Decor and Furnishing Stores
Hotels
Pharmacies
Recreation Centers
Recreation Retail Stores
Salons and Barber Shops
Sit-Down Restaurants

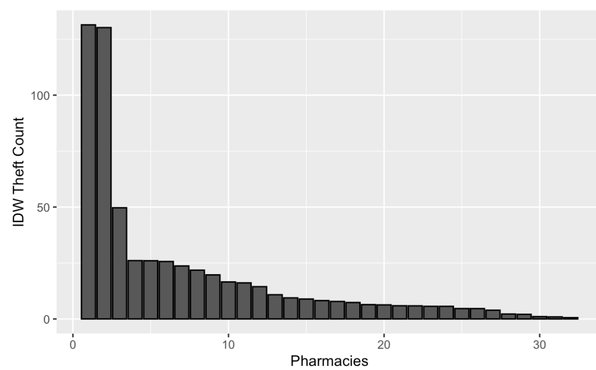
Table 40. J-Curve Charts of 2015 500ft Buffer Area Inverse Distance Weighted Facility Thefts, by Facility Set

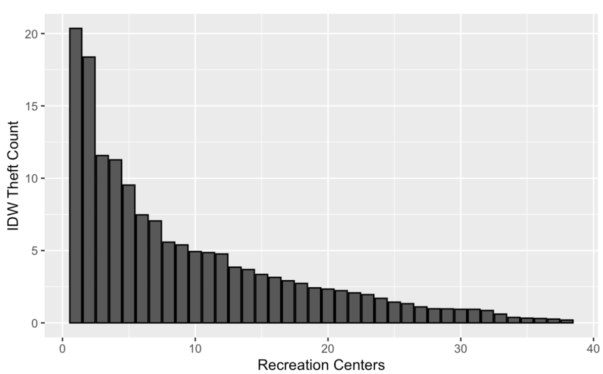


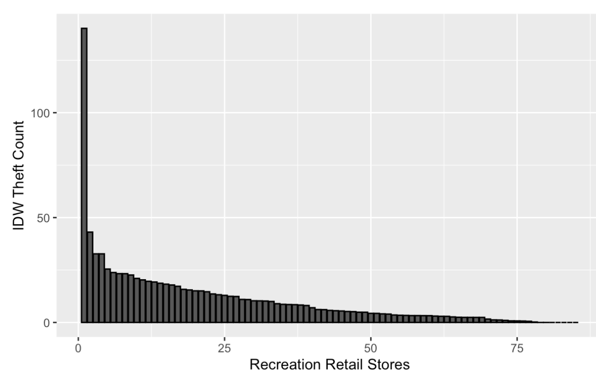

IDW Theft Count
0
100
200
300
0
10
20
Grocery Stores

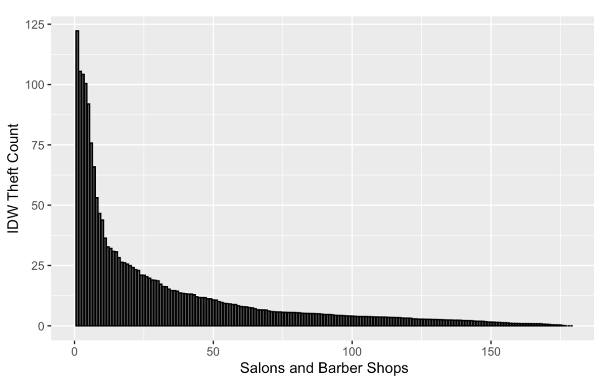

IDW Theft Count
0
50
100
0
20
40
60
80
Home Decor and Furnishing Stores


IDW Theft Count
0
25
50
75
100
0
10
20
Hotels


IDW Theft Count
0
50
100
0
10
20
30
Pharmacies


IDW Theft Count
0
5
10
15
20
0
10
20
30
40
Recreation Centers


IDW Theft Count
0
50
100
0
25
50
75
Recreation Retail Stores


IDW Theft Count
0
25
50
75
100
125
0
50
100
150
Salons and Barber Shops

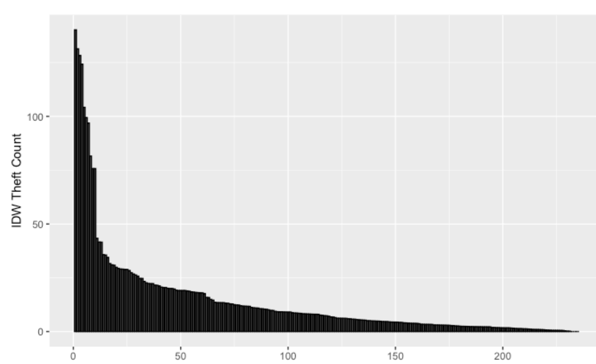
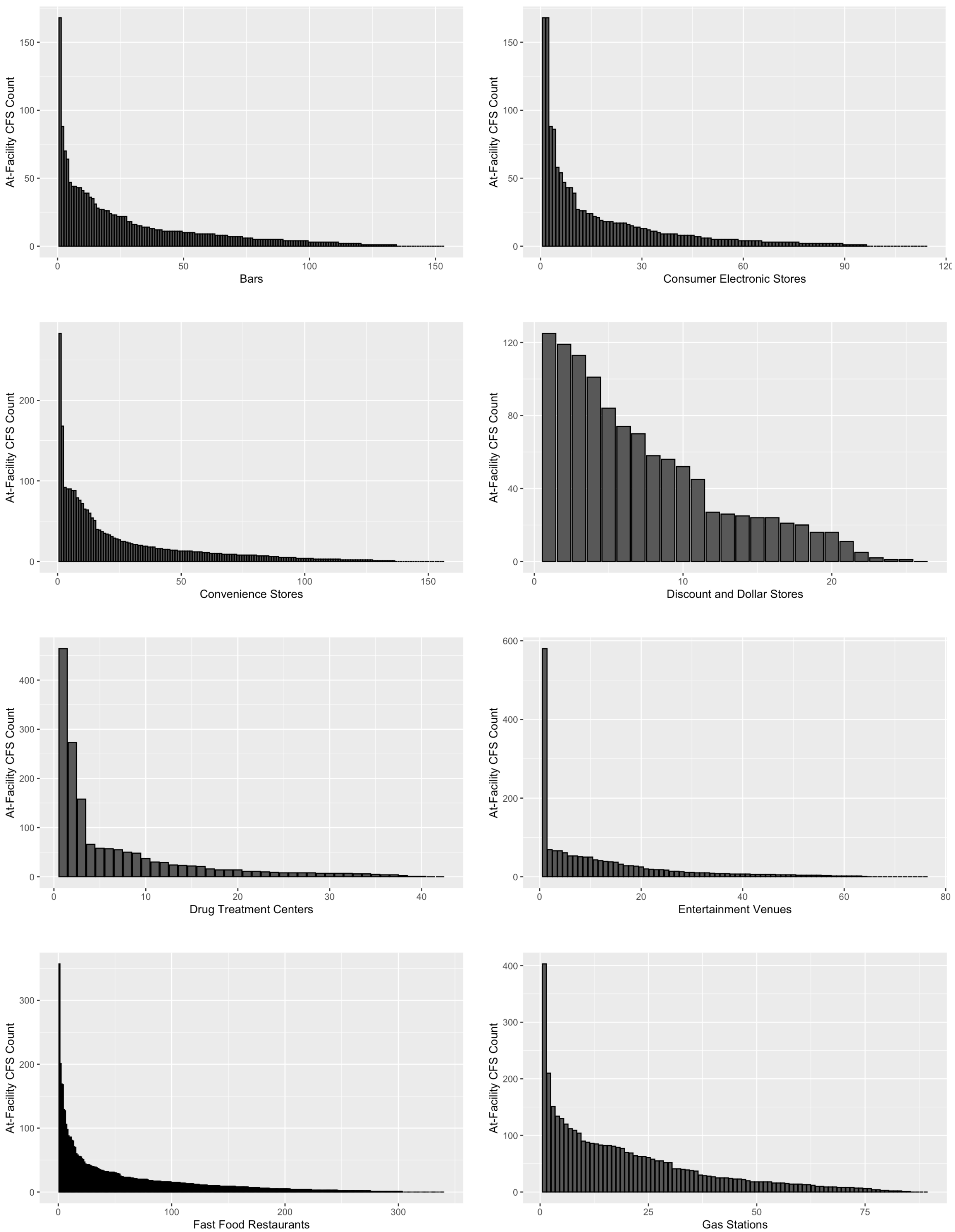
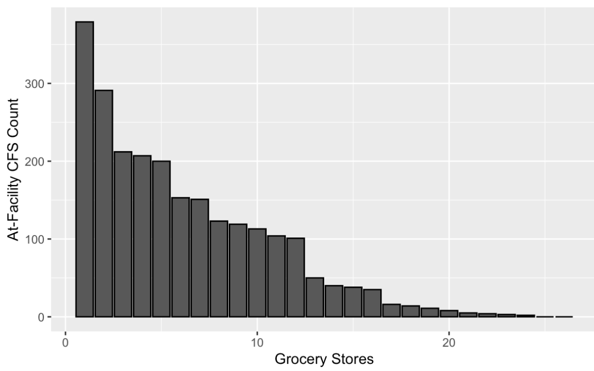
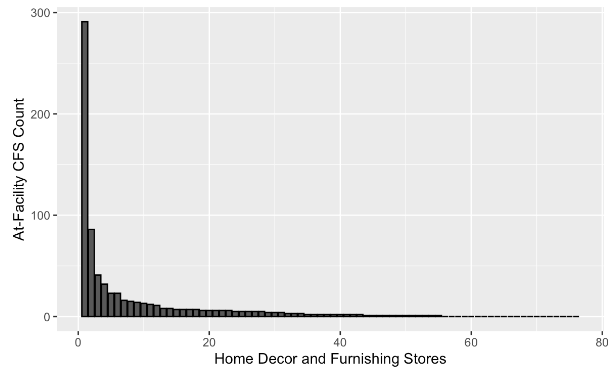

IDW Theft Count
0
50
100
0
50
100
150
200
Sit-Down Restaurants

Table 41. J-Curve Charts of 2015 At-Facility Calls for Service, by Facility Set

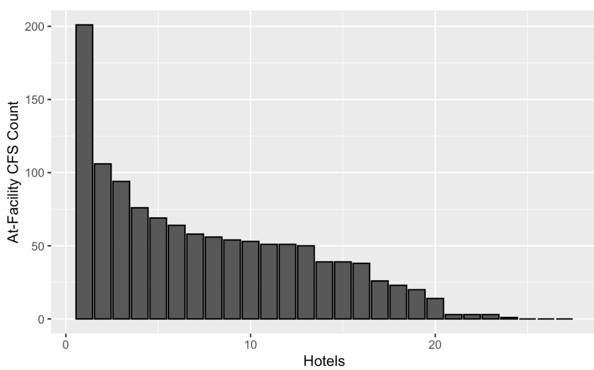




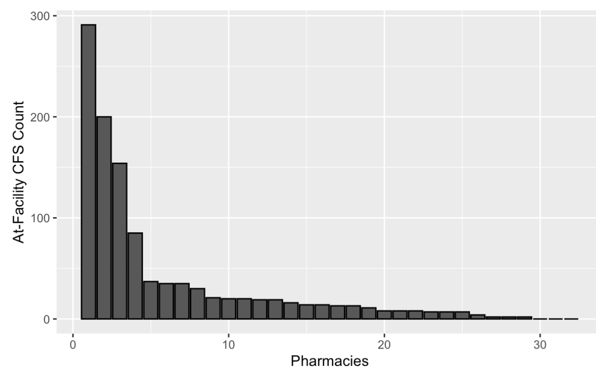
At-Facility CFS Count
0
100
200
300
0
10
20
Grocery Stores



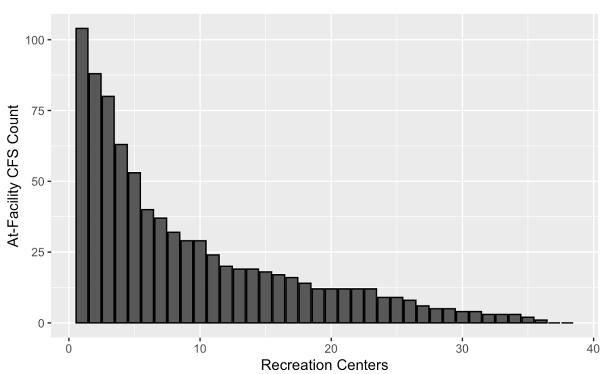
At-Facility CFS Count
0
100
200
300
0
20
40
60
80
Home Decor and Furnishing Stores



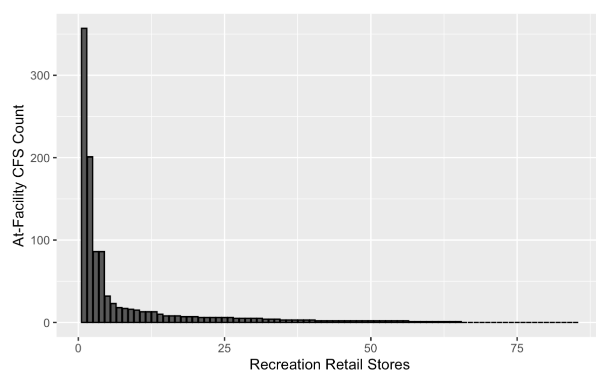
At-Facility CFS Count
0
50
100
150
200
0
10
20
Hotels



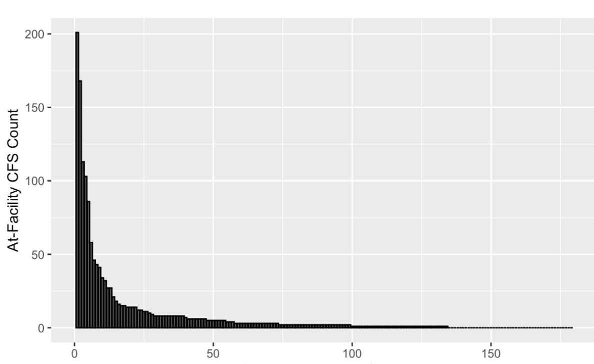
At-Facility CFS Count
0
100
200
300
0
10
20
30
Pharmacies



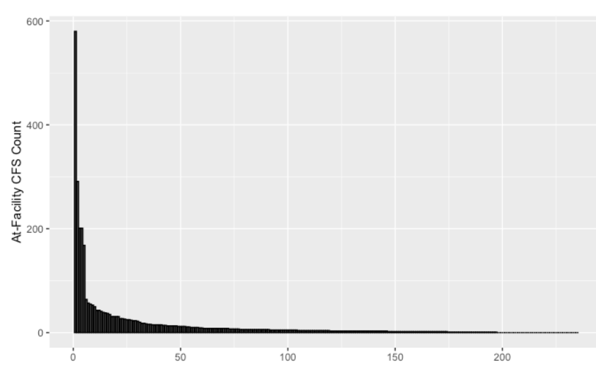
At-Facility CFS Count
0
25
50
75
100
0
10
20
30
40
Recreation Centers



At-Facility CFS Count
0
100
200
300
0
25
50
75
Recreation Retail Stores

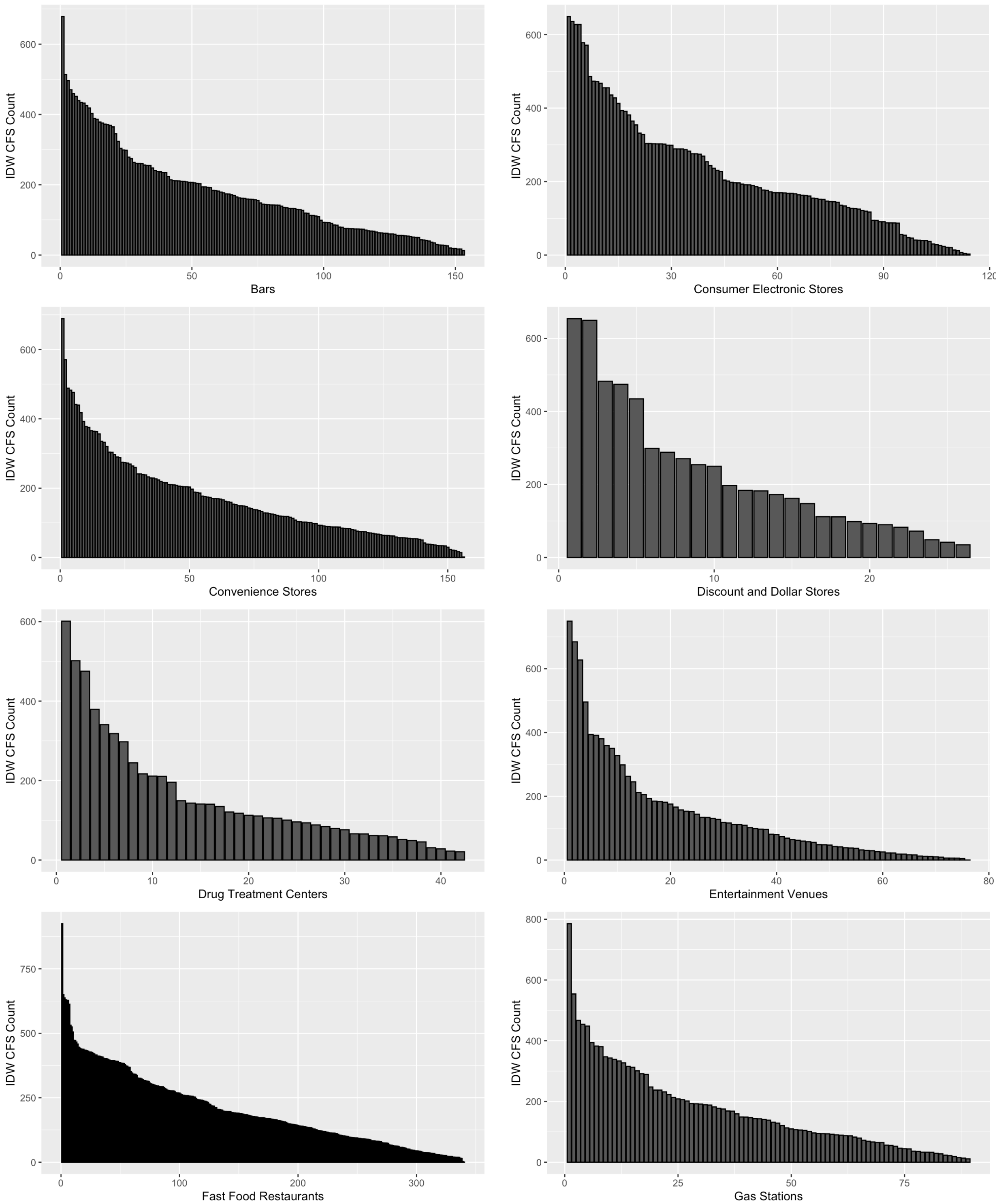


At-Facility CFS Count
0
50
100
150
200
0
50
100
150
Salons and Barber Shops



At-Facility CFS Count
0
200
400
600
0
50
100
150
200
Sit-Down Restaurants

Table 42. J-Curve Charts of 2015 500ft Buffer Area Inverse Distance Weighted Facility Calls for Service, by Facility Set



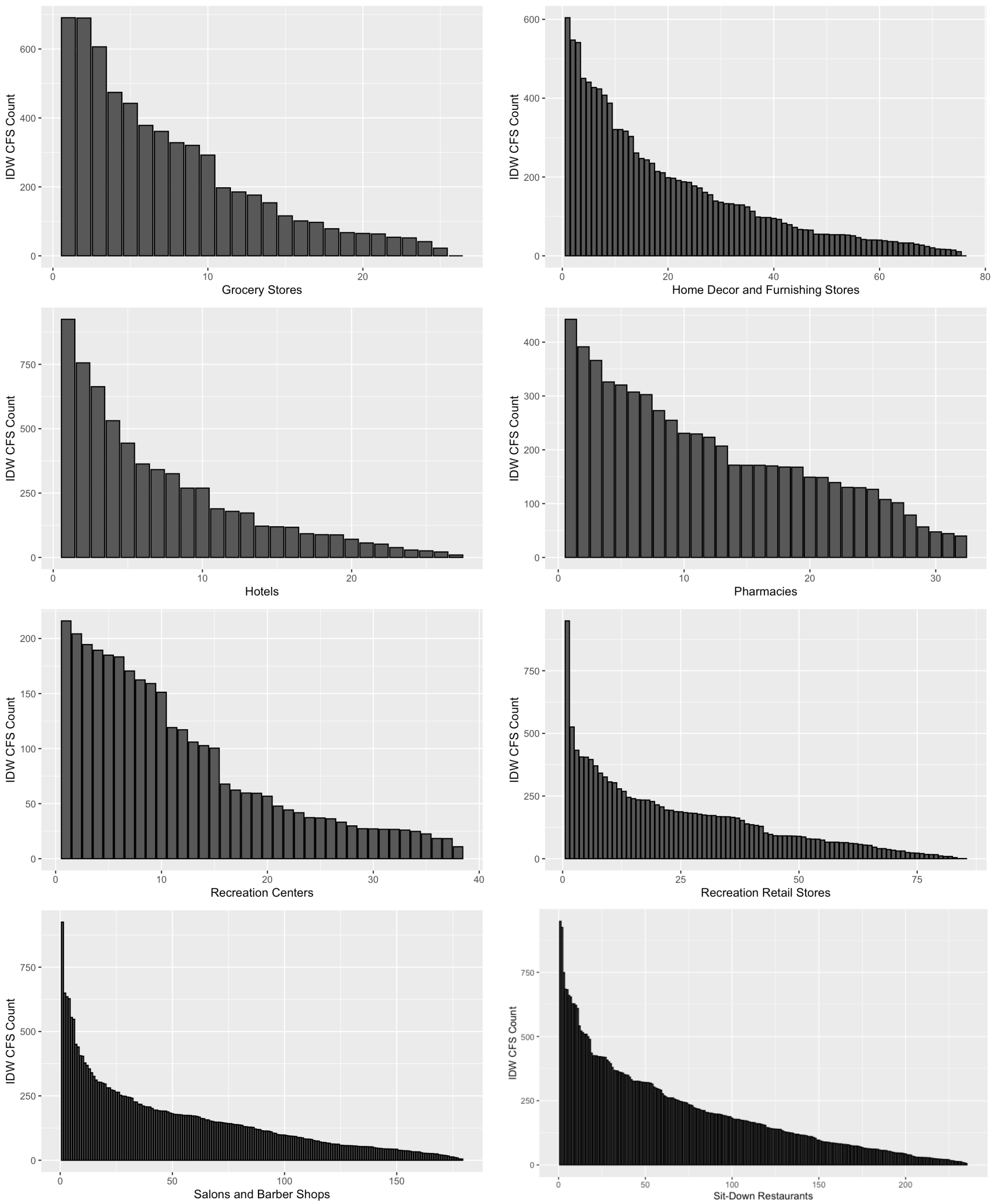
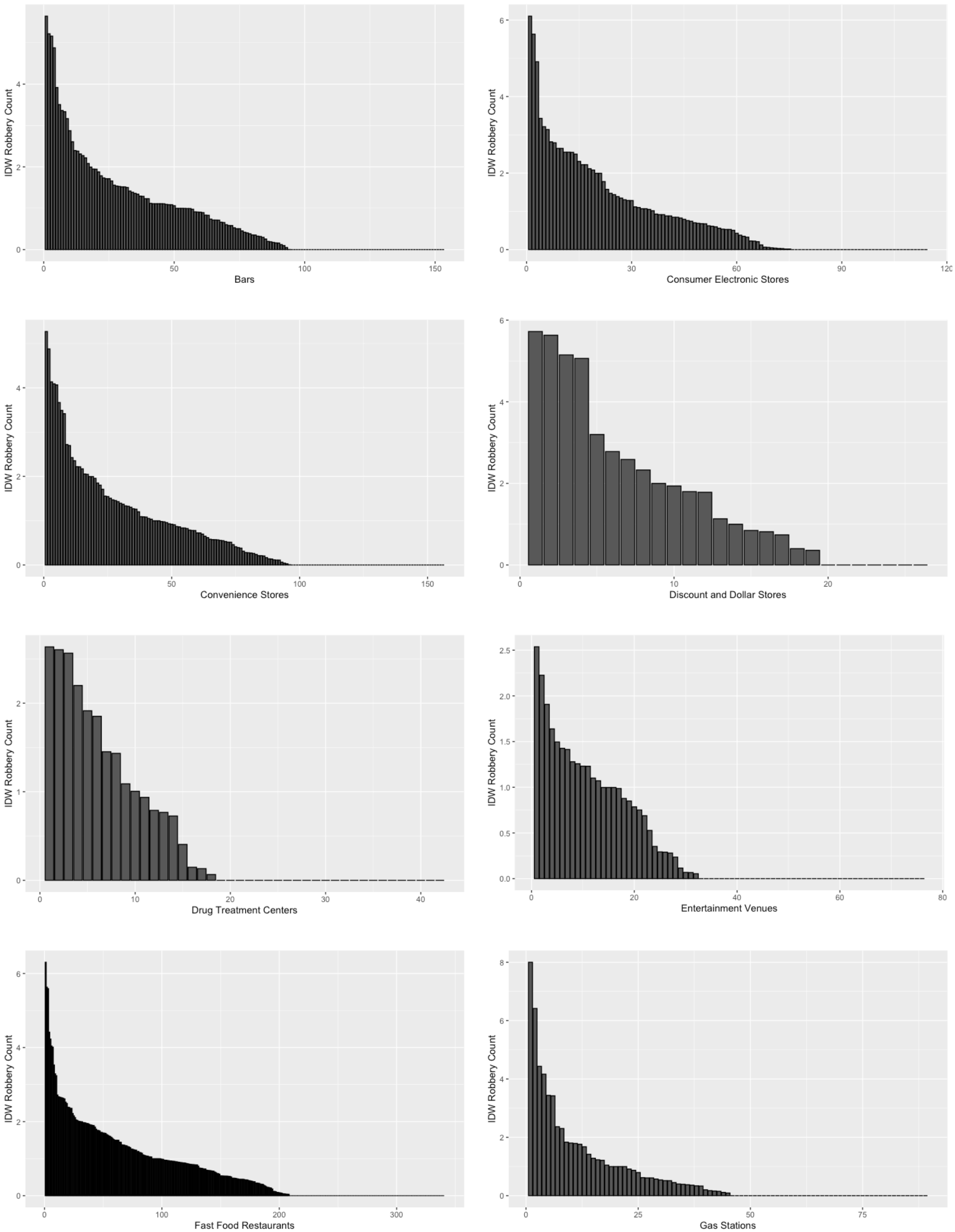
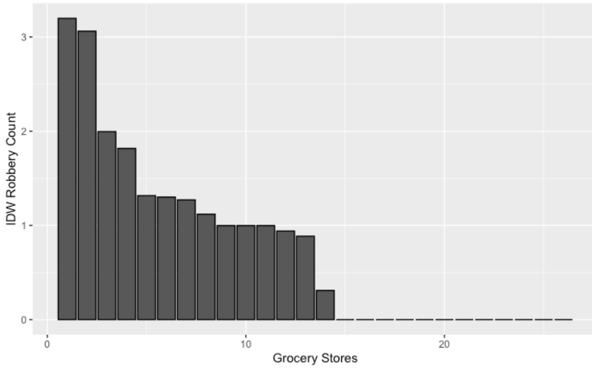
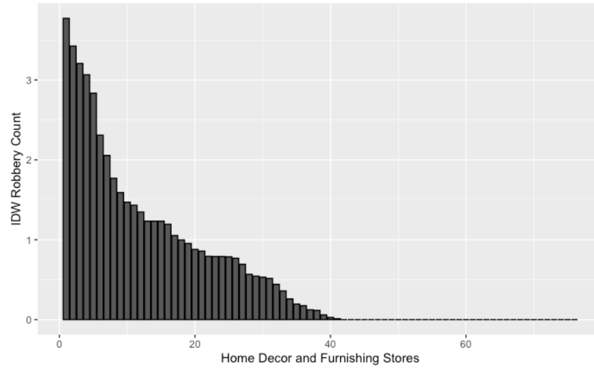
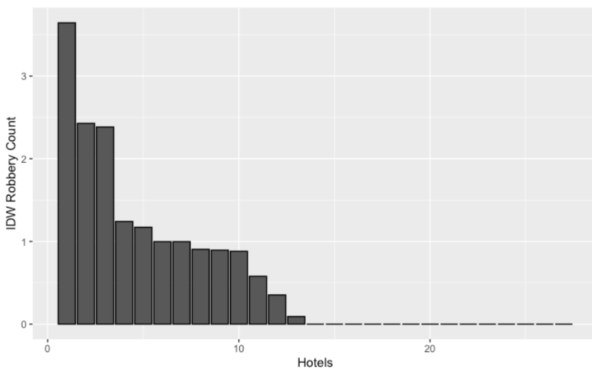

IDW CFS Count
Grocery Stores
Home Decor and Furnishing Stores
Hotels
Pharmacies
Recreation Centers
Recreation Retail Stores
Salons and Barber Shops
Sit-Down Restaurants

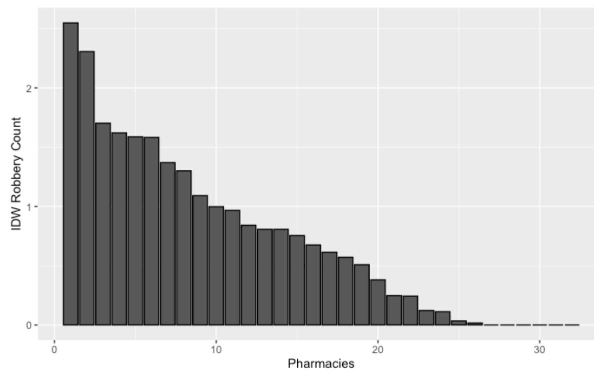
Table 43. J-Curve Charts of 2015 500ft Buffer Area Inverse Distance Weighted Facility Robberies, by Facility Set

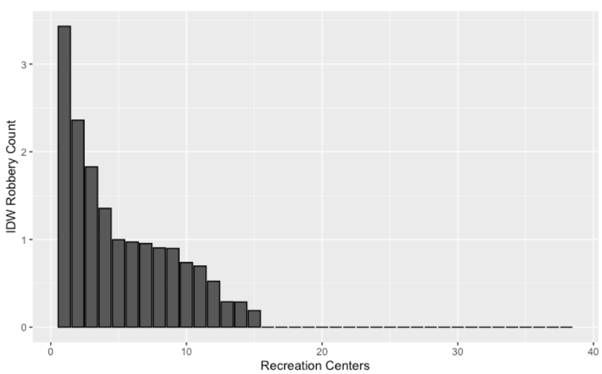


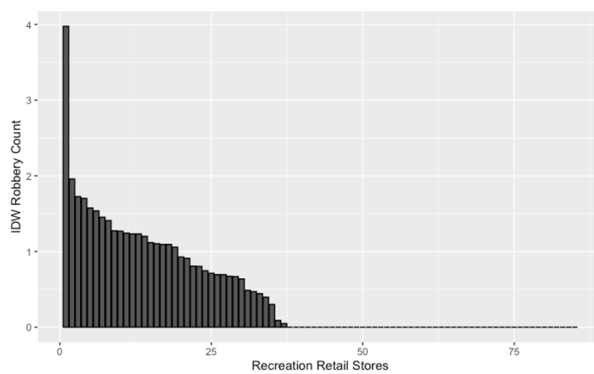

IDW Robbery Count
Grocery Stores

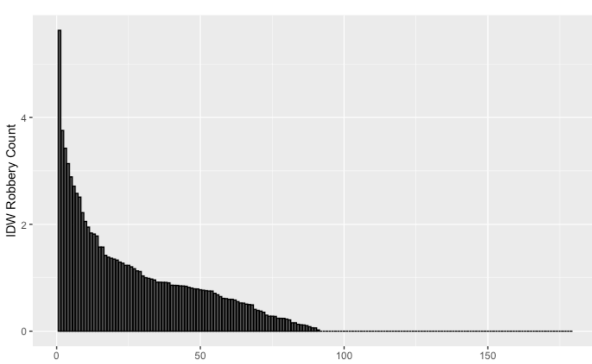

IDW Robbery Count
Home Decor and Furnishing Stores

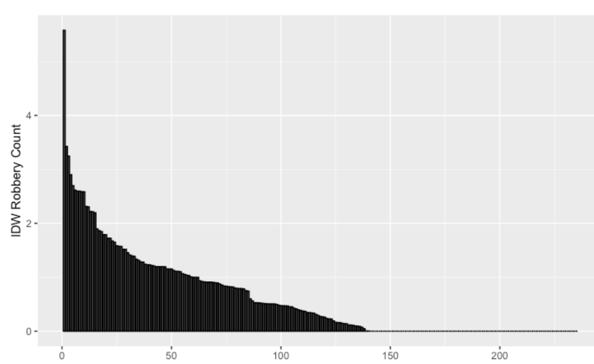

IDW Robbery Count
Hotels


IDW Robbery Count
Pharmacies


IDW Robbery Count
Recreation Centers


IDW Robbery Count
Recreation Retail Stores


IDW Robbery Count
Salons and Barber Shops


IDW Robbery Count
Sit-Down Restaurants

APPENDIX C – BASE AND ALTERNATE MODEL REGRESSION RESULTS

This appendix presents the full results of the two homogenous count negative binomial regression models, one for robbery and one for theft, as well as the regression models that incorporated each of the proposed *Assumption of Crime Concentration* facility risk measures.

Table 44. Robbery Model 1: Robbery Risk Using Homogenous Count of Facilities

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.425	(0.258)	1.5290	0.9217	2.5365	1.40
Consumer Electronics Stores	0.087	(0.274)	1.0914	0.6380	1.8673	1.56
Convenience Stores	0.836***	(0.227)	2.3074	1.4798	3.5981	1.26
Discount and Dollar Stores	-0.087	(0.515)	0.9162	0.3339	2.5140	1.33
Drug Treatment Centers	0.179	(0.505)	1.1959	0.4441	3.2205	1.31
Entertainment Venues	0.099	(0.451)	1.1040	0.4560	2.6727	1.27
Fast Food Restaurants	0.116	(0.149)	1.1230	0.8386	1.5039	1.89
Gas Stations	0.754*	(0.326)	2.1251	1.1222	4.0246	1.30
Grocery Stores	0.817	(0.645)	2.2631	0.6390	8.0145	1.43
Home Décor and Furniture Stores	0.549	(0.355)	1.7316	0.8630	3.4742	1.55
Hotels	0.742	(0.582)	2.1002	0.6706	6.5776	1.29
Pharmacies	0.470	(0.641)	1.5996	0.4551	5.6226	1.28
Recreation Centers	0.730	(0.498)	2.0760	0.7821	5.5103	1.23
Recreation Retail Stores	-0.456	(0.446)	0.6338	0.2644	1.5190	1.60
Salons and Barber Shops	-0.116	(0.289)	0.8904	0.5057	1.5676	1.81
Sit-Down Restaurants	0.111	(0.204)	1.1175	0.7498	1.6655	1.80
SL Bars	0.097	(0.119)	1.1020	0.8733	1.3905	1.59
SL Consumer Electronics Stores	0.472***	(0.121)	1.6026	1.2631	2.0335	1.74
SL Convenience Stores	0.477***	(0.111)	1.6119	1.2965	2.0041	1.33
SL Discount and Dollar Stores	0.561*	(0.245)	1.7522	1.0831	2.8347	1.44
SL Drug Treatment Centers	0.399	(0.205)	1.4901	0.9969	2.2273	1.34
SL Entertainment Venues	0.183	(0.189)	1.2012	0.8293	1.7400	1.38
SL Fast Food Restaurants	-0.059	(0.059)	0.9425	0.8390	1.0587	2.26
SL Gas Stations	0.029	(0.153)	1.0291	0.7621	1.3895	1.42
SL Grocery Stores	-0.125	(0.344)	0.8829	0.4499	1.7328	1.48
SL Home Décor and Furniture Stores	-0.290	(0.194)	0.7485	0.5120	1.0943	1.81
SL Hotels	0.333	(0.270)	1.3948	0.8221	2.3662	1.38
SL Pharmacies	-0.196	(0.322)	0.8217	0.4370	1.5452	1.43
SL Recreation Centers	0.613*	(0.254)	1.8456	1.1208	3.0392	1.23
SL Recreation Retail Stores	0.085	(0.189)	1.0885	0.7522	1.5752	1.93
SL Salons and Barber Shops	-0.079	(0.124)	0.9240	0.7241	1.1790	2.18
SL Sit-Down Restaurants	0.098	(0.085)	1.1029	0.9330	1.3037	2.34
Disadvantage	0.032***	(0.002)	1.0320	1.0276	1.0365	1.27
Residential Mobility	-0.005	(0.003)	0.9950	0.9883	1.0018	1.27
Racial Heterogeneity	0.878**	(0.271)	2.4049	1.4132	4.0925	1.08
Population	0.000***	(0.000)	1.0002	1.0001	1.0004	1.03
Street Length	0.000***	(0.000)	1.0005	1.0003	1.0006	1.04
Street Type	0.495***	(0.094)	1.6412	1.3647	1.9736	1.17
Constant	-4.865***	(0.180)	0.0077	0.0054	0.0110	--
AIC	5662.629				Mean VIF	1.48
BIC	5954.636					

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

Table 45. Robbery Model 2: Binary Robbery Risk Using Buffer-Area Street Robbery Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.576	(0.510)	1.7794	0.6549	4.8346	1.36
Consumer Electronics Stores	-0.251	(0.565)	0.7782	0.2572	2.3547	1.84
Convenience Stores	1.513**	(0.506)	4.5403	1.6839	12.2425	1.45
Discount and Dollar Stores	0.467	(0.814)	1.5947	0.3233	7.8668	1.45
Drug Treatment Centers	-0.288	(0.945)	0.7496	0.1177	4.7736	1.35
Entertainment Venues	0.062	(0.764)	1.0642	0.2381	4.7558	1.27
Fast Food Restaurants	-0.057	(0.319)	0.9449	0.5059	1.7648	1.68
Gas Stations	1.363*	(0.627)	3.9063	1.1423	13.3587	1.29
Grocery Stores	0.426	(1.143)	1.5305	0.1628	14.3841	1.35
Home Décor and Furniture Stores	0.587	(0.588)	1.7980	0.5678	5.6928	1.59
Hotels	0.624	(0.903)	1.8663	0.3181	10.9478	1.21
Pharmacies	-1.274	(1.873)	0.2797	0.0071	10.9931	1.38
Recreation Centers	1.253	(0.935)	3.5024	0.5599	21.9080	1.20
Recreation Retail Stores	-0.278	(0.819)	0.7571	0.1520	3.7699	1.82
Salons and Barber Shops	0.646	(0.504)	1.9088	0.7114	5.1220	1.50
Sit-Down Restaurants	0.237	(0.351)	1.2677	0.6375	2.5213	1.50
SL Bars	0.246	(0.222)	1.2791	0.8272	1.9776	1.51
SL Consumer Electronics Stores	0.660**	(0.234)	1.9344	1.2236	3.0584	2.20
SL Convenience Stores	0.085	(0.251)	1.0891	0.6661	1.7804	1.64
SL Discount and Dollar Stores	-0.087	(0.437)	0.9168	0.3894	2.1587	1.66
SL Drug Treatment Centers	0.404	(0.395)	1.4974	0.6904	3.2473	1.36
SL Entertainment Venues	0.540	(0.345)	1.7162	0.8721	3.3775	1.43
SL Fast Food Restaurants	0.072	(0.134)	1.0745	0.8268	1.3964	2.02
SL Gas Stations	0.166	(0.341)	1.1811	0.6049	2.3059	1.41
SL Grocery Stores	0.986	(0.599)	2.6800	0.8282	8.6720	1.36
SL Home Décor and Furniture Stores	-0.538	(0.382)	0.5837	0.2762	1.2337	1.96
SL Hotels	-0.045	(0.490)	0.9557	0.3659	2.4965	1.31
SL Pharmacies	-1.608	(0.850)	0.2003	0.0379	1.0589	1.42
SL Recreation Centers	0.403	(0.471)	1.4956	0.5938	3.7674	1.20
SL Recreation Retail Stores	0.561	(0.326)	1.7521	0.9253	3.3179	2.12
SL Salons and Barber Shops	0.237	(0.254)	1.2680	0.7701	2.0876	1.72
SL Sit-Down Restaurants	0.249	(0.150)	1.2824	0.9548	1.7223	1.81
Disadvantage	0.032***	(0.002)	1.0325	1.0281	1.0369	1.24
Residential Mobility	-0.004	(0.003)	0.9960	0.9894	1.0027	1.25
Racial Heterogeneity	0.700**	(0.270)	2.0140	1.1858	3.4207	1.08
Population	0.000**	(0.000)	1.0002	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0005	1.0004	1.0007	1.03
Street Type	0.692***	(0.089)	1.9970	1.6775	2.3775	1.07
Constant	-4.755***	(0.176)	0.0086	0.0061	0.0122	--
AIC	5700.247				Mean VIF	1.47
BIC	5992.254					

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

Table 46. Robbery Model 3: Continuous Robbery Risk Using Buffer-Area Street Robbery Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.316	(0.180)	1.3712	0.9627	1.9529	1.50
Consumer Electronics Stores	-0.061	(0.187)	0.9412	0.6521	1.3585	1.97
Convenience Stores	0.451*	(0.189)	1.5700	1.0848	2.2721	1.41
Discount and Dollar Stores	0.029	(0.193)	1.0291	0.7046	1.5031	1.65
Drug Treatment Centers	-0.166	(0.436)	0.8468	0.3604	1.9894	1.32
Entertainment Venues	-0.222	(0.536)	0.8007	0.2800	2.2903	1.31
Fast Food Restaurants	0.039	(0.127)	1.0395	0.8110	1.3325	1.78
Gas Stations	0.393	(0.223)	1.4812	0.9565	2.2937	1.34
Grocery Stores	0.405	(0.493)	1.4987	0.5707	3.9355	1.52
Home Décor and Furniture Stores	0.105	(0.250)	1.1102	0.6795	1.8139	1.70
Hotels	0.539	(0.449)	1.7145	0.7106	4.1367	1.23
Pharmacies	-0.174	(0.684)	0.8406	0.2201	3.2104	1.39
Recreation Centers	0.583	(0.643)	1.7917	0.5081	6.3176	1.25
Recreation Retail Stores	0.035	(0.434)	1.0351	0.4423	2.4228	1.74
Salons and Barber Shops	0.007	(0.277)	1.0074	0.5852	1.7340	1.99
Sit-Down Restaurants	0.160	(0.165)	1.1741	0.8499	1.6220	1.64
SL Bars	-0.007	(0.082)	0.9932	0.8461	1.1659	1.67
SL Consumer Electronics Stores	0.266**	(0.083)	1.3043	1.1087	1.5343	2.47
SL Convenience Stores	0.200*	(0.083)	1.2217	1.0380	1.4379	1.59
SL Discount and Dollar Stores	0.011	(0.102)	1.0111	0.8284	1.2340	1.92
SL Drug Treatment Centers	0.274	(0.189)	1.3157	0.9078	1.9070	1.32
SL Entertainment Venues	0.430*	(0.215)	1.5373	1.0094	2.3413	1.46
SL Fast Food Restaurants	-0.010	(0.053)	0.9897	0.8916	1.0987	2.33
SL Gas Stations	0.022	(0.099)	1.0224	0.8413	1.2424	1.48
SL Grocery Stores	0.325	(0.236)	1.3839	0.8720	2.1961	1.55
SL Home Décor and Furniture Stores	-0.230	(0.154)	0.7946	0.5879	1.0741	1.92
SL Hotels	-0.020	(0.264)	0.9803	0.5840	1.6455	1.42
SL Pharmacies	-0.429	(0.299)	0.6514	0.3627	1.1701	1.53
SL Recreation Centers	0.138	(0.255)	1.1480	0.6964	1.8923	1.26
SL Recreation Retail Stores	0.302	(0.198)	1.3527	0.9175	1.9945	2.00
SL Salons and Barber Shops	0.039	(0.131)	1.0395	0.8037	1.3445	2.41
SL Sit-Down Restaurants	0.139*	(0.070)	1.1488	1.0017	1.3175	2.01
Disadvantage	0.032***	(0.002)	1.0321	1.0277	1.0365	1.25
Residential Mobility	-0.004	(0.003)	0.9956	0.9890	1.0022	1.25
Racial Heterogeneity	0.680*	(0.269)	1.9748	1.1656	3.3458	1.08
Population	0.000***	(0.000)	1.0002	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0005	1.0004	1.0007	1.03
Street Type	0.652***	(0.089)	1.9184	1.6100	2.2859	1.08
Constant	-4.752***	(0.176)	0.0086	0.0061	0.0122	--
AIC	5671.251				Mean VIF	1.57
BIC	5963.258					

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

Table 47. Robbery Model 4: Binary Robbery Risk Using At-Facility Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.637	(0.480)	1.8912	0.7378	4.8475	1.28
Consumer Electronics Stores	0.230	(0.603)	1.2588	0.3858	4.1074	1.41
Convenience Stores	1.145*	(0.491)	3.1427	1.2002	8.2295	1.33
Discount and Dollar Stores	0.443	(0.953)	1.5575	0.2406	10.0841	1.27
Drug Treatment Centers	1.473	(1.009)	4.3618	0.6034	31.5321	1.22
Entertainment Venues	0.379	(1.122)	1.4606	0.1620	13.1666	1.30
Fast Food Restaurants	0.356	(0.358)	1.4272	0.7070	2.8814	1.46
Gas Stations	0.783	(0.560)	2.1877	0.7295	6.5607	1.24
Grocery Stores	1.353	(1.086)	3.8704	0.4608	32.5121	1.36
Home Décor and Furniture Stores	0.818	(0.913)	2.2657	0.3784	13.5664	1.76
Hotels	0.713	(1.266)	2.0407	0.1706	24.4052	1.47
Pharmacies	2.271	(1.325)	9.6910	0.7222	130.0417	1.40
Recreation Centers	0.884	(0.946)	2.4199	0.3787	15.4644	1.22
Recreation Retail Stores	-0.409	(1.181)	0.6643	0.0656	6.7286	1.33
Salons and Barber Shops	-0.163	(0.592)	0.8497	0.2662	2.7119	1.48
Sit-Down Restaurants	0.478	(0.438)	1.6124	0.6827	3.8083	1.43
SL Bars	0.378	(0.241)	1.4591	0.9093	2.3412	1.33
SL Consumer Electronics Stores	-0.239	(0.290)	0.7876	0.4464	1.3895	1.51
SL Convenience Stores	0.385	(0.256)	1.4691	0.8887	2.4287	1.35
SL Discount and Dollar Stores	1.073*	(0.433)	2.9244	1.2516	6.8326	1.28
SL Drug Treatment Centers	-0.275	(0.590)	0.7598	0.2393	2.4131	1.23
SL Entertainment Venues	-0.418	(0.507)	0.6583	0.2438	1.7772	1.41
SL Fast Food Restaurants	0.308	(0.160)	1.3600	0.9941	1.8607	1.71
SL Gas Stations	0.651*	(0.259)	1.9172	1.1532	3.1873	1.28
SL Grocery Stores	0.315	(0.542)	1.3697	0.4736	3.9611	1.35
SL Home Décor and Furniture Stores	-0.074	(0.448)	0.9284	0.3860	2.2331	1.89
SL Hotels	0.275	(0.605)	1.3161	0.4018	4.3108	1.69
SL Pharmacies	-0.635	(0.850)	0.5302	0.1002	2.8046	1.38
SL Recreation Centers	0.927	(0.493)	2.5266	0.9621	6.6354	1.23
SL Recreation Retail Stores	-1.054	(0.575)	0.3484	0.1129	1.0748	1.43
SL Salons and Barber Shops	0.189	(0.267)	1.2078	0.7154	2.0390	1.66
SL Sit-Down Restaurants	0.229	(0.181)	1.2572	0.8818	1.7922	1.68
Disadvantage	0.032***	(0.002)	1.0322	1.0278	1.0367	1.25
Residential Mobility	-0.006	(0.003)	0.9938	0.9871	1.0004	1.26
Racial Heterogeneity	0.958***	(0.270)	2.6059	1.5343	4.4261	1.08
Population	0.000**	(0.000)	1.0002	1.0001	1.0004	1.03
Street Length	0.000***	(0.000)	1.0005	1.0003	1.0006	1.03
Street Type	0.660***	(0.090)	1.9341	1.6199	2.3094	1.10
Constant	-4.764***	(0.177)	0.0085	0.0060	0.0121	--
AIC	5721.449				Mean VIF	1.37
BIC	6013.457					

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

Table 48. Robbery Model 5: Continuous Robbery Risk Using At-Facility Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.022	(0.014)	1.0223	0.9949	1.0506	1.89
Consumer Electronics Stores	-0.015	(0.014)	0.9849	0.9586	1.0118	2.59
Convenience Stores	0.016	(0.009)	1.0161	0.9977	1.0347	1.55
Discount and Dollar Stores	0.002	(0.008)	1.0015	0.9863	1.0170	1.35
Drug Treatment Centers	0.004	(0.006)	1.0038	0.9922	1.0155	1.21
Entertainment Venues	-0.004	(0.011)	0.9957	0.9745	1.0173	3.67
Fast Food Restaurants	0.002	(0.005)	1.0016	0.9911	1.0122	2.19
Gas Stations	0.009*	(0.004)	1.0093	1.0008	1.0179	1.23
Grocery Stores	0.006	(0.004)	1.0056	0.9984	1.0130	1.69
Home Décor and Furniture Stores	-0.032	(0.021)	0.9689	0.9302	1.0091	2.94
Hotels	0.013	(0.011)	1.0133	0.9918	1.0353	1.70
Pharmacies	0.032*	(0.016)	1.0321	1.0012	1.0640	2.81
Recreation Centers	0.019	(0.015)	1.0194	0.9905	1.0490	1.21
Recreation Retail Stores	0.042	(0.022)	1.0428	0.9995	1.0880	1.77
Salons and Barber Shops	0.022	(0.013)	1.0222	0.9955	1.0496	2.47
Sit-Down Restaurants	0.002	(0.009)	1.0018	0.9837	1.0201	4.92
SL Bars	0.005	(0.007)	1.0052	0.9922	1.0184	1.99
SL Consumer Electronics Stores	-0.003	(0.006)	0.9970	0.9854	1.0088	2.75
SL Convenience Stores	0.007	(0.004)	1.0066	0.9986	1.0146	1.72
SL Discount and Dollar Stores	0.015***	(0.004)	1.0147	1.0073	1.0222	1.39
SL Drug Treatment Centers	0.001	(0.003)	1.0006	0.9954	1.0059	1.22
SL Entertainment Venues	-0.003	(0.005)	0.9969	0.9879	1.0060	4.20
SL Fast Food Restaurants	0.006**	(0.002)	1.0058	1.0014	1.0103	2.54
SL Gas Stations	0.005**	(0.002)	1.0050	1.0018	1.0082	1.26
SL Grocery Stores	0.002	(0.002)	1.0021	0.9976	1.0066	1.80
SL Home Décor and Furniture Stores	0.009	(0.013)	1.0095	0.9845	1.0352	3.54
SL Hotels	0.007	(0.005)	1.0072	0.9974	1.0171	2.21
SL Pharmacies	-0.019	(0.012)	0.9816	0.9589	1.0047	3.53
SL Recreation Centers	0.011	(0.008)	1.0110	0.9950	1.0273	1.21
SL Recreation Retail Stores	-0.044*	(0.021)	0.9567	0.9172	0.9978	1.82
SL Salons and Barber Shops	-0.017*	(0.008)	0.9830	0.9686	0.9976	3.22
SL Sit-Down Restaurants	0.006	(0.004)	1.0062	0.9975	1.0150	6.48
Disadvantage	0.031***	(0.002)	1.0315	1.0271	1.0360	1.25
Residential Mobility	-0.006	(0.003)	0.9936	0.9870	1.0003	1.26
Racial Heterogeneity	0.926***	(0.270)	2.5242	1.4867	4.2857	1.08
Population	0.000***	(0.000)	1.0003	1.0001	1.0004	1.03
Street Length	0.000***	(0.000)	1.0005	1.0003	1.0006	1.03
Street Type	0.618***	(0.091)	1.8556	1.5531	2.2171	1.10
Constant	-4.750***	(0.177)	0.0086	0.0061	0.0122	--
AIC	5701.836				Mean VIF	2.18
BIC	5993.843					

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

Table 49. Robbery Model 6: Binary Robbery Risk Using Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.702	(0.486)	2.0184	0.7784	5.2340	1.39
Consumer Electronics Stores	-0.465	(0.503)	0.6281	0.2343	1.6841	1.69
Convenience Stores	0.647	(0.466)	1.9093	0.7655	4.7623	1.34
Discount and Dollar Stores	0.967	(0.797)	2.6301	0.5511	12.5507	1.48
Drug Treatment Centers	0.085	(0.922)	1.0890	0.1788	6.6328	1.35
Entertainment Venues	-0.111	(0.987)	0.8951	0.1294	6.1928	1.51
Fast Food Restaurants	-0.306	(0.349)	0.7366	0.3717	1.4597	2.19
Gas Stations	1.050	(0.623)	2.8582	0.8433	9.6874	1.27
Grocery Stores	1.112	(1.052)	3.0417	0.3869	23.9115	1.44
Home Décor and Furniture Stores	0.840	(0.672)	2.3155	0.6205	8.6412	1.50
Hotels	1.626	(0.941)	5.0822	0.8037	32.1381	1.35
Pharmacies	0.046	(1.379)	1.0469	0.0701	15.6340	1.49
Recreation Centers	0.474	(0.970)	1.6071	0.2400	10.7604	1.20
Recreation Retail Stores	0.235	(0.883)	1.2655	0.2241	7.1478	1.48
Salons and Barber Shops	-0.141	(0.571)	0.8686	0.2836	2.6602	1.79
Sit-Down Restaurants	0.396	(0.371)	1.4853	0.7173	3.0757	1.93
SL Bars	0.432	(0.243)	1.5399	0.9569	2.4780	1.66
SL Consumer Electronics Stores	0.769***	(0.230)	2.1571	1.3748	3.3846	2.06
SL Convenience Stores	0.946***	(0.227)	2.5766	1.6504	4.0225	1.48
SL Discount and Dollar Stores	0.140	(0.427)	1.1498	0.4980	2.6544	1.70
SL Drug Treatment Centers	0.701	(0.401)	2.0166	0.9181	4.4294	1.36
SL Entertainment Venues	-0.139	(0.384)	0.8703	0.4100	1.8473	1.78
SL Fast Food Restaurants	-0.106	(0.116)	0.8994	0.7162	1.1295	3.05
SL Gas Stations	0.213	(0.304)	1.2378	0.6819	2.2471	1.37
SL Grocery Stores	0.509	(0.598)	1.6636	0.5148	5.3756	1.45
SL Home Décor and Furniture Stores	-0.261	(0.351)	0.7703	0.3873	1.5321	1.66
SL Hotels	0.664	(0.502)	1.9422	0.7266	5.1913	1.58
SL Pharmacies	-0.861	(0.752)	0.4228	0.0969	1.8452	1.59
SL Recreation Centers	1.054*	(0.447)	2.8686	1.1952	6.8851	1.20
SL Recreation Retail Stores	-0.617	(0.438)	0.5397	0.2288	1.2733	1.73
SL Salons and Barber Shops	0.095	(0.311)	1.0995	0.5977	2.0226	2.64
SL Sit-Down Restaurants	0.109	(0.139)	1.1149	0.8488	1.4643	2.69
Disadvantage	0.031***	(0.002)	1.0315	1.0271	1.0359	1.25
Residential Mobility	-0.005	(0.003)	0.9945	0.9879	1.0012	1.25
Racial Heterogeneity	0.775**	(0.271)	2.1700	1.2768	3.6883	1.08
Population	0.000**	(0.000)	1.0002	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0005	1.0004	1.0007	1.03
Street Type	0.701***	(0.089)	2.0149	1.6917	2.3998	1.07
Constant	-4.730***	(0.178)	0.0088	0.0062	0.0125	--
AIC	5697.418				Mean VIF	1.58
BIC	5989.425					

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

Table 50. Robbery Model 7: Continuous Robbery Risk Using Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.001	(0.001)	1.0012	0.9992	1.0032	1.39
Consumer Electronics Stores	-0.000	(0.001)	0.9997	0.9977	1.0017	1.88
Convenience Stores	0.003**	(0.001)	1.0034	1.0013	1.0055	1.28
Discount and Dollar Stores	0.001	(0.001)	1.0007	0.9981	1.0033	1.39
Drug Treatment Centers	0.000	(0.002)	1.0003	0.9959	1.0048	1.34
Entertainment Venues	-0.000	(0.002)	1.0000	0.9956	1.0044	1.60
Fast Food Restaurants	0.000	(0.001)	1.0004	0.9992	1.0016	2.04
Gas Stations	0.003*	(0.001)	1.0032	1.0004	1.0060	1.30
Grocery Stores	0.003	(0.002)	1.0029	0.9996	1.0062	1.49
Home Décor and Furniture Stores	0.001	(0.001)	1.0009	0.9982	1.0036	1.54
Hotels	0.003	(0.001)	1.0025	0.9998	1.0052	1.50
Pharmacies	0.001	(0.003)	1.0005	0.9951	1.0060	1.34
Recreation Centers	0.004	(0.004)	1.0042	0.9957	1.0128	1.23
Recreation Retail Stores	-0.000	(0.002)	0.9997	0.9964	1.0029	1.49
Salons and Barber Shops	-0.001	(0.001)	0.9988	0.9962	1.0014	2.13
Sit-Down Restaurants	0.001	(0.001)	1.0008	0.9995	1.0021	2.04
SL Bars	0.001	(0.000)	1.0008	0.9999	1.0017	1.59
SL Consumer Electronics Stores	0.002***	(0.000)	1.0015	1.0006	1.0024	2.35
SL Convenience Stores	0.003***	(0.000)	1.0027	1.0017	1.0036	1.45
SL Discount and Dollar Stores	0.001	(0.001)	1.0013	0.9998	1.0027	1.56
SL Drug Treatment Centers	0.002*	(0.001)	1.0018	1.0002	1.0035	1.38
SL Entertainment Venues	-0.000	(0.001)	0.9999	0.9981	1.0017	2.02
SL Fast Food Restaurants	-0.000	(0.000)	0.9996	0.9992	1.0001	2.90
SL Gas Stations	0.000	(0.001)	1.0001	0.9988	1.0013	1.47
SL Grocery Stores	0.000	(0.001)	1.0001	0.9981	1.0021	1.53
SL Home Décor and Furniture Stores	-0.001	(0.001)	0.9993	0.9979	1.0007	1.71
SL Hotels	0.000	(0.001)	1.0005	0.9990	1.0019	1.89
SL Pharmacies	-0.000	(0.001)	0.9995	0.9968	1.0022	1.44
SL Recreation Centers	0.006**	(0.002)	1.0057	1.0017	1.0098	1.22
SL Recreation Retail Stores	-0.000	(0.001)	0.9999	0.9982	1.0015	1.84
SL Salons and Barber Shops	-0.000	(0.001)	0.9996	0.9983	1.0009	3.13
SL Sit-Down Restaurants	0.000	(0.000)	1.0003	0.9998	1.0008	3.00
Disadvantage	0.031***	(0.002)	1.0313	1.0269	1.0357	1.26
Residential Mobility	-0.005	(0.003)	0.9949	0.9883	1.0015	1.26
Racial Heterogeneity	0.773**	(0.269)	2.1673	1.2803	3.6689	1.08
Population	0.000***	(0.000)	1.0003	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0005	1.0004	1.0007	1.03
Street Type	0.553***	(0.091)	1.7387	1.4548	2.0780	1.12
Constant	-4.803***	(0.177)	0.0082	0.0058	0.0116	--
AIC	5624.984				Mean VIF	1.64
BIC	5916.991					

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

Table 51. Theft Model 1: Theft Risk Using Homogenous Count of Facilities

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.665***	(0.131)	1.9442	1.5029	2.5150	1.40
Consumer Electronics Stores	0.177	(0.157)	1.1935	0.8767	1.6247	1.56
Convenience Stores	0.906***	(0.139)	2.4751	1.8860	3.2480	1.26
Discount and Dollar Stores	1.718***	(0.312)	5.5744	3.0246	10.2738	1.33
Drug Treatment Centers	1.107***	(0.283)	3.0240	1.7380	5.2616	1.31
Entertainment Venues	0.948***	(0.197)	2.5793	1.7528	3.7955	1.27
Fast Food Restaurants	0.292***	(0.079)	1.3394	1.1474	1.5635	1.89
Gas Stations	1.181***	(0.179)	3.2590	2.2942	4.6297	1.30
Grocery Stores	3.045***	(0.354)	21.0136	10.4920	42.0865	1.43
Home Décor and Furniture Stores	0.256	(0.182)	1.2921	0.9050	1.8448	1.55
Hotels	0.555	(0.296)	1.7420	0.9749	3.1124	1.29
Pharmacies	0.853**	(0.263)	2.3471	1.4005	3.9334	1.28
Recreation Centers	0.491	(0.286)	1.6332	0.9323	2.8610	1.23
Recreation Retail Stores	0.326	(0.195)	1.3849	0.9451	2.0293	1.60
Salons and Barber Shops	-0.070	(0.133)	0.9321	0.7177	1.2104	1.81
Sit-Down Restaurants	0.256*	(0.108)	1.2912	1.0449	1.5956	1.80
SL Bars	0.139**	(0.052)	1.1487	1.0367	1.2729	1.59
SL Consumer Electronics Stores	0.074	(0.066)	1.0772	0.9474	1.2248	1.74
SL Convenience Stores	0.118	(0.061)	1.1255	0.9989	1.2682	1.33
SL Discount and Dollar Stores	0.386**	(0.145)	1.4708	1.1063	1.9554	1.44
SL Drug Treatment Centers	0.040	(0.116)	1.0409	0.8290	1.3069	1.34
SL Entertainment Venues	0.224*	(0.088)	1.2509	1.0532	1.4857	1.38
SL Fast Food Restaurants	-0.034	(0.030)	0.9665	0.9106	1.0258	2.26
SL Gas Stations	-0.090	(0.081)	0.9141	0.7791	1.0724	1.42
SL Grocery Stores	-0.006	(0.167)	0.9942	0.7164	1.3798	1.48
SL Home Décor and Furniture Stores	0.003	(0.083)	1.0026	0.8515	1.1806	1.81
SL Hotels	0.518***	(0.130)	1.6782	1.3014	2.1642	1.38
SL Pharmacies	0.044	(0.125)	1.0450	0.8178	1.3354	1.43
SL Recreation Centers	0.400**	(0.131)	1.4914	1.1547	1.9262	1.23
SL Recreation Retail Stores	0.032	(0.085)	1.0325	0.8739	1.2200	1.93
SL Salons and Barber Shops	0.022	(0.052)	1.0226	0.9242	1.1315	2.18
SL Sit-Down Restaurants	0.095*	(0.042)	1.0997	1.0121	1.1949	2.34
Disadvantage	0.010***	(0.001)	1.0098	1.0079	1.0118	1.27
Residential Mobility	0.006***	(0.002)	1.0057	1.0025	1.0088	1.27
Racial Heterogeneity	0.776***	(0.117)	2.1730	1.7277	2.7332	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0004	1.03
Street Length	0.001***	(0.000)	1.0014	1.0009	1.0011	1.04
Street Type	0.496***	(0.044)	1.6415	1.5067	1.7883	1.17
Constant	-2.241***	(0.077)	0.1064	0.0916	0.1236	--
AIC	24712.360				Mean	1.48
BIC	25004.367				VIF	

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

Table 52. Theft Model 2: Binary Theft Risk Using At-Facility Theft Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	1.554***	(0.281)	4.7301	2.7265	8.2058	1.23
Consumer Electronics Stores	0.144	(0.300)	1.1548	0.6420	2.0770	1.53
Convenience Stores	0.965***	(0.236)	2.6255	1.6522	4.1721	1.25
Discount and Dollar Stores	1.989**	(0.669)	7.3068	1.9679	27.1304	1.23
Drug Treatment Centers	1.632**	(0.533)	5.1146	1.7993	14.5380	1.20
Entertainment Venues	1.306***	(0.342)	3.6896	1.8892	7.2056	1.31
Fast Food Restaurants	0.470*	(0.205)	1.5993	1.0704	2.3896	1.69
Gas Stations	1.826***	(0.370)	6.2064	3.0044	12.8212	1.24
Grocery Stores	3.356***	(0.702)	28.6700	7.2422	113.4969	1.56
Home Décor and Furniture Stores	0.362	(0.304)	1.4356	0.7915	2.6038	1.38
Hotels	1.540*	(0.725)	4.6667	1.1270	19.3251	1.50
Pharmacies	1.235	(0.674)	3.4384	0.9182	12.8758	1.68
Recreation Centers	0.324	(0.526)	1.3823	0.4932	3.8745	1.20
Recreation Retail Stores	-0.220	(0.438)	0.8026	0.3401	1.8942	1.55
Salons and Barber Shops	0.565*	(0.283)	1.7590	1.0100	3.0635	1.40
Sit-Down Restaurants	0.242	(0.185)	1.2743	0.8868	1.8313	1.55
SL Bars	0.166	(0.122)	1.1806	0.9288	1.5008	1.26
SL Consumer Electronics Stores	0.087	(0.112)	1.0909	0.8756	1.3591	1.66
SL Convenience Stores	0.420***	(0.103)	1.5224	1.2440	1.8630	1.31
SL Discount and Dollar Stores	0.631*	(0.300)	1.8799	1.0444	3.3837	1.25
SL Drug Treatment Centers	0.028	(0.250)	1.0289	0.6303	1.6797	1.22
SL Entertainment Venues	0.404*	(0.166)	1.4978	1.0827	2.0720	1.45
SL Fast Food Restaurants	0.044	(0.083)	1.0445	0.8882	1.2283	2.00
SL Gas Stations	0.099	(0.165)	1.1044	0.7995	1.5258	1.26
SL Grocery Stores	0.570	(0.390)	1.7689	0.8238	3.7985	1.55
SL Home Décor and Furniture Stores	0.337*	(0.131)	1.4005	1.0832	1.8108	1.52
SL Hotels	-0.135	(0.288)	0.8737	0.4972	1.5355	1.69
SL Pharmacies	0.309	(0.368)	1.3619	0.6626	2.7992	1.64
SL Recreation Centers	0.507*	(0.230)	1.6597	1.0583	2.6030	1.21
SL Recreation Retail Stores	0.187	(0.193)	1.2054	0.8262	1.7587	1.69
SL Salons and Barber Shops	0.041	(0.121)	1.0417	0.8224	1.3196	1.52
SL Sit-Down Restaurants	0.425***	(0.074)	1.5288	1.3220	1.7680	1.84
Disadvantage	0.009***	(0.001)	1.0089	1.0070	1.0109	1.26
Residential Mobility	0.006***	(0.002)	1.0059	1.0026	1.0091	1.26
Racial Heterogeneity	0.699***	(0.119)	2.0123	1.5944	2.5399	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0010	1.0009	1.0011	1.03
Street Type	0.716***	(0.043)	2.0461	1.8819	2.2246	1.10
Constant	-2.123***	(0.078)	0.1197	0.1028	0.1394	--
AIC	24995.193				Mean VIF	1.40
BIC	25287.200					

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

Table 53. Theft Model 3: Continuous Theft Risk Using At-Facility Theft Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.379***	(0.079)	1.4607	1.2511	1.7054	2.02
Consumer Electronics Stores	-0.320**	(0.103)	0.7264	0.5936	0.8888	9.46
Convenience Stores	0.188***	(0.040)	1.2071	1.1166	1.3049	1.58
Discount and Dollar Stores	0.191***	(0.051)	1.2108	1.0963	1.3372	1.22
Drug Treatment Centers	0.241**	(0.087)	1.2722	1.0717	1.5100	1.23
Entertainment Venues	0.334***	(0.082)	1.3969	1.1906	1.6391	1.39
Fast Food Restaurants	0.205***	(0.061)	1.2276	1.0889	1.3841	6.75
Gas Stations	0.159***	(0.032)	1.1719	1.1010	1.2473	1.23
Grocery Stores	0.116***	(0.015)	1.1228	1.0895	1.1572	3.32
Home Décor and Furniture Stores	-0.209***	(0.046)	0.8114	0.7419	0.8873	9.67
Hotels	0.210*	(0.096)	1.2333	1.0212	1.4894	1.57
Pharmacies	0.050	(0.029)	1.0517	0.9936	1.1133	4.71
Recreation Centers	0.108	(0.120)	1.1140	0.8801	1.4101	1.20
Recreation Retail Stores	-0.035	(0.038)	0.9654	0.8953	1.0409	6.38
Salons and Barber Shops	0.164	(0.101)	1.1788	0.9673	1.4364	8.63
Sit-Down Restaurants	0.083*	(0.041)	1.0861	1.0019	1.1774	13.38
SL Bars	0.089**	(0.031)	1.0927	1.0281	1.1612	2.15
SL Consumer Electronics Stores	-0.065	(0.033)	0.9373	0.8783	1.0001	8.84
SL Convenience Stores	0.013	(0.018)	1.0131	0.9772	1.0504	1.75
SL Discount and Dollar Stores	0.038***	(0.011)	1.0383	1.0164	1.0607	1.25
SL Drug Treatment Centers	-0.012	(0.037)	0.9878	0.9187	1.0621	1.24
SL Entertainment Venues	0.066*	(0.030)	1.0679	1.0068	1.1327	1.45
SL Fast Food Restaurants	0.089***	(0.021)	1.0928	1.0484	1.1392	5.32
SL Gas Stations	0.008	(0.010)	1.0085	0.9885	1.0288	1.28
SL Grocery Stores	0.001	(0.007)	1.0012	0.9874	1.0151	3.84
SL Home Décor and Furniture Stores	-0.002	(0.013)	0.9980	0.9734	1.0233	9.56
SL Hotels	0.050	(0.033)	1.0516	0.9850	1.1228	1.86
SL Pharmacies	0.038***	(0.009)	1.0392	1.0216	1.0571	6.59
SL Recreation Centers	0.117*	(0.054)	1.1246	1.0119	1.2500	1.21
SL Recreation Retail Stores	0.011	(0.014)	1.0106	0.9832	1.0387	5.91
SL Salons and Barber Shops	-0.014	(0.050)	0.9860	0.8942	1.0872	9.35
SL Sit-Down Restaurants	-0.026*	(0.013)	0.9746	0.9504	0.9994	11.15
Disadvantage	0.008***	(0.001)	1.0083	1.0064	1.0103	1.25
Residential Mobility	0.006***	(0.002)	1.0060	1.0028	1.0092	1.26
Racial Heterogeneity	0.755***	(0.118)	2.1273	1.6880	2.6811	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0010	1.0009	1.0011	1.03
Street Type	0.661***	(0.043)	1.9359	1.7806	2.1048	1.09
Constant	-2.118***	(0.077)	0.1202	0.1035	0.1397	--
AIC	24901.045				Mean VIF	4.03
BIC	25193.052					

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

Table 54. Theft Model 4: Binary Theft Risk Using Buffer-Area Theft Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.849**	(0.296)	2.3370	1.3075	4.1771	1.37
Consumer Electronics Stores	1.406**	(0.497)	4.0805	1.5404	10.8092	2.79
Convenience Stores	1.347***	(0.303)	3.8442	2.1230	6.9607	1.29
Discount and Dollar Stores	1.588*	(0.693)	4.8940	1.2578	19.0416	1.37
Drug Treatment Centers	1.822**	(0.614)	6.1866	1.8559	20.6232	1.30
Entertainment Venues	1.293**	(0.458)	3.6439	1.4841	8.9473	1.37
Fast Food Restaurants	-0.170	(0.216)	.84355	0.5523	1.2883	3.30
Gas Stations	1.096**	(0.395)	2.9925	1.3796	6.4908	1.25
Grocery Stores	3.418***	(0.708)	30.4994	7.6160	122.1393	1.62
Home Décor and Furniture Stores	-0.196	(0.408)	0.8224	0.3694	1.8306	1.90
Hotels	1.089	(0.718)	2.9713	0.7281	12.1262	1.49
Pharmacies	1.091	(0.705)	2.9767	0.7482	11.8422	2.07
Recreation Centers	0.553	(0.614)	1.7378	0.5218	5.7868	1.31
Recreation Retail Stores	0.457	(0.441)	1.5796	0.6662	3.7456	2.55
Salons and Barber Shops	0.037	(0.367)	1.0382	0.5053	2.1332	4.26
Sit-Down Restaurants	0.202	(0.240)	1.2233	0.7636	1.9598	2.44
SL Bars	0.465***	(0.115)	1.5925	1.2703	1.9963	1.48
SL Consumer Electronics Stores	-0.406*	(0.165)	0.6662	0.4822	0.9205	3.16
SL Convenience Stores	0.597***	(0.132)	1.8166	1.4021	2.3538	1.34
SL Discount and Dollar Stores	0.400	(0.261)	1.4920	0.8945	2.4887	1.47
SL Drug Treatment Centers	-0.158	(0.262)	0.8540	0.5106	1.4284	1.33
SL Entertainment Venues	0.856***	(0.192)	2.3530	1.6149	3.4284	1.68
SL Fast Food Restaurants	0.060	(0.081)	1.0613	0.9051	1.2445	3.22
SL Gas Stations	0.246	(0.178)	1.2787	0.9017	1.8134	1.37
SL Grocery Stores	0.473	(0.380)	1.6053	0.7619	3.3824	1.57
SL Home Décor and Furniture Stores	0.186	(0.163)	1.2050	0.8746	1.6600	2.18
SL Hotels	0.489	(0.255)	1.6308	0.9887	2.6902	1.68
SL Pharmacies	0.982**	(0.357)	2.6696	1.3254	5.3769	1.96
SL Recreation Centers	0.527	(0.270)	1.6936	0.9970	2.8768	1.28
SL Recreation Retail Stores	-0.343	(0.211)	0.7094	0.4695	1.0717	2.74
SL Salons and Barber Shops	0.106	(0.139)	1.1118	0.8473	1.4589	4.73
SL Sit-Down Restaurants	-0.128	(0.088)	0.8802	0.7412	1.0449	2.80
Disadvantage	0.008***	(0.001)	1.0083	1.0063	1.0103	1.24
Residential Mobility	0.006***	(0.002)	1.0061	1.0029	1.0093	1.25
Racial Heterogeneity	0.722***	(0.120)	2.0587	1.6266	2.6055	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0011	1.0010	1.0012	1.03
Street Type	0.825***	(0.042)	2.2826	2.1027	2.4779	1.06
Constant	-2.139***	(0.078)	0.1177	0.1010	0.1373	--
AIC	25074.460				Mean VIF	1.90
BIC	25366.467					

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

Table 55. Theft Model 5: Continuous Theft Risk Using Buffer-Area Theft Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.058***	(0.011)	1.0594	1.0362	1.0832	1.48
Consumer Electronics Stores	0.006	(0.011)	1.0057	0.9834	1.0286	6.54
Convenience Stores	0.096***	(0.016)	1.1009	1.0669	1.1359	1.32
Discount and Dollar Stores	0.080***	(0.017)	1.0834	1.0470	1.1211	2.04
Drug Treatment Centers	0.095**	(0.032)	1.0997	1.0335	1.1702	1.42
Entertainment Venues	0.086***	(0.020)	1.0899	1.0486	1.1329	2.84
Fast Food Restaurants	0.012	(0.007)	1.0122	0.9992	1.0254	4.87
Gas Stations	0.087***	(0.017)	1.0911	1.0558	1.1275	1.38
Grocery Stores	0.060***	(0.013)	1.0616	1.0356	1.0882	1.55
Home Décor and Furniture Stores	-0.005	(0.012)	0.9953	0.9718	1.0194	3.12
Hotels	0.027*	(0.014)	1.0275	1.0001	1.0557	2.30
Pharmacies	0.027	(0.014)	1.0270	0.9984	1.0564	2.87
Recreation Centers	0.064	(0.049)	1.0658	0.9681	1.1733	1.35
Recreation Retail Stores	0.024	(0.015)	1.0243	0.9937	1.0558	1.99
Salons and Barber Shops	-0.010	(0.012)	0.9899	0.9660	1.0143	8.82
Sit-Down Restaurants	-0.001	(0.007)	0.9989	0.9857	1.0123	6.09
SL Bars	0.018***	(0.004)	1.0185	1.0102	1.0268	1.55
SL Consumer Electronics Stores	-0.011*	(0.004)	0.9892	0.9807	0.9977	8.15
SL Convenience Stores	0.033***	(0.006)	1.0335	1.0205	1.0467	1.38
SL Discount and Dollar Stores	0.021***	(0.006)	1.0215	1.0090	1.0341	2.25
SL Drug Treatment Centers	0.005	(0.012)	1.0051	0.9826	1.0281	1.44
SL Entertainment Venues	0.015	(0.008)	1.0154	0.9991	1.0320	4.12
SL Fast Food Restaurants	0.000	(0.002)	1.0000	0.9953	1.0047	6.14
SL Gas Stations	-0.001	(0.007)	0.9985	0.9858	1.0114	1.64
SL Grocery Stores	0.002	(0.002)	1.0018	0.9972	1.0064	1.57
SL Home Décor and Furniture Stores	0.002	(0.005)	1.0016	0.9928	1.0105	4.23
SL Hotels	0.004	(0.005)	1.0043	0.9949	1.0138	2.87
SL Pharmacies	0.010	(0.006)	1.0097	0.9989	1.0207	2.84
SL Recreation Centers	0.047*	(0.021)	1.0480	1.0049	1.0930	1.30
SL Recreation Retail Stores	0.002	(0.005)	1.0024	0.9919	1.0131	2.25
SL Salons and Barber Shops	-0.004	(0.005)	0.9964	0.9874	1.0056	9.78
SL Sit-Down Restaurants	0.001	(0.002)	1.0007	0.9959	1.0056	6.84
Disadvantage	0.009***	(0.001)	1.0087	1.0068	1.0107	1.25
Residential Mobility	0.006***	(0.002)	1.0059	1.0028	1.0091	1.25
Racial Heterogeneity	0.709***	(0.117)	2.0311	1.6149	2.5544	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0011	1.0010	1.0012	1.03
Street Type	0.639***	(0.043)	1.8955	1.7439	2.0603	1.09
Constant	-2.172***	(0.076)	0.1140	0.0981	0.1323	--
AIC	24768.163				Mean VIF	3.03
BIC	25060.170					

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

Table 56. Theft Model 6: Binary Theft Risk Using At-Facility Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	1.289***	(0.292)	3.6299	2.0479	6.4337	1.28
Consumer Electronics Stores	0.709*	(0.336)	2.0323	1.0515	3.9278	1.41
Convenience Stores	1.533***	(0.316)	4.6316	2.4940	8.6012	1.33
Discount and Dollar Stores	1.672*	(0.689)	5.3231	1.3803	20.5279	1.27
Drug Treatment Centers	1.458*	(0.583)	4.2961	1.3702	13.4694	1.22
Entertainment Venues	1.596***	(0.432)	4.9330	2.1136	11.5132	1.30
Fast Food Restaurants	0.341	(0.207)	1.4068	0.9378	2.1103	1.46
Gas Stations	1.874***	(0.395)	6.5155	3.0057	14.1239	1.24
Grocery Stores	2.265**	(0.691)	9.6352	2.4861	37.3430	1.36
Home Décor and Furniture Stores	1.079*	(0.489)	2.9431	1.1295	7.6689	1.76
Hotels	1.515*	(0.762)	4.5515	1.0231	20.2486	1.47
Pharmacies	1.100	(0.654)	3.0031	0.8337	10.8181	1.40
Recreation Centers	0.378	(0.635)	1.4600	0.4202	5.0726	1.22
Recreation Retail Stores	0.924*	(0.412)	2.5184	1.1222	5.6518	1.33
Salons and Barber Shops	0.586*	(0.297)	1.7960	1.0042	3.2121	1.48
Sit-Down Restaurants	0.453	(0.246)	1.5731	0.9713	2.5479	1.43
SL Bars	0.244*	(0.123)	1.2767	1.0042	1.6233	1.33
SL Consumer Electronics Stores	-0.064	(0.135)	0.9383	0.7207	1.2217	1.51
SL Convenience Stores	0.248	(0.143)	1.2815	0.9686	1.6954	1.35
SL Discount and Dollar Stores	0.535	(0.306)	1.7079	0.9379	3.1099	1.28
SL Drug Treatment Centers	-0.208	(0.285)	0.8125	0.4647	1.4206	1.23
SL Entertainment Venues	0.184	(0.204)	1.2018	0.8049	1.7942	1.41
SL Fast Food Restaurants	0.119	(0.086)	1.1265	0.9512	1.3341	1.71
SL Gas Stations	0.123	(0.174)	1.1303	0.8044	1.5884	1.28
SL Grocery Stores	0.322	(0.325)	1.3793	0.7289	2.6101	1.35
SL Home Décor and Furniture Stores	0.259	(0.206)	1.2950	0.8649	1.9390	1.89
SL Hotels	-0.027	(0.288)	0.9731	0.5534	1.7111	1.69
SL Pharmacies	0.872**	(0.322)	2.3906	1.2717	4.4941	1.38
SL Recreation Centers	0.375	(0.292)	1.4545	0.8201	2.5795	1.23
SL Recreation Retail Stores	0.291	(0.180)	1.3378	0.9405	1.9029	1.43
SL Salons and Barber Shops	0.282*	(0.121)	1.3252	1.0452	1.6800	1.66
SL Sit-Down Restaurants	0.251**	(0.096)	1.2857	1.0656	1.5512	1.68
Disadvantage	0.009***	(0.001)	1.0091	1.0071	1.0111	1.25
Residential Mobility	0.005**	(0.002)	1.0046	1.0013	1.0078	1.26
Racial Heterogeneity	0.819***	(0.122)	2.2682	1.7860	2.8807	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0011	1.0010	1.0012	1.03
Street Type	0.806***	(0.043)	2.2385	2.0583	2.4344	1.10
Constant	-2.169***	(0.079)	0.1143	0.0979	0.1335	--
AIC	25105.016				Mean VIF	1.37
BIC	25397.023					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 57. Theft Model 7: Continuous Theft Risk Using Count of At-Facility Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.043***	(0.008)	1.0439	1.0272	1.0609	1.89
Consumer Electronics Stores	-0.004	(0.009)	0.9961	0.9791	1.0133	2.59
Convenience Stores	0.028***	(0.005)	1.0280	1.0184	1.0377	1.55
Discount and Dollar Stores	0.039***	(0.009)	1.0403	1.0231	1.0577	1.35
Drug Treatment Centers	0.009*	(0.004)	1.0095	1.0017	1.0174	1.21
Entertainment Venues	0.028***	(0.006)	1.0280	1.0150	1.0411	3.67
Fast Food Restaurants	0.009*	(0.003)	1.0087	1.0020	1.0154	2.19
Gas Stations	0.017***	(0.003)	1.0168	1.0108	1.0228	1.23
Grocery Stores	0.022***	(0.003)	1.0219	1.0160	1.0278	1.69
Home Décor and Furniture Stores	0.019	(0.017)	1.0190	0.9865	1.0525	2.94
Hotels	0.013*	(0.006)	1.0128	1.0008	1.0250	1.70
Pharmacies	0.023**	(0.008)	1.0228	1.0063	1.0396	2.81
Recreation Centers	0.015	(0.010)	1.0151	0.9961	1.0346	1.21
Recreation Retail Stores	-0.001	(0.006)	0.9994	0.9880	1.0109	1.77
Salons and Barber Shops	0.010	(0.007)	1.0098	0.9953	1.0246	2.47
Sit-Down Restaurants	0.011*	(0.005)	1.0109	1.0015	1.0203	4.92
SL Bars	0.010**	(0.003)	1.0096	1.0037	1.0155	1.99
SL Consumer Electronics Stores	-0.002	(0.003)	0.9978	0.9925	1.0031	2.75
SL Convenience Stores	0.001	(0.002)	1.0010	0.9967	1.0054	1.72
SL Discount and Dollar Stores	0.007**	(0.002)	1.0072	1.0025	1.0119	1.39
SL Drug Treatment Centers	-0.000	(0.001)	0.9996	0.9967	1.0025	1.22
SL Entertainment Venues	0.002	(0.002)	1.0023	0.9982	1.0062	4.20
SL Fast Food Restaurants	0.003	(0.001)	1.0025	0.9999	1.0052	2.54
SL Gas Stations	0.002*	(0.001)	1.0021	1.0003	1.0040	1.26
SL Grocery Stores	0.001	(0.001)	1.0008	0.9984	1.0033	1.80
SL Home Décor and Furniture Stores	0.002	(0.003)	1.0024	0.9956	1.0092	3.54
SL Hotels	0.006*	(0.002)	1.0061	1.0014	1.0108	2.21
SL Pharmacies	0.006*	(0.003)	1.0063	1.0009	1.0118	3.53
SL Recreation Centers	0.008*	(0.004)	1.0082	1.0002	1.0163	1.21
SL Recreation Retail Stores	0.001	(0.002)	1.0007	0.9962	1.0052	1.82
SL Salons and Barber Shops	-0.002	(0.003)	0.9981	0.9918	1.0045	3.22
SL Sit-Down Restaurants	-0.002	(0.002)	0.9982	0.9947	1.0017	6.48
Disadvantage	0.009***	(0.001)	1.0088	1.0068	1.0107	1.25
Residential Mobility	0.006***	(0.002)	1.0059	1.0027	1.0091	1.26
Racial Heterogeneity	0.750***	(0.118)	2.1170	1.6797	2.6682	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0010	1.0009	1.0011	1.03
Street Type	0.621***	(0.043)	1.8604	1.7105	2.0234	1.10
Constant	-2.142***	(0.076)	0.1174	0.1011	0.1364	--
AIC	24860.441				Mean VIF	2.18
BIC	25152.448					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 58. Theft Model 8: Binary Theft Risk Using Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.638*	(0.304)	1.8918	1.0431	3.4313	1.39
Consumer Electronics Stores	0.213	(0.435)	1.2377	0.5273	2.9050	1.69
Convenience Stores	1.209***	(0.325)	3.3491	1.7724	6.3282	1.34
Discount and Dollar Stores	0.677	(0.605)	1.9672	0.6007	6.4424	1.48
Drug Treatment Centers	1.505*	(0.634)	4.5023	1.2983	15.6129	1.35
Entertainment Venues	1.754***	(0.482)	5.7773	2.2460	14.8606	1.51
Fast Food Restaurants	-0.103	(0.179)	0.9023	0.6349	1.2822	2.19
Gas Stations	1.020*	(0.420)	2.7725	1.2184	6.3092	1.27
Grocery Stores	3.849***	(0.718)	46.9486	11.5040	191.6004	1.44
Home Décor and Furniture Stores	0.837	(0.558)	2.3094	0.7737	6.8935	1.50
Hotels	1.116	(0.728)	3.0534	0.7323	12.7310	1.35
Pharmacies	1.980*	(0.809)	7.2456	1.4845	35.3632	1.49
Recreation Centers	1.213*	(0.609)	3.3639	1.0206	11.0878	1.20
Recreation Retail Stores	0.834	(0.452)	2.3024	0.9490	5.5859	1.48
Salons and Barber Shops	-0.175	(0.362)	0.8395	0.4129	1.7069	1.79
Sit-Down Restaurants	0.505*	(0.229)	1.6570	1.0577	2.5960	1.93
SL Bars	0.472***	(0.130)	1.6037	1.2440	2.0674	1.66
SL Consumer Electronics Stores	-0.019	(0.151)	0.9815	0.7304	1.3189	2.06
SL Convenience Stores	0.388**	(0.140)	1.4739	1.1204	1.9391	1.48
SL Discount and Dollar Stores	0.059	(0.324)	1.0609	0.5618	2.0035	1.70
SL Drug Treatment Centers	0.003	(0.275)	1.0027	0.5845	1.7201	1.36
SL Entertainment Venues	-0.305	(0.207)	0.7370	0.4915	1.1051	1.78
SL Fast Food Restaurants	-0.032	(0.066)	0.9681	0.8501	1.1024	3.05
SL Gas Stations	0.427*	(0.181)	1.5324	1.0740	2.1865	1.37
SL Grocery Stores	-0.125	(0.362)	0.8824	0.4337	1.7954	1.45
SL Home Décor and Furniture Stores	0.155	(0.186)	1.1674	0.8101	1.6824	1.66
SL Hotels	0.860**	(0.282)	2.3642	1.3602	4.1095	1.58
SL Pharmacies	0.884**	(0.313)	2.4214	1.3113	4.4714	1.59
SL Recreation Centers	0.487	(0.282)	1.6273	0.9368	2.8267	1.20
SL Recreation Retail Stores	0.052	(0.198)	1.0537	0.7150	1.5530	1.73
SL Salons and Barber Shops	0.135	(0.161)	1.1450	0.8351	1.5699	2.64
SL Sit-Down Restaurants	-0.056	(0.086)	0.9454	0.7980	1.1201	2.69
Disadvantage	0.008***	(0.001)	1.0076	1.0056	1.0096	1.25
Residential Mobility	0.008***	(0.002)	1.0080	1.0048	1.0113	1.25
Racial Heterogeneity	0.799***	(0.121)	2.2227	1.7530	2.8183	1.08
Population	0.000***	(0.000)	1.0002	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0012	1.0011	1.0013	1.03
Street Type	0.847***	(0.043)	2.3320	2.1454	2.5348	1.07
Constant	-2.186***	(0.080)	0.1124	0.0961	0.1314	--
AIC	25218.861				Mean VIF	1.58
BIC	25510.869					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 59. Theft Model 9: Continuous Theft Risk Using Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.003***	(0.001)	1.0027	1.0014	1.0040	1.39
Consumer Electronics Stores	0.000	(0.001)	1.0000	0.9987	1.0014	1.88
Convenience Stores	0.005***	(0.001)	1.0049	1.0034	1.0064	1.28
Discount and Dollar Stores	0.008***	(0.001)	1.0081	1.0052	1.0109	1.39
Drug Treatment Centers	0.005***	(0.001)	1.0049	1.0020	1.0078	1.34
Entertainment Venues	0.005***	(0.001)	1.0051	1.0028	1.0075	1.60
Fast Food Restaurants	0.001**	(0.000)	1.0010	1.0003	1.0018	2.04
Gas Stations	0.005***	(0.001)	1.0049	1.0031	1.0066	1.30
Grocery Stores	0.007***	(0.001)	1.0074	1.0049	1.0099	1.49
Home Décor and Furniture Stores	0.001	(0.001)	1.0013	0.9991	1.0034	1.54
Hotels	0.002*	(0.001)	1.0024	1.0004	1.0044	1.50
Pharmacies	0.004**	(0.001)	1.0036	1.0010	1.0063	1.34
Recreation Centers	0.004	(0.003)	1.0042	0.9987	1.0098	1.23
Recreation Retail Stores	0.003*	(0.001)	1.0025	1.0005	1.0046	1.49
Salons and Barber Shops	-0.001	(0.001)	0.9994	0.9978	1.0010	2.13
Sit-Down Restaurants	0.001	(0.000)	1.0006	0.9997	1.0014	2.04
SL Bars	0.001***	(0.000)	1.0008	1.0004	1.0013	1.59
SL Consumer Electronics Stores	0.000	(0.000)	1.0000	0.9995	1.0005	2.35
SL Convenience Stores	0.001**	(0.000)	1.0008	1.0002	1.0014	1.45
SL Discount and Dollar Stores	0.001	(0.001)	1.0007	0.9998	1.0017	1.56
SL Drug Treatment Centers	0.000	(0.001)	1.0001	0.9990	1.0012	1.38
SL Entertainment Venues	0.000	(0.000)	1.0000	0.9991	1.0009	2.02
SL Fast Food Restaurants	-0.000	(0.000)	0.9998	0.9995	1.0000	2.90
SL Gas Stations	0.000	(0.000)	1.0003	0.9996	1.0010	1.47
SL Grocery Stores	0.001	(0.001)	1.0005	0.9994	1.0016	1.53
SL Home Décor and Furniture Stores	0.000	(0.000)	1.0002	0.9994	1.0010	1.71
SL Hotels	0.001*	(0.000)	1.0010	1.0002	1.0018	1.89
SL Pharmacies	0.001*	(0.001)	1.0014	1.0002	1.0025	1.44
SL Recreation Centers	0.003**	(0.001)	1.0031	1.0008	1.0054	1.22
SL Recreation Retail Stores	0.000	(0.000)	1.0002	0.9993	1.0010	1.84
SL Salons and Barber Shops	0.000	(0.000)	1.0000	0.9993	1.0006	3.13
SL Sit-Down Restaurants	0.000	(0.000)	1.0000	0.9997	1.0004	3.00
Disadvantage	0.008***	(0.001)	1.0083	1.0064	1.0102	1.26
Residential Mobility	0.007***	(0.002)	1.0073	1.0041	1.0104	1.26
Racial Heterogeneity	0.735***	(0.117)	2.0863	1.6595	2.6229	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0011	1.0010	1.0012	1.03
Street Type	0.572***	(0.043)	1.7715	1.6289	1.9266	1.12
Constant	-2.199***	(0.076)	0.1109	0.0955	0.1288	--
AIC	24768.408				Mean VIF	1.64
BIC	25060.415					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

APPENDIX D – DISTANCE SENSITIVITY CHECK REGRESSION RESULTS

This appendix presents the full results of the distance sensitivity check regression models, which used 1000ft instead of 500ft for the intensity value analysis buffer area facility risk calculations.

Table 60. Sensitivity Check 1: Binary Robbery Risk Using 1000ft Buffer-Area Robbery Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.814	(0.480)	2.2560	0.8813	5.7754	1.33
Consumer Electronics Stores	0.254	(0.610)	1.2890	0.3899	4.2613	1.63
Convenience Stores	1.224**	(0.475)	3.3996	1.3411	8.6180	1.35
Discount and Dollar Stores	-0.058	(0.821)	0.9432	0.1886	4.7179	1.29
Drug Treatment Centers	-0.970	(1.001)	0.3791	0.0533	2.6975	1.34
Entertainment Venues	0.305	(0.854)	1.3565	0.2542	7.2378	1.30
Fast Food Restaurants	0.026	(0.307)	1.0262	0.5627	1.8713	1.72
Gas Stations	1.742**	(0.638)	5.7111	1.6366	19.9293	1.28
Grocery Stores	-0.750	(1.167)	0.4724	0.0480	4.6516	1.33
Home Décor and Furniture Stores	0.713	(0.661)	2.0408	0.5584	7.4595	1.44
Hotels	1.717	(0.973)	5.5664	0.8266	37.4828	1.22
Pharmacies	-0.039	(1.321)	0.9621	0.0723	12.8097	1.43
Recreation Centers	0.095	(1.061)	1.1001	0.1376	8.7968	1.22
Recreation Retails Stores	-0.116	(0.892)	0.8902	0.1550	5.1134	1.77
Salons and Barber Shops	1.011	(0.538)	2.7475	0.9573	7.8853	1.50
Sit-Down Restaurants	0.183	(0.365)	1.2003	0.5874	2.4527	1.64
SL Bars	0.431*	(0.216)	1.5389	1.0086	2.3480	1.46
SL Consumer Electronics Stores	0.657**	(0.228)	1.9299	1.2337	3.0190	1.79
SL Convenience Stores	0.739**	(0.228)	2.0939	1.3394	3.2735	1.61
SL Discount and Dollar Stores	0.548	(0.440)	1.7296	0.7295	4.1007	1.48
SL Drug Treatment Centers	0.788*	(0.377)	2.1990	1.0513	4.5995	1.34
SL Entertainment Venues	0.038	(0.342)	1.0391	0.5317	2.0309	1.42
SL Fast Food Restaurants	-0.118	(0.144)	0.8890	0.6704	1.1788	2.41
SL Gas Stations	0.067	(0.353)	1.0690	0.5349	2.1364	1.36
SL Grocery Stores	0.528	(0.601)	1.6947	0.5214	5.5086	1.49
SL Home Décor and Furniture Stores	-0.742	(0.453)	0.4760	0.1958	1.1573	1.76
SL Hotels	0.500	(0.524)	1.6483	0.5905	4.6013	1.39
SL Pharmacies	-1.186	(0.719)	0.3056	0.0746	1.2511	1.47
SL Recreation Centers	0.843*	(0.425)	2.3226	1.0107	5.3376	1.23
SL Recreation Retails Stores	0.430	(0.335)	1.5365	0.7969	2.9624	2.11
SL Salons and Barber Shops	-0.106	(0.292)	0.8996	0.5075	1.5946	1.85
SL Sit-Down Restaurants	0.210	(0.131)	1.2336	0.9536	1.5959	2.18
Disadvantage	0.031***	(0.002)	1.0317	1.0273	1.0361	1.25
Residential Mobility	-0.004	(0.003)	0.9956	0.9890	1.0023	1.24
Racial Heterogeneity	0.649*	(0.271)	1.9143	1.1249	3.2578	1.09
Population	0.000***	(0.000)	1.0003	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0006	1.0004	1.0007	1.03
Street Type	0.707***	(0.088)	2.0275	1.7049	2.4111	1.06
Constant	-4.773***	(0.177)	0.0085	0.0060	0.0120	--
AIC	5669.046				Mean VIF	1.47
BIC	5961.053					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 61. Sensitivity Check 2: Continuous Robbery Risk Using 1000ft Buffer-Area Robbery Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.112	(0.064)	1.1181	0.9870	1.2665	1.44
Consumer Electronics Stores	0.017	(0.095)	1.0172	0.8449	1.2247	1.63
Convenience Stores	0.220*	(0.087)	1.2457	1.0512	1.4761	1.41
Discount and Dollar Stores	-0.029	(0.115)	0.9712	0.7752	1.2168	1.44
Drug Treatment Centers	-0.113	(0.199)	0.8932	0.6042	1.3206	1.25
Entertainment Venues	-0.049	(0.175)	0.9518	0.6757	1.3408	1.34
Fast Food Restaurants	0.040	(0.054)	1.0405	0.9358	1.1570	1.82
Gas Stations	0.323*	(0.145)	1.3807	1.0393	1.8341	1.35
Grocery Stores	0.158	(0.239)	1.1707	0.7335	1.8685	1.45
Home Décor and Furniture Stores	0.051	(0.101)	1.0523	0.8629	1.2832	1.82
Hotels	0.223	(0.148)	1.2492	0.9341	1.6707	1.24
Pharmacies	-0.025	(0.283)	0.9758	0.5609	1.6976	1.33
Recreation Centers	0.176	(0.238)	1.1929	0.7478	1.9030	1.21
Recreation Retails Stores	-0.054	(0.186)	0.9476	0.6578	1.3651	1.87
Salons and Barber Shops	0.048	(0.128)	1.0492	0.8164	1.3484	1.73
Sit-Down Restaurants	0.049	(0.053)	1.0497	0.9466	1.1641	1.66
SL Bars	0.025	(0.029)	1.0255	0.9690	1.0854	1.57
SL Consumer Electronics Stores	0.147***	(0.039)	1.1583	1.0736	1.2497	2.03
SL Convenience Stores	0.130***	(0.039)	1.1393	1.0560	1.2292	1.69
SL Discount and Dollar Stores	0.052	(0.061)	1.0529	0.9343	1.1865	1.67
SL Drug Treatment Centers	0.164*	(0.073)	1.1788	1.0212	1.3607	1.26
SL Entertainment Venues	0.051	(0.066)	1.0523	0.9242	1.1981	1.49
SL Fast Food Restaurants	-0.015	(0.021)	0.9854	0.9450	1.0275	2.42
SL Gas Stations	-0.024	(0.066)	0.9762	0.8585	1.1100	1.53
SL Grocery Stores	0.020	(0.107)	1.0205	0.8273	1.2587	1.62
SL Home Décor and Furniture Stores	-0.105	(0.062)	0.9000	0.7968	1.0166	2.06
SL Hotels	0.103	(0.083)	1.1082	0.9420	1.3037	1.46
SL Pharmacies	-0.063	(0.112)	0.9389	0.7541	1.1689	1.43
SL Recreation Centers	0.183	(0.101)	1.2014	0.9864	1.4632	1.22
SL Recreation Retails Stores	0.106	(0.077)	1.1118	0.9568	1.2919	2.14
SL Salons and Barber Shops	0.015	(0.063)	1.0153	0.8974	1.1488	2.28
SL Sit-Down Restaurants	0.028	(0.021)	1.0286	0.9872	1.0717	2.17
Disadvantage	0.031***	(0.002)	1.0314	1.0270	1.0358	1.25
Residential Mobility	-0.004	(0.003)	0.9957	0.9891	1.0023	1.25
Racial Heterogeneity	0.635*	(0.270)	1.8874	1.1111	3.2061	1.08
Population	0.000***	(0.000)	1.0003	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0005	1.0004	1.0007	1.03
Street Type	0.622***	(0.090)	1.8618	1.5607	2.2210	1.09
Constant	-4.781***	(0.177)	0.0084	0.0059	0.0119	--
AIC	5640.701				Mean VIF	1.55
BIC	5932.709					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 62. Sensitivity Check 3: Binary Robbery Risk Using 1000ft Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.631	(0.505)	1.8787	0.6979	5.0574	1.30
Consumer Electronics Stores	-0.057	(0.576)	0.9444	0.3052	2.9222	1.38
Convenience Stores	1.098*	(0.491)	2.9993	1.1460	7.8498	1.36
Discount and Dollar Stores	-0.118	(0.821)	0.8888	0.1778	4.4436	1.34
Drug Treatment Centers	-1.082	(1.161)	0.3388	0.0348	3.2959	1.31
Entertainment Venues	-0.595	(1.144)	0.5516	0.0585	5.1967	1.42
Fast Food Restaurants	-0.233	(0.400)	0.7919	0.3616	1.7345	2.17
Gas Stations	1.501*	(0.624)	4.4839	1.3195	15.2369	1.26
Grocery Stores	0.997	(1.071)	2.7094	0.3320	22.1139	1.32
Home Décor and Furniture Stores	0.590	(0.568)	1.8036	0.5923	5.4918	1.36
Hotels	1.560	(0.933)	4.7590	0.7642	29.6352	1.35
Pharmacies	-0.450	(1.363)	0.6378	0.0441	9.2150	1.26
Recreation Centers	0.508	(0.909)	1.6618	0.2797	9.8751	1.20
Recreation Retails Stores	-1.064	(0.946)	0.3452	0.0541	2.2042	1.33
Salons and Barber Shops	0.413	(0.614)	1.5106	0.4530	5.0374	1.57
Sit-Down Restaurants	0.337	(0.358)	1.4006	0.6937	2.8278	1.59
SL Bars	0.401	(0.225)	1.4937	0.9611	2.3214	1.46
SL Consumer Electronics Stores	0.683**	(0.227)	1.9805	1.2684	3.0921	1.60
SL Convenience Stores	0.771***	(0.222)	2.1612	1.4000	3.3364	1.53
SL Discount and Dollar Stores	0.806	(0.465)	2.2382	0.8991	5.5713	1.50
SL Drug Treatment Centers	0.872*	(0.427)	2.3920	1.0356	5.5250	1.33
SL Entertainment Venues	-0.008	(0.400)	0.9925	0.4532	2.1735	1.71
SL Fast Food Restaurants	-0.206	(0.119)	0.8140	0.6444	1.0282	2.93
SL Gas Stations	0.224	(0.324)	1.2511	0.6627	2.3622	1.35
SL Grocery Stores	0.226	(0.564)	1.2536	0.4148	3.7882	1.45
SL Home Décor and Furniture Stores	-0.197	(0.303)	0.8214	0.4536	1.4874	1.52
SL Hotels	0.885	(0.529)	2.4241	0.8595	6.8371	1.76
SL Pharmacies	0.345	(0.515)	1.4125	0.5145	3.8779	1.30
SL Recreation Centers	1.228**	(0.409)	3.4142	1.5313	7.6121	1.21
SL Recreation Retails Stores	0.233	(0.419)	1.2618	0.5553	2.8669	1.68
SL Salons and Barber Shops	-0.054	(0.310)	0.9471	0.5155	1.7401	2.18
SL Sit-Down Restaurants	0.135	(0.130)	1.1448	0.8871	1.4773	2.35
Disadvantage	0.030***	(0.002)	1.0309	1.0265	1.0353	1.25
Residential Mobility	-0.006	(0.003)	0.9941	0.9874	1.0009	1.25
Racial Heterogeneity	0.805**	(0.273)	2.2360	1.3106	3.8148	1.08
Population	0.000***	(0.000)	1.0003	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0006	1.0004	1.0007	1.03
Street Type	0.736***	(0.089)	2.0881	1.7535	2.4866	1.07
Constant	-4.759***	(0.179)	0.0086	0.0060	0.0122	--
AIC	5700.378				Mean VIF	1.48
BIC	5992.385					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 63. Sensitivity Check 4: Continuous Robbery Risk Using 1000ft Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.001	(0.000)	1.0006	0.9998	1.0014	1.35
Consumer Electronics Stores	0.000	(0.000)	1.0001	0.9992	1.0010	1.64
Convenience Stores	0.001***	(0.000)	1.0015	1.0007	1.0023	1.27
Discount and Dollar Stores	0.000	(0.001)	1.0000	0.9985	1.0015	1.27
Drug Treatment Centers	-0.000	(0.001)	0.9998	0.9977	1.0020	1.33
Entertainment Venues	0.000	(0.001)	1.0000	0.9984	1.0016	1.52
Fast Food Restaurants	0.000	(0.000)	1.0002	0.9998	1.0007	2.07
Gas Stations	0.002*	(0.001)	1.0019	1.0003	1.0034	1.30
Grocery Stores	0.002	(0.001)	1.0015	0.9996	1.0035	1.38
Home Décor and Furniture Stores	0.001	(0.001)	1.0006	0.9993	1.0018	1.46
Hotels	0.001*	(0.001)	1.0012	1.0002	1.0022	1.40
Pharmacies	0.000	(0.001)	1.0004	0.9980	1.0028	1.29
Recreation Centers	0.001	(0.001)	1.0014	0.9988	1.0040	1.19
Recreation Retails Stores	-0.000	(0.001)	0.9996	0.9981	1.0011	1.44
Salons and Barber Shops	-0.000	(0.001)	0.9996	0.9985	1.0007	1.79
Sit-Down Restaurants	0.000	(0.000)	1.0003	0.9999	1.0008	1.86
SL Bars	0.000	(0.000)	1.0003	1.0000	1.0007	1.55
SL Consumer Electronics Stores	0.001***	(0.000)	1.0008	1.0004	1.0012	1.97
SL Convenience Stores	0.001***	(0.000)	1.0011	1.0007	1.0015	1.50
SL Discount and Dollar Stores	0.001**	(0.000)	1.0011	1.0003	1.0019	1.39
SL Drug Treatment Centers	0.001**	(0.000)	1.0011	1.0003	1.0019	1.38
SL Entertainment Venues	-0.000	(0.000)	0.9999	0.9992	1.0006	1.90
SL Fast Food Restaurants	-0.000**	(0.000)	0.9998	0.9996	0.9999	3.09
SL Gas Stations	-0.000	(0.000)	0.9999	0.9993	1.0006	1.46
SL Grocery Stores	-0.000	(0.001)	0.9998	0.9987	1.0009	1.47
SL Home Décor and Furniture Stores	-0.000	(0.000)	0.9996	0.9990	1.0003	1.64
SL Hotels	0.000	(0.000)	1.0002	0.9996	1.0008	1.77
SL Pharmacies	-0.000	(0.001)	0.9998	0.9987	1.0009	1.36
SL Recreation Centers	0.002**	(0.001)	1.0017	1.0006	1.0029	1.20
SL Recreation Retails Stores	0.000	(0.000)	1.0001	0.9994	1.0009	1.79
SL Salons and Barber Shops	-0.000	(0.000)	0.9999	0.9993	1.0004	2.58
SL Sit-Down Restaurants	0.000	(0.000)	1.0001	0.9999	1.0003	2.72
Disadvantage	0.030***	(0.002)	1.0308	1.0264	1.0352	1.26
Residential Mobility	-0.005	(0.003)	0.9946	0.9880	1.0012	1.26
Racial Heterogeneity	0.738**	(0.269)	2.0915	1.2343	3.5440	1.08
Population	0.000***	(0.000)	1.0003	1.0001	1.0004	1.03
Street Length	0.001***	(0.000)	1.0005	1.0004	1.0007	1.023
Street Type	0.555***	(0.091)	1.7418	1.4574	2.0816	1.12
Constant	-4.797***	(0.177)	0.0083	0.0058	0.0117	--
AIC	5615.755				Mean VIF	1.56
BIC	5907.762					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 64. Sensitivity Check 5: Binary Theft Risk Using 1000ft Buffer-Area Theft Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.888**	(0.311)	2.4308	1.3224	4.4682	1.41
Consumer Electronics Stores	0.323	(0.430)	1.3811	0.5950	3.2059	2.36
Convenience Stores	1.115***	(0.308)	3.0493	1.6675	5.5763	1.26
Discount and Dollar Stores	1.719*	(0.761)	5.5774	1.2562	24.7620	1.32
Drug Treatment Centers	1.519*	(0.646)	4.5671	1.2881	16.1941	1.30
Entertainment Venues	1.532**	(0.466)	4.6296	1.8565	11.5448	1.42
Fast Food Restaurants	0.182	(0.238)	1.1995	0.7522	1.9128	2.85
Gas Stations	1.299**	(0.415)	3.6673	1.6250	8.2765	1.30
Grocery Stores	2.967***	(0.759)	19.4244	4.3898	85.9515	1.60
Home Décor and Furniture Stores	0.171	(0.418)	1.1862	0.5232	2.6895	1.52
Hotels	1.401*	(0.549)	4.0593	1.3828	11.9162	1.44
Pharmacies	0.409	(0.580)	1.5050	0.4832	4.6874	1.61
Recreation Centers	1.034	(0.644)	2.8121	0.7953	9.9431	1.29
Recreation Retails Stores	0.348	(0.413)	1.4166	0.6307	3.1818	1.76
Salons and Barber Shops	0.834**	(0.308)	2.3028	1.2598	4.2096	2.26
Sit-Down Restaurants	0.266	(0.241)	1.3050	0.8140	2.0922	1.94
SL Bars	0.468***	(0.114)	1.5969	1.2761	1.9982	1.57
SL Consumer Electronics Stores	-0.082	(0.165)	0.9215	0.6674	1.2724	2.81
SL Convenience Stores	0.692***	(0.133)	1.9973	1.5393	2.5916	1.42
SL Discount and Dollar Stores	0.529	(0.318)	1.6980	0.9109	3.1653	1.50
SL Drug Treatment Centers	-0.141	(0.274)	0.8688	0.5078	1.4865	1.36
SL Entertainment Venues	0.498*	(0.202)	1.6461	1.1087	2.4440	1.75
SL Fast Food Restaurants	-0.223*	(0.087)	0.8000	0.6744	0.9489	3.72
SL Gas Stations	0.276	(0.190)	1.3182	0.9080	1.9137	1.44
SL Grocery Stores	0.699	(0.387)	2.0125	0.9427	4.2962	1.67
SL Home Décor and Furniture Stores	-0.230	(0.200)	0.7946	0.5366	1.1766	1.90
SL Hotels	0.134	(0.229)	1.1430	0.7303	1.7891	1.70
SL Pharmacies	0.310	(0.311)	1.3639	0.7407	2.5114	1.66
SL Recreation Centers	-0.060	(0.297)	0.9420	0.5261	1.6865	1.29
SL Recreation Retails Stores	0.103	(0.196)	1.1090	0.7560	1.6270	2.04
SL Salons and Barber Shops	0.181	(0.147)	1.1989	0.8996	1.5976	2.68
SL Sit-Down Restaurants	0.101	(0.090)	1.1064	0.9270	1.3205	2.46
Disadvantage	0.009***	(0.001)	1.0088	1.0068	1.0108	1.25
Residential Mobility	0.007***	(0.002)	1.0066	1.0034	1.0099	1.25
Racial Heterogeneity	0.633***	(0.121)	1.8827	1.4866	2.3843	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0012	1.0011	1.0013	1.03
Street Type	0.858***	(0.042)	2.3586	2.1720	2.5613	1.06
Constant	-2.167***	(0.079)	0.1146	0.0982	0.1337	--
AIC	25127.729				Mean VIF	1.69
BIC	25419.736					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 65. Sensitivity Check 6: Continuous Theft Risk Using 1000ft Buffer-Area Theft Incidents

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.023***	(0.005)	1.0229	1.0136	1.0322	1.37
Consumer Electronics Stores	0.007	(0.005)	1.0073	0.9973	1.0175	3.93
Convenience Stores	0.048***	(0.007)	1.0491	1.0343	1.0642	1.29
Discount and Dollar Stores	0.053***	(0.010)	1.0546	1.0331	1.0765	1.57
Drug Treatment Centers	0.055***	(0.016)	1.0564	1.0230	1.0910	1.38
Entertainment Venues	0.032***	(0.008)	1.0320	1.0158	1.0485	1.99
Fast Food Restaurants	0.006*	(0.003)	1.0055	1.0006	1.0105	3.25
Gas Stations	0.057***	(0.010)	1.0582	1.0370	1.0799	1.32
Grocery Stores	0.037***	(0.008)	1.0375	1.0222	1.0530	1.59
Home Décor and Furniture Stores	-0.001	(0.007)	0.9985	0.9859	1.0113	2.12
Hotels	0.012**	(0.004)	1.0122	1.0037	1.0207	1.60
Pharmacies	0.011	(0.008)	1.0111	0.9960	1.0264	1.85
Recreation Centers	0.028	(0.018)	1.0286	0.9920	1.0665	1.23
Recreation Retails Stores	0.009	(0.008)	1.0087	0.9928	1.0248	1.77
Salons and Barber Shops	-0.003	(0.006)	0.9967	0.9857	1.0078	4.62
Sit-Down Restaurants	0.003	(0.003)	1.0034	0.9978	1.0090	3.07
SL Bars	0.008***	(0.002)	1.0076	1.0045	1.0108	1.50
SL Consumer Electronics Stores	-0.002	(0.002)	0.9978	0.9938	1.0019	5.05
SL Convenience Stores	0.011***	(0.003)	1.0114	1.0062	1.0166	1.53
SL Discount and Dollar Stores	0.010*	(0.004)	1.0105	1.0020	1.0190	1.86
SL Drug Treatment Centers	0.001	(0.006)	1.0006	0.9884	1.0130	1.42
SL Entertainment Venues	0.007*	(0.003)	1.0065	1.0004	1.0127	2.61
SL Fast Food Restaurants	-0.003**	(0.001)	0.9974	0.9957	0.9991	4.49
SL Gas Stations	0.001	(0.004)	1.0014	0.9934	1.0096	1.56
SL Grocery Stores	0.002	(0.002)	1.0019	0.9981	1.0058	1.63
SL Home Décor and Furniture Stores	0.001	(0.002)	1.0010	0.9964	1.0057	2.86
SL Hotels	0.002	(0.002)	1.0019	0.9981	1.0056	2.20
SL Pharmacies	0.004	(0.003)	1.0044	0.9987	1.0102	1.81
SL Recreation Centers	0.017*	(0.008)	1.0172	1.0015	1.0331	1.22
SL Recreation Retails Stores	0.004	(0.003)	1.0041	0.9982	1.0100	1.99
SL Salons and Barber Shops	-0.001	(0.002)	0.9990	0.9949	1.0031	5.73
SL Sit-Down Restaurants	0.001	(0.001)	1.0006	0.9986	1.0027	3.89
Disadvantage	0.009***	(0.001)	1.0088	1.0069	1.0108	1.25
Residential Mobility	0.006***	(0.002)	1.0061	1.0030	1.0093	1.25
Racial Heterogeneity	0.656***	(0.117)	1.9263	1.5316	2.4228	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0011	1.0010	1.0012	1.03
Street Type	0.642***	(0.043)	1.9006	1.7484	2.0661	1.10
Constant	-2.171***	(0.076)	0.1140	0.0982	0.1325	--
AIC	24787.350				Mean VIF	2.16
BIC	25079.357					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 66. Sensitivity Check 7: Binary Theft Risk Using 1000ft Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.896**	(0.305)	2.4500	1.3479	4.4533	1.30
Consumer Electronics Stores	0.207	(0.370)	1.2304	0.5957	2.5411	1.38
Convenience Stores	1.040**	(0.345)	2.8289	1.4380	5.5650	1.36
Discount and Dollar Stores	0.590	(0.684)	1.8036	0.4719	6.8937	1.34
Drug Treatment Centers	1.531*	(0.689)	4.6230	1.1970	17.8552	1.31
Entertainment Venues	1.551***	(0.470)	4.7166	1.8766	11.8548	1.42
Fast Food Restaurants	-0.002	(0.170)	0.9977	0.7150	1.3921	2.17
Gas Stations	1.125**	(0.432)	3.0797	1.3215	7.1773	1.26
Grocery Stores	3.892***	(0.728)	49.0017	11.7542	204.2823	1.32
Home Décor and Furniture Stores	0.408	(0.355)	1.5044	0.7508	3.0145	1.36
Hotels	1.054	(0.635)	2.8700	0.8261	9.9703	1.35
Pharmacies	0.417	(0.568)	1.5177	0.4989	4.6165	1.26
Recreation Centers	0.606	(0.648)	1.8325	0.5144	6.5273	1.20
Recreation Retails Stores	0.741	(0.443)	2.0989	0.8815	4.9976	1.33
Salons and Barber Shops	0.113	(0.342)	1.1195	0.5730	2.1873	1.57
Sit-Down Restaurants	0.386	(0.229)	1.4712	0.9386	2.3059	1.69
SL Bars	0.458***	(0.118)	1.5810	1.2554	1.9911	1.46
SL Consumer Electronics Stores	0.015	(0.148)	1.0151	0.7595	1.3569	1.60
SL Convenience Stores	0.266	(0.143)	1.3052	0.9853	1.7289	1.53
SL Discount and Dollar Stores	0.113	(0.340)	1.1191	0.5745	2.1801	1.50
SL Drug Treatment Centers	-0.177	(0.290)	0.8379	0.4747	1.4790	1.33
SL Entertainment Venues	0.144	(0.207)	1.1552	0.7704	1.7321	1.71
SL Fast Food Restaurants	-0.110	(0.058)	0.8959	0.7989	1.0047	2.93
SL Gas Stations	0.567**	(0.193)	1.7630	1.2075	2.5741	1.35
SL Grocery Stores	-0.275	(0.359)	0.7592	0.3758	1.5338	1.45
SL Home Décor and Furniture Stores	0.267	(0.162)	1.3057	0.9501	1.7945	1.52
SL Hotels	0.736*	(0.305)	2.0874	1.1470	3.7987	1.76
SL Pharmacies	0.414	(0.262)	1.5125	0.9052	2.5271	1.30
SL Recreation Centers	0.638*	(0.281)	1.8926	1.0913	3.2824	1.21
SL Recreation Retails Stores	0.002	(0.211)	1.0024	0.6632	1.5152	1.68
SL Salons and Barber Shops	0.421**	(0.153)	1.5232	1.1284	2.0562	2.18
SL Sit-Down Restaurants	-0.076	(0.087)	0.9270	0.7823	1.0986	2.35
Disadvantage	0.006***	(0.001)	1.0057	1.0037	1.0078	1.25
Residential Mobility	0.008***	(0.002)	1.0082	1.0048	1.0115	1.25
Racial Heterogeneity	0.864***	(0.124)	2.3723	1.8607	3.0247	1.08
Population	0.000***	(0.000)	1.0002	1.0001	1.0003	1.03
Street Length	0.001***	(0.000)	1.0013	1.0012	1.0014	1.03
Street Type	0.821***	(0.043)	2.2727	2.0875	2.4744	1.07
Constant	-2.161***	(0.081)	0.1152	0.0982	0.1351	--
AIC	25403.990				Mean VIF	1.48
BIC	25695.998					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 67. Sensitivity Check 8: Continuous Theft Risk Using 1000ft Buffer-Area Calls for Service

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.001***	(0.000)	1.0010	1.0006	1.0015	1.35
Consumer Electronics Stores	0.000	(0.000)	1.0001	0.9995	1.0007	1.64
Convenience Stores	0.002***	(0.000)	1.0020	1.0014	1.0027	1.27
Discount and Dollar Stores	0.004***	(0.001)	1.0039	1.0025	1.0054	1.27
Drug Treatment Centers	0.002***	(0.001)	1.0023	1.0009	1.0036	1.33
Entertainment Venues	0.002***	(0.000)	1.0016	1.0008	1.0023	1.52
Fast Food Restaurants	0.000**	(0.000)	1.0004	1.0001	1.0007	2.07
Gas Stations	0.003***	(0.001)	1.0027	1.0017	1.0037	1.30
Grocery Stores	0.005***	(0.001)	1.0055	1.0038	1.0072	1.38
Home Décor and Furniture Stores	0.001*	(0.000)	1.0010	1.0000	1.0019	1.46
Hotels	0.001*	(0.000)	1.0009	1.0002	1.0016	1.40
Pharmacies	0.002**	(0.001)	1.0018	1.0005	1.0031	1.29
Recreation Centers	0.001	(0.001)	1.0012	0.9995	1.0029	1.19
Recreation Retails Stores	0.001	(0.000)	1.0008	0.9999	1.0017	1.44
Salons and Barber Shops	-0.000	(0.000)	0.9999	0.9993	1.0006	1.79
Sit-Down Restaurants	0.000*	(0.000)	1.0003	1.0000	1.0007	1.86
SL Bars	0.000***	(0.000)	1.0004	1.0002	1.0006	1.55
SL Consumer Electronics Stores	0.000	(0.000)	1.0001	0.9999	1.0003	1.97
SL Convenience Stores	0.000**	(0.000)	1.0003	1.0001	1.0005	1.50
SL Discount and Dollar Stores	0.000	(0.000)	1.0005	0.9999	1.0010	1.39
SL Drug Treatment Centers	-0.000	(0.000)	1.0000	0.9995	1.0005	1.38
SL Entertainment Venues	0.000	(0.000)	1.0001	0.9998	1.0005	1.90
SL Fast Food Restaurants	-0.000***	(0.000)	0.9998	0.9997	0.9999	3.09
SL Gas Stations	0.000	(0.000)	1.0002	0.9998	1.0006	1.46
SL Grocery Stores	0.000	(0.000)	1.0003	0.9996	1.0009	1.47
SL Home Décor and Furniture Stores	0.000	(0.000)	1.0000	0.9997	1.0004	1.64
SL Hotels	0.000**	(0.000)	1.0004	1.0001	1.0007	1.77
SL Pharmacies	0.000	(0.000)	1.0004	0.9999	1.0009	1.36
SL Recreation Centers	0.001**	(0.000)	1.0011	1.0003	1.0018	1.20
SL Recreation Retails Stores	0.000	(0.000)	1.0001	0.9997	1.0005	1.79
SL Salons and Barber Shops	0.000	(0.000)	1.0001	0.9999	1.0004	2.58
SL Sit-Down Restaurants	-0.000	(0.000)	1.0000	0.9999	1.0001	2.72
Disadvantage	0.008***	(0.001)	1.0081	1.0062	1.0101	1.26
Residential Mobility	0.007***	(0.002)	1.0069	1.0038	1.0100	1.26
Racial Heterogeneity	0.709***	(0.117)	2.0319	1.6153	2.5558	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0011	1.0010	1.0012	1.03
Street Type	0.580***	(0.043)	1.7861	1.6423	1.9425	1.12
Constant	-2.202***	(0.077)	0.1106	0.0952	0.1285	--
AIC	24772.491				Mean VIF	1.56
BIC	25064.498					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

APPENDIX E – MULTI-FACILITY SENSITIVITY CHECK REGRESSION RESULTS

This appendix presents results of the multi-facility sensitivity check regression models, which used a rate calculation of at-facility crime at multi-facility addresses (i.e. the number of crimes at an address divided by the number of facilities at that address).

Table 68. Sensitivity Check 9: Binary Robbery Risk Using At-Facility Calls for Service Rate

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.609	(0.481)	1.8378	0.7157	4.7191	1.30
Consumer Electronics Stores	0.831	(0.519)	2.2946	0.8302	6.3420	1.33
Convenience Stores	1.062*	(0.490)	2.8911	1.1059	7.5580	1.29
Discount and Dollar Stores	-0.029	(0.988)	0.9713	0.1401	6.7364	1.24
Drug Treatment Centers	1.515	(0.987)	4.5497	0.6577	31.4748	1.22
Entertainment Venues	0.363	(0.968)	1.4383	0.2155	9.5980	1.20
Fast Food Restaurants	0.258	(0.325)	1.2948	0.6852	2.4465	1.28
Gas Stations	0.871	(0.561)	2.3886	0.7960	7.1672	1.24
Grocery Stores	1.323	(1.012)	3.7560	0.5167	27.3009	1.25
Home Décor and Furniture Stores	-0.776	(0.809)	0.4603	0.0943	2.2458	1.60
Hotels	1.907	(1.053)	6.7339	0.8558	52.9859	1.32
Pharmacies	2.799*	(1.253)	16.4360	1.4110	191.4595	1.22
Recreation Centers	0.924	(0.915)	2.5203	0.4197	15.1353	1.22
Recreation Retails Stores	1.048	(0.780)	2.8506	0.6186	13.1361	1.33
Salons and Barber Shops	0.037	(0.597)	1.0373	0.3221	3.3405	1.36
Sit-Down Restaurants	0.323	(0.416)	1.3810	0.6112	3.1203	1.39
SL Bars	0.415	(0.235)	1.5141	0.9552	2.4002	1.36
SL Consumer Electronics Stores	0.310	(0.242)	1.3640	0.8496	2.1899	1.43
SL Convenience Stores	0.381	(0.259)	1.4634	0.8801	2.4331	1.31
SL Discount and Dollar Stores	1.214**	(0.424)	3.3662	1.4655	7.7320	1.27
SL Drug Treatment Centers	-0.391	(0.594)	0.6762	0.2112	2.1647	1.24
SL Entertainment Venues	-0.149	(0.458)	0.8616	0.3514	2.1126	1.25
SL Fast Food Restaurants	0.249	(0.146)	1.2833	0.9636	1.7092	1.40
SL Gas Stations	0.629*	(0.266)	1.8762	1.1142	3.1595	1.29
SL Grocery Stores	0.364	(0.504)	1.4391	0.5356	3.8663	1.26
SL Home Décor and Furniture Stores	0.679*	(0.325)	1.9712	1.0415	3.7307	1.75
SL Hotels	1.085*	(0.521)	2.9589	1.0661	8.2120	1.36
SL Pharmacies	-0.874	(0.856)	0.4173	0.0779	2.2360	1.29
SL Recreation Centers	1.057*	(0.477)	2.8779	1.1295	7.3327	1.22
SL Recreation Retails Stores	-0.456	(0.397)	0.6338	0.2909	1.3810	1.43
SL Salons and Barber Shops	-0.072	(0.264)	0.9303	0.5547	1.5602	1.50
SL Sit-Down Restaurants	0.168	(0.182)	1.1824	0.8277	1.6892	1.56
Disadvantage	0.032***	(0.002)	1.0323	1.0279	1.0368	1.25
Residential Mobility	-0.007*	(0.003)	0.9932	0.9865	0.9999	1.27
Racial Heterogeneity	0.895***	(0.270)	2.4470	1.4416	4.1536	1.08
Population	0.000**	(0.000)	1.0002	1.0001	1.0004	1.03
Street Length	0.000***	(0.000)	1.0005	1.0003	1.0006	1.03
Street Type	0.613***	(0.091)	1.8462	1.5438	2.2077	1.11
Constant	-4.750***	(0.178)	0.0086	0.0061	0.0122	--
AIC	5693.664				Mean VIF	1.30
BIC	5985.672					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 69. Sensitivity Check 10: Continuous Robbery Risk Using At-Facility Calls for Service Rate

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.024	(0.014)	1.0242	0.9957	1.0536	1.31
Consumer Electronics Stores	0.023	(0.028)	1.0230	0.9683	1.0807	1.29
Convenience Stores	0.018	(0.010)	1.0186	0.9986	1.0389	1.30
Discount and Dollar Stores	-0.002	(0.009)	0.9983	0.9808	1.0161	1.25
Drug Treatment Centers	0.003	(0.006)	1.0034	0.9920	1.0149	1.21
Entertainment Venues	-0.002	(0.014)	0.9976	0.9697	1.0264	2.29
Fast Food Restaurants	0.003	(0.006)	1.0028	0.9909	1.0149	1.49
Gas Stations	0.008	(0.004)	1.0084	1.0000	1.0168	1.22
Grocery Stores	0.004	(0.004)	1.0041	0.9960	1.0123	1.30
Home Décor and Furniture Stores	-0.012	(0.042)	0.9884	0.9098	1.0737	1.51
Hotels	0.015	(0.011)	1.0148	0.9929	1.0373	1.34
Pharmacies	0.046*	(0.019)	1.0466	1.0083	1.0864	1.46
Recreation Centers	0.019	(0.015)	1.0192	0.9906	1.0486	1.21
Recreation Retails Stores	0.035	(0.037)	1.0354	0.9633	1.1129	1.44
Salons and Barber Shops	0.026	(0.017)	1.0261	0.9929	1.0605	1.29
Sit-Down Restaurants	-0.001	(0.012)	0.9993	0.9757	1.0236	2.47
SL Bars	0.010	(0.007)	1.0104	0.9969	1.0240	1.36
SL Consumer Electronics Stores	0.016	(0.011)	1.0156	0.9943	1.0374	1.34
SL Convenience Stores	0.009*	(0.005)	1.0094	1.0005	1.0184	1.35
SL Discount and Dollar Stores	0.013**	(0.004)	1.0127	1.0046	1.0210	1.28
SL Drug Treatment Centers	0.001	(0.003)	1.0008	0.9956	1.0061	1.22
SL Entertainment Venues	-0.001	(0.006)	0.9990	0.9875	1.0107	2.60
SL Fast Food Restaurants	0.006*	(0.003)	1.0064	1.0015	1.0114	1.64
SL Gas Stations	0.005**	(0.002)	1.0046	1.0015	1.0077	1.26
SL Grocery Stores	0.001	(0.002)	1.0010	0.9963	1.0056	1.33
SL Home Décor and Furniture Stores	0.020	(0.019)	1.0201	0.9820	1.0598	1.64
SL Hotels	0.007	(0.005)	1.0073	0.9976	1.0171	1.45
SL Pharmacies	-0.017	(0.014)	0.9831	0.9564	1.0104	1.60
SL Recreation Centers	0.012	(0.008)	1.0120	0.9961	1.0282	1.21
SL Recreation Retails Stores	-0.038	(0.033)	0.9626	0.9027	1.0264	1.42
SL Salons and Barber Shops	-0.009	(0.012)	0.9915	0.9693	1.0143	1.36
SL Sit-Down Restaurants	0.007	(0.006)	1.0070	0.9961	1.0180	2.93
Disadvantage	0.032***	(0.002)	1.0321	1.0277	1.0366	1.25
Residential Mobility	-0.007*	(0.003)	0.9926	0.9860	0.9994	1.27
Racial Heterogeneity	0.888***	(0.270)	2.4291	1.4319	4.1206	1.08
Population	0.000***	(0.000)	1.0003	1.0001	1.0004	1.03
Street Length	0.000***	(0.000)	1.0005	1.0003	1.0006	1.03
Street Type	0.571***	(0.092)	1.7708	1.4800	2.1186	1.12
Constant	-4.748***	(0.177)	0.0087	0.0061	0.0123	--
AIC	5680.319				Mean	1.45
BIC	5972.326				VIF	

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 70. Sensitivity Check 11: Binary Theft Risk Using At-Facility Theft Incident Rate

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	1.504***	(0.285)	4.4994	2.5750	7.8622	1.23
Consumer Electronics Stores	0.192	(0.362)	1.2116	0.5955	2.4651	1.52
Convenience Stores	1.083***	(0.244)	2.9539	1.8329	4.7607	1.26
Discount and Dollar Stores	2.088**	(0.663)	8.0726	2.2033	29.5766	1.22
Drug Treatment Centers	1.834***	(0.529)	6.2616	2.2203	17.6588	1.20
Entertainment Venues	1.417***	(0.383)	4.1265	1.9462	8.7491	1.23
Fast Food Restaurants	0.435**	(0.160)	1.5442	1.1286	2.1129	1.42
Gas Stations	1.877***	(0.365)	6.5371	3.1958	13.3717	1.24
Grocery Stores	3.768***	(0.667)	43.2882	11.7023	160.1282	1.34
Home Décor and Furniture Stores	0.417	(0.378)	1.5175	0.7238	3.1817	1.44
Hotels	0.726	(0.715)	2.0673	0.5087	8.4012	1.34
Pharmacies	1.432*	(0.648)	4.1882	1.1752	14.9266	1.41
Recreation Centers	0.357	(0.520)	1.4290	0.5156	3.9605	1.20
Recreation Retails Stores	0.575	(0.361)	1.7763	0.8763	3.6007	1.61
Salons and Barber Shops	0.312	(0.282)	1.3666	0.7861	2.3758	1.36
Sit-Down Restaurants	0.419*	(0.202)	1.5204	1.0228	2.2602	1.43
SL Bars	0.240	(0.128)	1.2707	0.9885	1.6336	1.26
SL Consumer Electronics Stores	-0.108	(0.142)	0.8973	0.6793	1.1854	1.58
SL Convenience Stores	0.284**	(0.106)	1.3289	1.0787	1.6372	1.32
SL Discount and Dollar Stores	0.641*	(0.297)	1.8978	1.0605	3.3961	1.24
SL Drug Treatment Centers	-0.179	(0.253)	0.8360	0.5088	1.3737	1.21
SL Entertainment Venues	0.445*	(0.185)	1.5599	1.0847	2.2431	1.25
SL Fast Food Restaurants	0.197**	(0.070)	1.2179	1.0616	1.3971	1.61
SL Gas Stations	0.108	(0.164)	1.1136	0.8072	1.5363	1.26
SL Grocery Stores	0.325	(0.341)	1.3845	0.7091	2.7031	1.38
SL Home Décor and Furniture Stores	0.676***	(0.189)	1.9658	1.3571	2.8475	1.68
SL Hotels	0.747*	(0.290)	2.1101	1.1953	3.7250	1.39
SL Pharmacies	0.244	(0.338)	1.2766	0.6586	2.4744	1.46
SL Recreation Centers	0.487*	(0.228)	1.6275	1.0416	2.5430	1.21
SL Recreation Retails Stores	0.057	(0.167)	1.0585	0.7632	1.4680	1.80
SL Salons and Barber Shops	0.156	(0.115)	1.1692	0.9325	1.4659	1.47
SL Sit-Down Restaurants	0.386***	(0.086)	1.4711	1.2440	1.7397	1.59
Disadvantage	0.009***	(0.001)	1.0089	1.0070	1.0109	1.25
Residential Mobility	0.005**	(0.002)	1.0053	1.0021	1.0085	1.27
Racial Heterogeneity	0.662***	(0.118)	1.9396	1.5396	2.4434	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0010	1.0009	1.0011	1.03
Street Type	0.665***	(0.043)	1.9442	1.7886	2.1133	1.12
Constant	-2.111***	(0.077)	0.1211	0.1041	0.1408	--
AIC	24915.284				Mean VIF	1.34
BIC	25207.291					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 71. Sensitivity Check 12: Continuous Theft Risk Using At-Facility Theft Incident Rate

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.468***	(0.090)	1.5963	1.3383	1.9041	1.22
Consumer Electronics Stores	-0.037	(0.214)	0.9637	0.6341	1.4646	1.56
Convenience Stores	0.210***	(0.044)	1.2338	1.1324	1.3443	1.31
Discount and Dollar Stores	0.185***	(0.051)	1.2033	1.0878	1.3311	1.21
Drug Treatment Centers	0.251**	(0.087)	1.2854	1.0838	1.5246	1.23
Entertainment Venues	0.337***	(0.094)	1.4001	1.1655	1.6820	1.32
Fast Food Restaurants	0.206**	(0.077)	1.2284	1.0553	1.4298	1.56
Gas Stations	0.158***	(0.031)	1.1709	1.1019	1.2443	1.22
Grocery Stores	0.116***	(0.016)	1.1231	1.0877	1.1595	1.47
Home Décor and Furniture Stores	-0.182	(0.112)	0.8332	0.6687	1.0383	3.54
Hotels	0.186	(0.099)	1.2039	0.9922	1.4609	1.50
Pharmacies	0.070	(0.040)	1.0728	0.9922	1.1599	1.95
Recreation Centers	0.104	(0.117)	1.1099	0.8822	1.3964	1.20
Recreation Retails Stores	-0.013	(0.095)	0.9871	0.8189	1.1898	2.06
Salons and Barber Shops	0.240	(0.157)	1.2710	0.9352	1.7273	1.40
Sit-Down Restaurants	0.177*	(0.076)	1.1941	1.0290	1.3856	4.27
SL Bars	0.086*	(0.035)	1.0899	1.0177	1.1672	1.25
SL Consumer Electronics Stores	-0.001	(0.077)	0.9988	0.8592	1.1611	1.58
SL Convenience Stores	0.014	(0.020)	1.0140	0.9757	1.0537	1.33
SL Discount and Dollar Stores	0.034**	(0.011)	1.0349	1.0131	1.0572	1.25
SL Drug Treatment Centers	-0.017	(0.037)	0.9831	0.9136	1.0578	1.24
SL Entertainment Venues	0.104**	(0.040)	1.1101	1.0254	1.2017	1.38
SL Fast Food Restaurants	0.153***	(0.031)	1.1649	1.0965	1.2377	1.69
SL Gas Stations	0.005	(0.010)	1.0054	0.9857	1.0254	1.27
SL Grocery Stores	0.003	(0.007)	1.0032	0.9887	1.0179	1.51
SL Home Décor and Furniture Stores	-0.025	(0.033)	0.9754	0.9150	1.0398	3.84
SL Hotels	0.038	(0.033)	1.0387	0.9739	1.1078	1.70
SL Pharmacies	0.073***	(0.018)	1.0756	1.0392	1.1133	2.37
SL Recreation Centers	0.119*	(0.053)	1.1264	1.0146	1.2505	1.21
SL Recreation Retails Stores	0.023	(0.040)	1.0233	0.9461	1.1067	2.20
SL Salons and Barber Shops	0.026	(0.071)	1.0268	0.8939	1.1794	1.46
SL Sit-Down Restaurants	0.015	(0.028)	1.0153	0.9607	1.0730	4.30
Disadvantage	0.009***	(0.001)	1.0086	1.0066	1.0105	1.25
Residential Mobility	0.005**	(0.002)	1.0050	1.0018	1.0082	1.27
Racial Heterogeneity	0.743***	(0.117)	2.1025	1.6708	2.6458	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0010	1.0009	1.0011	1.03
Street Type	0.622***	(0.043)	1.8620	1.7132	2.0238	1.11
Constant	-2.110***	(0.076)	0.1212	0.1044	0.1407	--
AIC	24825.699				Mean VIF	1.69
BIC	25117.707					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 72. Sensitivity Check 13: Binary Theft Risk Using At-Facility Calls for Service Rate

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	1.408***	(0.289)	4.0885	2.3186	7.2097	1.30
Consumer Electronics Stores	0.279	(0.325)	1.3222	0.6997	2.4984	1.33
Convenience Stores	1.645***	(0.305)	5.1788	2.8482	9.4166	1.29
Discount and Dollar Stores	1.874**	(0.661)	6.5127	1.7827	23.7924	1.24
Drug Treatment Centers	1.604**	(0.569)	4.9748	1.6313	15.1715	1.22
Entertainment Venues	1.634***	(0.414)	5.1241	2.2750	11.5415	1.20
Fast Food Restaurants	0.492*	(0.196)	1.6353	1.1146	2.3992	1.28
Gas Stations	1.925***	(0.381)	6.8559	3.2480	14.4715	1.24
Grocery Stores	3.822***	(0.653)	45.6932	12.7109	164.2578	1.25
Home Décor and Furniture Stores	0.942**	(0.348)	2.5651	1.2978	5.0701	1.60
Hotels	0.764	(0.711)	2.1464	0.5326	8.6500	1.32
Pharmacies	2.078***	(0.604)	7.9847	2.4430	26.0976	1.22
Recreation Centers	0.538	(0.611)	1.7119	0.5165	5.6738	1.22
Recreation Retails Stores	0.984**	(0.372)	2.6742	1.2887	5.5494	1.33
Salons and Barber Shops	0.531	(0.296)	1.7009	0.9523	3.0378	1.36
Sit-Down Restaurants	0.623**	(0.242)	1.8653	1.1614	2.9959	1.39
SL Bars	0.197	(0.119)	1.2181	0.9647	1.5380	1.36
SL Consumer Electronics Stores	0.072	(0.132)	1.0748	0.8293	1.3929	1.43
SL Convenience Stores	0.217	(0.142)	1.2417	0.9395	1.6413	1.31
SL Discount and Dollar Stores	0.626*	(0.296)	1.8707	1.0479	3.3398	1.27
SL Drug Treatment Centers	-0.309	(0.283)	0.7343	0.4219	1.2779	1.24
SL Entertainment Venues	0.164	(0.195)	1.1777	0.8038	1.7256	1.25
SL Fast Food Restaurants	0.195*	(0.081)	1.2148	1.0368	1.4234	1.40
SL Gas Stations	0.135	(0.169)	1.1448	0.8215	1.5951	1.29
SL Grocery Stores	0.100	(0.302)	1.1053	0.6114	1.9981	1.26
SL Home Décor and Furniture Stores	0.438*	(0.178)	1.5491	1.0929	2.1957	1.75
SL Hotels	0.873**	(0.283)	2.3951	1.3751	4.1719	1.36
SL Pharmacies	0.782**	(0.303)	2.1853	1.2058	3.9604	1.29
SL Recreation Centers	0.426	(0.283)	1.5308	0.8790	2.6659	1.22
SL Recreation Retails Stores	0.059	(0.175)	1.0603	0.7531	1.4929	1.43
SL Salons and Barber Shops	0.127	(0.131)	1.1357	0.8778	1.4695	1.50
SL Sit-Down Restaurants	0.227*	(0.100)	1.2542	1.0302	1.5269	1.56
Disadvantage	0.008***	(0.001)	1.0083	1.0064	1.0103	1.25
Residential Mobility	0.006***	(0.002)	1.0056	1.0024	1.0088	1.27
Racial Heterogeneity	0.725***	(0.119)	2.0650	1.6360	2.6066	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0011	1.0010	1.0012	1.03
Street Type	0.703***	(0.042)	2.0201	1.8587	2.1955	1.11
Constant	-2.100***	(0.077)	0.1224	0.1053	0.1423	--
AIC	24938.106				Mean VIF	1.30
BIC	25230.113					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion

Table 73. Sensitivity Check 14: Continuous Theft Risk Using At-Facility Calls for Service Rate

	Coef.	S.E.	IRR	95% Confidence Interval		VIF
Bars	0.048***	(0.009)	1.0488	1.0303	1.0676	1.31
Consumer Electronics Stores	0.012	(0.014)	1.0116	0.9835	1.0405	1.29
Convenience Stores	0.029***	(0.005)	1.0291	1.0188	1.0395	1.30
Discount and Dollar Stores	0.039***	(0.009)	1.0401	1.0226	1.0579	1.25
Drug Treatment Centers	0.010*	(0.004)	1.0099	1.0021	1.0179	1.21
Entertainment Venues	0.034***	(0.007)	1.0342	1.0193	1.0493	2.29
Fast Food Restaurants	0.012**	(0.004)	1.0123	1.0038	1.0209	1.49
Gas Stations	0.016***	(0.003)	1.0164	1.0106	1.0223	1.22
Grocery Stores	0.024***	(0.003)	1.0244	1.0179	1.0310	1.30
Home Décor and Furniture Stores	0.082**	(0.029)	1.0851	1.0250	1.1486	1.51
Hotels	0.012	(0.006)	1.0117	0.9991	1.0246	1.34
Pharmacies	0.036**	(0.011)	1.0370	1.0144	1.0602	1.46
Recreation Centers	0.016	(0.010)	1.0161	0.9973	1.0354	1.21
Recreation Retails Stores	0.022	(0.021)	1.0222	0.9817	1.0644	1.44
Salons and Barber Shops	0.020	(0.013)	1.0201	0.9941	1.0469	1.29
Sit-Down Restaurants	0.018*	(0.008)	1.0186	1.0028	1.0347	2.47
SL Bars	0.011**	(0.003)	1.0107	1.0041	1.0175	1.36
SL Consumer Electronics Stores	0.005	(0.005)	1.0048	0.9941	1.0156	1.34
SL Convenience Stores	0.003	(0.002)	1.0029	0.9981	1.0076	1.35
SL Discount and Dollar Stores	0.007**	(0.003)	1.0070	1.0017	1.0123	1.28
SL Drug Treatment Centers	-0.000	(0.001)	0.9997	0.9968	1.0026	1.22
SL Entertainment Venues	0.001	(0.003)	1.0008	0.9952	1.0064	2.60
SL Fast Food Restaurants	0.002	(0.002)	1.0020	0.9989	1.0052	1.64
SL Gas Stations	0.002*	(0.001)	1.0019	1.0000	1.0037	1.26
SL Grocery Stores	0.000	(0.001)	1.0005	0.9979	1.0030	1.33
SL Home Décor and Furniture Stores	0.018*	(0.009)	1.0180	1.0008	1.0356	1.64
SL Hotels	0.009***	(0.003)	1.0092	1.0039	1.0146	1.45
SL Pharmacies	0.009	(0.005)	1.0093	0.9993	1.0194	1.60
SL Recreation Centers	0.009*	(0.004)	1.0086	1.0007	1.0165	1.21
SL Recreation Retails Stores	0.005	(0.005)	1.0054	0.9965	1.0145	1.42
SL Salons and Barber Shops	0.006	(0.005)	1.0064	0.9963	1.0166	1.36
SL Sit-Down Restaurants	0.002	(0.003)	1.0021	0.9968	1.0073	2.93
Disadvantage	0.009***	(0.001)	1.0089	1.0070	1.0109	1.25
Residential Mobility	0.005**	(0.002)	1.0051	1.0020	1.0082	1.27
Racial Heterogeneity	0.716***	(0.117)	2.0458	1.6280	2.5709	1.08
Population	0.000***	(0.000)	1.0003	1.0002	1.0003	1.03
Street Length	0.001***	(0.000)	1.0010	1.0009	1.0011	1.03
Street Type	0.568***	(0.042)	1.7646	1.6236	1.9178	1.12
Constant	-2.132***	(0.075)	0.1187	0.1023	0.1376	--
AIC	24728.020				Mean VIF	1.45
BIC	25020.028					

Notes: ***p < .001; **p < .01; *p < .05. Coef. = Coefficient; S.E. = Standard error; IRR = Incident Rate Ratio; VIF = Variance Inflation Factor; SL = Spatially lagged; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion