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Here Today, Gone Tomorrow: The Temporal Stability of Crime Hot Spots and the Criminology of Place

Michael J. Deckard
michaeljdeckard@umsl.edu

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Michael J. Deckard
M.A. in Criminology & Criminal Justice, May 2012, University of Missouri-St. Louis
B.S. in Justice Systems, May 2009, Truman State University

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Advisory Committee

Richard Rosenfeld, Ph.D

Chairperson

Beth Huebner, Ph.D

Lee Ann Slocum, Ph.D

Daniel Isom II, Ph.D

David Weisburd, Ph.D

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DISCLAIMER

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ABSTRACT

It is widely recognized that the distribution of crime in urban areas is not randomly distributed, but is highly concentrated in small pockets of space known as crime "hot spots" (Sherman, Gartin, and Buerger 1989; Eck and Weisburd 1995a; Weisburd, Groff, and Yang 2012; Weisburd et al. 2016). This phenomenon was recently dubbed "the law of crime concentration", and has become a topic of recent debate in the criminological literature. While the empirical evidence supporting the law of crime concentration is strong, most studies that have examined the stability of crime hot spots over time have aggregated crime across years. This dissertation seeks to expand our understanding of the temporal stability of micro-geographic crime hot spots by addressing three research questions: (1) How are high-crime micro-places distributed at the monthly level? How much variation exists in the distribution of crime across micro-places when crimes are aggregated on a monthly rather than an annual basis?; (2) Do structural characteristics associated with micro-geographic crime hot spots differ compared to low-crime and crime-free places?; and (3) Are structural characteristics of micro-geographic hot spots associated with hot spot periodicity? Can the likelihood that a place will experience multiple high-crime months be determined by its structural characteristics? To address these questions, the dissertation examines data from the St. Louis Metropolitan Police Department (SLMPD), the American Communities Survey (ACS), the decennial Census of the United States, and the St. Louis Open Data Portal. In response to the first question, this dissertation explores monthly crime concentrations at the micro-geographic level using street segments in St. Louis, Missouri. Logistic and negative binomial regression models are estimated to address the second research question regarding the structural attributes of violent and property crime hot spots. Finally, the structural characteristics of temporary and violent crime hot spots are compared using a Cox regression model commonly used in survival analyses. Results from these analyses produced several substantively interesting findings, including: (1) there is significant within-year variation in the distribution of crime hot spots, including differences in the temporal stability of high-crime street segments depending on the type of crime studied; (2) violent and property crime hot spots can be distinguished based on their specific sets of structural attributes, with some characteristics of place exhibit inverse relationships between crime types; and (3) the attributes of micro-geographic places may influence the temporal stability of crime hot spots. Implications of these findings for criminal justice policy and directions for future research are discussed.

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CHAPTER ONE: INTRODUCTION

It is widely recognized that the distribution of crime in urban areas is not randomly distributed, but is highly concentrated in small pockets of space known as crime "hot spots" (Sherman, Gartin, and Buerger 1989; Eck and Weisburd 1995a; Weisburd, Groff, and Yang 2012; Weisburd et al. 2016). Over the past four decades, scores of studies have examined the distribution of crime in micro-geographic areas and found similar levels of concentration in cities across the United States and abroad (Weisburd and Amram 2014; Groff, Weisburd, and Yang 2010; Mazeika and Kumar 2016). Independent city-wide analyses of crime concentration have found that approximately 80% of all crime occurs at just 20% of places, with roughly 5% of places accounting for 50% of crime (Weisburd, Groff, and Yang 2012; Weisburd et al. 2016). This phenomenon was recently dubbed "the law of crime concentration" and has become a topic of debate in the criminological literature. These concentrations are similar to concentrations in other areas of social life, such as the proportion of drivers who are responsible for the majority of motor vehicle accidents (see Weisburd and Amram 2014; Weisburd 2015). While the empirical evidence supporting the law of crime concentration is strong, most studies that have examined the stability of crime hot spots over time have aggregated crime across years.[1] This dissertation seeks to expand on our understanding of the temporal stability of micro-geographic crime hot spots by analyzing crime distributions across time using sub-annual units of analysis.

[1] For a recent exception, see Haberman, Sorg, and Ratcliffe (2016)

Among the many significant findings in the crime and place literature is that even within high-crime neighborhoods, crime is highly concentrated, with many areas experiencing little or no crime (Sherman, Gartin, and Buerger 1989; Weisburd, Groff, and Yang 2012; Weisburd, Bushway, and Lum 2004).[2] This phenomenon is known as averaging, and is not limited to units of geography, but can apply any time larger units of analysis are used when smaller units are available (Weisburd et al. 2016; Jelinski and Wu 1996). In the case of time, years are among the largest units available for studying micro-spatial crime patterns, and as such, are vulnerable to averaging. Take the following hypothetical scenario as an example: using annual data, a study finds that a small number of street segments are responsible for a large percentage of all crime in a city. The study finds that these places are among the highest-crime places every year over a long period of time. However, without examining variation in crime concentration within years, it is impossible to tell whether these places are hot all year long, or whether a single month or group of months is responsible for their consistent annual ranking among the highest-crime places. The dissertation seeks to address this problem by analyzing the monthly distribution of crime hot spots and comparing them to annual distributions used in previous studies. To that end, the first research question asks:

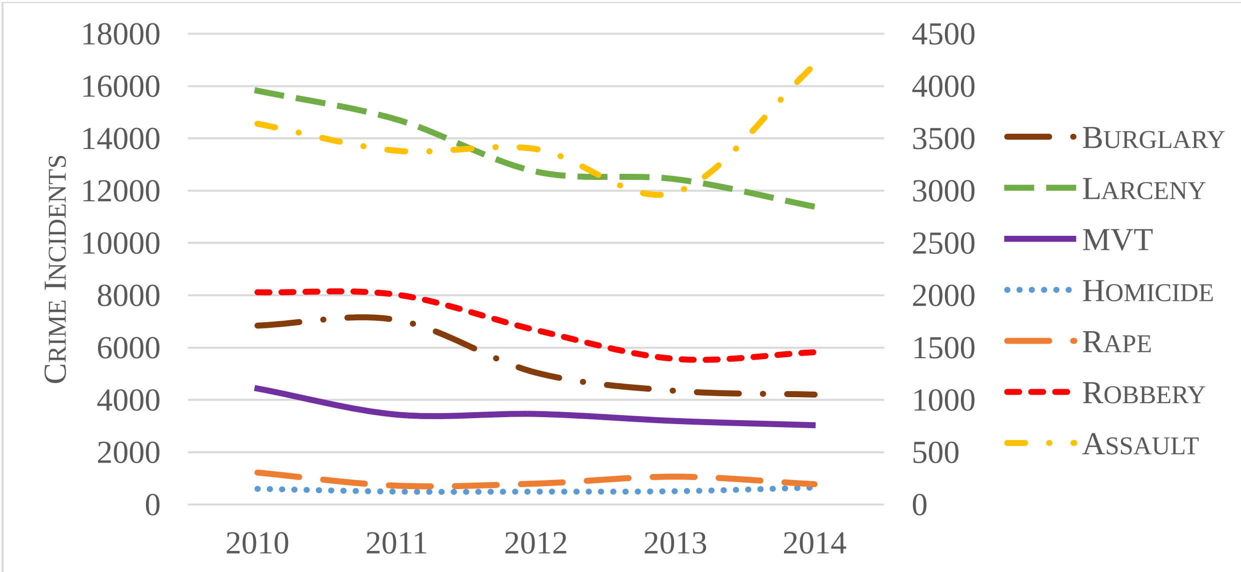
[2] Interestingly, renowned Chicago-school sociologist Albert J. Reiss, Jr. claimed that Henry McKay observed that entire blocks within Chicago's high-crime neighborhoods were free of offenders, though these findings were never published (see Sherman, Gartin, and Buerger 1989, 29).

(1) How are high-crime micro-places distributed at the monthly level? How much variation exists in the distribution of crime across micro-places when crimes are aggregated on a monthly rather than an annual basis?

To answer this question, the dissertation analyzes Uniform Crime Report (UCR) Part 1 Offense data provided by the St. Louis Metropolitan Police Department (SLMPD) for a five-year period from 2010-2014 (see Figure 1.1). Analyzing crime concentration at the monthly level adds important detail to our knowledge about the stability of crime in micro-geographic places. Comparing high-crime months to high-crime years addresses the problem of averaging inherent in annual studies of crime concentration and carries potentially significant policy implications for law enforcement responses to areas with high crime patterns.

The second goal of the dissertation is to examine the structural characteristics of high-crime street segments, and how they might inform our understanding of why some places experience brief, intense periods of elevated crime, some experience prolonged, chronic high-crime periods, and others are largely crime-free or have low, stable levels of crime.

Figure 1.1. UCR Part 1 Crime Trends, St. Louis, MO, 2010-2014[3]



Criminology has a long tradition of studying the relationship between social ecology and crime. The ecological school of criminology began at the University of Chicago in the early 20th century. Sociologists Clifford Shaw and Henry McKay were influential figures in the study of the ecology of crime. Their renowned study on delinquency patterns in Chicago provided the theoretical framework that has been the basis of thousands of studies on neighborhoods and crime over the past 75 years (see Shaw and McKay 1942). Their theory on social disorganization is based on the observation that while the social structure of neighborhoods changed over time, patterns of crime did not change, but rather appeared to be tied to place (Shaw and McKay 1942). Research on neighborhoods and crime has produced a set of reliable indicators that are associated with elevated levels of crime. Poverty, racial/ethnic heterogeneity, and

[3] Property crime displayed on the primary axis, violent crime displayed on the secondary axis.

population turnover are among the oldest and best tested indicators of social disorganization and crime. Others include education, age distribution, family disruption, and land use. While these structural variables have been used extensively in the crime and place literature to identify and compare high-crime areas, or hot spots, few studies have analyzed the structural characteristics of crime hot spots compared to low crime and crime-free places using monthly crime data; nor have prior studies compared the structural characteristics of temporary and chronic crime hot spots. This represents a significant gap in the research literature, which is addressed in the second research question: Do structural characteristics associated with micro-geographic crime hot spots differ compared to low-crime and crime-free places?

This question is designed to extend existing research on social structure and crime hot spots to the micro-temporal level. Existing longitudinal studies of crime hot spots use annual data, which may mask important within-year variation in crime distributions. By drawing hot spots on a monthly basis, the current study tests the application of traditional indicators of social disorganization to a smaller temporal unit of analysis. This could enhance our understanding of crime patterns and crime concentration in micro-geographic areas, as well as the relationship between neighborhood social characteristics and the prevalence of serious crime. Related to this question, the third and final research question asks: Are structural characteristics of micro-geographic hot spots associated with hot spot periodicity? Can the likelihood that a place will experience multiple high-crime months be determined by its structural characteristics?

This research question extends theoretical predictors of crime to the stability of crime hot spots over time. The existing literature on this topic is limited: only a handful of studies on crime and place make use of monthly data, and to my knowledge none have directly tested the impact of structural correlates on temporary and chronic hot spots using monthly data (see Gorr and Lee 2012; Gorr and Lee 2014).

These research questions are addressed using data from a single Midwestern city: St. Louis, Missouri. The purpose of the dissertation is to address these gaps in the crime and place literature using rigorous statistical analyses to answer the stated research questions, which might provide valuable insight into the nature of micro-geographic crime distributions. The findings from this study could be used by criminal justice administrators, public policy makers, and academic researchers to develop new evidence-based crime policies, to better address structural inequalities tied to high-crime areas, and to inspire future research that will improve our understanding of crime in urban areas.

The remainder of the dissertation is organized as follows: Chapter Two reviews the relevant theoretical and empirical literature on spatial crime distributions, crime concentration, place-based appraisals of the structural characteristics of place, and the policy implications of crime and place research. Chapter Three describes the empirical data and analytic methods used to answer the research questions, including summary statistics, operationalization of dependent and independent variables, and the analysis plan. Chapter Four presents results related to the first research question, including monthly distributions of crime concentration from 2010-2014 and a novel method for selecting crime hot spots that is empirically based and controls for seasonal variation in crime levels. Chapter Five presents multivariate regression analysis results in response to the second and third research questions. Chapter Six discusses the significance of the findings for public policy, as well as limitations of the study and directions for future research.

CHAPTER TWO: BACKGROUND

To answer the research questions presented in Chapter One, the dissertation draws from three theoretical perspectives that deal with the intersection of crime in space and time: social disorganization theory, routine activity theory, and crime pattern theory. These perspectives can be categorized more broadly as ecological theories of crime; each posits that criminal events are more likely to occur in some places and not in others, that the characteristics of places and the institutions and people who are situated within them will have a strong influence on the distribution of crime.

THE ECOLOGY OF CRIME AND THE CRIMINOLOGY OF PLACE

The study of crime distributions has a long tradition in criminology and sociology dating back to the 18th century. André-Michel Guerry first mapped the distribution of crimes against persons and property alongside the level of education in France (Guerry 1833; see Figure 2.1). Guerry's work represents one of the first attempts to visualize the geographic concentration of crime alongside other social phenomena. Guerry collaborated with renowned astronomer, mathematician, and pioneer sociologist Adolphe Quetelet to develop the field of moral statistics (Friendly 2008). Through their development of new statistical analysis techniques, Quetelet and Guerry analyzed the relationships between crime and other relevant aspects of social life. Their legacy led some scholars to credit them as the originators of ecological sociology (Beirne 1987). Despite these significant contributions to the study of crime concentration, interest in the geography of crime did not achieve mainstream popularity among sociological scholars for over a century (Beirne 1987).

The criminology of place grew, in part, out of the social ecology literature of the early- to mid-20th century. At the turn of the 20th century, immigration in America was at its peak. In Chicago during this time, sociological inquiry flourished; The University of Chicago was founded in 1890, and two years later, Albion Small founded the Department of Sociology. By 1900, 75% of Chicago's residents were foreign born: an increase of more than 200% from just a decade prior (Bursik 2009). The rapidly shifting demographics in American cities was accompanied by a significant increase in crime. Starting at the beginning of the 20th century, homicide rates in the U.S. rose steadily for several decades (Linder and Grove 1947). Over the next several decades, some of the most influential advances in sociology and criminology were made by members of The Chicago School of Sociology, including Robert Park, Ernest Burgess, George Herbert Mead, Clifford Shaw, and Henry McKay (Bulmer 1984).

The influx of immigrants into America's major cities made places like Chicago natural laboratories for social scientists. Much of the early work by University of Chicago sociologists focused on immigrant neighborhoods where people from different cultures often lived in close proximity (Cortese 1995). Research conducted by these scholars on the social ecology of the city was instrumental to the later development of the criminology of place. While he is primarily known for his seminal work on delinquency in Chicago neighborhoods conducted with McKay, Shaw created one of the first point maps depicting the location of offenders. A high-resolution scan of one of Shaw's point maps is displayed in Figure 2.2. This hand-drawn map is comparable to modern computer-generated crime maps. It would be over 70 years before the technology was available to recreate such maps using geospatial analysis software.

Social Disorganization

In the 35 years since the opening line of Bob Bursik and Jim Webb's influential paper on patterns of delinquency in Chicago neighborhoods was published (see Bursik and Webb 1982), scholarly interest in the spatial distributions of crime has thrived. Bursik, Webb, and other modern urban criminologists have relied heavily on social disorganization theory to explain patterns of crime and delinquency in American cities. Originally proposed by Shaw and McKay (1942), social disorganization theory is based on the premise that certain structural characteristics of neighborhoods – poverty, ethnic heterogeneity, residential mobility, and the absence of strong social ties – precipitate chronic patterns of crime and delinquency (Bursik and Webb 1982; Bursik 1988; Kornhauser 1978; Kubrin and Weitzer 2003; Shaw and McKay 1942). The revival of the social disorganization perspective had a tremendous influence on American criminology. Thousands of journal articles, monographs, and conference presentations have examined the relationships between neighborhoods, their residents, and crime and delinquency. A great deal of the literature produced during this period focused on the macroscopic relationships between urban neighborhoods and characteristics of the people who inhabit them.

Following the revival of the social disorganization perspective (e.g. Bursik 1986, 1988; Bursik and Webb 1993) and amidst the highest crime rates in a generation, scholars again focused on the structural aspects of neighborhoods to explain why some urban areas were consistently high-crime even as the groups of people living in those neighborhoods changed over time. Chicago served as the laboratory for this new era of neighborhoods research, as it had for the urban sociologists whose theoretical work laid the foundation for a neighborhood-oriented perspective. Until recently, however, relatively little was known about the distribution of crime *within* neighborhoods. Around the same time that Kornhauser, Bursik, Webb, and others published their seminal works reinvigorating interest in social disorganization theory, the first studies of what would become a new criminological paradigm were being conducted. In contrast to the macro-geographic scope that dominates the literature on neighborhoods and crime, this new ecological perspective focused on the distribution of crime at the micro-geographic level of street addresses, street segments, intersections, and facilities (Eck and Weisburd 1995a; Weisburd, Bushway, and Lum 2004; Weisburd et al. 2016).

This new sub-field of criminology shifted the focus from macro-level units of analysis to micro places, notably the street segment (Weisburd et al. 2016). One reason for this shift in scope was the capability of smaller units of analysis to unmask potentially important variations in crime levels that is lost when aggregated to macro-level units such as neighborhoods. Analyzing spatial crime concentration at micro-geographic places lead researchers to conclude that even within high-crime neighborhoods, most street segments are crime-free (see Groff, Weisburd, and Yang 2010; Weisburd, Bushway, and Lum 2004; Weisburd et al. 2012).

Figure 2.1. "Statistical Comparison of the State of Instruction and the Number of Crimes in the various Educational Authorities and Courts of France" – A. Balbi & A.M. Guerry, 1833

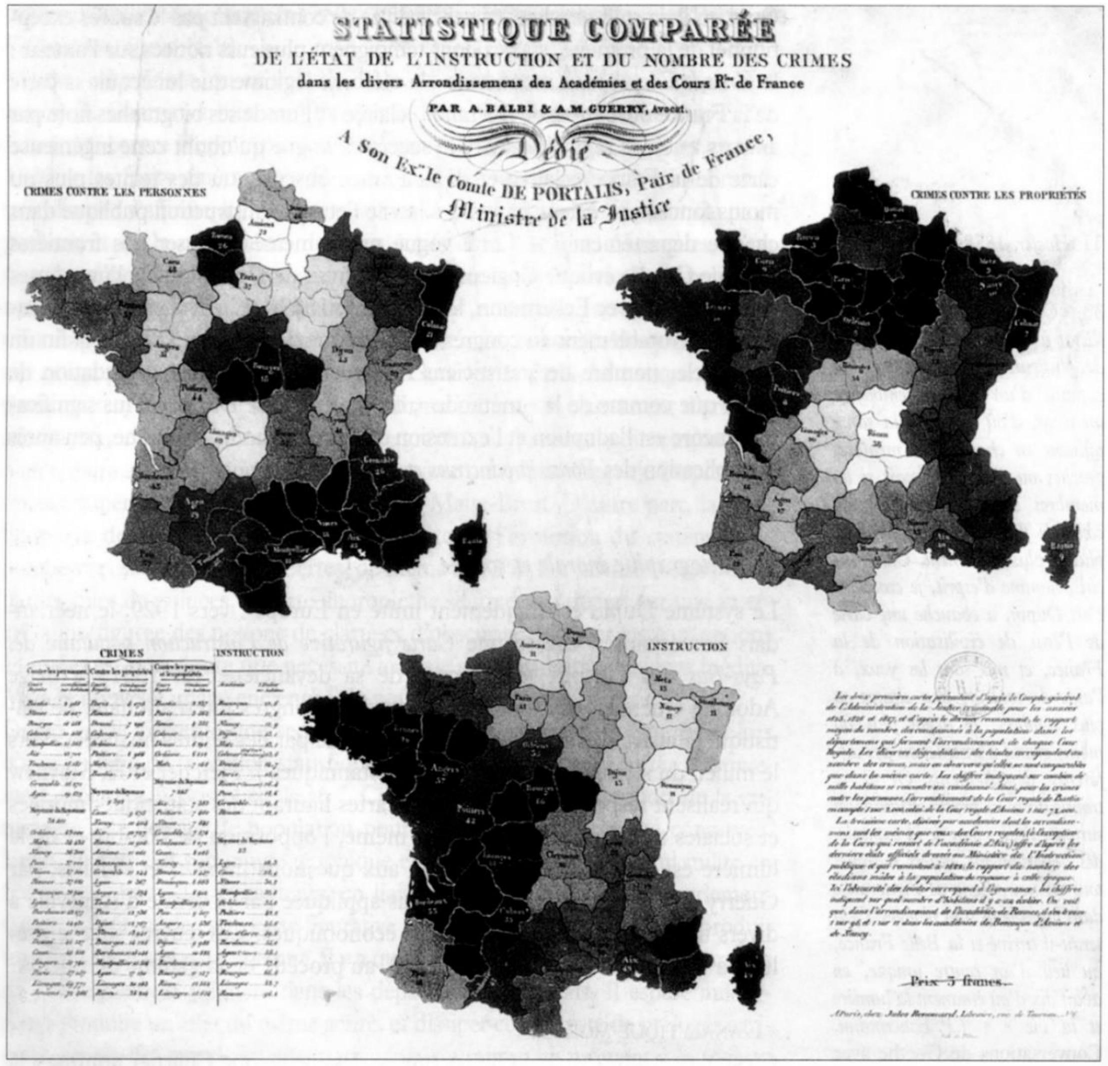
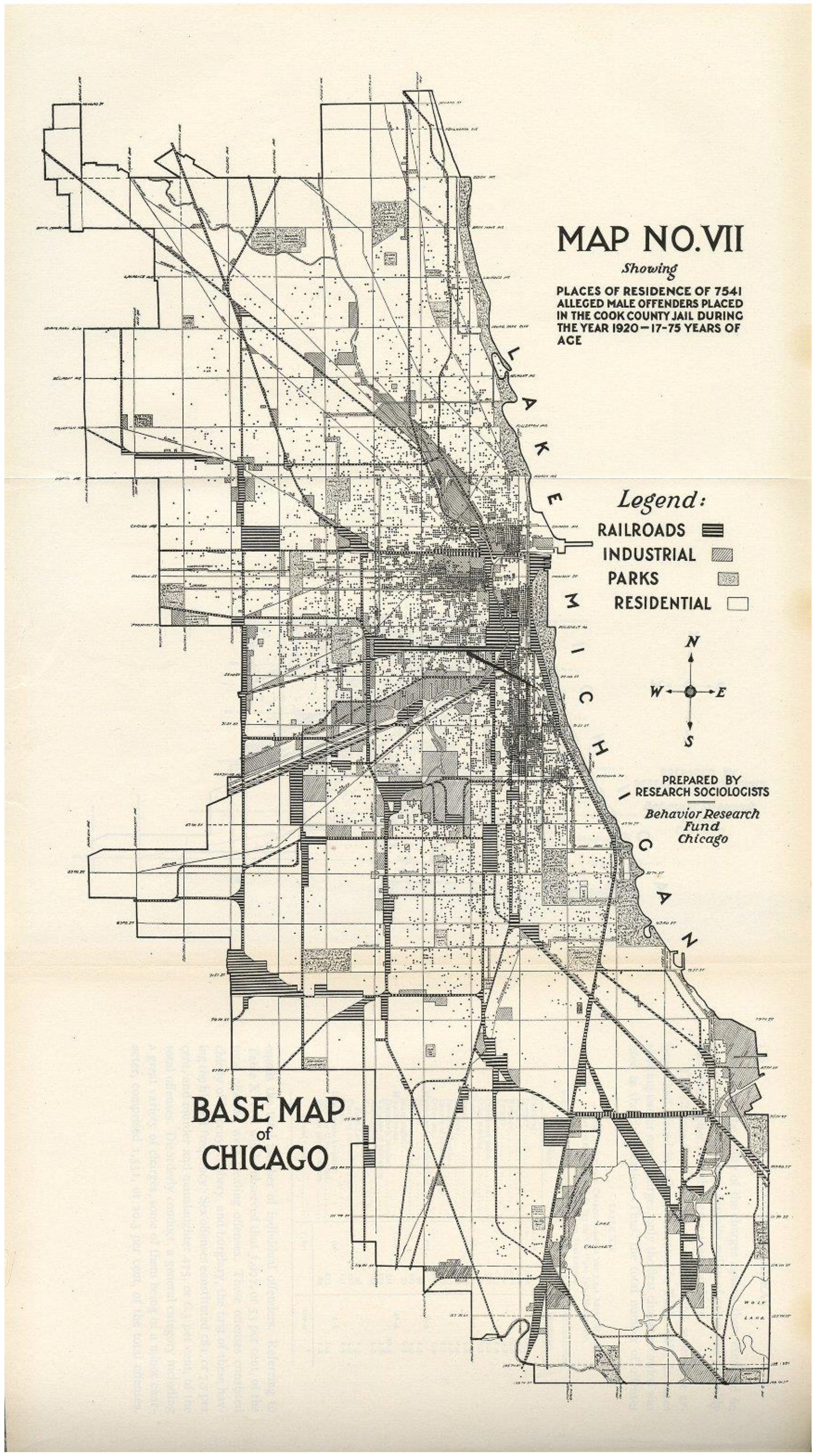


Figure 2.2. Hand-Drawn Map of Chicago Featuring Residences of Alleged Male Offenders Ages 17-75 Placed in the Cook County Jail, Chicago, ca. 1920



The past forty years have seen unprecedented growth in research on the distribution of crime. This wave of new research can be tied to several factors, including rising crime trends in the late 20th century, advances in computing power and technology for analyzing spatial data, and increases in funding for evidence-based crime policy. Modern research on the distribution of crime has become known as the *criminology of place* (Sherman, Gartin, and Buerger 1989), and is organized around the well-documented phenomenon that a significant proportion of crime is committed at a small number of places within a city (Weisburd et al. 2016). While *criminology* is a straightforward term, encompassing the study of crime, deviance, and the criminal justice system, the meaning of *place* is dependent on the context of what is being studied. In political science, nations, states, and regions may be categorized as distinct places. Geographers may conceptualize place as a point of reference on a map. Within sociology and criminology, place has often been conceptualized as the neighborhood and similar areas tied to communities (see, e.g. Sampson 2013). Sherman, Gartin, and Buerger (1989) first coined the term "criminology of place" in their seminal paper on crime hot spots and routine activity theory, and offer the following definition that conceptualizes place as it pertains to the study of crime concentration in micro-geographic areas:

> The concept of place lies at the nexus of the physical and social environments, providing a unit of analysis rich in both symbolic content and social organization. We do not mean *place* [sic] in the sense of social position in a group (Goffman, 1971), nor in the broader geographical sense of a community (Cobb, 1975). Our more precise geographic concept of place can be defined *as a fixed physical environment that can be seen completely and simultaneously, at least on its surface, by one's naked eyes* [sic] (Sherman, Gartin, and Buerger 1989, 31)

This new criminological paradigm emerged as a descendent of traditional social disorganization theory and established two new theoretical perspectives concerned with the intersection of crime and place: routine activity theory and crime pattern theory.

Routine Activity Theory

The routine activity perspective posits that crime occurs through the convergence of three elements in space and time: (1) a motivated offender, (2) a suitable target, and (3) the absence of a capable guardian (Cohen and Felson 1979). This perspective rejects the notion that crime is random; rather, the convergence of these elements in time and space enables crime, while the absence of any one of the elements protects against crime (Felson 2000; Sherman, Gartin, and Buerger 1989). The rational decision making of potential offenders is a key element of the routine activity perspective. Rational actors will weigh the potential benefits of a crime against the consequences of apprehension (Cornish and Clarke 1986). Thus, the motivation to commit crime is mitigated by both the attractiveness of potential targets and the presence of elements that might thwart an attempted crime. If a place is not regularly visited by individuals inclined to commit crime, it is much less likely that a crime will occur there. Thus, some places will be consistently crime free, even if they have a surplus of attractive, unguarded targets. Without a supply of individuals motivated to engage in criminal activity, potential targets will remain unmolested, regardless of the presence of a capable guardian.

The routine activity perspective asserts that crime can be prevented by removing opportunity through the use of formal and informal social control vis-à-vis guardianship. In many cases, formal guardians are police officers on patrol in the community (Cohen and Felson 1979; Felson 1987; Rosenfeld 2013). Guardianship can take other forms, as well, including parents, spouses, and teachers (Felson 1987), or place managers such as store clerks, doormen, and security guards (Eck 1994; Reppetto 1976; Sherman 1995). Many place-based crime prevention strategies focus on removing criminal opportunities to commit crime by increasing formal guardianship, such as committing more patrol officers to saturate places with the highest concentrations of calls for service or firearm crimes (Sherman et al. 1998; Weisburd and Telep 2014a).

Tests of routine activity theory largely support the assumptions of the perspective. One of the first studies to test routine activity as a predictor of crime looked at bars, taverns, and lounges in Cleveland, Ohio. The study found that blocks with higher concentrations of these facilities also exhibited higher crime rates (Roncek and Bell 1981). These findings were affirmed for seven index crimes in a follow-up study in Cleveland, Ohio (Roncek and Maier 1991). Block and Block (1995) conducted a follow-up study of taverns in Chicago, finding that crime around liquor establishments is not necessarily correlated with alcohol, but rather the proximity to mass transit stations and other demographic elements of the adjacent blocks. Their analysis concludes that the routine activities of high-crime taverns is the result of the convergence of offenders and victims in a physical space, mediated by the availability of public transportation, which serves as both a supplier of victims and an escape route for offenders (Block and Block, 1995).

The temporal and spatial convergence of the human elements of crime is key to the study of crime concentrations in micro-geographic areas. While some places have physical attributes or social structural characteristics that increase the likelihood of repeat crimes, ultimately crime cannot occur in the absence of a motivated offender and a suitable target. The presence of formal and informal guardians serves to mitigate the likelihood of a criminal event by deterring potential offenders from committing crime in that time and place. Studies have shown that if a crime can be postponed, delayed, or otherwise stopped, the net result is a reduction in the overall number of crimes, without strong evidence that such crimes are displaced to other times, places, or people (Reppetto 1976; Weisburd et al. 2006; Weisburd and Telep 2011). The convergence of victims, offenders, and guardians in the physical environment is the focus of crime pattern theory, which examines the environmental factors that make a place more susceptible to high concentrations of crime.

Crime Pattern Theory

Crime pattern theory is an opportunity perspective that focuses on the physical attributes of places and their role in facilitating or protecting against crime (Brantingham and Brantingham 1981; Brantingham and Brantingham 1981). Similar to the routine activity perspective, crime pattern theory posits that places with high levels of crime tend to have active or potential offenders moving in and around them regularly (Brantingham and Brantingham 1993; Eck and Weisburd 1995b). Paul and Patricia Brantingham first proposed crime pattern theory, and describe the role of the built environment in the creation as crime against the backdrop of routine activities:

> The urban settings that create crime and fear are human constructions, the by-product of the environments we build to support the requirements of everyday life: homes and residential neighbourhoods [sic]; shops and offices; factories and warehouses; government buildings; parks and recreational sites; sports stadia and theatres; transport systems, bus stops, roadways and parking garages. The ways in which we assemble these large building blocks of routine activity into the urban backcloth can have enormous impact on our fear levels and on the quantities, types and timing of the crimes we suffer (P. L. Brantingham and Brantingham 1995, 7).

However, crime pattern theory diverges from routine activity theory in its conceptualization of the role of place. While both perspectives focus on the interactions between people and places, crime pattern theory emphasizes the importance of place design in controlling the movement of people through space. This perspective relies on the assumption of the rational criminal: potential offenders will note the availability of targets, the presence or absence of guardians, and the physical elements of places, and choose locations to commit crime accordingly (Brantingham and Brantingham, 1993; Eck and Weisburd, 1995). According to Brantingham and Brantingham (1995), there are four general types of places in the urban landscape that facilitate crime concentration: crime generators, crime attractors, crime-neutral areas, and fear generators (Brantingham and Brantingham 1995).

Crime generators concentrate people and targets at predictable times, creating ample opportunities for motivated offenders, such as entertainment districts, sports and concert venues, office complexes, and shopping centers. The rhythmic gathering of targets in high volume for brief periods of time makes these places more susceptible to crime during specific days and times when motivated offenders know they have a high likelihood of success. The crowd serves as a protective mechanism for both targets and offenders: while the likelihood of an individual becoming a victim at these places is low, the likelihood of apprehension by formal guardians (i.e. law enforcement or security) for potential offenders is also low, since they can easily slip back into the crowd. It is not necessarily the case that motivated offenders journey to crime generators specifically for the purpose of committing a crime; rather, crime pattern theory posits that these places put sufficient quantities of potential targets or victims in close proximity with motivated offenders through their routine daily activities. During a summer in St. Louis, Busch Stadium and the surrounding entertainment district attracts tens of thousands of baseball fans to a small geographic area that is otherwise modestly populated with daytime professionals and patrons of the bars and restaurants in the vicinity. It is also directly adjacent to a light-rail station ('Stadium'), located in the middle of both lines of service of the St. Louis Metro Transit Metrolink system[4]. Other examples of crime generators abound in St. Louis, including several nightlife and entertainment districts, such as the Delmar Loop, Central West End, Soulard, The Grove, Laclede's Landing, and Washington Avenue.

While crime generators enable opportunistic offenders to take advantage of criminal opportunities in the course of their routine daily activities, *crime attractors* facilitate crime due to their reputation as being target-rich and having relatively low risks of apprehension:

> Crime attractors are particular places, areas, neighbourhoods [sic], districts which create well-known criminal opportunities to which strongly motivated, intending criminal offenders are attracted because of the known opportunities for particular types of crime. Examples might include bar districts; prostitution areas; drug markets; large shopping malls, particularly those near major public transit exchanges; large, insecure parking lots in business or commercial areas…Crimes in such locations are often committed by outsiders to the area. Strongly motivated offenders will travel relatively long distances in search of a target. (When insiders commit crimes in such areas, they may have previously moved to those areas because of their crime- attracting qualities; or, as in many cities, because poor areas are located near commercial areas thus creating many accessible targets near home) [sic] (Brantingham and Brantingham 1995, 8).

[4] The St. Louis Metrolink recorded over 15.7 million trips in 2016. Because Metrolink does not use traditional light-rail turnstiles or any other mechanism (other than security personnel) for preventing un-paid access to platforms, actual ridership is likely to be significantly higher than recorded (Federal Transit Administration 2017).

Where crime generators facilitate crimes of opportunity by bringing the elements of routine activity theory together in specific places largely through chance, crime attractors serve as beacons to motivated offenders in search of potential targets. These similar roles may predispose certain places to become either temporary or chronic crime hot spots. While I am aware of no existing research comparing crime generators and attractors with regards to temporary and chronic hot spots, there is reason to suspect that some type of relationship might exist. Crime generators, for instance, might be more likely to exhibit the characteristics of temporary hot spots, with spikes in crime occurring seemingly at random, tied to historical events (e.g. baseball games or concerts), or following changes in weather. Conversely, the predictable and stable opportunities of crime attractors might predispose them to conditions associated with chronic crime hot spots: consistent, elevated crime concentrations that persist year over year without much of a cooling off period.

Crime neutral areas, by contrast, do not have any of the attributes that facilitate crime in the way of crime generators and attractors. Rather, neutral areas are likely to be relatively crime-free:

> Crime-neutral areas neither attract intending offenders because they expect to do a particular crime in the area, nor do they produce crimes by creating criminal opportunities that are too tempting to resist. Instead, they experience occasional crimes by local insiders (Brantingham and Brantingham 1995, 8).

These areas might also be prime candidates for temporary hot spots; their baseline crime levels are likely to be very low or even crime-free. A small disruption to the social order of such places could result in a significant but short-lived spike in crime, such as a series of related domestic disputes or a small group of juveniles breaking in to cars.

LONGITUDINAL TRENDS IN CRIME CONCENTRATION

This dissertation is primarily concerned with the investigation of how crime is concentrated at micro-geographic places in urban areas over time, and the question of why some places experience stable patterns of crime while others fluctuate between periods of high and low crime. The longitudinal distribution of high-crime places is a relatively new area of research in criminology. The first large-scale study of crime concentration over time examined the longitudinal crime trajectories of street segments in Seattle, Washington over a 14-year period (Weisburd, Bushway, and Lum 2004). Weisburd and colleagues analyzed more than 24,000 street segments, identifying 22 crime trajectory groups, which were consolidated into eight trajectory patterns (Weisburd, Groff, and Yang 2012; Weisburd, Bushway, and Lum 2004). These trajectories include a significant number of crime-free or relatively crime-free streets (as many as 25% of streets had little or no crime across the 16-year study period), areas with stable low crime levels, chronic-high pattern segments, and segments in transition from high-to-low or low-to-high crime levels (Weisburd, Bushway, and Lum 2004). In Seattle, less than 1% of street segments fit the high chronic pattern, yet they accounted for 22% of the crime incidents (Weisburd and Telep 2014a).

The stability of crime concentration over time is not unique to Seattle. In Boston, Braga and colleagues analyzed gun violence incidents at street segments and intersections over a 29-year period (1980-2008), finding very high levels of concentration in two trajectories: stable and volatile hot spots of gun assaults (Braga, Papachristos, and Hureau

2009). The volatile trajectory places comprised less than 3% of street segments and intersections in Boston, yet accounted for over half of all reports of assault and battery with a firearm (Braga, Papachristos, and Hureau 2009). Robbery patterns in Boston were also consistent with those in Seattle: half of all commercial robberies and two-thirds of street robberies during the study period occurred at between 1% and 8% of street segments and intersections (Braga, Hureau, and Papachristos 2011). Andresen and Malleson (2011) analyzed the spatial patterning of crime in Vancouver using calls for service from the Vancouver Police Department in 1991, 1996, and 2001. They found that crime in Vancouver was more highly concentrated at the street-segment level than at larger areal units of analysis. The authors note that 50% of robberies in Vancouver occur at just 6% of street segments, concordant with the results from Seattle and Boston (Andresen and Malleson 2011). Within those chronic robbery hot spots, the researchers found further evidence of spatial concentration, with 50% of crime occurring at just 15% of street segments (Andresen and Malleson 2011, 66). The Vancouver study also analyzed spatial overlap of crime hot spots for different crime types and found that while similar crimes tended to concentrate in the same places (such as theft from motor vehicles, assault and robbery), there did not appear to be any "super chronic" places that were among the most concentrated across numerous crime types (Andresen and Malleson 2011, 67).

The consistency of these findings across cities prompted one researcher to propose a "law of crime concentration" (Weisburd 2015). According to Weisburd, crime is distributed within a "narrow bandwidth" of concentration – about 80% of crime is concentrated at 20% of places, while 50% of crime is found at just 5% of places. These concentrations are stable over time, showing little year-to-year variation (Weisburd 2015). The following section highlights the limitations of using macro-temporal units of analysis in crime and place research and the potential of micro-temporal units of analysis to uncover hidden trends in urban crime concentration.

MICRO-TEMPORAL UNITS OF ANALYSIS

Though there is widespread acceptance of the existence of crime hot spots and the general stability of crime concentration over time, little attention has been given to the temporal unit of analysis used to aggregate crime incidents. Longitudinal research on crime concentration to date has largely relied on annual data to measure the temporal stability of crime hot spots (see Andresen, Linning, and Malleson 2016; Braga et al. 2011; Weisburd et al. 2012, 2004; Weisburd and Amram 2014)[5]. While a limited number of studies have used monthly data to analyze the periodicity of chronic and temporary hot spots, these studies did not calculate monthly distributions of crime, but used monthly counts or monthly averages to identify ‘on’ and ‘off’ periods to detect chronic and temporary hot spots (Gorr and Lee 2012). In a recent longitudinal study of crime hot spots, Wilpen Gorr and Yon Jei Lee identified chronic hot spots using two criteria: (1) street segments in the top one third standard deviation of the distribution of crime events on a kernel density smoothing (KDS) map, equivalent to a z-score of 2.833 or higher; and (2) street segments with at least 250 Part 1 violent crimes over the study period, equivalent to an average of one per month (Gorr and Lee 2012). Chronic hot spots were deemed to be “off” when their monthly concentration of crime was lower than the average crime density for non-chronic hot spots. A follow-up study in 2014 used the

[5] For a recent exception, see Hvastaberman, Sorg, and Ratcliffe 2016.

same detection criteria as Gorr and Lee (2012), testing the effects of hot spot policing on chronic and temporary hot spots. The study found that the best crime-reduction strategy involved supplementing chronic hot spot enforcement efforts with additional policing measures in temporary crime hot spots (Gorr and Lee 2014). These studies highlight the need to better understand the nature of chronic and temporary crime hot spots for the creation of new evidenced-based crime policies and future research on crime and place. While these few studies use monthly crime data to examine crime concentration, they focus more on the predictive power of monthly distributions and average crime levels rather than on the micro-temporal distribution itself.

When data are aggregated to large temporal units (i.e. years), they are subject to the same limitations that led scholars away from macro-geographic units of analysis in favor of micro-geographic places. Annual data may mask important variations in crime concentration at smaller time units, such as months. In a recent study on police activity in Philadelphia hot spots, Groff et al. (2015) note that within chronic hot spots, crime is less stable at the monthly level then it is over years. The authors suggest that for place-based policing to have the most impact on criminal justice policy, more research on temporary hot spots is necessary:

> Hot spot analyses using the previous 1 to 3 years to identify reliably high violent crime places may need to be supplemented with analyses of more recent crime fluctuations over the previous 90 days to ensure the candidates for hot spots are still viable, at least from the perspective of the officers expected to implement the intervention. We must better understand and quantify the short-term temporal stability of crime hot spots in order to choose most accurately the areas for hot spot policing (Groff et al. 2015, 22-24).

Just as scholars have found important variations in the ecology of crime by disaggregating neighborhoods to smaller spatial units, moving from years to months could yield substantively important detail about the stability of high-crime areas. If the data show that a small number of high-crime months can significantly influence annual crime trends, existing ideas about the stability of crime patterns in micro-geographic areas would need to be re-examined.

While a number of theories could be used to inform research on the distribution of crime in micro-geographic areas, the perspectives outlined above – social disorganization, routine activity, and crime pattern theory – best fit the data available in this dissertation. Routine activity and crime pattern theory highlight the fluid dynamics of places and human interactions within them. The degree to which the characteristics of micro-geographic places can change significantly over short periods of time is addressed in the first research question, which examines the distribution of crime over months compared to years. Routine activity theory ties the distribution of violent and property crime to the movement of people in and around risky facilities and the interaction of offenders, targets, and guardians in public space, measured in the current study by the location of drinking establishments and the use of public transportation. Crime pattern theory informs the use of geographic space and how it facilitates or protects against crime. This perspective ties data on land use to the distribution of crime, as well as risky facilities such as payday loan and check cashing businesses.

Social disorganization theory provides the context for examining the relationship between crime and several sociodemographic variables that serve as proximate measures for the structural characteristics of places, and include measures of family structure, income and poverty, residential mobility, age, racial composition, and education. These measures are used to address the second and third research questions, which compare the structural characteristics of places by crime type and temporal stability. The second research question is also informed by the routine activity and crime pattern perspectives. From the routine activity perspective, violent and property crimes are likely to have distinct distributions. Violent crime may be more mobile and tied to people rather than specific places, while property crime is more directly tied to place, since structures themselves are often the targets (e.g. homes, garages, businesses). The temporal stability of crime hot spots, addressed in the third research question, is tied to all three perspectives. Temporary or episodic crime hot spots can be attributed to place attributes emphasized in the opportunity perspectives of routine activity and crime pattern theory. Chronic, stable crime hot spots may experience less drastic change over time, and could be tied to more systemic structural characteristics of place advanced by the social disorganization perspective.

THEORETICAL DRIVERS OF CRIME CONCENTRATION

The theoretical perspectives highlighted above offer some insight into the attributes of places we might expect to be chronic or temporary hot spots. They also offer a set of place characteristics that serve protective functions that might prevent a place from becoming a crime hot spot. This section discusses the physical attributes of micro-geographic places that are posited by social disorganization, routine activity, and crime pattern theory to drive crime concentration in chronic and temporary hot spots, as well as characteristics that keep some places consistently crime free (i.e. ‘cold spots’).

Chronic Hot Spots

Social disorganization and opportunity perspectives of crime posit a range of place characteristics that can be expected to influence the likelihood that a place will be a chronic hot spot. Classic indicators of social disorganization such as low property values, high levels of public assistance, and the presence of physical disorder (e.g. litter, graffiti, broken windows) have been found to be significantly correlated with street segments with chronic crime concentrations (Weisburd, Groff, and Yang 2012; Smith, Frazee, and Davison 2000). Racial heterogeneity and mixed land use have also been cited as primary indicators of chronic crime hot spots, though the impact of these variables on chronic hot spots in the literature is mixed. A recent study suggests that the significance of racial heterogeneity and mixed land use may depend on the spatial unit used (Boessen and Hipp 2015).

Routine activity and crime pattern theory offer more concrete evidence of the role of land use in the creation of chronic hot spots. The role of crime generators and crime attractors in generating criminal opportunities posited by crime pattern theory and the presence of motivated offenders and suitable targets posited by routine activity theory are supported by the empirical literature on chronic crime hot spots. Weisburd et al. (2012) found that street segments fitting the chronic trajectory pattern were associated with several measures of criminal opportunity, including the presence of high-risk juveniles, public facilities located on the block (e.g. libraries, middle and high schools, parks, and hospitals), higher residential populations, and modes of transportation (bus stops and arterial roads).

Generally speaking, these place characteristics are associated with chronic crime hot spots as a function of their stability over time. The aforementioned indicators – property values, physical disorder, property value, public facilities, high-risk juveniles, and transportation avenues – are not expected to vary significantly over time, but rather change gradually. Other opportunity structures, however, are more susceptible to change.

Temporary Hot Spots

The emergence and disappearance of temporary crime hot spots has received significantly less attention in the empirical literature compared to chronic hot spots. Still, plausible theoretical explanations for the existence of temporary hot spots can be identified. Opportunity perspectives posit several place characteristics associated with short-term spikes in crime concentration. Entertainment districts and sports stadia invite a massive influx of both motivated offenders and potential targets to small geographic areas intermittently. Most of the time, these venues are either closed or relatively unpopulated. During games and other cultural events, however, the dynamics of such places can change dramatically, with tens of thousands of people congregating in an environment flush with cash, cars, and alcohol. This can attract motivated offenders from outside the area, as posited by crime pattern theory (Brantingham and Brantingham 1995; Brantingham and Brantingham 2008). The presence of drinking establishments has been tied not only to these districts, but also to residential streets, though the mechanism is the same: the convergence of motivated offenders with suitable targets in an environment conducive to antisocial behavior (Roncek and Bell 1981; Roncek and Maier 1991).

Other forms of land use can also be tied to temporary hot spots. While vacant land has many fewer opportunities than retail and entertainment space, vacant lots and buildings are often host to illicit markets (e.g. drugs and prostitution), which can be packed up and moved to another location at the first sign of unwanted attention by the authorities (Weisburd, Groff, and Yang 2012; Weisburd et al. 2016). Payday lending and check cashing facilities have also been associated with higher levels of violent and property crime (Wilcox and Eck 2011; Kubrin et al. 2011).

Cold Spots

Unlike chronic and temporary hot spots, crime free places, or ‘cold spots’, are the default status for microplaces. Weisburd et al. (2012) find that over 80% of street segments in Seattle were essentially crime free throughout the 16-year observation period. This finding has been replicated in cities across the United States and abroad (Weisburd and Amram 2014; Weisburd 2015; Weisburd et al. 2016). The mechanisms that protect against crime in these places are equally important to understand the complete picture of crime concentration. While there is virtually no empirical or theoretical literature directly focused on crime free places, there is abundant evidence of their existence and the characteristics that define them.

Street segments in stable, working- and middle-class residential neighborhoods with few high-risk juveniles, not adjacent to arterial roads, without bars and other public facilities are the least likely to become crime hot spots. This picture is not meant to suggest that such places are completely removed from the public sphere in social deserts. At the micro scale, such places can be within walking distance of shopping and entertainment districts, schools, bars and restaurants, public transportation, and major thoroughfares. Aside from residential areas, there are other place characteristics that protect against crime. Crime pattern theory suggests that large institutions not generally open to the public limit crime opportunities through the use of defensible space and formal and informal guardianship. Large industrial and commercial spaces will generally have the resources to employ consistent, round-the-clock security, secured exterior access, manned parking lots and structures, and thus have few suitable targets. Similarly, streets with high-end residential structures, such as luxury apartments and condominiums, will be more capable of guarding against would-be offenders than areas with single-family or small multi-family structures. Put simply, in the absence of place characteristics associated with chronic and temporary hot spots, places are likely to be relatively crime-free, as appears to be the case given the consistent evidence that in cities of varying size, region, and structure, the clear majority of places can be categorized as cold spots.

This chapter has presented the relevant theoretical and empirical literature on crime concentration and the stability of crime hot spots. The next section discusses the setting, data, methods, and analyses used in the current study.

CHAPTER THREE: DATA AND METHODS

This chapter discusses the data and research methods to be used to answer the research questions, provides sources and descriptive statistics for all variables, and lays out the analytic plan for examining the data.

SETTING

The setting for the current study – the independent City of St. Louis, Missouri – is a medium sized Midwestern city situated on the Mississippi River near the geographic center of the United States. Once the fourth largest city in the United States, St. Louis City has experienced massive depopulation since the middle of the 20th century, when the city reached its peak population of 857,000 (estimate from the 1950 decennial census)[6]. As of the 2010 census, the city had a population of approximately 319,000 spread over 64 square miles. The city is 46% white and 49% black, with 5% of the population identifying as mixed race, Asian, or Hispanic/Latino. The foreign-born population of St. Louis is 6.8%. Approximately 44% of St. Louisans own their home, with a median value of owner-occupied housing units of $118,600. Slightly over 80% of residents have a high school diploma or higher, and approximately 30% hold a bachelor's degree or higher. Median household income is $34,900, and nearly 30% of the city's residents live in poverty (US Census Bureau 2010).

St. Louis has struggled with high crime for many years. Since the growth of the suburbs starting in the 1950s, the population has steadily declined as over half a million

[6] The dissertation refers specifically to the City of St. Louis, which is not to be confused with the St. Louis Metropolitan Area. While the area commonly referred to as "St. Louis, Missouri" covers several hundred square miles and more than one million residents, the City of St. Louis comprises only the urban core of the metropolitan area, covering only a few dozen square miles and a population of roughly one third that of the county.

residents moved across the border into the various municipalities of St. Louis County[7]. This resulted in massive depopulation of the city, especially in the predominantly black North St. Louis, which continues to struggle with concentrated disadvantage, high poverty, an underfunded and underperforming public school system, many vacant and abandoned buildings, and much higher levels of violent crime than other areas of the city. St. Louis is one of the few major U.S. cities that is not situated within a parent county. The "Great Divorce" that separated St. Louis City from St. Louis County was passed by ballot initiative by residents of the County (including City residents) in 1876 (Cassella 1959). This divide has been partially blamed for St. Louis City's high crime rate, since the City comprises only the urban core of the area colloquially referred to as "St. Louis", with most of the land and residents living in St. Louis County.

DATA

Data for the dissertation come from a variety of public repositories. Crime incident data were provided by the SLMPD as part of the ongoing St. Louis Public Safety Partnership, founded in 2014 via a memorandum of understanding between the Office of Mayor Francis Slay, Jr., The SLMPD, and the University of Missouri – St. Louis (UMSL). While the SLMPD provided these data, it is important to note than all the crime incident data used in the dissertation are publicly available for download from the department's website: http://www.slmpd.org/Crimereports.shtml (URL stable as of April 27, 2018).

[7] St. Louis County is comprised of 90 independent municipalities and 10 unincorporated census areas, not including the City of St. Louis ("Municipalities of St. Louis County" 2017).

Data for seven UCR Part 1 index crimes (homicide, aggravated assault, rape, robbery, larceny, burglary, and motor vehicle theft) were obtained for a five-year period from January 1, 2010 through December 31, 2014[8]. The distribution of index crimes in St. Louis is consistent with national averages for large cities: about 80% of UCR Part 1 index crimes are property offenses, while 20% are violent. St. Louis mirrored the national average on several crime types during the study period; homicide (0.5%), rape (0.7%), robbery (6.3%), and burglary (18.9%), were nearly identical to the national averages for large cities, differing by less than 1% of the total. St. Louis had a lower proportion of larceny (49.1%) compared to the national average (54.7%), but slightly higher levels of aggravated assault (12.1% to 9.3%) and motor vehicle theft (12.5% to 10%). Table 3.1 displays annual crime data by type for St. Louis (national data omitted).

[8] For detailed descriptions of each crime type, see Appendix A.

Figure 3.1. St. Louis City and St. Louis County Boundaries

Table 3.1. FBI UCR Part 1 Offenses, 2010-2014

Year	Homicide	Rape	Robbery	Assault	Violent	Burglary	Larceny	MVT	Property*	Total
2010	150	305	2,029	3,640	6,124	6,841	15,822	4,435	27,098	33,222
2011	123	180	2,006	3,382	5,961	7,056	14,722	3,437	25,215	31,176
2012	123	200	1,667	3,398	5,388	5,042	12,730	3,463	21,235	26,623
2013	127	266	1,392	2,984	4,769	4,346	12,441	3,194	19,981	24,327
2014	162	194	1,456	4,204	4,923	4,204	11,389	3,032	18,625	23,548
Total	685	1,145	8,550	16,515	26,895	27,489	67,104	17,561	112,154	139,049

* Arson omitted.

STRUCTURAL COVARIATES

Data for structural covariates come from three sources: (1) the 2010 Decennial Census, (2) the American Communities Survey (ACS) Five-Year estimates for 2010-2014, and (3) the St. Louis Open Data Portal. Census data are available at the block-group level and are available for a variety of structural covariates. The ACS provides a more limited scope of data at the census block level, and include information on age, the number of housing units, occupancy status, racial heterogeneity, and household structure. The St. Louis Open Data Portal is a repository of publicly available municipal data for the City of St. Louis and provided data on land use and the locations of fringe banking establishments (i.e. payday lenders and check cashing businesses) and drinking establishments. In multivariate analyses, the following structural variables are included:

Family Disruption

Studies of neighborhood structure and crime have consistently found that family disruption is among the most important structural characteristics for explaining differences in crime. Messner and Sampson (1991) found that controlling for female-headed households mitigated the effects of other gendered variables, such as the ratio of males to females (Messner and Sampson 1991, 705). This measure is calculated on the percentage of female-headed households with children ages 18 and under at the census block level.

Residential Instability and Place Attachments

Studies have shown that higher rates of home ownership, fewer vacant buildings, and long-term residency increase place attachments and residential stability, both of which have been associated with lower crime levels in urban areas (Sampson, Raudenbush, and Earls 1997; Brown, Perkins, and Brown 2003). In the current study, place attachments and residential stability are measured using three variables: (1) the percentage of residents who rent their home, (2) the number of vacant buildings, and (3) the number of residents who have lived at their current address less than a year (a measure of residential mobility). It is expected that places with fewer homeowners, more vacant buildings, and higher residential mobility will be more likely to experience repeat crime incidents, making them more likely candidates for crime hot spots. Data for these variables come from the ACS 2014 5-year estimates at the census block group level.

Racial Heterogeneity

A key tenet of social disorganization theory is that places with more diverse populations will have lower levels of community cohesion, leading to higher community social disorganization and higher levels of criminal victimization and offending (Shaw and McKay 1942; Bursik and Webb 1982; Sampson and Groves 1989a). In St. Louis, racial heterogeneity is the most appropriate metric for measuring this structural attribute of place, since the majority of residents identify as either black (49.5%) or white (47.7%). This measure is calculated using the percentage of residents in census blocks that identify as black using the ACS 2014 5-year estimates.

Age

Research on the age of offending has consistently shown that for the majority of offenders, the criminal career is limited to between the ages of 15-24, and that both criminal victimization and offending drop dramatically after age 50 (Farrington 1986;

Nagin, Farrington, and Moffitt 1995; Sampson and Laub 2003). Two measures are used to control for the age of the population at the block group level: (1) the percentage of residents ages 15-24 and (2) the percentage of the population age 50 and older. Based on the existing literature on age, victimization, and offending, it is expected that places with larger youth populations will experience more frequent crime incidents, while those with older populations will have lower crime rates.

Education

Prior studies have shown that educational attainment and crime are closely correlated. Researchers have examined the link between education and crime, finding that the likelihood of committing property and violent offenses decreases as educational attainment increases (Lochner and Moretti 2004; Lochner 2007), and that completing high school has a significant negative impact on crime and incarceration rates (Groot and Maassen van den Brink 2009). This is measured in the current study using the 2014 ACS 5-Year estimates for the percentage of census block group residents whose highest formal education culminated in a high school diploma or G.E.D.

Poverty

Sociological studies of crime have long focused on poverty as a leading predictor of crime and social disorder (Sampson 2000). Even as other social processes were examined and found to be significantly correlated with elevated crime rates, controlling for poverty, studies showed that living in areas with concentrated poverty led to negative outcomes on individual and community rates of offending. In a randomized housing mobility experiment, researchers found that relocating families from high- to low-poverty neighborhoods reduced juvenile involvement in violent crime (Ludwig, Duncan, and Hirschfield 2001). Other recent tests of the relationship between poverty and homicide have found consistent, positive effects indicating that higher levels of poverty are associated with higher crime rates (Hipp and Yates 2011; Pridemore 2008). A measure of poverty in the current study is calculated using the percentage of households that live at or below the poverty threshold at the census block level as reported in the 2014 ACS 5-Year estimates.

Public Transportation:

Recent ecological studies have found that regular use of public transportation can put people at an increased risk of victimization, especially at bus stops (Ariel and Partridge 2017). From the empirical literature available, it is reasonable to hypothesize that those who frequently use public transportation are more likely to experience criminal victimization than those with access to alternate modes of transportation. In places where a large number of people regularly access public transportation, there will be a consistent supply of suitable targets for opportunistic offenders. At the census block level, places with higher rates of public transportation ridership are theoretically likely to have crime hot spots related to bus stops. This variable is measured in the current study using the percentage of census block residents who use public transportation as their primary mode of transportation.

Risky Facilities

Numerous crime and place studies have examined the impact of so-called ‘risky facilities’ as attractors of crime (Eck, Clarke, and Guerette 2007). Two types of risky facilities in particular have been found to be positively associated with crime hot spots:

fringe banking establishments and on-premise drinking establishments (i.e. bars, restaurants, and nightclubs) (Kubrin et al. 2011; Roncek and Bell 1981; Roncek and Maier 1991). In the current study, two measures of risky facilities are calculated using data from the St. Louis City Open Data Portal: (1) the number of licensed payday loan facilities located on each street segment and (2) the number of establishments holding a current or recently-expired liquor license.

Hospitals

Due to mandatory reporting laws that require medical facilities to disclose serious injuries to law enforcement, the presence of a hospital on a block may significantly increase the apparent crime concentration of an otherwise crime-free street segment. A binary measure is included to control for this phenomenon by indicating whether a street segment has a hospital located within its boundary (1) or not (0).

Land Use

While the study of crime and place is dominated by examinations of small areal units of analysis to study the distribution of crime, recent research has emphasized the need to consider the context of the broader geographical environment. For example, Boessen and Hipp (2015) found that including data on census block and block group land use significantly altered the results of a series of commonly used structural attributes (e.g. racial heterogeneity, concentrated disadvantage, economic inequality, residential mobility, vacancy, and age) at the micro-geographic level. As the authors note, the inclusion of broader measures of physical space in micro-level studies of place is consistent with foundational theoretical work that stimulated the emergency and growth of the criminology of place, such as crime pattern theory (Brantingham and Brantingham 1981; 1993). In the current study, ten land use classifications are included in a categorical control variable at the street segment level. Data for this measure come from the City of St. Louis Strategic Planning Initiative, and the categories and definitions are those provided by the City. Land use categories are as follows:

- Business/Industrial Preservation Areas (BIPA): areas that have experienced a decline in economic activity from an earlier peak where new development is encouraged, such as vacant warehouses and large tracts of undeveloped land near major roadways, railroads, or rivers.
- Industrial Preservation and Development Areas (IPDA): areas with stable, major commercial and industrial business locations, such as the Anheuser-Busch Brewery.
- Neighborhood Commercial Areas (NCA): commercial 'strips' that serve nearby neighborhoods; these areas are primarily located along major thoroughfares, and include locations such as South Grand Blvd in Tower Grove, Shaw Blvd in The Hill, Euclid Ave in the Central West End, and Manchester Ave in The Grove.
- Neighborhood Preservation Areas (NPA): existing residential neighborhoods that are designated only for new residential infill and corner commercial businesses that cater to and are integrated in the immediate neighborhood. These areas are by far the most common in the city, with over seven times as many NPA parcels as the next largest classification (6,977 to 980 NCA parcels).
- Neighborhood Development Areas (NDA): Areas with large numbers of vacant lots and abandoned buildings; heavily concentrated in North St. Louis.

- ❖ Opportunity Areas (OA): underutilized areas in transition; open to all proposed development including residential, retail, commercial, industrial use.
- ❖ Regional Commercial Areas (RCA): major retail outlets serving large areas of the city; examples include large ‘big-box’ stores such as Home Depot on S. Kingshighway, Hampton Village, and Loughborough Commons.
- ❖ Recreational/Open Space Preservation/Development Areas (ROSPDA): encompasses existing parks, open spaces, and recreational facilities as well as areas that are available for similar development, such as community gardens.
- ❖ SMUA: primarily concentrated in Downtown St. Louis and the central corridor, these areas have unique mixes of land use that should be preserved.
- ❖ Institutional Preservation and Development Areas (IPDA): areas with significant institutional use and heritage, such as the Basilica Cathedral, Saint Louis University, and Washington University Medical Center.

It is important to note that while the dependent variables are based on monthly crime counts, data for the independent variables are only available at the annual level. This is an unfortunate reality of studying issues at very small geographic units of analysis. Since most of the data used to construct the independent variables comes from the United States Census Bureau, sub-annual data is not available. Future studies may be able to overcome this limitation, given sufficient resources and partnerships with local agencies, but such efforts are beyond the scope of this dissertation.

SPATIAL UNITS OF ANALYSIS

Street Segments

As described in Chapter 2, crime and place studies typically use the street segment to aggregate crime incidents or calls for service. A street segment (also known as a block or face block) consists of both sides of a street between two cross-streets. In St. Louis, crime incidents are recorded by police officers using either an address (e.g. '2101 S Grand) or two intersecting streets (e.g. 'Grand / Arsenal'). There are 16,056 street segments in the City of St. Louis, with an average length of approximately 400 feet. Of these, 1,950 do not have address information attached; these places are mostly interstate highways, bridges, and their associated on and off ramps. Since crime incidents cannot be geocoded to these locations, they are excluded from the study, leaving 14,106 street segments in the data set. While some studies include incidents or calls tied to intersections in addition to street segments (e.g. Braga et al. 2011), most studies have excluded crimes incidents at intersections because they cannot be attributed to a single street segment (see Gill, Wooditch, and Weisburd 2016; Telep, Mitchell, and Weisburd 2012; Weisburd et al. 2006; Weisburd et al. 2012). The data used in the current study had very few intersection crimes (fewer than 6% of all incidents were coded to intersections) and they were thus excluded from the data. An additional 963 segments are located in census blocks with no population; these places are included in calculations of crime concentration and descriptive results but are excluded from multivariate models due to missing covariate data (see Table 3.9).

Census Blocks and Block Groups

Covariate data for this study are taken from the American Communities Survey (ACS) and the Decennial Census. Census blocks and block groups are administrative geographic units used by the U.S. Census Bureau to conduct surveys of the population on a wide variety of topics, include family size and structure, household income, racial and ethnic background, transportation, and hundreds of other variables of interest. For this study, traditional criminogenic predictors are taken from the census block when available, and the census block group when data is unavailable at the block level. While neither the block nor the block group are ideal units for studying crime at the micro-geographic level, they are nonetheless the most readily available, and in many cases are the only available data. Prior studies have used census blocks and block groups extensively, stemming from the fact that sociodemographic data cannot be obtained at the street segment level (e.g., Roncek and Bell 1981; Gonzales, Schofield, and Hart 2005; Ratcliffe 2004; Weisburd et al. 2015).

In the City of St. Louis, there are 8,988 census blocks nested within 360 block groups. Census blocks in St. Louis are small: the average area is just over 17,000 square feet, or approximately 400 feet per side (the average length of a St. Louis City street segment). Because of their small size, census blocks are the best unit with data available to study correlations between crime and theoretical covariates at the street segment level. Using an imputation technique described by Kim (2016), census block covariate data are assigned to street segments by taking the simple average of all blocks that share a boundary with each street segment. This technique has been shown to be an effective way to impute block-level data to street segments. In his recent study detailing the procedure, Kim (2018) compares imputed block data with address-level data obtained for three cities in California. Kim found that address data aggregated to the street segment were indistinguishable from imputed block data using the simple average technique (Kim 2018). Descriptive statistics for covariates are displayed in Table 3.3.

Geocoding Crime Incidents. A key component of all studies of crime and place is the ability to accurately match crime incidents to units of place. Low match rates can lead to spatially biased data, especially if the unmatched incidents are not randomly distributed. To address this issue, Ratcliffe (2004) identified a minimum geocoding rate of 85% success to serve as a guideline for the study of crime and place. This threshold has become the de-facto standard in the field and is cited in nearly all recent studies of micro-geographic crime distribution. In the current study, crime data were geocoded using the ESRI ArcMap 10.3.1 geospatial mapping package with an address locator provided by the SLMPD[9].

In the data provided by the SLMPD, there were 144,933 reported crimes over the five-year observation period. This number differs slightly from the FBI UCR published statistics, which put the number of reported index crimes at 144,235 – a difference of less than 0.5%. The discrepancy is likely due to some crimes being flagged as ‘unfounded’ after data were collected. Using the address locator provided by the SLMPD, I was able to successfully geocode nearly 99% of crime incidents (N = 143,625), well above the minimum acceptable hit rate of 85% posited by Ratcliffe (2004). The unmatched data do

[9] Emily Blackburn – manager of the SLMPD Crime Analysis Unit – provided valuable assistance in the early stages of the dissertation, including access to the address locator optimized for St. Louis City streets. An updated version of the address locator can also be downloaded from the city’s website: https://www.stlouis-mo.gov/data/.

not differ in type or year from the matched data and appear to be random. Geocoding results are displayed in Table 3.3.

Street segments were then joined to geocoded crime incidents using a street centerline shape file provided by the City of St. Louis[10]. The ESRI ArcMap *spatial join* function was used to match each incident with the street segment it is located on. Of the successfully matched incidents, 5,884 (4.1%) were tied to intersections, and were dropped from the data set since they cannot be tied to a street segment (see Gill, Wooditch, and Weisburd 2016; Telep, Mitchell, and Weisburd 2012; Weisburd et al. 2006, 2012)[11]. Prior studies have used buffers around street segments to create polygons representing intersections where the buffers overlap (Andresen, Linning, and Malleson 2016). While this technique can marginally improve data integrity and avoid spatial bias, the small number of serious crimes in St. Louis that occur at intersections made this procedure unnecessary.

After crime incidents were geocoded and joined to the street centerline file, binomial monthly variables were generated based on the date each incident occurred (i.e. m1, m2, …, m60). Each incident can be coded to only a single month: for example, if a crime occurred on July 4th, 2010, the variable corresponding to July 2010 (m7) would receive a value of 1, with all other monthly variables coded as 0. Data were then aggregated in SPSS using the unique street segment id as the key variable. Aggregated

[10] All GIS data files are publicly available for download at http://data.stlouis-mo.gov/downloads.cfm.
[11] An additional 2% of crime incidents occurred at intersections previously mentioned as excluded due to being located on highways, on ramps, and off ramps.

monthly crime counts serve as the basis for determining if a segment was hot (or not hot) for each month.

MISSING DATA

Fortunately, there is very little missing data on the dependent variables, and relatively little missing data on independent variables. As previously mentioned, 1,950 street segments in the centerline shape file do not have data in the address fields, so crime incidents could not be geocoded to these places. This resulted in a loss of 6,212 incidents, or 4.3% of all crime incidents. An additional 987 segments were located in census blocks with zero population and are thus missing data on all block and block-group level structural covariates and multivariate analyses.

Table 3.2. Descriptive Statistics for Structural Covariates

Independent Variables	N	Mean	Std. Dev.	Min	Max
fhh	13,136	16.38	17.29	0	100
rent	13,143	33.60	29.04	0	100
black	13,143	36.67	38.15	0	100
15-24	13,143	5.63	9.17	0	100
50+	13,143	19.34	21.57	0	100
vacant	13,143	32.67	30.05	0	271
pubassist	13,143	4.41	5.45	0	42.0
resmobil	13,143	33.29	14.83	0	78.0
poverty	13,143	30.95	19.55	0	86.0
education	13,143	25.37	11.82	0	65.0
enrollment	13,143	26.50	12.48	0	86.0
bars	13,143	.061	.381	0	10
hospitals	13,143	.001	.028	0	1
payday	13,143	.002	.066	0	3
land use[12]					
BIDA	355	.01	.05	$1x10^{-5}$	.60
BIPA	382	.02	.04	$4x10^{-4}$	.51
IPDA	758	.004	.009	$5x10^{-4}$	.12
NCA	980	.002	.002	$1.7x10^{-4}$	.02
NDA	893	.002	.002	$5.9x10^{-4}$	.03
NPA	6,977	.003	.003	$2x10^{-5}$	.05
OA	348	.004	.008	$4.4x10^{-4}$	.09
RCA	64	.01	.02	$7.0x10^{-3}$	.09
ROSPDA	261	.03	.14	0.0	1.96
SMUA	418	.004	.007	$4.0x10^{-4}$	.08

[12] Land use statistics report the area by classification in square miles.

Table 3.3. Geocoding Results: Matched Crime Incidents, 2010-2014

Year	Match (%)	Violent (%)	Property (%)	All Crime
2010	99.0	6,124 (18.4)	27,098 (81.6)	33,222
2011	99.1	5,691 (18.4)	25,215 (81.6)	30,906
2012	98.5	5,338 (20.0)	21,235 (80.0)	26,623
2013	98.7	4,769 (19.3)	19,981 (20.7)	24,750
2014	98.8	4,923 (20.9)	18,625 (80.1)	23,548
Total	99.1	26,895 (19.3)	112,154 (80.7)	139,049

Table 3.4. Street Segments and Reported Crime Incidents by Crime Type

	Street Segments	Property	Violent	All Crimes
Total	16,056	111,020	26,555	137,575
With valid address data	14,106	110,757	26,491	137,248
With no missing data	13,143	103,718	24,737	128,455

CALCULATING CRIME CONCENTRATION

To differentiate crime hot spots from non-hot places, a measure must be created to determine which places are in the top 5% of the distribution each month. Because UCR Part 1 crime data are sparse compared to other metrics used for calculating crime concentration (e.g. all crime reports or calls for service), raw crime counts are transformed using standardized crime distributions at street segments, so that each month has a mean of 0 and a standard deviation of 1 (i.e. z-scores).

Standardized values are preferable to raw crime counts for numerous reasons. First, they provide an empirical basis for selecting high-crime months. Rather than choosing an arbitrary cutoff point, an empirically-based threshold can be established. Standardized scores also have the benefit of naturally dealing with the issue of seasonal variation in crime levels. Prior longitudinal studies have addressed seasonality by aggregating crime at the annual level, where seasonal variation becomes moot. Analyses at the micro-temporal level, however, must account for such variation across months. Using standardized values, each month has a unique cutoff point for determining if a place is hot, based on distribution of crimes in each month. So, while during a winter month a segment could cross the hot spot threshold with just a few crime incidents, it might take as many as seven or eight crimes for the same place to become hot in a summer month. Table 3.6 displays a sample of this process for the first three months (January-March 2010) for 20 of the highest-crime places over the study period. These data show the unique distributions in each month. Looking at the violent crime data, two incidents in month 1 correspond to a z-score of 0.656, while the same number of crimes in month 3 corresponds a z-score of 0.909. The same concept holds for the property crime data, albeit at a different scale due to the higher frequency at which property crimes occur. It is important to note that these standardized distributions were created excluding crime-free areas. As discussed below, there are both methodological and practical reasons for excluding crime-free areas.

The Issue of Crime-Free Places

There is an ongoing debate in the crime and place literature regarding the inclusion of crime-free areas when calculating crime concentration in micro-geographic places. Most longitudinal studies of crime concentration to date have included crime-free street segments when calculating crime distributions and identifying crime hot spots.[13] However, recent studies testing the propositions of Weisburd's law of crime concentration have raised important questions regarding the inclusion of crime-free areas when calculating crime concentrations. Levin, Rosenfeld, and Deckard (2017) tested the impact of crime-free places on the observed concentration of violent and property crimes

[13] See, for example, Braga, Papachristos, and Hureau 2009; Braga, Hureau, and Papachristos 2011; Weisburd, Bushway, and Lum 2004; Andresen, Curman, and Linning 2016; Wheeler, Worden, and McLean 2015; Groff, Weisburd, and Yang 2010.

in St. Louis over a 15-year period (2000-2014) by comparing Poisson simulated and observed crime counts, both including and excluding crime-free places. They found that when crime-free places are included, crime appears to be more densely concentrated compared to calculations that exclude crime-free street segments (Levin, Rosenfeld, and Deckard 2017).

Similar results were found by Andresen using an analysis technique known as the 'spatial point pattern test' (Andresen 2009) to compare property crime density in Vancouver over an 11-year period. The spatial point pattern test was developed to compare the degree of similarity between two or more distinct spatial point patterns, such as clusters of crime. The test is based on the nonparametric Monte Carlo simulation and is particularly useful for comparing spatial patterns with different numbers of points and identifying clusters of events (e.g. crimes) with similar patterns in different spatial areas, such as urban neighborhoods or other large geographic units (see Andresen 2009). Andresen found that when crime-free places are included, crime concentration appears to be stable and increasing, even while crime decreased over the study period. When crime-free places are excluded, however, crime appears to be less concentrated; that is, "when one considers only the places in which crime is occurring, crime is becoming even more dispersed…so there is less crime, it is occurring in fewer places, with within those places the distribution of criminal events is becoming more evenly distributed" (Andresen, Linning, and Malleson 2017, 271–72). Hipp and Kim (2017) also take up this issue in their analysis of the stability of crime concentration across cities, noting that traditional measures of crime concentration (i.e. using annual data at street segments and including crime-free areas) overestimate the level and stability of crime concentration across different cities. Since inter-city stability is a cornerstone of the law of crime concentrations and is influential in crime and place research, it is vital that this issue be addressed.

The issue of crime-free places is particularly salient in the current study due to the shorter time units used to calculate crime concentration, which exacerbate the sparse data problem prevalent in studies based on reported crime data. In studies that examine the nature of crime hot spots (such as this dissertation), the argument can be made that including crime-free areas is illogical, since places that are consistently crime-free are unlikely candidates to become temporary hot spots and cannot be chronic hot spots by definition. Excluding crime-free areas can significantly alter the level of observed crime concentration, which carries important methodological and practical implications for studying and addressing crime concentration in urban areas.

The impact of including or excluding crime-free areas is highlighted in the current study in the descriptive analyses. In a zero-inflated data set (i.e. one that includes crime-free areas), the mean number of incidents in a given month is lowered substantially, meaning that a single crime can correspond to a z-score above the cutoff threshold. To test the potential impact of crime-free places on the current study, crime-free segments which were originally coded as missing were re-coded as zero, and the standardized distributions re-calculated. Tables 3.7 and 3.8 replicate the data in Table 3.6 for violent and property crime (respectively), comparing the standardized distributions when crime-free areas are included (zeros-in) and excluded (zeros-out). In line with the existing literature, including crime-free areas increases both the apparent crime concentration and its stability over time. This effect is more pronounced for violent crime due to the lower base rate of offending. As shown in Table 3.7, nearly all violent crime segments were affected by the change in the distribution, which resulted in an increase in the number of months each place was hot (highlighted in blue). By contrast, slightly more than half of the segments in the property crime sample experienced a change in the number of hot months (highlighted in green, see Table 3.8). From these data, we can see the immediate impact of including crime-free areas: by lowering the mean number of crimes per month, more segments meet the cutoff threshold for inclusion as hot spots, resulting in more hot months per segment when compared to results calculated without crime-free places. In some cases, a single crime was sufficient to elevate a segment to hot spot status (particularly in low-crime months when the mean was already small). While it could be argued that a single serious crime such as a homicide or aggravated assault with a firearm *should* make a place a temporary hot spot, in the context of the existing literature, a single crime is necessary, but not sufficient. Based on these analyses, the decision to exclude crime-free areas appears to be the best course of action. However, to fully examine the impacts of this issue, the subsequent analyses will be conducted for two versions of the data: one including crime-free places and one excluding them.

In total, excluding crime-free segments reduced the total number of hot segment-months by nearly 95%, from 20,470 to 1,148 for violent crime and 67,279 to 3,925 for property crime over the five-study period[14]. Another way to conceptualize this methodological choice is to say that including crime-free segments increases the number of high-crime segment-months by over 1,700%[15]. While these numbers suggest that

[14] $\left(\left[\frac{1{,}148}{20{,}470}\ x\ 100\right] - 100 = \ 94.39\%\ ;\ \left[\frac{3{,}925}{67{,}279}\ x\ 100\right] - 100 = 94.17\%\right)$
[15] $\left(\left[\frac{20{,}470}{1{,}148} x\ 100\right] = 1{,}783.10\%\ ;\ \left[\frac{67{,}279}{3{,}925} x\ 100\right]\ = 1{,}714.11\%\right)$

excluding crime-free places is likely the preferred method for calculating crime concentration, it is important to fully examine this issue throughout the analyses. Therefore, in the following chapters, results from the multivariate regression models will be presented and discussed using two versions of the data: one including zeros representing crime-free segment-months, and one with zeros coded as missing.

DESCRIPTION OF MULTIVARIATE MODELS

To examine the relationship between structural characteristics and crime concentration at street segments in St. Louis, three regression models are used. First, a logistic regression model is fitted to a binary outcome variable that indicates whether a place was hot at any point during the study period. Logit models are commonly used for examining social data with binary outcome variables (Long 1997). This model compares places that were hot at least one month to those that were either not hot or were crime-free (see Table 3.6). Positive coefficients indicate that higher values of the variable are associated with places that experienced a hot month.

To estimate the impact of structural variables on the *frequency* of hot months at street segments, the negative binomial regression model is used. The negative binomial model is commonly used for examining the relationship between fixed effects covariates and continuous (count) outcomes (Allison and Waterman 2002). The negative binomial model is appropriate for data with over-dispersion, while the zero-inflated negative binomial model is particularly well-suited for data sets with large numbers of zeros, which is used in the model where crime-free months are coded as 0. The negative binomial model is fitted to the standardized data set with zeros coded as missing.

Repeated Events Survival Models

Survival analysis – also referred to as event history or duration analysis – is a form of multivariate data analysis used for examining the time it takes for a specific event to occur or re-occur (Cleves, Gould, and Gutierrez 2004). While the use of survival models in criminology is rare, it is not unprecedented. Bowers, Lab, and Johnson (2008) used a survival model to study the time to victimization following a target-hardening program in the UK. A more recent study by Koper (2013) examined risk factors related to firearm trafficking using survival analysis to estimate the likelihood that guns sold in Baltimore will be used in a crime or obtained by someone legally barred from possessing a firearm. Unlike other types of regression analyses, survival models are designed to take in to account the duration of time a subject survived until an event occurred, such as a mechanical failure or the onset of disease. Analysis of time-to-event data using traditional linear regression analyses (such as OLS) is problematic due to the assumed normal distribution of the residuals (Cleves, Gould, and Gutierrez 2004). The problem is further illustrated by Cleves et al. (2004):

> The simple fact is that the assumed normality of time to an event is unreasonable for many events. It is unreasonable, for instance, if we are thinking about an event that has an instantaneous risk of occurring that is constant over time. In that case, the distribution of time would follow an exponential distribution. It is also unreasonable if we are analyzing survival times following a particularly serious surgical procedure. In that case, the distribution might have two modes: many patients die shortly after the surgery, but if they survive, the disease might be expected to return.

Table 3.5. Crime-Free, Low-Crime, and High-Crime Places by Crime Type

Crime Type	N_{total}	N_{hot}	$N_{low\text{-}crime}$	$N_{crime\text{-}free}$
Violent	13,143	847	7,324	4,972
Property	13,143	1,393	7,789	3,961

In the current study, the assumed normality of the distribution of time is invalid for numerous reasons. First, time to an event must always be positive (Cleves, Gould, and Gutierrez 2004). It is nonsensical to have negative time until something happens, therefore time cannot be normally distributed. The nature of the events under investigation also poses a problem to the normality assumption of linear regression. In the current study, events are defined by a place's crime level relative to all other places that had at least one crime that month: an event occurs whenever a place has enough crime to push it into the top 5% of the distribution of places with at least one crime that month. This event definition further violates the normality assumption, since only a small fraction of all subjects can experience an event (i.e. be 'hot') each month.

All survival analyses operate under the conditions of two functions: the survivor function, $S(t)$, and the hazard function, $h(t)$. Both functions are described in terms of the time to a failure event, T. The survivor function is essentially the reverse cumulative distribution function of T, or the probability that a subject does not fail prior to t (Cleves, Gould, and Gutierrez 2004):

$$S(t) = 1 - F(t) = \Pr(T > t)$$

The survivor function is equal to one at t = 0 and decreases toward zero as t approaches infinity. The hazard function $h(t)$ (also known as the conditional failure rate) represents the rate of failure at each time interval t and is “the (limiting) [sic] probability that the failure event occurs in a given interval, conditional upon the subject having survived to the beginning of that interval, divided by the width of the interval” (Cleves, Gould, and Gutierrez 2004, 7). The hazard function is defined as:

$$h(t) = \lim_{\Delta_t \to 0} \frac{(\Pr(t + \Delta t > T > t | T > t))}{\Delta \mathrm{t}} = \frac{f(t)}{S(t)}$$

Survival models can also be used to estimate correlations between the independent variables of interest and an outcome variable (i.e. the event) that has repeated occurrences over a given time period (Box-Steffensmeier and Jones 2006). Several competing models for repeated events analysis are popular in the biomedical, political, and social sciences. Generally, these models are organized into two categories: unordered events and ordered events. In unordered event models, all possible events are at risk from the start of the study, and can occur in any order, such as a patient testing positive for a disease given a series of blood work panels (Dickman et al. 2012; Cleves, Gould, and Gutierrez 2004). These models assume that each event is independent of subsequent events, and thus occur in a random order. Ordered events, on the other hand, assume that subsequent events are related to the first event; the second event cannot occur before the first event was observed:

> …the issue of repeated events is one of dependence: second and subsequent events are likely to be influenced by, and therefore different from, first events. As a result, analyses that treat repeated events as independent, when in fact they are not, run the risk of yielding misleading results (Box-Steffensmeier and Zorn 2002, 1071).

In the current study, only models of ordered events are considered, since a place cannot be at risk of a second or subsequent hot month until it has experienced its first hot month. The most commonly used survival model in the political and social sciences is the Cox proportional hazards model (Cox 1972), an extension to the nonparametric estimator for censored observations developed by Kaplan and Meier (1958). In the Cox model, positive values for the coefficient indicate an increased likelihood that the hazard rate is increasing in response to the covariate; thus, positive coefficients in the Cox model indicate decreased survival time (Box-Steffensmeier and Jones 2006). Interpreting the Cox model is straightforward. Positive coefficients indicate an increasing hazard rate, and thus a shorter survival time. In contrast, negative coefficients indicate a decreasing hazard rate, resulting in longer survival periods (Box-Steffensmeier and Jones 2006).

The Cox model is set up using a variation described by Prentice, Williams, and Peterson (1981), known as the conditional risk set model (hereafter PWP; Box-Steffensmeier and Jones 2006; Box-Steffensmeier and Zorn 2002). The model differs from the original Cox survival model in two important ways: (1) it treats events as ordered, so that only subjects that have experienced $k - 1$ events are "at risk" for event k at time t; and (2) the model use robust variance estimates to account for interdependence due to repeated events, which produce robust standard errors that assume independent observations across clusters (i.e. subjects) but do not assume independence within those clusters (Box-Steffensmeier and Zorn 2002; Therneau and Hamilton 1997).

This chapter has described the data, variables, and analyses used in the dissertation to answer the primary research questions proposed in Chapter 1. In the following chapter, results from the logistic regression analysis are presented and discussed.

Table 3.6. Sample of Aggregated Crime Counts, Standardized Values, and Hot Months, January – March, 2010

Violent Crime								Property Crime							
id	m1	m1z	m2	m2z	m3	m3z	hot months	id	m1	m1z	m2	m2z	m3	m3z	hot months
2818	.	.	.	.	1	-0.391	0	877	12	10.273	13	11.128	19	13.816	3
11517	1	-0.278	.	.	2	0.909	0	1197	10	8.347	5	3.513	8	5.193	3
3093	.	.	1	-0.316	1	-0.391	0	1341	5	3.532	8	6.369	6	3.625	3
3030	2	0.656	.	.	.	.	0	1287	10	8.347	14	12.080	16	11.465	3
1272	.	.	.	.	.	.	0	3248	3	1.606	7	5.417	11	7.545	2
10496	1	-0.278	.	.	.	.	0	1521	7	5.458	1	-0.294	9	5.977	2
1287	4	2.526	1	-0.316	.	.	1	1064	8	6.421	3	1.610	8	5.193	2
2494	.	.	1	-0.316	.	.	0	2479	4	2.569	9	7.321	10	6.761	3
14317	.	.	.	.	.	.	0	11056	8	6.421	8	6.369	10	6.761	3
12687	.	.	.	.	.	.	0	2818	4	2.569	11	9.224	9	5.977	3
13824	.	.	.	.	1	-0.391	0	3093	2	0.643	.	.	3	1.273	0
2097	.	.	.	.	.	.	0	2439	3	1.606	4	2.561	1	-0.295	1
1652	2	0.656	.	.	.	.	0	2180	1	-0.320	4	2.561	.	.	1
3047	.	.	1	-0.316	1	-0.391	0	1566	6	4.495	.	.	5	2.841	2
12283	.	.	.	.	1	-0.391	0	3104	4	2.569	7	5.417	12	8.329	3
8689	.	.	.	.	.	.	0	3247	4	2.569	1	-0.294	6	3.625	2
10336	.	.	.	.	1	-0.391	0	1526	3	1.606	1	-0.294	3	1.273	0
8610	1	-0.278	1	-0.316	.	.	0	1685	.	.	.	.	8	5.193	1
3248	1	-0.278	1	-0.316	.	.	0	11009	2	0.643	.	.	1	-0.295	0
11673	.	.	.	.	1	-0.391	0	3617	3	1.606	1	-0.294	1	-0.295	0

Table 3.7. Sample Data for Hot Spot Selection, Violent Crime

Zeros In								Zeros Out							
ID	M1	M1Z	M2	M2Z	M3	M3Z	HOT MONTHS	ID	M1	M1Z	M2	M2Z	M3	M3Z	HOT MONTHS
2818	0	-0.108	0	-0.113	1	4.213	1	2818	.	.	.	.	1	-0.391	0
11517	1	4.206	0	-0.113	2	8.560	2	11517	1	-0.278	.	.	2	0.909	0
3093	0	-0.108	1	5.994	1	4.213	2	3093	.	.	1	-0.316	1	-0.391	0
3030	2	8.519	0	-0.113	0	-0.133	1	3030	2	0.656	.	.	.	.	0
10496	1	4.206	0	-0.113	0	-0.133	1	1272	.	.	.	.	.	.	0
1272	0	-0.108	0	-0.113	0	-0.133	0	10496	1	-0.278	.	.	.	.	0
2494	0	-0.108	1	5.994	0	-0.133	1	1287	4	2.526	1	-0.316	.	.	1
1287	4	17.146	1	5.994	0	-0.133	2	2494	.	.	1	-0.316	.	.	0
14317	0	-0.108	0	-0.113	0	-0.133	0	14317	.	.	.	.	.	.	0
12687	0	-0.108	0	-0.113	0	-0.133	0	12687	.	.	.	.	.	.	0
13824	0	-0.108	0	-0.113	1	4.213	1	13824	.	.	.	.	1	-0.391	0
2097	0	-0.108	0	-0.113	0	-0.133	0	2097	.	.	.	.	.	.	0
1652	2	8.519	0	-0.113	0	-0.133	1	1652	2	0.656	.	.	.	.	0
3047	0	-0.108	1	5.994	1	4.213	2	3047	.	.	1	-0.316	1	-0.391	0
12283	0	-0.108	0	-0.113	1	4.213	1	12283	.	.	.	.	1	-0.391	0
8689	0	-0.108	0	-0.113	0	-0.133	0	8689	.	.	.	.	.	.	0
10336	0	-0.108	0	-0.113	1	4.213	1	10336	.	.	.	.	1	-0.391	0
8610	1	4.206	1	5.994	0	-0.133	2	8610	1	-0.278	1	-0.316	.	.	0
3248	1	4.206	1	5.994	0	-0.133	2	3248	1	-0.278	1	-0.316	.	.	0
11673	0	-0.108	0	-0.113	1	4.213	1	11673	.	.	.	.	1	-0.391	0

Table 3.8. Sample Data for Hot Spot Selection, Property Crime

		ZEROS IN									ZEROS OUT				
ID	M1	M1Z	M2	M2Z	M3	M3Z	HOT MONTHS	ID	M1	M1Z	M2	M2Z	M3	M3Z	HOT MONTHS
877	12	24.286	13	29.200	19	33.71592	3	877	12	10.273	13	11.128	19	13.816	3
1197	10	20.198	5	11.098	8	14.063	3	1197	10	8.347	5	3.513	8	5.193	3
1341	5	9.978	8	17.886	6	10.489	3	1341	5	3.532	8	6.369	6	3.625	3
1287	10	20.198	14	31.462	16	28.356	3	1287	10	8.347	14	12.080	16	11.465	3
3248	3	5.890	7	15.624	11	19.423	3	3248	3	1.606	7	5.417	11	7.545	2
1521	7	14.066	1	2.048	9	15.849	3	1521	7	5.458	1	-0.294	9	5.977	2
1064	8	16.110	3	6.573	8	14.063	3	1064	8	6.421	3	1.610	8	5.193	2
2479	4	7.934	9	20.149	10	17.636	3	2479	4	2.569	9	7.321	10	6.761	3
11056	8	16.110	8	17.886	10	17.636	3	11056	8	6.421	8	6.369	10	6.761	3
2818	4	7.934	11	24.674	9	15.849	3	2818	4	2.569	11	9.224	9	5.977	3
3093	2	3.846	0	-0.215	3	5.130	2	3093	2	0.643	.	.	3	1.273	0
2439	3	5.890	4	8.836	1	1.556	2	2439	3	1.606	4	2.561	1	-0.295	1
2180	1	1.802	4	8.836	0	-0.230	2	2180	1	-0.320	4	2.561	.	.	1
1566	6	12.022	0	-0.215	5	8.703	2	1566	6	4.495	.	.	5	2.841	2
3104	4	7.934	7	15.624	12	21.209	3	3104	4	2.569	7	5.417	12	8.329	3
3247	4	7.934	1	2.048	6	10.489	3	3247	4	2.569	1	-0.294	6	3.625	2
1526	3	5.890	1	2.048	3	5.130	3	1526	3	1.606	1	-0.294	3	1.273	0
1685	0	-0.242	0	-0.215	8	14.063	1	1685	.	.	.	.	8	5.193	1
11009	2	3.846	0	-0.215	1	1.556	1	11009	2	0.643	.	.	1	-0.295	0
3617	3	5.890	1	2.048	1	1.556	2	3617	3	1.606	1	-0.294	1	-0.295	0

CHAPTER FOUR: THE DISTRIBUTION OF MICRO-TEMPORAL HOT SPOTS

This dissertation is primarily concerned with the micro-spatial and micro-temporal distribution of serious crime in urban areas. A primary goal of the dissertation is to explore the distribution of crime at street segments at the sub-annual level by measuring crime concentration across months. Multiple independent studies have confirmed that at the micro-geographic level, about half of all crime occurs in just 5% of places (Weisburd 2015; Levin, Rosenfeld, and Deckard 2017; Weisburd and Telep 2014b; Braga, Papachristos, and Hureau 2009). Thus, the natural starting point for identifying violent and property crime hot spots is to examine the top 5% of the distribution of crimes at street segments. In a one-tailed normal distribution, the 5% cutoff corresponds to a z-score of 1.645 and higher.

As mentioned in the previous chapter, the monthly crime data are not normally distributed, but rather have a significant right-hand skew due to the high number of crime-free segment-months. To address this issue, I transformed the raw crime counts by converting them into their natural logs, standardized the monthly distributions (again coding crime-free months as missing) and re-drew the hot spots. While the transformed distribution was much less skewed, there was virtually no change in the distribution of hot spots. Thus, the original, non-transformed data were used. Figure 4.1.1 presents the full distribution of violent and property crime hot spots. The x-axis displays all possible values for the number of months a place could be hot, ranging from zero to 60. The y-axis displays the number of segments that were hot for *K* months. Table 4.1 shows the distribution of street segments by the number of months they were hot (i.e. the number of months they ranked in the top 5% of the distribution of segments that had at least one crime).

Table 4.1. Street Segments by Number of High-Crime (Top 5%) Months, 2010-2014

Total Hot Months	Violent Crime	Property Crime
0	13,210	12,623
1	726	900
2-6	170	488
7-12	0	48
13-24	0	28
25-60	0	19
Total Segments	14,106	14,106

DISTRIBUTION OF HIGH CRIME STREET SEGMENTS IN ST. LOUIS

As expected, most segments were never hot. Over the five-year observation period, 93.65% of segments (n=13,210) were never a violent crime hot spot, while 89.5% of places (n=12,263) never crossed the threshold to be categorized as hot spots property crime. At first glance, this appears to support the law of crime concentrations Clearly, the distribution is significantly skewed on the left-hand side, making it difficult to distinguish details past the first two or three months. Figure 4.1.2 displays a truncated distribution, removing street segments that were never hot. Again, the distribution is highly skewed. Even among segments that ranked in the top 5% of the distribution at least one month, most places were hot only once in five years. Of the segments that were hot at least once (N_V=896, N_P=1,483), 81% had only one violent hot month, and 61% of hot property segments were hot only one month out of 60. Figure 4.1.3 further truncates the chart, removing single month hot spots and limiting the range to places hot between two and six months. While the distribution remains skewed, it is now possible to distinguish differences from one frequency to the next. A total of 170 violent crime segments and 488 property crime segments ranked among the top 5% between two and six months. Hot months are not necessarily consecutive. While it is possible that some segments have contiguous hot months, these results are simple counts of the number of months places were in the top 5% of the distribution. Hot spot periodicity – the temporal clustering of high-crime months – is discussed in Chapter Five.

Beyond six hot months, the distribution starts to look very different. Figure 4.1.4 displays results for places that were hot more than six months but less than two years, cumulatively (N=76). The most obvious difference in this set of results is the complete absence of any violent crime hot spots. Referring to Table 4.1, we see that there were *no segments that ranked among the most violent places for more than six months*. Put another way, the most chronic violent crime segments were hot for only 10% of the study period. This finding raises new questions about the nature of violent crime hot spots. If places are low-crime or crime-free 90% of the time, is it logical to categorize them as chronic? These results seem to suggest a phenomenon raised in at least one prior study: while overall crime concentrations may be stable over time, individual places may move in and out of the top 5% of the distribution. A recent study testing the distribution of crime and the law of crime concentration of annual hot spots in St. Louis over a 15-year period found a high degree of *spatial mobility* in the data. While the degree of crime concentration was stable over time (indicating high *spatial inequality*), the same places were not necessarily hot year after year.

This appears to be true of violent crime hot spots at the monthly level, as well, indicated by the lack of any chronic violent crime hot spots using the 5% threshold. Property crime hot spots exhibit greater temporal stability than violent crime hot spots. Figure 4.1.4 shows the distribution of property crime hot spots that were ‘on’ more than six months but less than two years (N=76). As before, the distribution is highly skewed: most high-crime places were hot less than 16 months throughout the study period. The remainder of the distribution is shown in figure 4.1.5, truncated to places that were hot more than 24 months. Again, we see that very few places fall into this category. Only 19 street segments ranked among the highest-crime areas for more than two years. Even fewer places were hot more than 50% of the observation period (N=12). These chronic property crime hot spots are extremely rare, making up just .08% of all street segments, and accounting for 3.8% of all property crime.

Figure 4.1.1. The Frequency of High-Crime Months, St. Louis Street Segments, 2010-2014

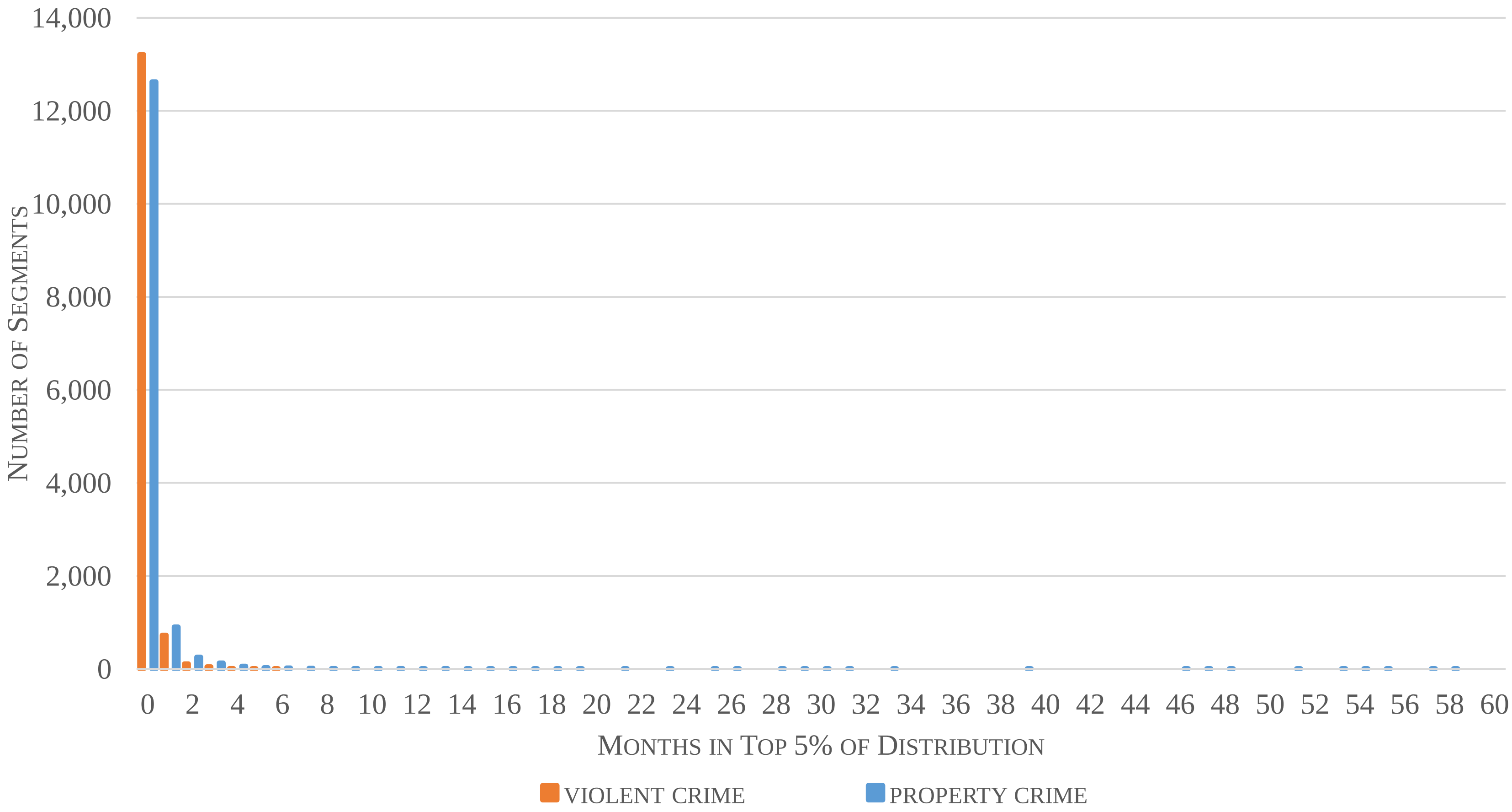


Figure 4.1.2. The Frequency of High-Crime Months, St. Louis Street Segments, 2010-2014

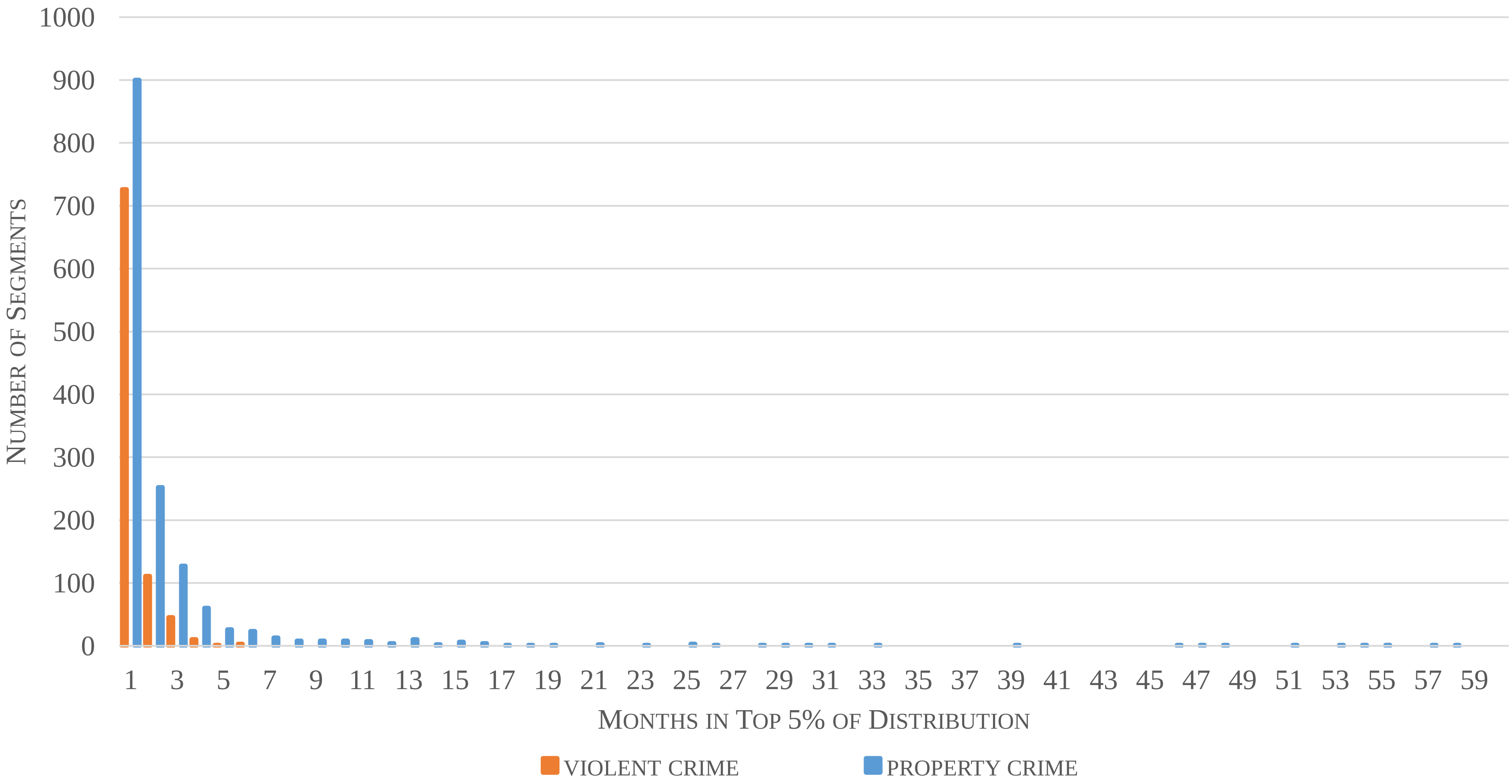
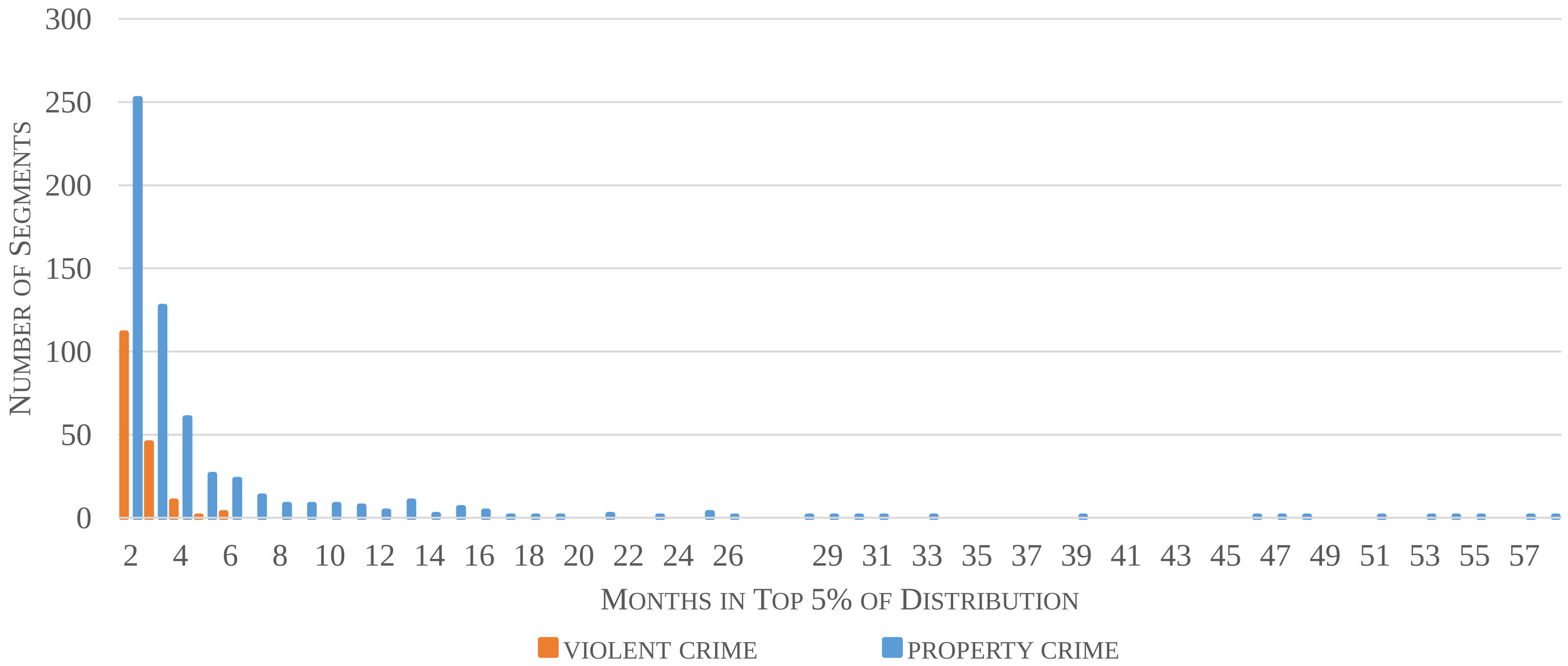
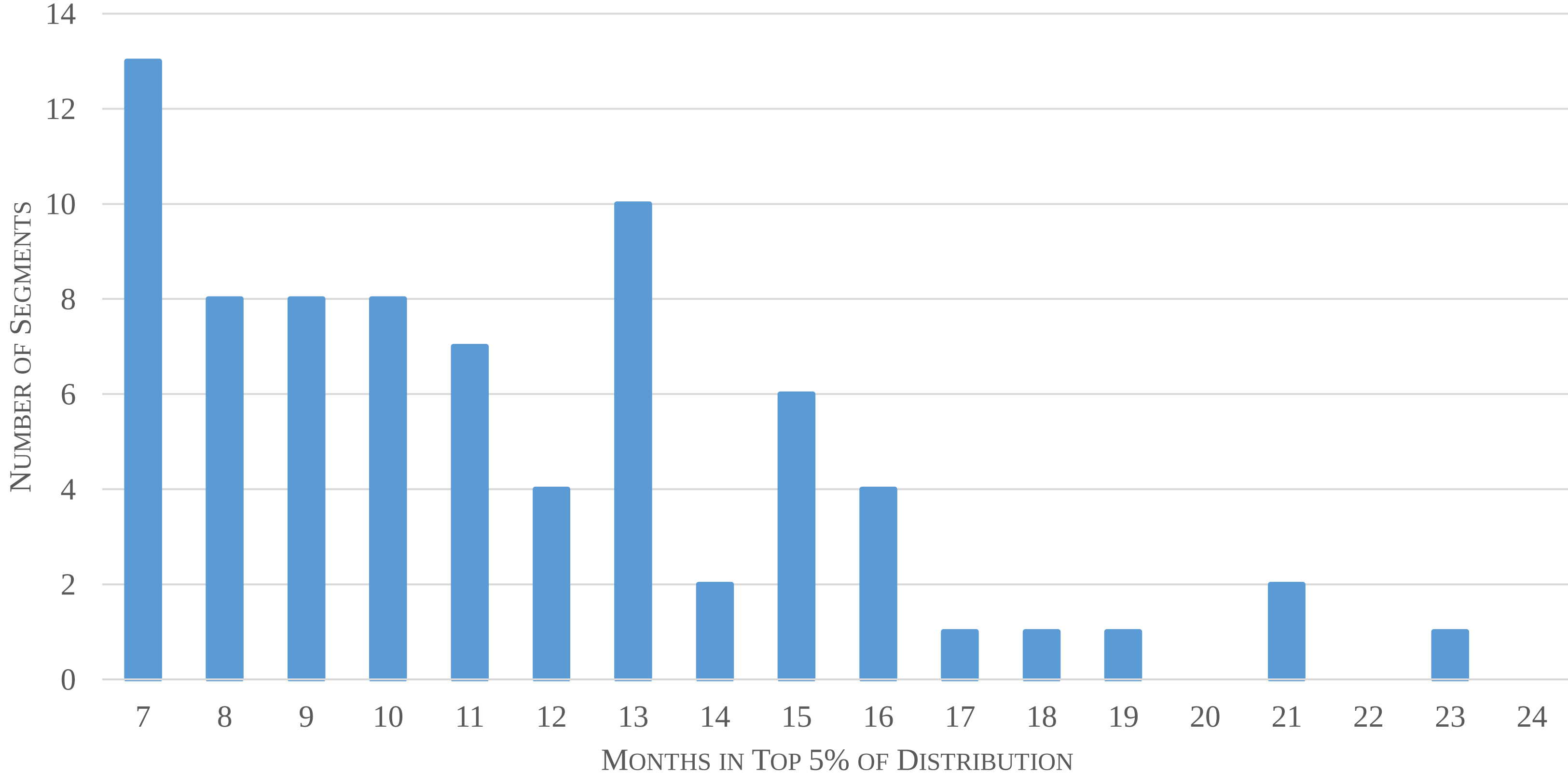


Figure 4.1.3. The Frequency of High-Crime Months, St. Louis Street Segments, 2010-2014[16]



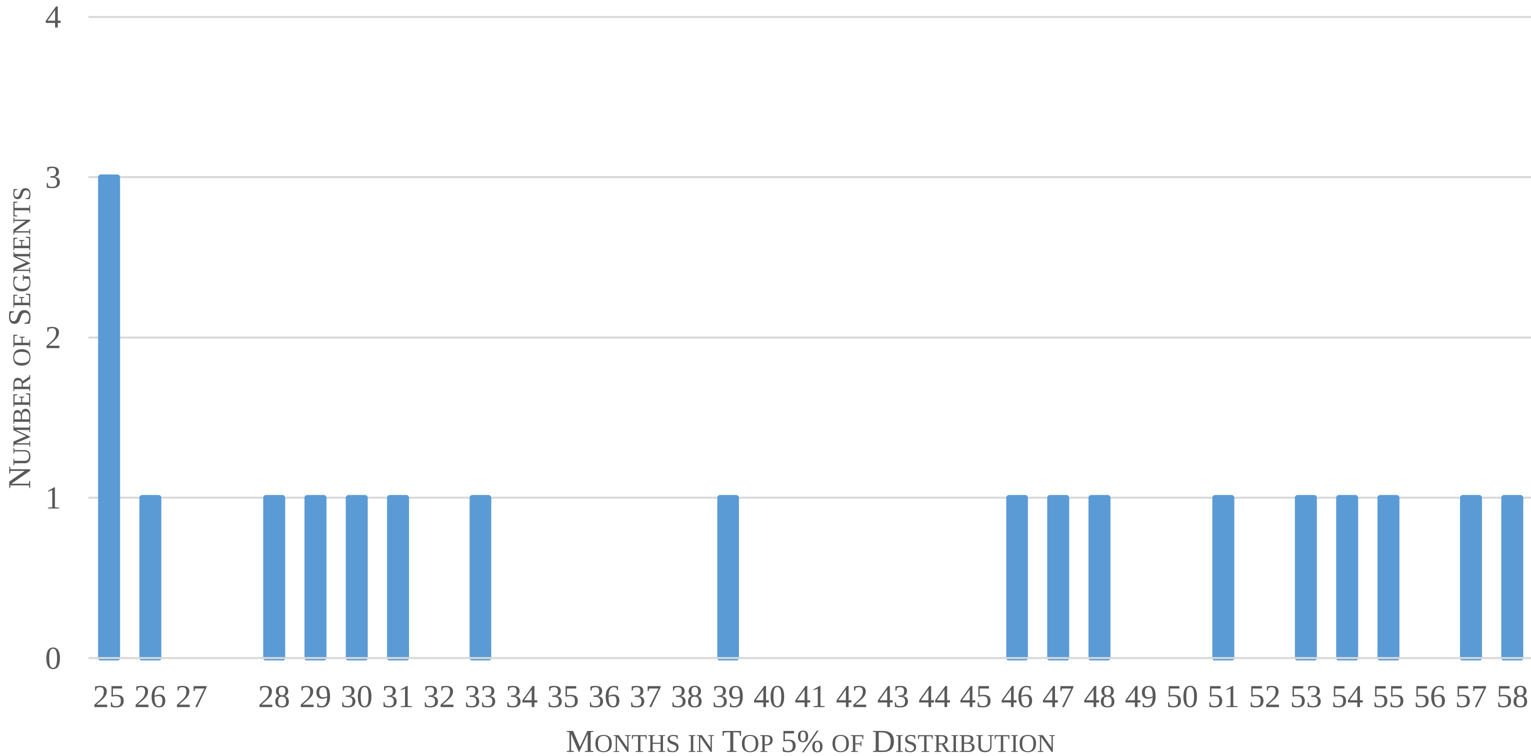
[16] Truncated 2-6 months.

Figure 4.1.4. The Frequency of High-Crime Months, Property Crime, St. Louis Street Segments, 2010-2014[17]



[17] Truncated 7-24 months.

Figure 4.1.5. The Frequency of High-Crime Months, Property Crime, St. Louis Street Segments, 2010-2014[18]



[18] Truncated 25-60 months

CUTOFF LEVELS FOR DETERMINING CRIME HOT SPOTS

These results are based on the commonly used 5% threshold for distinguishing high-crime places. While this threshold is based on existing theories of crime and place, there is an ongoing debate in the empirical literature that questions using such firm limits to identify crime hot spots. For example, it could be the case that some places are consistently in the top 10 or 15% of the distribution. These places would not traditionally be categorized as hot spots. To examine this issue, I re-calculated the distribution of hot months and hot places using two additional cutoff thresholds using the top 10% and 15% of the distribution, capturing additional detail about the distribution of crime at micro-places over time. If the number of street segments categorized as high-crime increases significantly at one of these relaxed thresholds, it would indicate that there are moderate-crime places where crime is highly concentrated but are not classified as hot using the traditional 5% cutoff. Tables 4.2.1 and 4.2.2 display the distribution of violent and property crime hot spots using three cutoff points at the top 5%, 10%, and 15%.

Table 4.2.1. Crime Hot Spots at Three Cutoff Points, Violent Crime

		Cutoff Level[19]		
		Top 5%	Top 10%	Top 15%
# Hot Months	1	726	834	963
	2-6	170	230	295
	7-24	0	0	2
	25-60	0	0	0
	Total Hot Segments (% change)	896	1064 (+18.8)	1260 (+18.4)
	Total Hot Months (% change)	1146	1408 (+22.9)	1719 (22.1)
	% Crime Incidents (% change)	38.5	43.6 (+5.1)	49.0 (+5.2)
	Min[20]	3	2	2
	Max[11]	62	62	62
	Mean (Std. Dev.)[11]	11.4 (7.8)	10.9 (7.6)	10.3 (7.4)

Table 4.2.2. Crime Hot Spots at Three Cutoff Points, Property Crime

		Cutoff Level[10]		
		Top 5%	Top 10%	Top 15%
Hot Months	1	900	1,034	1,149
	2-6	488	624	719
	7-24	76	95	108
	25-60	19	19	19
	Total Hot Segments (% change):	1,483	1,772 (+19.5)	1,995 (+12.6)
	Total Hot Months (% change):	3,916	4,743 (+21.1)	5,328 (+12.3)
	% Crime Incidents (% change):	45.9	51.0 (+5.1)	54.3 (+3.3)
	Min:[11]	3	3	2
	Max:[11]	515	515	515
	Mean (Std. Dev.):[11]	34.2 (36.1)	31.9 (33.7)	30.2 (32.2)

[19] The number of segments that were hot for each category of time (months) using each cutoff level.
[20] Descriptive statistics for the number of crimes per segment-month.

For violent crime, loosening the cutoff threshold from 5% to 10% increases the total number of hot segments and hot months by approximately 19% and 23%, respectively. Moving the cutoff from 10% to 15% yields similar increases, with 18% more hot segments and 22% more hot months. These relaxed thresholds yield a corresponding increase in the total percentage of crime represented by high-crime segments: 38.5% of all violent crime is found at the top 5% of street segments, 43.6% at the top 10%, and 49% at the top 15%. The distribution of property crime hot spots also changes in response to the relaxed thresholds. There are approximately 20% more hot segments, 21% more hot months, and an additional 5% of total property crime incidents at the 10% cutoff compared to the 5% default. The difference between the 10% and 15% threshold is less pronounced for property crime, with only a 13% increase in the total number of street segments, 12% more hot months, and 3% more incidents. For both crime types, expanding the cutoff threshold appears to affect only the number of temporary hot spots: neither crime type had an increase in the number of places hot more than 25 months. Most of the overall increase in hot segments can be attributed to places hot for a single month throughout the observation period. So, while a looser threshold can capture some places that are hot for short periods of time, there is little impact on the overall picture of crime concentration.

These results have shown the distribution of high-crime micro-places in St. Louis using the month as the temporal unit of analysis. It is clear that over the five-year period covered by the dissertation, most street segments had little to no serious crime. When places did experience periods of high crime concentration, they tended to be short lived, lasting only one or two months. No segments sustained elevated levels of violent crime over the five-year period examined, and very few places were consistent property crime hot spots.

One of the primary goals of the dissertation is to compare the monthly distribution of crime hot spots to annual distributions. The last section of this chapter examines the impact of hot months on hot years. If annual concentrations hold at the monthly level, then places exhibiting chronic crime concentration across years will have similar temporal stability at the monthly level. If there is within-year variation in crime concentration, then the relationship between macro- and micro-temporal units of analysis will be similar to that found in spatial units: a small number of high-crime months drive annual crime distributions the same way that a small number of high-crime street segments drive neighborhood crime rates.

COMPARING ANNUAL AND MONTHLY CRIME DISTRIBUTIONS

One of the central theses of this study is to determine if high-crime months influence high-crime years in similar ways as high-crime micro-places (e.g. street segments) influence high-crime macro-places (e.g. neighborhoods). To address this issue, I calculated annual crime distributions, following the same procedures used for the monthly data, and flagged segments that ranked in the top 5% of the distribution. Since the expanded cutoff thresholds did not produce substantial differences in the overall distribution of crime, the remainder of the dissertation proceeds using the 5% cutoff to identify crime hot spots. Table 4.3 shows the distribution of high-crime street segments that reached the top 5% cutoff at least one year, arranged by the total number of months the segment was hot over the five-year period.

Table 4.3. Annual and Monthly Hot Street Segments

		Hot Months					
		Violent Crime[21]					Total Segments
		1	2	3	4	5-6	
Hot Years	1	279	57	7	0	0	453
	2	37	33	22	1	0	116
	3	9	8	9	5	3	43
	4	2	2	4	1	0	11
	5	0	0	3	3	1	7
	Total	328	102	48	14	15	630
		Property Crime					
		1	2-6	7-12	13-24	25-60	
	1	101	172	1	0	0	274
	2	9	94	3	0	0	106
	3	0	46	10	1	0	57
	4	0	13	18	6	0	37
	5	0	3	16	21	19	59
	Total	110	328	48	28	19	533

Among street segments that were annual hot spots ($N_V = 630$, $N_P = 533$), the number of hot months is strongly correlated with the number of hot years ($R_V = 0.70$, $R_P = 0.74$; see Figure 4.2). Conversely, the few that were hot all five years ranked in the top 5% of the distribution about four months per year on average. Still, for violent crime, a small number of high-crime months appear to drive annual hot spots: even among the

[21] Violent crime is truncated to the maximum number of months any street segment ranked in the top 5% of the distribution (n=6).

chronic violet crime hot spots, most months were crime-free. Table 4.4 summarizes the average number of crime-free months per year. Segments that were never annual hot spots averaged just one hot month in five years. Places that were among the top 5% for one to four years averaged between 37 and 52 crime-free months, while the few places that were hot all five years of the study period (i.e. the "chronic crime hot spots") had approximately 31 months without recording a single violent crime incident.

Table 4.4. Crime-Free Months by Number of Years, Street Segments in St. Louis, MO 2010-2014

	Violent					Property				
Years	N	Mean	S.D.	Min	Max	N	Mean	S.D..	Min	Max
1	453	52.53	3.7	42	59	322	35.7	4.9	23	50
2	116	47.48	3.5	40	56	107	30.0	4.9	17	50
3	43	43.49	4.3	34	52	57	25.1	4.3	17	34
4	11	37.45	6.5	22	46	37	20.0	3.4	12	37
5	7	30.85	5.4	21	37	59	10.8	6.3	0	23

The modified selection methodology used to identify serious crime hot spots in the current study yields slightly lower concentrations than have been found in prior studies that include crime-free areas. In total, violent crime hot spots comprise 6.4% of all street segments (N=896) and account for 38.4% of all violent crime in St. Louis over a five-year period (N=10,185). Property crime hot spots comprise 10.5% of all segments (N=1,483) and 45.8% (N=50,709) of all property crimes. These concentrations fall within the "narrow bandwidth" described in the law of crime concentrations (Weisburd 2015).

Figure 4.2. Mean Crime-Free Months, Annual Crime Hot Spots, St. Louis, MO, 2010-2014

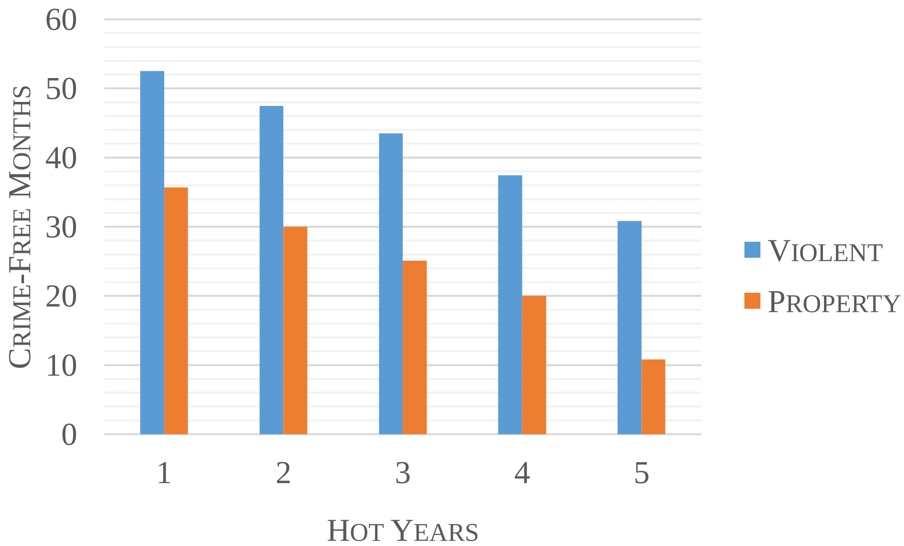


Figure 4.3. High Crime Street Segments in St. Louis, Property Crime (2010-2014)

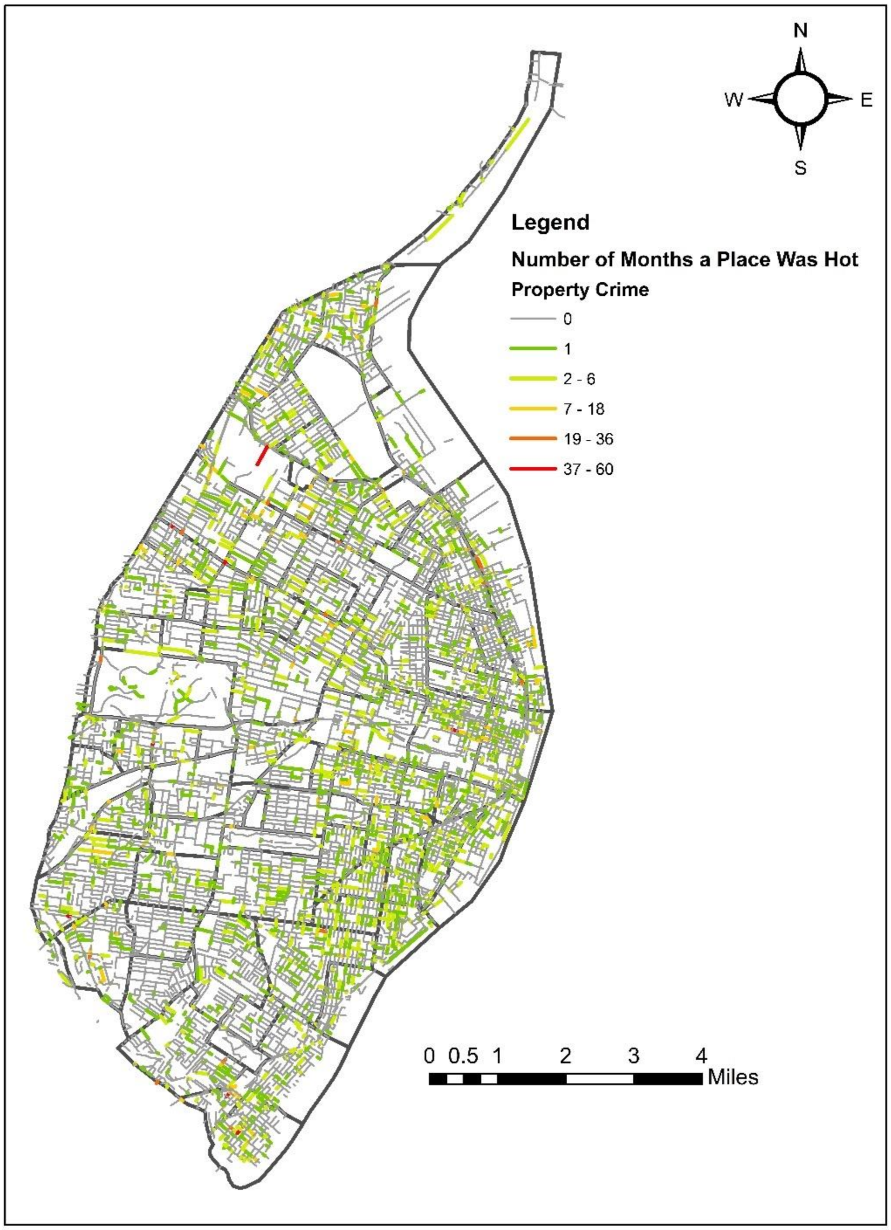
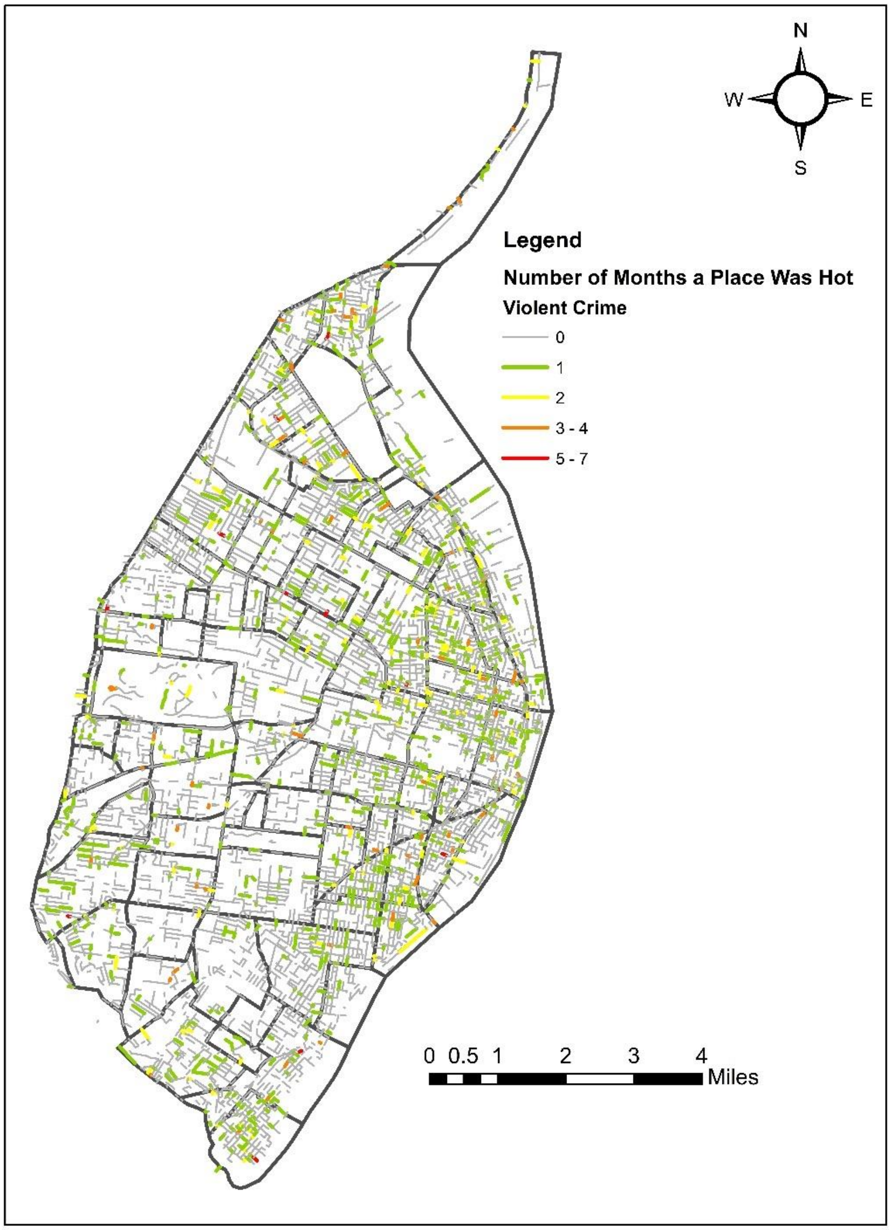


Figure 4.4. High Crime Street Segments in St. Louis, Violent Crime (2010-2014)



SUMMARY

Studies have consistently found that a great deal of urban crime occurs at a very small number of micro-geographic hot spots within cities[22]. Longitudinal studies of crime concentration primarily rely on annual crime data to describe the long-term stability of high-crime areas. This contradicts advice given in a recent monograph co-authored by members of the Crime and Place Working Group – leaders in the study of micro-spatial crime concentration – that advocates for using the smallest units of analysis feasible when studying the distribution of crime:

> …when there is a good deal of variability at the very local level of geography (e.g., a street segment or group of street segments), we might in measuring higher order geographic units miss local area effects. This can be referred to as "averaging" [sic] and presents today, as in earlier decades, an important challenge to crime and place research (Weisburd et al. 2016, 11).

While the authors were referring to spatial units of analysis, I propose that the same logical argument should also be applied to the temporal units of analysis used to aggregate criminal events in studies of crime and place. To date, there is very little information on the distribution of high-crime places at temporal units other than years. One recent study tested the application of the law of crime concentrations at sub-annual units, finding that the bandwidth of concentration expected by Weisburd (2015) holds for robbery patterns across hours of the day, days of the week, and seasons of the year (Haberman, Sorg, and Ratcliffe 2017). As with most crime concentration studies, Haberman and colleagues include crime-free places in their assessment of spatial

[22] This phenomenon has been documented in suburban areas as well, albeit to a lesser degree (see Gill, Wooditch, and Weisburd 2016).

concentration of robbery in Philadelphia Across the three time scales used, the percentage of micro-places experiencing zero street robberies varied from 88-98%, with 83% of places not experiencing a robbery at any time scale (Haberman, Sorg, and Ratcliffe 2017).

This dissertation fills another theoretically relevant gap in the application of the law of crime concentration to sub-annual temporal units by examining the distribution of high-crime street segments at the monthly level. The month is a suitable unit of time for exploring within-year variations in crime distributions for both theoretical and policy-related reasons. Aside from seasons of the year, months are the largest sub-annual temporal units, allowing for sufficient accumulation of crime data. Furthermore, months are popular with law enforcement administrators and crime analysts: agencies operating under the Compstat model typically compare recent crime trends to previous months and the same month in the previous year (Weisburd et al. 2003) . In St. Louis, the SLMPD holds weekly Compstat meetings, which include a packet of tables and maps showing crime levels by administrative unit for the prior week, prior month, and changes from the same time in the previous year. So, while practitioners and policy-makers are using monthly data to analyze recent and historical hot spots, crime concentration research to date has not specifically analyzed these sub-annual distributions. To address this issue, the first research question asked:

(1) How are high-crime micro-places distributed at the monthly level? How much variation exists in the distribution of crime across micro-places when crimes are aggregated on a monthly basis?

To answer this question, the dissertation aggregated UCR Part 1 crime data (aggravated assault, rape, robbery, homicide, burglary, larceny, and motor vehicle theft) at street segments and months using indexed counts of violent and property crime. Then, using a modified standardized distribution coding all crime-free segments as missing, places were categorized as either hot (1) or not (0) for each month over the five-year study period from 2010-2014 (N=60) using a cutoff threshold corresponding to the top 5% of a one-tailed distribution ($Z \geq 1.645$).

The results from the monthly hot spot frequency distribution presented in this chapter were somewhat surprising: for violent crime, not a single place was hot for more than six months – or 10% of the study. Even when the threshold was relaxed to the top 10-15% of the distribution ($Z \geq 1.28$-1.04), violent crime hot spots were never hot more than seven months, and most places that were added by loosening the threshold were hot only one or two months. Although the current study uses a much stricter metric to define high-crime places, most street segments never reached the cutoff threshold at any of the three levels tested. Based on the parameters imposed in the current study, there do not appear to be any chronic violent crime hot spots in St. Louis. The few places that were hot all five years at the annual temporal level spent more than 90% of months outside the top 5% of the distribution for high-crime street segments. Violent crime hot spots were hot an average of 1.3 months, or about 2% of the observation period. The distribution of monthly property crime hot spots is somewhat different. A very small number of places were among the 5% highest-crime segments for nearly the entire study period. Only 19 street segments (0.13%) were hot more than two years cumulatively at the monthly level. The most stable, chronic property crime street segment was hot a total of 58 months, or nearly 97% of the study period. Property crime hot spots were hot an average of 2.6 months (4.4%) of the study period, indicating that while there is greater stability in the distribution of property crime hot spots, most places that reach the top 5% of the distribution do not stay there very long. These findings indicate that prior research supporting the existence of chronic crime hot spots over long time periods may over-estimate the stability of crime patterns at street segments within years.

CHAPTER FIVE: STRUCTURAL CHARACTERISTICS OF MICRO-TEMPORAL HOT SPOTS

The second objective of the dissertation is to test classic ecological social predictors of crime and deviance at the micro-spatial and micro-temporal level. Prior studies have applied social disorganization and opportunity theories to micro-places (Smith, Frazee, and Davison 2000; Kurtz, Koons, and Taylor 1998; Perkins et al. 1990; Boessen and Hipp 2015) but to my knowledge, none have done so using micro-temporal hot spots as the unit of analysis. This represents an important gap in the literature, as monthly crime hot spots may differ substantially from annual hot spots on theoretically relevant structural characteristics of place. This chapter presents results from three multivariate regression models: (1) a logistic regression model designed to compare places that were hot at any point during the observation period to places that were never hot, (2) a negative binomial count model to estimate the impact of structural covariates on hot spot frequency, and (3) a Cox proportional hazard (survival) model to estimate the effect of micro-spatial neighborhood structural characteristics on the periodicity of micro-temporal hot spots.

MULTIVARIATE REGRESSION MODEL SETUP

As with the descriptive analyses, all regression models were estimated using two versions of the data set: one with crime-free months coded as 0 (zeros-in) and one coded as missing (zeros-out). Only results from the latter data set are presented here, but all regression output is included in Appendix D. The logistic regression model is based on a bivariate outcome variable that indicates whether a place was hot at least one month over the study period (1) or was never hot (0). All covariates described in Chapter Three are included in the full model. Each subject is a unique street segment, with covariate data corresponding to the imputed census block (the simple average of the blocks adjacent to the segment) or block group the segment resides in. Land use variables are coded at the census block level, assigning blocks to the nearest census block. An imputation method described by Kim (2016) was used to check the robustness of the nearest-neighbor assignment strategy. This imputation method uses the simple weighted average of all census blocks that share a line segment with the street segment (see Kim 2016). Regression output from both versions of the land-use data produced virtually identical results, so the nearest-neighbor strategy was kept for the results presented here. The negative binomial model is estimated using the exact same data as the logistic regression, substituting a continuous variable in place of the binomial outcome measure. The continuous outcome variable indicates the total number of months each segment was hot for each crime type, and ranges from zero to six for violent crime and zero to 58 for property crime.

The survival models use the same set of independent variables as the logistic and negative binomial regression analyses, but the data are structured much differently. To prepare the data for analysis using the PWP gap-time Cox model, the data are converted from wide format to long using the '*reshape'* command in Stata 13, with the street segment ID set as the i() option and month indicator as the sub-observation identifier j(). This procedure converts the data set from 14,106 subjects to 846,360 observations grouped in 14,106 clusters (one observation for every segment-month). To utilize the Cox model, the data must first be declared to be survival-time data using the '*stset'* command. For the PWP gap-time Cox model, four parameters must be defined: (1) the time variable (time); (2) the failure indicator (event = 0/1); (3) the time each observation becomes at risk (time0); and (4) the time each observation exits the study (end). The time variable simply tells the program how time is being kept; in the current study, time is counted by months starting at 1 (January 2010) and ending at 60 (December 2014). Unlike traditional survival analysis data, none of the observations in the dissertation data set are censored: every subject is observed from the beginning to the end of the study period. In time-to-first-event and single-failure analyses, observations are typically right-censored due to either failure or attrition (Ezell, Landy, and Cohenz 2003; Kelly and Lim 2006; Cleves, Gould, and Gutierrez 2004). Neither is an issue in the current study, and thus no observations are censored.

In the PWP gap-time model, the clock is "reset" to zero after each failure, so that the program is estimating the impact of the time since last failure, rather than the time since entry (i.e. the PWP cumulative time model). This means that the "start time" for each observation is zero, with the duration variable (month) indicating the number of months since the segment was last hot. If a place was never hot, it is represented by a single observation with a duration of 60. Figure 5.1 shows a sample of the survival analysis data structure. Note that while most places never experienced an event (duration = 60), two segments had at least one hot month. Segment 848 was hot once (month 54), while segment 858 was hot twice, first at month 11 and again at month 23. The duration variable for segment 858 corresponds to the gaps between the beginning of the study and the first event (11) and the first event and second event (12).

Figure 5.1. Sample Survival-Time Data Structure

placeid	month	duration	event	enter	exit	riskev~t
840	60	60	0	0	60	1
841	60	60	0	0	60	1
842	60	60	0	0	60	1
843	60	60	0	0	60	1
844	60	60	0	0	60	1
845	60	60	0	0	60	1
846	60	60	0	0	60	1
847	60	60	0	0	60	1
848	54	54	1	0	60	1
849	60	60	0	0	60	1
850	60	60	0	0	60	1
851	60	60	0	0	60	1
852	60	60	0	0	60	1
853	60	60	0	0	60	1
854	60	60	0	0	60	1
855	60	60	0	0	60	1
856	60	60	0	0	60	1
857	60	60	0	0	60	1
858	11	11	1	0	60	1
858	23	12	1	0	60	2
859	60	60	0	0	60	1
860	60	60	0	0	60	1
861	60	60	0	0	60	1

STRUCTURAL PREDICTORS OF CRIME HOT SPOTS

Results from multivariate regression models are summarized in Table 5.1, with "+" and "-" indicating the direction of the correlation. Statistical significance is represented by asterisks corresponding to three significance levels: $p < .05$ (*), $p < .01$

(**) and $p < .001$ (***). The logistic regression models indicate several statistically significant correlations between structural covariates and high-crime places. Consistent with prior research at both the macro and micro-geographic level, several indicators of structural disadvantage were found to be positively associated with high-crime areas. Segments in areas with higher percentages of renters, more black residents, and higher poverty were more likely to become a hot spot for both violent and property crime.[23]

Street segments located on the same block as a hospital and those with bars were also significantly more likely to be among the highest-crime places for both crime types, although it is important to note that there are fewer than ten hospitals in the City of St. Louis, so these data are highly skewed and likely reflect at least some mandatory reporting of crime incidents that likely occurred elsewhere in the city. Several land use categories were found to have statistically significant positive relationships with both violent and property crime hot spots, including Industrial Preservation/Development Areas, Neighborhood Commercial Areas, Neighborhood Preservation Areas, Regional Commercial Areas, and Specialty Mixed-Use Areas. Opportunity Areas were positively associated with both crime types, though were only marginally significant for violent crime.

Some variables were statistically significant for only one crime type. Areas with higher populations of residents age 50 and older were significantly less likely to become violent crime hots ($p < .001$). Interestingly, areas with higher percentages of young people ages 15-24 were negatively associated with violent crime hot spots (although

[23] Racial composition (percent black) and home ownership (percent rent) experience significant autocorrelation.

statistically insignificant) but have a positive, strong statistical correlation with property crime hot spots ($p < .001$). Neighborhood Development Areas ($p < .05$), Regional Open Space Development Areas ($p < . 05$), and places where more residents have at least a high school education ($p < .05$) were more likely to be violent crime hot spots but had no statistically significant correlation with property crime hot spots. Residential mobility and the percentage of children enrolled in school have inverse relationships for violent and property crime hot spots. Areas with more new residents were less likely to have high levels of violent crime ($p < .05$) and were significantly associated with higher levels of property crime ($p < .001$). The relationship between school enrollment and crime is in the opposite direction, with higher enrollment associated with violent crime hot spots ($p < .05$) and lower K-12 enrollment associated with property crime hot spots.

The logistic regression analyses are useful for understanding general relationships between high-crime areas compared to those that never ranked in the top 5% of the distribution at the monthly level. Because they are based on a binary outcome variable, however, it is not possible to distinguish temporary crime hot spots that had a handful of high-crime months from more stable, chronic areas. To model the effects of structural covariates on the frequency of high crime months, a negative binomial count model is fitted by substituting the binary outcome variable from the logistic regression for a continuous variable representing the number of months each segment was hot over the observation period. The negative binomial regression results are very similar to the output from logistic regression, with a few important differences. For violent crime, the only substantive change from the logit model involves changes in statistical significance for two variables.

Table 5.1. Summary of Results from Three Multivariate Regression Models

	Model 1 (Logit)				Model 2 (Negative Binomial)				Model 3 (Cox)			
	Violent		Property		Violent		Property		Violent		Property	
Independent Vars.	Dir.	Sig.	Dir.	Sig.	Dir.	Sig.	Dir.	Sig.	Dir.	Sig.	Dir.	Sig.
%fhh	+		+		+		-		+		-	
%rent	+	**	+	***	+	***	+	***	+	**	+	
%black	+	***	+	***	+	***	+	***	+	***	+	**
%15-24	-		+	***	-		+	***	-		+	*
%50+	-	***	-		-	***	-		-		-	
%vacant	+		+		+		+	***	+	**	+	
%publicassist	+		+		+	**	-	**	+		+	
%resmobility	-	*	+	***	-	***	+	***	-	*	+	*
%poverty	+	*	+		+	**	-		+	**	-	
%hsged	+	*	-		+		-	***	+	**	-	*
%pubtransit	+		+		+		+	***	+	**	+	
%k-12	+	*	-	*	+	**	-	**	+		-	
#payday	+		+		+		-		+		-	*
#hospitals	+	**	+	**	+	**	+	***	+	***	+	**
#bars	+	**	+	***	+	***	+	***	+	***	+	**
Land Use												
BIPA	-		+		-		+		-		+	
IPDA	+	*	+	***	+	***	+	***	+	***	+	***
NCA	+	***	+	***	+	***	+	***	+	***	+	***
NDA	+	*	+		+	**	+		+	**	+	
NPA	+	***	+	***	+	***	+	***	+	***	+	**
OA	+		+	*	+	*	+	***	+	*	+	**
RCA	+	***	+	***	+	***	+	***	+	***	+	***
ROSPDA	+	*	+		+	**	+	***	+	**	+	
SMUA	+	***	+	***	+	***	+	***	+	***	+	***

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

The percentage of households with public assistance income is statistically significant ($p < .01$) in the negative binomial model, whereas it was nonsignificant in the logit model. Conversely, the percentage of residents with a high-school education – statistically significant and positive in the logit model – is nonsignificant in the negative binomial regression. Both independent variables remain positively correlated with violent crime hot spots in the count model. The property crime count model departed from the logit analysis more than the violent crime model, although the two models produce similar results for most variables. All of the statistically significant correlations in the property crime logistic regression maintain their direction and statistical significance in the negative binomial model (a few variables moved to a higher level of statistical significance). Four variables that were nonsignificant predictors of property crime hot spots in the logit model become statistically significant in the count model: the percentage of vacant buildings and the use of public transportation are correlated with increased property crime hot spot frequency ($p < .001$), while public assistance ($p < .01$) and high-school education ($p < .001$) were associated with fewer property crime hot spots. The direction of the public assistance variable also flipped, from positive (and nonsignificant) in the logistic regression to negative in the count model. Finally, while recreational and outdoor space land use was not statistically correlated with property crime hot spots when the outcome was binary, the variable is highly significant and positively correlated with increased property crime hot spot frequency.

Results from the logistic and negative binomial regression models describe the structural characteristics of crime hot spots and how they might indicate whether some places are more likely to experience periods of elevated crime relative to other areas. These findings suggest that several traditional indicators of crime concentration are correlated with increased criminal activity in micro-geographic places. The final set of analyses presented here are designed to examine the relationship between these variables and the temporal periodicity of micro-spatial crime hot spots, or how often places rank among the highest-crime areas in the city on a monthly basis.

The literature on the temporal distribution of crime hot spots is dominated by studies that examine longitudinal trends in high-crime places at the annual level. As discussed in Chapter Three, such analyses are informative of the general distributions of high-crime places but are susceptible to the same large-unit problem that prompted scholars to narrow their focus from neighborhoods to street segments. When crime incidents are aggregated over longer time periods, variations in crime concentration at micro-places over shorter periods of time cannot be identified. The descriptive results for violent crime hot spots presented in the previous chapter highlight this issue by showing that street segments that were hot all five years of the study period using annual data were only among the highest-crime places about 10% of the time. In the final regression analyses, a variance-corrected Cox proportional hazards model for repeated events is fitted to examine the relationship between structural characteristics of place and the temporal distribution of high-crime months. These models are interpreted somewhat differently from Models 1 and 2. In survival analyses, positive correlations indicate shorter intervals between events (hot months), suggesting more chronic patterns of crime concentration. Conversely, negative correlations indicate longer survival (i.e. fewer events), suggesting more temporary distributions.

Results from the Cox regression analyses show several variables that are significantly associated with chronic hot spots for both crime types. Areas with higher percentages of black residents, streets with more liquor establishments and those with a hospital had more chronic patterns of high-crime months for both violent and property crime. In addition, the presence of vacant buildings, higher poverty, more residents with a high-school education, and the use of public transportation were all significantly associated with chronic violent crime places. Segments with greater numbers of young people and higher residential mobility experienced more chronic patterns of elevated property crime.

Fewer variables were significantly associated with temporary crime hot spots. A single indicator was significantly associated with temporary violent crime hot spots: greater residential mobility is linked to longer stretches of low-crime or crime-free months. Again, it is important to remember that the most chronic violent crime hot spots were outside the top 5% of the distribution for 90% of the observation period, so interpretation of these results should keep this in mind. Two structural covariates were associated with temporary property crime hot spots: the percentage of residents with a high school education ($p<.05$) and the presence of predatory lending facilities ($p<.05$).

As was the case in the logit and negative binomial models, some predictors have inverse relationships between crime types. Residential mobility is associated with temporary violent crime hot spots and chronic property crime hot spots, while high school education has the reverse relationship. Places with a higher proportion of residents with a high school diploma or GED are more likely to have chronic violent crime hot spots and temporary property crime hot spots.

Interestingly, only two variables never reached statistical significance at the .05 level across the three regression models: the percentage of female headed households with minor children and the Business/Industrial Preservation land use category (BIPA).

SUMMARY

The second main goal of the dissertation was to examine the relationship between micro-place hot spots and structural covariates that have been shown to be associated with high-crime areas in prior ecological studies. Prior studies have applied social disorganization and opportunity theories to micro-geographic places but to date, no study that I am aware of has tested the relationship between structural characteristics of micro-place hot spots using monthly data. The second research question addresses this gap by asking: Are traditional indicators of social disorganization associated with crime hot spots compared to low-crime and crime-free places?

Consistent with the existing literature, several structural covariates are significantly associated with elevated crime levels in micro-geographic places. Indicators of economic disadvantage are significantly correlated with places that were hot at least once: compared to segments that were never hot, hot spots had lower levels of home ownership and higher rates of poverty. This finding supports the idea that within-unit variability in crime levels is tied to similar variability in structural characteristics previously tied to crime at the neighborhood level. Segments with liquor establishments were also much more likely to become hot spots for both crime types; this is consistent with prior crime and place literature on bars and neighborhood crime at street segments (Roncek and Bell 1981; Roncek and Maier 1991).

Some structural attributes of micro-places were associated with only one crime or had inverse effects by crime type. For example, residential mobility is a negative indicator of violent crime hot spots but is positively correlated with property crime hot spots across both models. This can be the case for several reasons: first, places with lower residential turnover may be more likely to have higher levels of violent crime because the people living there are incapable of moving to less crime-prone areas. Prior research has shown that violent crime tends to be cyclical, with a high-degree of victim-offender overlap, and that individual victimization and offending are tied to structural risk factors (Sampson and Lauritsen 1994; Berg and Loeber 2011). Additionally, high residential mobility may be conducive to higher levels of property crime. High population turnover has been found to be associated with lower collective efficacy, as neighbors are less likely to know one another, and thus are not able to tell when someone in the area might not belong (Sampson and Groves 1989b; Xie and McDowall 2008; Rice and Smith 2002). School enrollment also had an inverse relationship for violent and property crime hot spots: places with higher k-12 enrollment were more likely to be violent crime hot spots, but less likely to be property crime hot spots. Receipt of public assistance was positively associated with repeat violent crime hot spots but negatively associated with repeat property crime hot spots. This could indicate that economic stress leads to more interpersonal violence, while areas with more affluent residents (and thus, lower reliance on public assistance) have property that is attractive to thieves.

Population age was also found to be a significant predictor of high-crime places. Older populations serve as a protective factor against places becoming violent crime hot spots, while higher numbers of young adults increase the likelihood that a segment will experience repeat high property crime months. Although all but one of the land use categories were positively associated with crime hot spots, interpreting the meaning of such results is difficult because if all types of land use have the same relationship with high-crime areas, there is nothing to compare to. The only land use category with a negative coefficient – Business/Industrial Preservation Areas (BIPA) – was associated with violent crime hot spots but did not achieve statistical significance at the $p < .05$ level.

The final goal of the dissertation is to examine the structural characteristics of high-crime areas to determine if there are significant differences between temporary and chronic hot spots. To my knowledge, no prior studies have compared temporary and chronic hot spots to determine if structural attributes are correlated with their temporal stability. The third research question addresses this by asking: Are traditional indicators of social disorganization associated with hot spot periodicity? Can the likelihood that a place will experience multiple high-crime months be determined by its structural characteristics?

To answer this question, the data are transformed so that the number of observations is determined by the number of months each place was hot. The data are set up in this way so that they can be analyzed using survival analysis. As discussed in Chapter Three, survival models are designed to allow for the examination of the time interval between when a subject becomes at risk of an event occurring and when a subject either experiences the event or is no longer observed. In the current study, a variation of the Cox proportional hazards model (Cox 1972) is used to model the relationship between structural predictors of crime concentration and the number of times a place experience a high-crime month. The Prentice-Williams-Peterson (PWP) conditional risk-set model for gap time alters the way that risk is defined at each failure. In this model, each time a subject experiences an event, the clock is reset to zero, so that the time being measured is not time to first failure or time since the subject entered the study, but rather the time since the previous event occurred (Box-Steffensmeier and Jones 2006; Dickman et al. 2012). This means that the structural characteristics of places are modeled against the length of time between hot months, which can be interpreted as being associated with either temporary hot spots (longer spans between events) or chronic hot spots (shorter spans). In survival models, positive relationships indicate increased likelihood of event occurrence (or re-occurrence), while negative correlations indicate increased survival (Dickman et al. 2012).

Findings from the final set of regression analyses largely mirror those from the logit and negative binomial models. For violent crime, two variables gain statistical significance in the Cox model: public transportation and vacancy are associated with shorter intervals between hot months. Percent rent, black, poverty, high school education, public transportation, hospitals, and bars were all correlated with shorter intervals as well. The only statistically significant variable associated with greater survival was residential mobility. For property crime, there is greater deviation from the binary and count models. Chronic property crime hot spots are more likely to be found in areas with more black residents, greater numbers of young people, places with higher residential mobility, and those with hospitals and bars. Consistent with the previous models, high school education is associated with temporary property crime hot spots. Interestingly, more payday loan and check cashing businesses are also associated with temporary crime hot spots.

This chapter presented results from three regression analyses designed to examine the relationship between traditional structural attributes of high-crime places and the presence of chronic and temporary crime hot spots at the micro-geographic and micro-temporal level. The following chapter includes a discussion of the findings from the dissertation alongside implications for public policy, suggestions for future research in area of crime concentration and the criminology of place, as well as conclusions from the current study.

CHAPTER SIX: DISCUSSION

This dissertation has sought to examine the causes and correlates of crime concentration at micro-geographic places over time. Using crime data obtained from the SLMPD, this study described the distribution of crime at street segments in St. Louis over a 60-month period from 2010-2014. Consistent with prior research and the law of crime concentration (Weisburd 2015), the first part of the dissertation found that crime is highly concentrated at a small number of street segments, and that over half of these micro-geographic places are crime-free throughout the entire observation period. In addition, by shifting the temporal unit of analysis to months rather than years, the dissertation identified a previously unknown phenomenon regarding the influence of high-crime months on annual crime distributions. Whereas prior research has indicated that micro-geographic crime hot spots are largely stable over time (Weisburd, Groff, and Yang 2012; Braga, Hureau, and Papachristos 2011), evidence from the current study indicates that a small number of high-crime months may push some street segments into the top of annual distributions. This appears to be the case for violent crime hot spots, where the most chronic street segments in St. Louis ranked in the top 5% of the distribution a maximum of seven months out of 60, or just slightly more than 10% of the observation period.

Property crime, by contrast, exhibits somewhat different patterns of concentration. While most property crime hot spots were short-lived, a small number of street segments ranked in the top of the distribution nearly every month, indicating the they are true chronic hot spots. These findings persist even when the cutoff threshold for determining high-crime street segments is loosened from the top 5% to the top 10 or 15% of the monthly distributions; while loosening the threshold necessarily increases the number of temporary hot spots, it does not alter the number of chronic hot spots in any meaningful way.

While these findings are substantively significant, it is not yet clear *why* we do not find more stable levels of violent crime at the monthly level. It could be that violent crimes are more closely tied to people than to places; people are highly mobile, unlike buildings and public facilities. Therefore, even if people are targeted in the same general areas consistently (e.g. in areas described by crime pattern theory as crime generators or crime attractors), the exact block where a crime occurs can change depending on the time of day or day of the week it occurs (e.g., whether a victim is targeted at home, at work, whilst traveling, or at a public facility), as well as where the crime is reported and recorded by the police. The precise locations of violent crimes are not always known, and officers may have to rely on eyewitness testimony to determine the closest address for recording a crime, which can lead to some dispersion of criminal events across geographically proximate street segments. This is more likely for violent crimes than property crimes, since the target is often a structure or facility rather than a person.

Still, the findings from the monthly crime analyses indicate that there is substantial variation in crime concentration at the monthly level that is masked when crime hot spots are analyzed using annual data. This large-unit problem is similar to the one described by crime and place scholars as one of the primary justifications for studying crime at the micro-geographic level rather than the traditional unit of neighborhoods championed by 20th Century ecological criminologists and sociologists (see Weisburd et al. 2016).

THE TALE OF TWO NEIGHBORHOODS: CRIME HOT SPOTS IN CONTEXT

Many crime and place studies discuss the distribution of crime in urban neighborhoods without discussing the particular characteristics of the neighborhoods themselves. To put the data in the current study in context, I present profiles of two neighborhoods that are very different in their structural characteristics yet face similar problems in terms of crime concentration: Baden and the Patch. Both neighborhoods are similar in size at just over one square mile in area yet have drastically different demographics. Baden is 92% black, while the Patch is nearly 73% white. Baden has more than twice the number of housing units at the Patch and well over twice as much Part 1 crime. While both neighborhoods have similar levels of vacant buildings, slightly lower than the city average (approximately 19%), Baden has nearly three times the population density as the Patch. The neighborhoods are located on opposite sides of the city, with Baden bordering St. Louis County to the North and the Patch bordering the County to the South.

These neighborhoods highlight the dysmorphia of the population distribution in St. Louis, characterized by the locally notorious "Delmar Divide", a term used to separate the largely black, impoverished North City from the mostly white, more affluent South City, separated by a narrow strip running East to West through the geographic center of the city known as the Central Corridor, which is bordered by Delmar Boulevard to the North and Interstate 64 / Missouri Highway 40 to the South, and which comprises nearly the entirety of Downtown St. Louis, St. Louis University's campus, Washington

University Medical Center, and the affluent residential and nightlife district, the Central West End.

Despite their many differences, both Baden and the Patch struggle with both temporary and chronic crime hot spots. Nearly half of all street segments in each neighborhood were hot at least one month during the observation period, and both have at least one chronic crime hot spot. This illustrates the complexity and variety in predicting and explaining the distribution of crime in urban areas. While Baden has suffered from massive depopulation and economic deprivation since the mid-20th century and the Patch has remained a relatively stable working-class neighborhood, both areas are subject to intermittent and stable crime patterns.

The Importance of Crime-Free Places

One of the distinctive aspects of this dissertation is that all the analyses were conducted using two versions of the data set: one including crime-free areas and one coding such places as missing (see also Andresen et al. 2016). There are important methodological reasons for analyzing the data in this way. Most prior studies of crime concentration have included crime-free places in determining the distribution of crime, which has influenced the theory and practice of the crime and place literature. However, recently scholars have begun to question this practice and the role of crime-free areas in the broader context of the ecology of micro-geographic areas and what it means for places to be ‘hot’. In the current study, the inclusion or omission of crime-free places had a substantial impact on the results. While the results and findings presented in the previous chapters were based on data without crime-free places included, the appendices report the results from both versions of the data. The most obvious and striking difference between the two sets of data can be seen in the total number of hot months. When crime-free places are omitted, there are a total of 1,148 and 3,925 violent and property crime hot months, respectively. Including crime-free segments in the distributions skews the standardized measures towards zero, lowering the threshold for the minimum number of crimes necessary to rank among the highest-crime segments in a given month. The results are staggering: violent crime hot segment-months increase to 20,470, while property crime hot segment-months rise to 67,279 – increases of over 1,700%.

The influence of crime-free places is not limited to changes in the distribution or number of high-crime months. Appendix D reports results from the logistic regression model for both versions of the data (see Tables D.1 and D.2). In several instances, significant coefficients become insignificant (e.g. vacancy, RCA and ROSPDA), insignificant coefficients become significant or increase statistical significance levels (e.g. %15-24, poverty), and in some cases the direction of the coefficient changes (e.g. %50+, predatory lending facilities). These are not benign changes in the data but constitute substantial variation in the results and subsequent findings of both the descriptive and regression analyses.

Taken separately, the two versions of the data tell quite different stories. While these findings should be interpreted carefully, they could be representative of a larger issue in the crime and place literature. Studies that make broad claims about the distribution of crime in urban areas that include crime-free areas could be subject to similar distortion. It is impossible to know the influence of crime-free places without further replication of past studies, controlling for the inclusion of crime-free places in the calculation of crime distributions. However, based on these findings and those from recent studies by Andresen and colleagues, this issue appears to be one that will remain unresolved until more rigorous studies can be conducted to determine the impact of crime-free places on the distribution of crime.

WHAT CAUSES CHRONICITY? USING SURVIVAL ANALYSIS TO COMPARE THE STRUCTURAL CHARACTERISTICS OF TEMPORARY AND CHRONIC CRIME HOT SPOTS

Another noteworthy contribution of the dissertation is the novel method used to compare the structural attributes of temporary and chronic hot spots. To my knowledge, no previous study has used survival analysis in a comparative study of chronic and temporary crime hot spots. While the analyses presented here are rudimentary compared to the complex models often used in medical, pharmaceutical, and engineering research, this study represents the first step towards a more nuanced understanding of what differentiates temporary and chronic hot spots. By structuring the data using a repeated events history model, I was able to calculate the effect of the independent variables on the periodicity of segments that were hot at least one month during the observation period. The results from these analyses (presented in Table D.4) indicate that there are structural characteristics of place that are correlated with a segment experiencing more or fewer hot months over a five-year period.

The results from the survival analyses are in line with what we would expect given the theoretical drivers discussed at the end of Chapter 2. Street segments with fewer homeowners, more black residents, and those with public facilities had more chronic crime patterns, regardless of crime type. Segments with higher poverty, fewer residents with post-secondary education, and more public assistance were associated with chronic violent crime patterns; those with more at-risk youth and higher residential mobility were associated with chronic property crime hot spots.

In contrast to chronic patterns of high crime months, there were no variables that were significantly associated with a temporary hot spot pattern for both crime types. Street segments with older residents (age 50 and older) were more likely to have temporary patterns of violent crime. The presence of predatory lending facilities was associated with temporary property crime patterns. Additionally, two variables had statistically significant inverse relationships compared with the chronic pattern. Higher residential mobility was significantly associated with temporary violent crime patterns, whereas the same variable was correlated with chronic property crime patterns. Lower levels of post-secondary education correlated with the temporary property crime pattern and the chronic violent crime pattern.

The differences in the place characteristics of violent and temporary hot spots by crime type is, to my knowledge, a novel finding in the crime and place literature. Several logical explanations could provide clues to understanding differences in the significance of theoretically relevant variables by crime type. For example, streets with older populations might be more likely to experience temporary violent crime patterns because older people are easier targets for violent crimes, such as robbery. During the observation period, there were also several reported incidents of senseless acts of violence against the elderly by teenagers in St. Louis, often attributed to the locally notorious “knock-out game", where young people in groups would attack unsuspecting passersby without provocation or motive[24].

These findings are not so precise that any one attribute can be concretely associated with chronic or temporary crime hot spots, nor used to definitively predict which places will become hot or when they will become hot. Rather, the findings presented in Chapter Five represent the building blocks that can be refined to create better models to further our understanding of the complexities of crime hot spots, including why some persist over long time periods while others flicker and disappear in a manner that appears sporadic. Better understanding the nature of the longevity of crime hot spots will not only satisfy academic inquiry in to the nature of crime concentrations but could also be translated to assist criminal justice and social service professionals in the delivery of services and the amelioration of chronic social problems in urban areas. Others are more difficult to explain, such as the correlation between at-risk youth and chronic property crime and public assistance and chronic violent crime. One possible explanation is that these mechanisms impact violent and property crime at different levels of analysis, as suggested in a recent article by Boessen and Hipp (2015).

Another curious finding is that three variables – residential mobility, poverty, and education – display inverse relationships, correlating to chronic patterns for one crime type and temporary patterns for the other. This could be an artifact of the survival analysis technique used, coupled with the small baseline crime levels in the dataset. Because a small number of incidents is sufficient to push a street segment into or out of

[24] http://www.stltoday.com/news/local/metro/updates-on-other-knockout-game-cases/article_3ae2a002-2bb4-5056-8a28-db5c5fa795b6.html

the threshold for a high crime month, some of these results could be spurious. Further investigation across a longer time period and multiple cities will be necessary to determine if these findings are real and can be replicated.

POLICY IMPLICATIONS AND FUTURE DIRECTIONS

The most significant contribution of this dissertation to crime control policy is the lack of evidence of chronic crime hot spots. Previous studies of hot spot stability find evidence of stable, chronic crime hot spots spanning several years; these findings have been cited as the basis of policy recommendations that place-based crime interventions should focus on chronic crime hot spots to achieve the greatest crime reduction effects (Weisburd et al. 2016; Weisburd, Groff, and Yang 2012). The findings in this dissertation suggest that chronic crime hot spots are not hot and may even be crime free most of the time, with a small number of high crime months driving annual crime totals. This suggests that the stability of crime hot spots depends on the temporal unit of analysis used. This contribution carries implications for place-based policing policies and future studies of crime and place.

A significant obstacle to place-based policing efforts is sustaining an intervention over a long period of time (Weisburd 2000, 2005). Though prior studies have not examined the impact of longer interventions on officer fatigue, data from a nine-month hot spot policing experiment in St. Louis showed a precipitous drop in police activity treatment areas after 3 months (Rosenfeld, Deckard, and Blackburn 2014). The absence of chronic crime hot spots in the current study suggests that crime is more mobile that has been found in previous studies. Crime hot spots that change over periods of months rather than years should encourage police and other stakeholders to design place-based initiatives that focus police resources in crime hot spots for brief periods of time, perhaps one to three months. While additional research is needed to identify the optimal duration of hot spot interventions, shorter interventions are likely to have better treatment fidelity as officers are continually directed to emerging hot spots.

The same policy implication holds for the delivery of other public services and social services. Scholars have recently argued that these services should also be place-based and that crime hot spots have critical service needs in the form of improved street lighting, building and road repairs, family counseling, crisis intervention, job training, and drug treatment (Weisburd 2018; Weisburd et al. 2018). The results of this dissertation suggest that such services might help to improve the economic and social disadvantages that contribute to crime. If crime hot spots are not stable over time, then public and social service delivery should be as data-driven and nimble as targeted policing in bringing resources to bear where and when they are needed.

Shortening the length of place-based crime interventions could also improve police legitimacy. One concern with the development and increased use of place-based policing (and hot spot policing in particular) is that increased targeted enforcement activities can aggravate already strained relationships between the police and communities in areas with high crime concentrations, especially communities of color (Weisburd et al. 2011; Rinehart Kochel 2010; Higginson and Mazerolle 2014). Reducing the amount of time the police remain at crime hot spots would help mitigate these concerns, as residents are likely to be more receptive to increased police activity for brief periods of time, rather than feeling sustained police pressure for months on end. Coupling short-term place-based policing with community and problem-solving policing can strengthen relationships between police and communities within crime hot spots.

Prior studies have also found that longitudinal crime patterns at micro-geographic places can vary significantly by crime type, and caution against aggregating crime across differing crime types for the purposes of place-based crime interventions (Andresen, Curman, and Linning 2017; Andresen and Linning 2012). The findings presented in this dissertation add to this knowledge on the distribution of crime in urban areas and emphasize the importance of crime type to public policies aimed at reducing crime where it is highly concentrated. While the spatial and temporal scales used to measure crime in the current study required some aggregation by offense type (property and violent crime), the results clearly show that crime type is important for understanding the duration of crime hot spots. While no chronic violent crime hot spots were found, some property crime hot spots persisted for nearly the entire 60-month observation period. As with violent crime hot spots, however, most property crime hot spots are temporary, and so the same strategies for pursuing violent crime hot spots as they move over time should be applied to property crime hot spots. For the property crime hot spots that are more permanent, one recommendation would be to create a specialized property crime unit that focuses on those areas.

Overall, the contribution of this dissertation to crime control policy rests on the evidence that suggests that chronic crime hot spots are not as stable as reported in prior studies and that crime hot spots move from place to place within years. These findings suggest that place-based policies and programs to reduce crime at hot spots should focus police and other public and social service resources to high crime street segments for short periods of time. Modern GIS technologies allow police administrators and crime analysts to identify emerging hot spots on a monthly basis, coordinate with other service providers, and allocate resources to high crime areas accordingly. These policy recommendations have the potential to increase police efficiency, improve police-community relations, and prevent officer burnout from place-based interventions.

CONCLUSION

This dissertation was undertaken to improve our understanding of the nature of chronic and temporary hot spots through the lens of the criminology of place. From the outset, the struggle to constrain the scope of the study to a manageable scale was formidable. Hundreds of studies on this subject have been conducted by scholars of the highest caliber in recent years; their collective work has created a new criminological paradigm that will shape the discussion of crime and place for the foreseeable future. The findings presented in this dissertation represent a small step forward in the ongoing endeavor to better understand how and why crime concentrates in chronic and temporary hot spots. As with many research projects, this dissertation likely raises more questions than it answers; I have attempted to provide plausible explanations for these lingering questions where appropriate, but many will require further investigation. It is my hope that this dissertation will spark new interest and inquiry in to the problem of differentiating chronic and temporary crime hot spots, as well as provide guidance for stakeholders interested in crafting better evidence-based crime policy to address crime concentration in urban areas.

Table 6.1. Baden and Patch Neighborhood Characteristics (2010 Census)

Area (mi^2)		1.127	1.078
Population		7,268	2,695
	White	6.34%	71.3%
	Black	91.9%	21.2%
	Other	1.8%	7.6%
Housing Units		3,448	1,418
	Occupied	82.1%	81%
	Vacant	17.9%	19%
Part 1 Crime		3,933	1,474
	Property	3,079	1,207
	Rate / 1,000	423.6	447.9
	Violent	854	267
	Rate / 1,000	117.5	99.1

Figure 6.1. High Crime Street Segments in the Baden Neighborhood of St. Louis, Violent Crime (2010-2014)

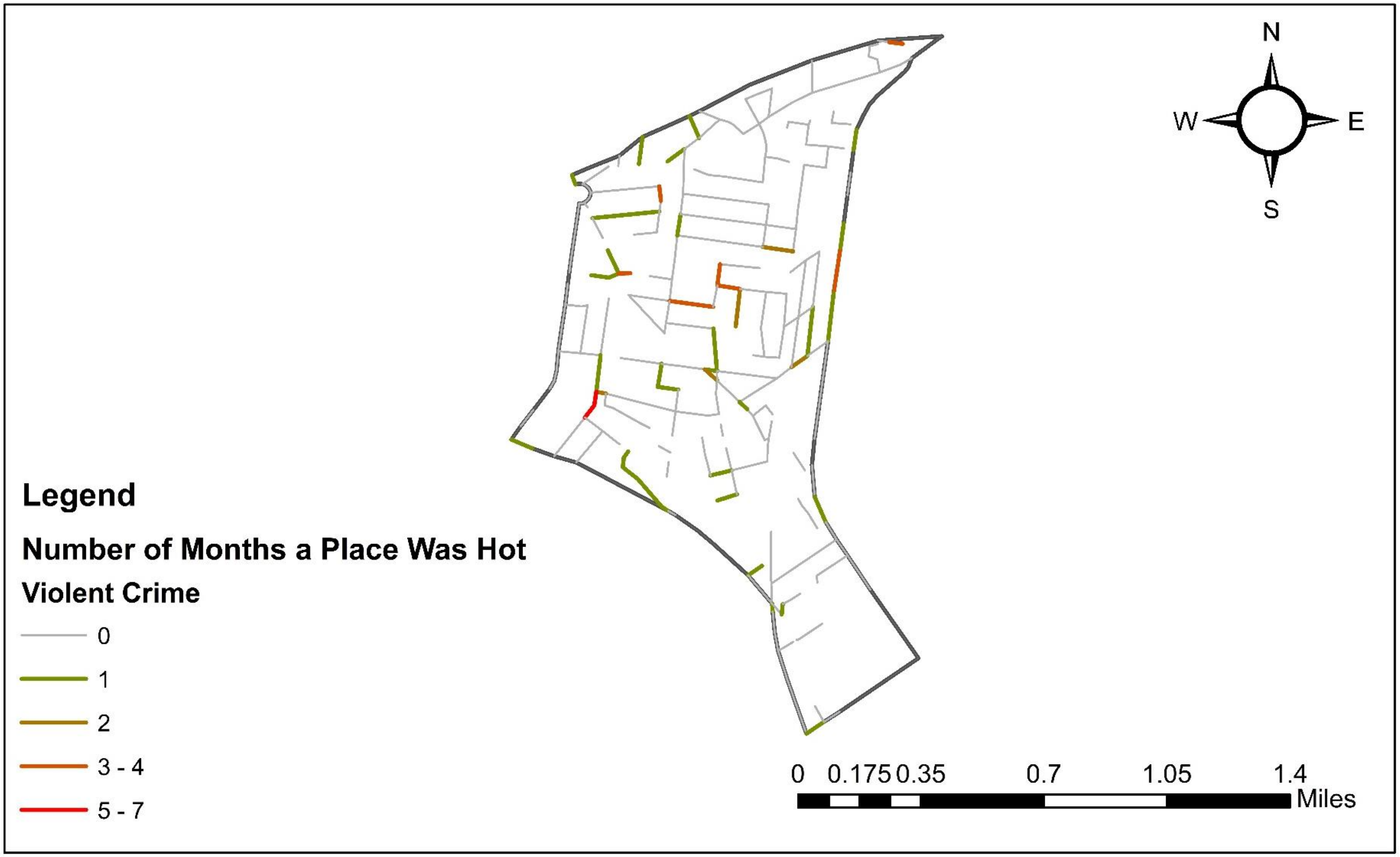


Figure 6.2 High Crime Street Segments in the Baden Neighborhood of St. Louis, Property Crime (2010-2014)

Figure 6.3. High Crime Street Segments in the Patch Neighborhood of St. Louis, Violent Crime (2010-2014)

Figure 6.4. High Crime Street Segments in the Patch Neighborhood of St. Louis, Property Crime (2010-2014)

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APPENDIX A: UCR PART 1 OFFENSE DEFINITIONS

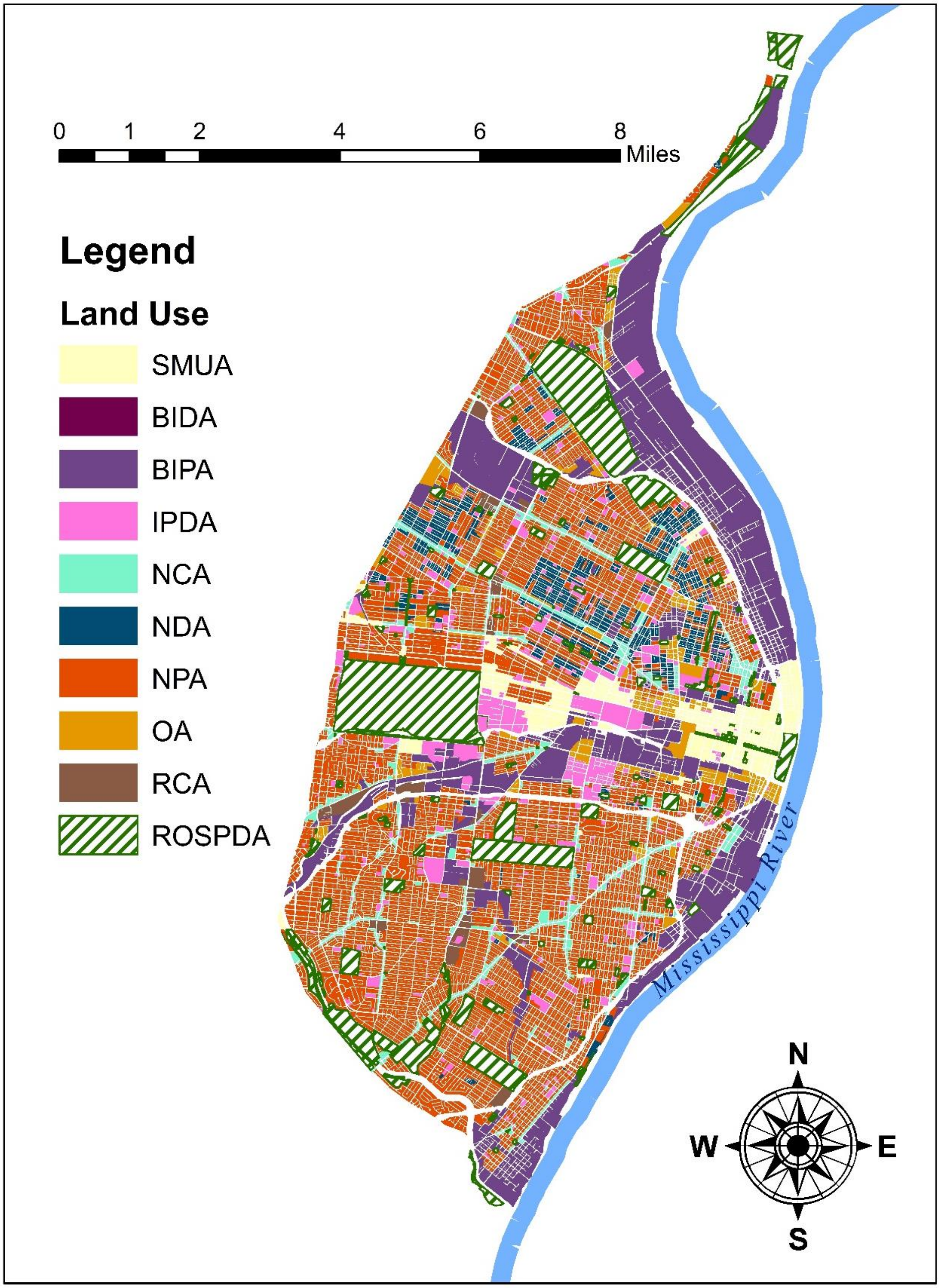
Homicide	a.) Murder and nonnegligent manslaughter: the willful (nonnegligent) killing of one human being by another. Deaths caused by negligence, attempts to kill, assaults to kill, suicides, and accidental deaths are excluded. The program classifies justifiable homicides separately and limits the definition to: (1) the killing of a felon by a law enforcement officer in the line of duty; or (2) the killing of a felon, during the commission of a felony, by a private citizen. b.) Manslaughter by negligence: the killing of another person through gross negligence. Deaths of persons due to their own negligence, accidental deaths not resulting from gross negligence, and traffic fatalities are not included in the category Manslaughter by Negligence.
Rape	Forcible Rape (through 2010): The carnal knowledge of a female forcibly and against her will. Rapes by force and attempts or assaults to rape, regardless of the age of the victim, are included. Statutory offenses (no force used—victim under age of consent) are excluded. Revised Rape (2011-present): penetration, no matter how slight, of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim. Attempts or assaults to commit rape are also included; however, statutory rape and incest are excluded.
Robbery	The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.
Aggravated Assault	An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded.
Burglary	The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.
Larceny	The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples are thefts of bicycles, motor vehicle parts and accessories, shoplifting, pocket-picking, or the stealing of any property or article that is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, confidence games, forgery, check fraud, etc., are excluded.
Motor Vehicle Theft	The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on land surface and not on rails. Motorboats, construction equipment, airplanes, and farming equipment are specifically excluded from this category.

APPENDIX B: LAND USE CLASSIFICATION

Neighborhood Preservation Area (NPA)	Areas where the existing housing and corner commercial building stock will be preserved and augmented with new infill residential and corner commercial development physically integrated with, and primarily serving the immediate neighborhood. These areas generally consist of stable residential areas of the City, including but not limited to historic districts, where the character of the neighborhood is currently well preserved with relatively few vacant lots and abandoned buildings. The Plan contemplates continued preservation and improvement, with quality rehabilitation and infill new construction that is sensitive to the character of existing residences. Commercial and institutional uses catering to the immediate needs of the neighborhood are acceptable and reflect the traditional role such activity has played in the history of the City.
Neighborhood Development Area (NDA)	Residential and non-residential areas with substantial amounts of vacant land and abandoned buildings suitable for new residential construction of scale/associated neighborhood services, respecting stable properties that may be considered as part of any new development. Opportunities for new housing construction/re-platting at critical mass scale defining a new neighborhood character over time.
Neighborhood Commercial Area (NCA)	Areas where the development of new and the rehabilitation of existing commercial uses that primarily serve adjacent neighborhoods should be encouraged. These areas include traditional commercial streets at relatively major intersections and along significant roadways where commercial uses serve multiple neighborhoods or where the development of new commercial uses serving adjacent neighborhoods is intended. Mixed use buildings with commercial at grade and a mix of uses on upper floors are an ideal type within these areas. These areas may include higher density mixed use residential and commercial and may initially include flexibility in design to allow ground floor uses to change over time e.g., ground floor space that can transition from residential to commercial use as the local demand for retail goods and services strengthens in the area.
Recreational/open space preservation /development area (rospda)	Areas including the existing network of parks, open space and recreational facilities within the City that should be preserved and enhanced, as well as locations for new permanent green space, including planned new greenways and permanent locations for some community gardens. The City's Department of Parks, Recreation and Forestry is currently at work on a city-wide parks and recreation plan that will be overlaid on the Strategic Land Use Plan when complete.

Regional Commercial Area (RCA)	Areas where the development of existing and commercial uses intended to serve a regional clientele should be encouraged. Developments in these areas will often be new projects. These areas generally consist of existing regional commercial uses or large sites at intersections of major roads/highways with regional access and visibility. Several large and currently underutilized sites exist in the City at prominent intersections. These locations provide “ready to go” locations for large format retailers with strong adjacent markets.
Business/Industrial Preservation Area (BIDA)	Areas where stable businesses currently exist and are encouraged to remain. This designation includes industrial and non-retail commercial uses where the location, condition of buildings and the low level of vacancy warrant preservation and infill industrial development where possible.
Business/Industrial Development Area (BIDA)	Areas where new business/industrial uses or campuses will be encouraged. New business activity may range from larger business parks to smaller scale development. BIDA areas shown on the Plan typically consist of underutilized buildings and land adjacent to major roadways, railroads or the river, providing local or regional access. These areas have experienced a drop in the level of economic activity from its earlier peak. A change of use on such lands is usually not appropriate due to environmental concerns, and the opportunity exists to rejuvenate these locations to create new employment opportunities.
Institutional Preservation & Development Area (IPDA)	Areas where significant nodes of educational, medical, religious or other institutional uses currently exist and are appropriately situated, as well as areas for expansion of such institutional uses. These large scale institutional centers are intended to positively influence the enhancement of surrounding areas.
Specialty Mixed Use Area (SMUA)	Areas like Downtown St. Louis where it is intended that a unique mix of uses be preserved and developed.
Opportunity Area (OA)	Key underutilized locations where the use of the land is in transition. Location and site characteristics of these areas offer particular challenges/opportunities that could be advantageous to a range of development activity. This designation is intended to be flexible and specific development proposals will be entertained as they present themselves.

Figure B.1. Land-Use Classification Map, St. Louis, MO



APPENDIX C: SUPPLEMENTARY FIGURES

Figure C.1.1. Number of Hot Months by Number of Hot Years, Segments Hot 1 Year, Violent Crime, 2010-2014

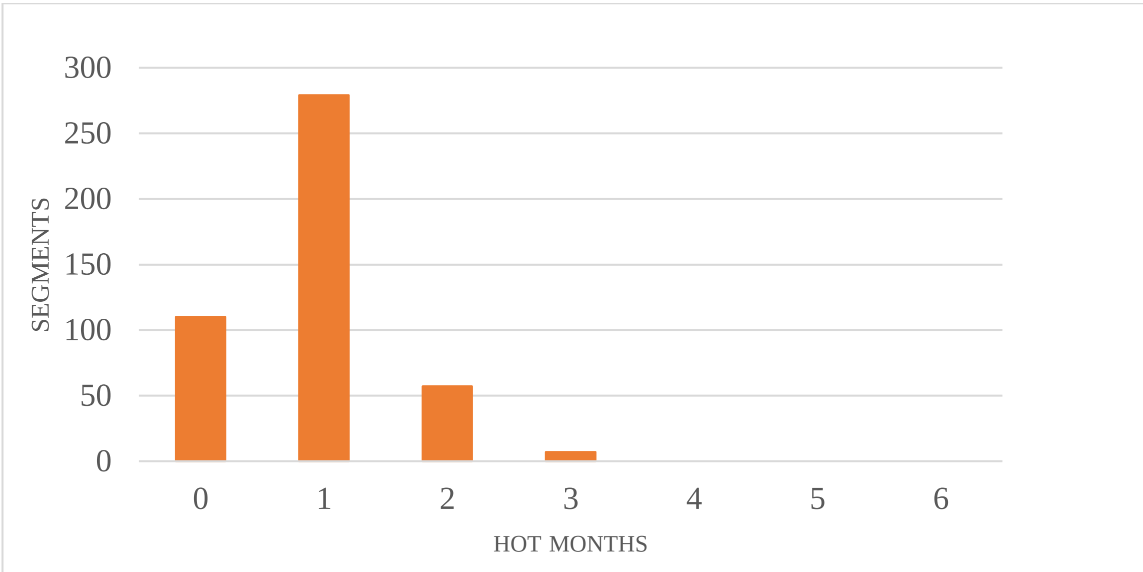


Figure C.1.2. Number of Hot Months by Number of Hot Years, Segments Hot 1 Year, Property Crime, 2010-2014

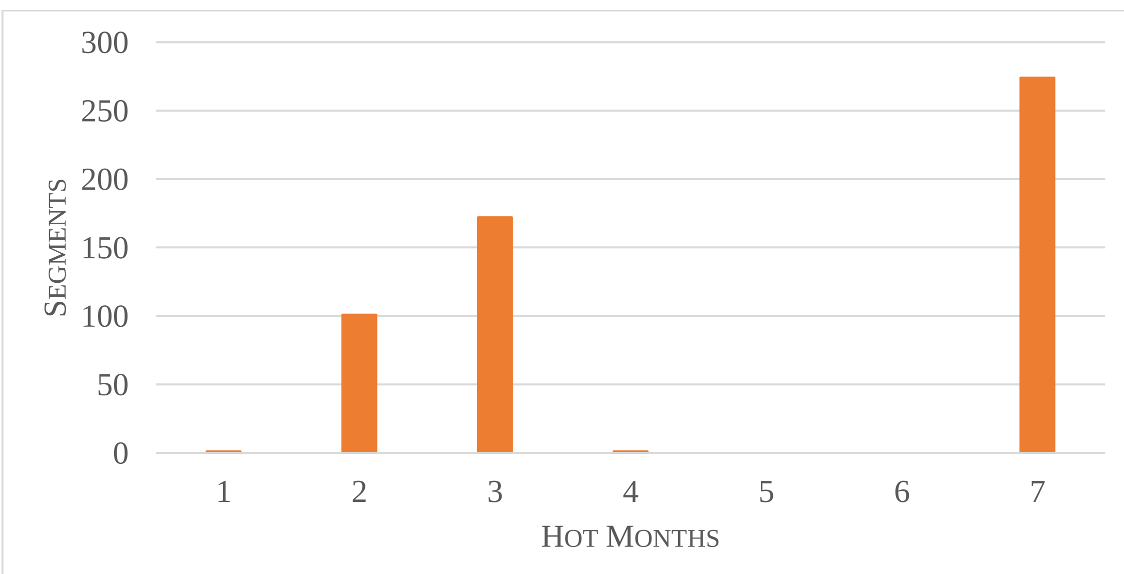


Figure C.2.1. Number of Hot Months by Number of Hot Years, Segments Hot 2 Years, Violent Crime, 2010-2014

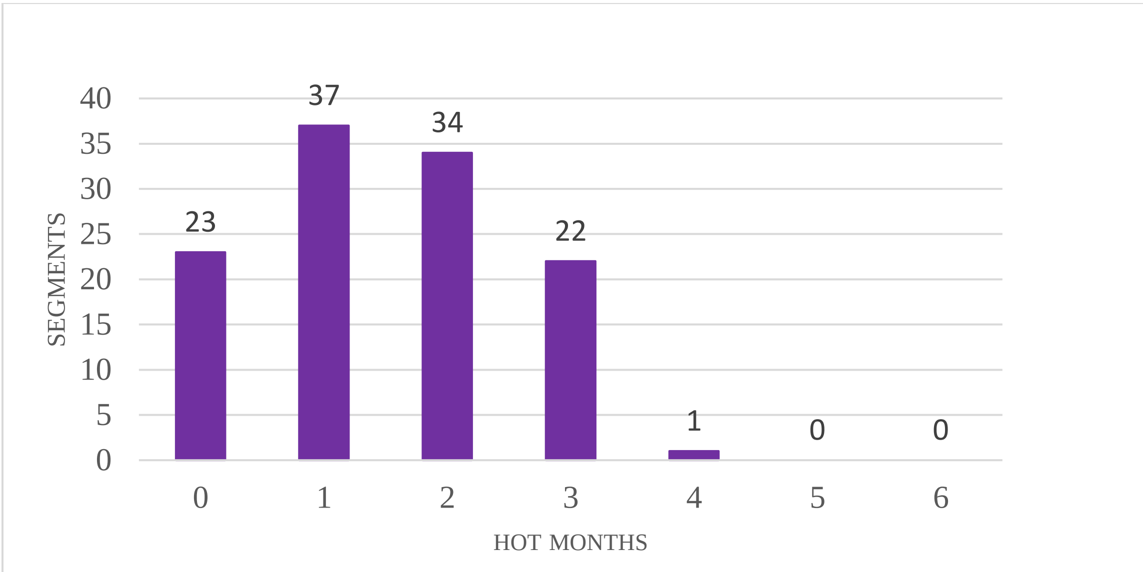


Figure C.2.2. Number of Hot Months by Number of Hot Years, Segments Hot 2 Years, Violent Crime, 2010-2014

Figure C.3.1. Number of Hot Months by Number of Hot Years, Segments Hot 3 Years, Violent Crime, 2010-2014

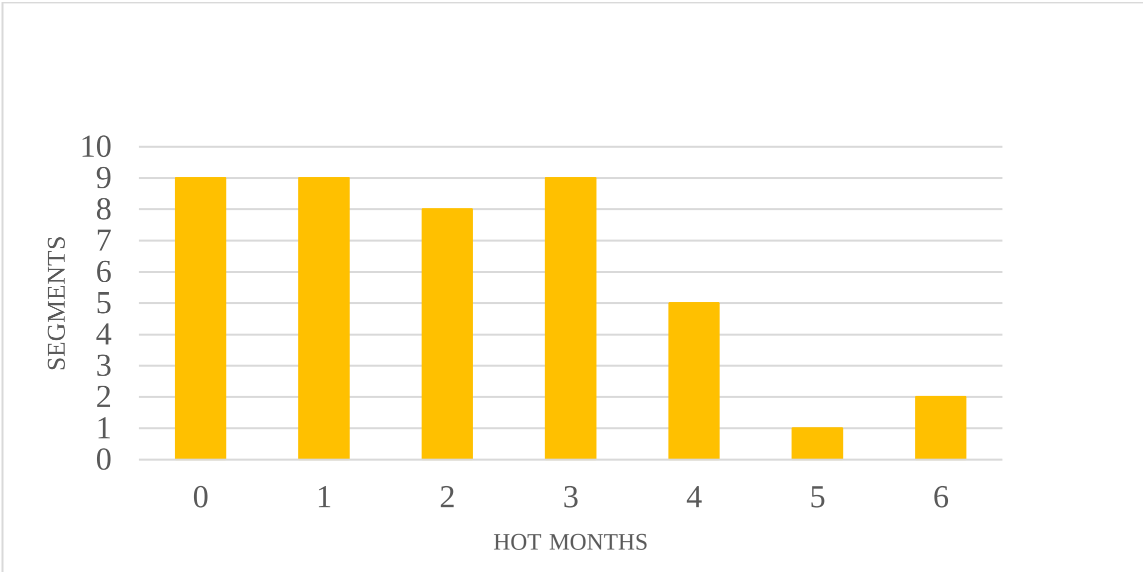


Figure C.3.2. Number of Hot Months by Number of Hot Years, Segments Hot 3 Years, Property Crime, 2010-2014

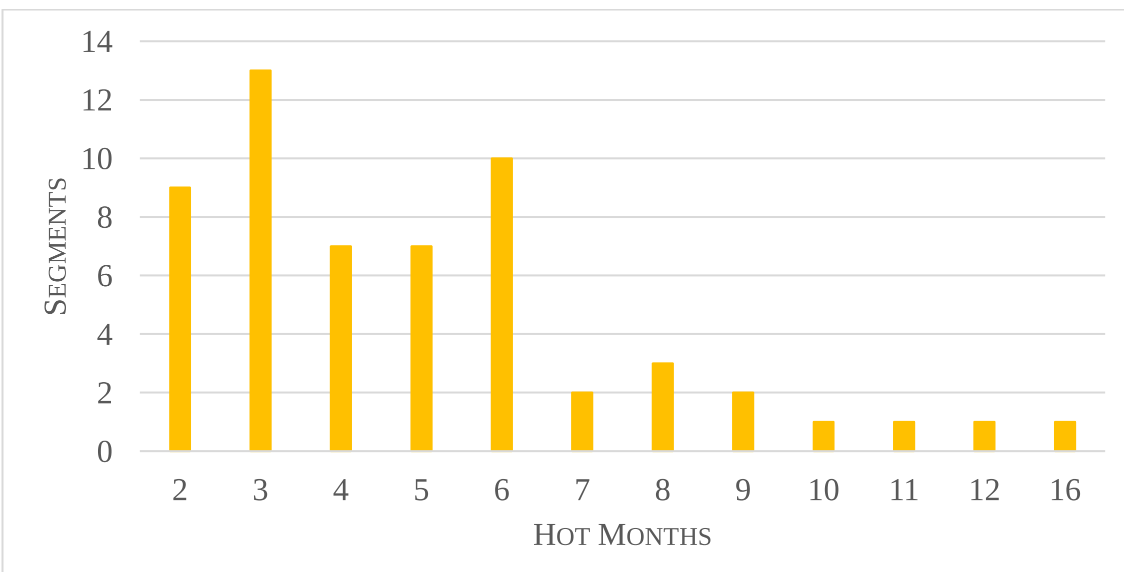


Figure C.4.1. Number of Hot Months by Number of Hot Years, Segments Hot 4 Years, Violent Crime, 2010-2014

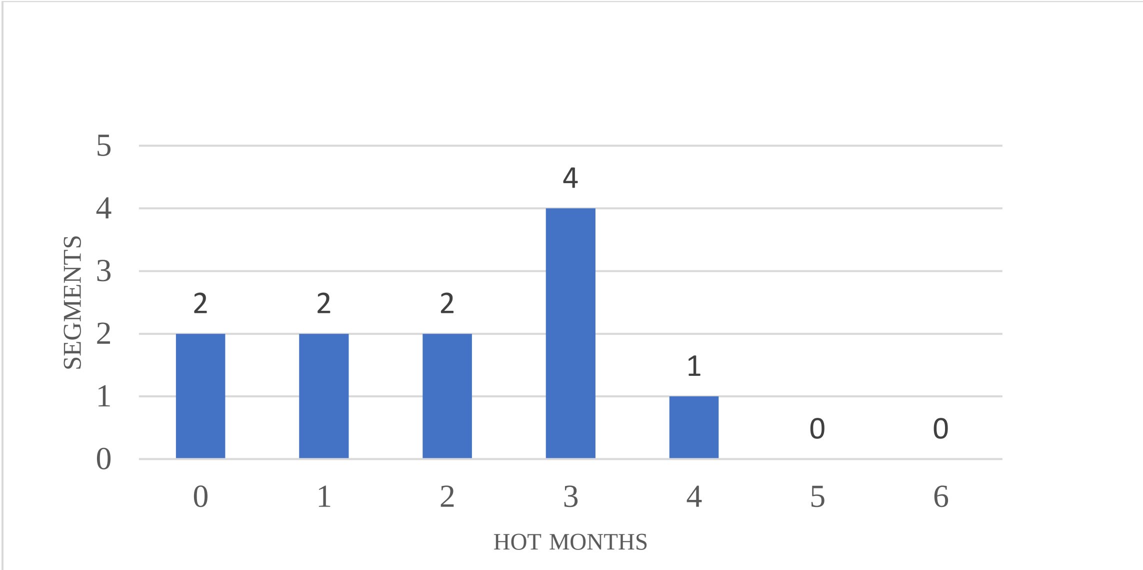


Figure C.4.2. Number of Hot Months by Number of Hot Years, Segments Hot 4 Years, Property Crime, 2010-2014

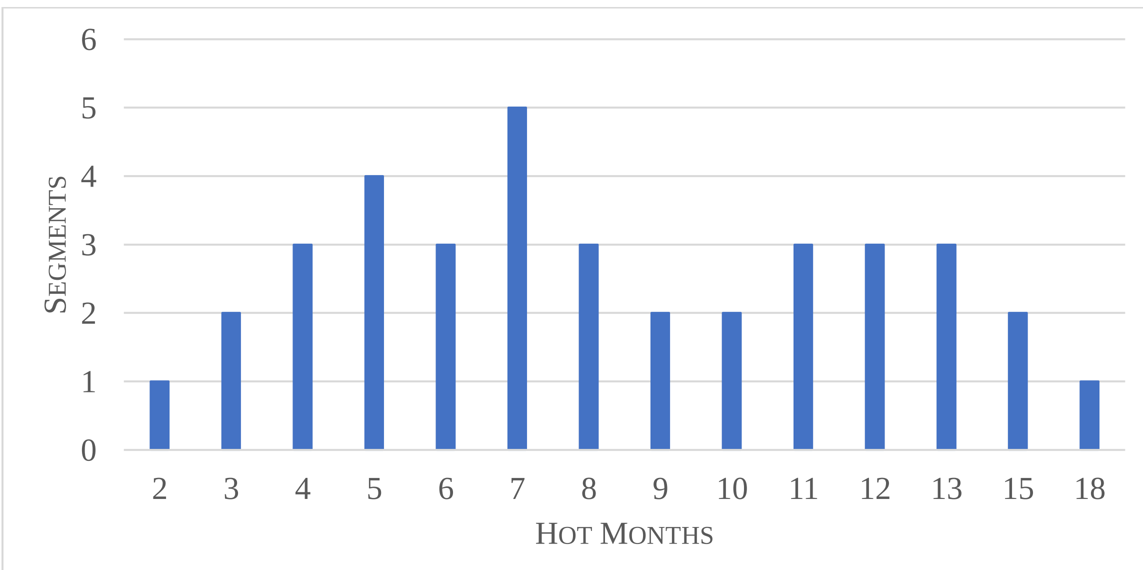


Figure C.5.1. Number of Hot Months by Number of Hot Years, Segments Hot 5 Years, Violent Crime, 2010-2014

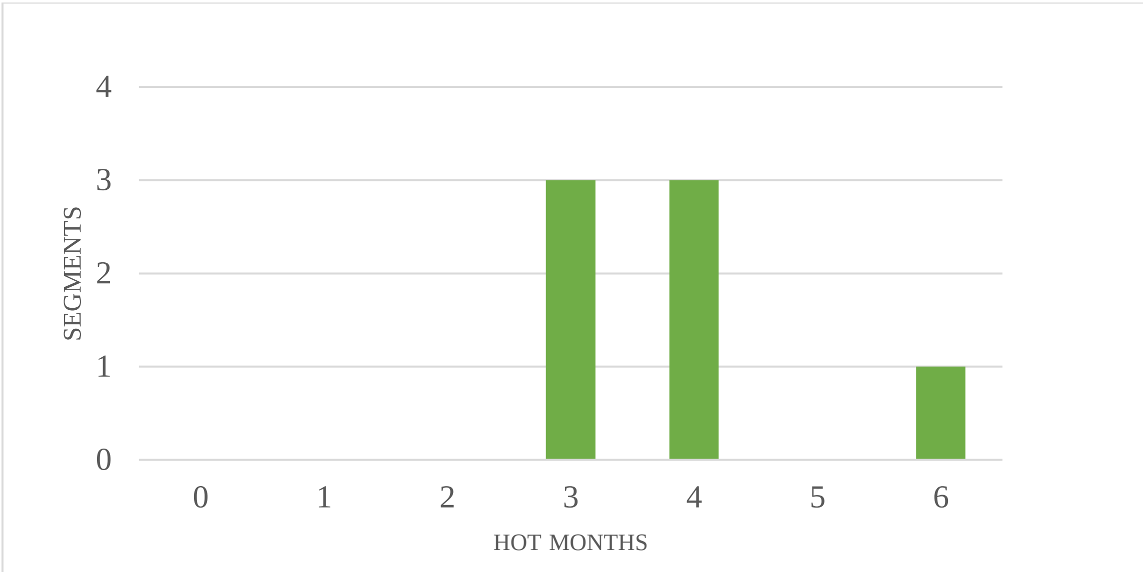
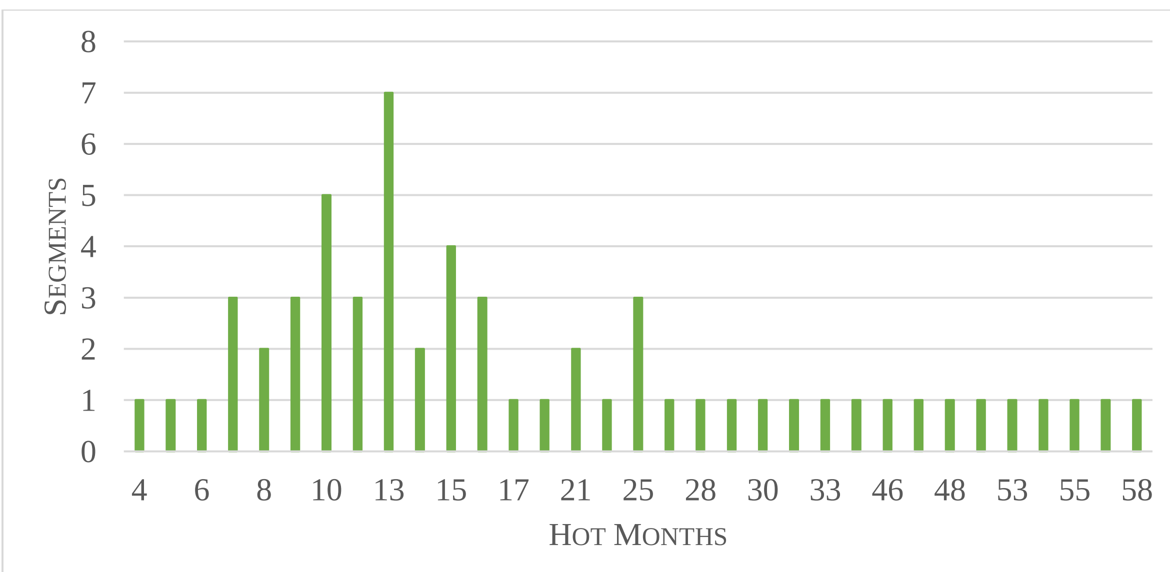


Figure C.5.2. Number of Hot Months by Number of Hot Years, Segments Hot 5 Years, Property Crime, 2010-2014



APPENDIX D: FULL MULTIVARIATE REGRESSION RESULTS

Table D.1. Logistic Regression Model – Violent & Property Crime (Zeros Included)

	N	13.136			13.136		
	LR chi2(25)	2428.12			2014.88		
	Prob< chi2	0.000			0.000		
	Log likelihood	-8716.40			-9012.6187		
	Pseudo R2	0.122			0.1005		
	N hot months	20,470			67,279		
	hotspot (0,1)	violent			property		
		b	*SE*	*P<|Z|*	*b*	*SE*	*P<|Z|*
block	%fhh	0.00284	0.00172		0.00343	0.00179	~*
	%rent	0.00599	0.000833	***	0.00413	0.000863	***
	%black	0.0122	0.000857	***	0.00717	0.000891	***
	%15-24	0.00440	0.00216	*	0.0106	0.00233	***
	%50+	-0.00160	0.000935		0.00671	0.000975	***
	%vacant	0.00215	0.000710	**	0.00000489	0.000700	
	%publicassistance	0.00301	0.00381		0.00582	0.00378	
	%newres	0.00441	0.00145	**	0.00393	0.00139	**
block group	%poverty	0.00319	0.00149	*	-0.00549	0.00145	***
	%hsged	0.0131	0.00229	***	0.00944	0.00232	***
	%usepubtransit	0.00227	0.00201		-0.00119	0.00202	
	%k-12	-0.00649	0.00208	**	-0.00804	0.00204	***
segment	#paydaylenders	-0.201	0.262		-0.303	0.263	
	#hospitals	1.10	0.668		0.655	0.699	
	#bars	1.17	0.0836	***	2.00	0.167	***
	Land Use Category						
block	BIPA	0.0370	0.127		-0.0273	0.099448	
	IPDA	0.903	0.119	***	0.773	0.101	***
	NCA	1.41	0.117	***	1.07	0.102	***
	NDA	0.715	0.126	***	0.591	0.112	***
	NPA	0.996	0.106	***	0.863	0.0858	***
	OA	0.636	0.142	***	0.232	0.122	~*
	RCA	0.977	0.179	***	0.214	0.163	
	ROSPDA	0.601	0.132	***	-0.097	0.110	
	SMUA	1.20	0.129	***	0.715	0.112	***

Table D.2. Logistic Regression Model – Violent & Property Crime (Zeros Coded as Missing)

	N	13.136			13.136	13.136	
	LR chi2(25)	720.05				640.31	
	Prob< chi2	0.000				0.000	
	Log likelihood	-2882.99				-4297.91	
	Pseudo R2	0.111				0.0693	
	N hot months	1,148				3,925	
	hotspot (0,1)		violent			property	
		b	*SE*	*P<|Z|*	*b*	*SE*	*P<|Z|*
	%fhh	0.00254	0.00277		-0.00182	0.00255	
	%rent	0.00412	0.00161	**	0.00516	0.00125	***
block level	%black	0.0132	0.00159	***	0.00756	0.00132	***
	%15-24	-0.00113	0.00383		0.00961	0.00286	***
	%50+	-0.00660	0.00182	***	-0.00183	0.00147	
	%vacant	0.000111	0.00133		6.46E-06	0.00115	
	%publicassistance	0.00819	0.00662		-0.00714	0.00635	
	%newres	-0.00716	0.00306	*	0.0094	0.00233	***
block group level	%poverty	0.00570	0.00283	*	0.00444	0.00241	~*
	%hsged	0.0105	0.00456	*	-0.00295	0.00359	
	%usepubtransit	0.00412	0.00344		0.00201	0.00316	
	%k-12	0.00948	0.0042	*	-0.00678	0.00322	*
	#paydaylenders	0.280	0.366		0.143	0.342	
segment level	#hospitals	1.92	0.735	**	1.72	0.622	**
	#bars	0.575	0.0677	***	0.865	0.0663	***
	Land Use Category						
	BIPA	-0.190	0.407		0.00762	0.269	
	IPDA	1.019	0.326	*	1.27	0.235	***
	NCA	1.45	0.318	***	1.18	0.234	***
block level	NDA	0.744	0.326	*	0.346	0.261	
	NPA	1.16	0.306	***	1.05	0.223	***
	OA	0.698	0.368	~*	0.564	0.281	*
	RCA	1.42	0.406	***	1.50	0.294	***
	ROSPDA	0.810	0.370	*	0.334	0.277	
	SMUA	1.30	0.355	***	0.966	0.248	***

Table D.3. Negative Binomial Regression Results – Violent and Property Crime

	Observations	13.136			13.136		
	LR chi2(25)	2455.02			1780.94		
	Prob< chi2	0.000			0.000		
	Log likelihood	-20345.914			-34657.4		
	Pseudo R2	0.0569			0.025		
	N hot months	1,148			3,925		
		violent			property		
		b	*SE*	*P<|Z|*	*b*	*SE*	*P<|Z|*
	%fhh	0.00410	0.00221	~*	-0.00209	0.00163	
	%rent	0.00497	0.00134	***	0.00272	0.000740	***
	%black	0.0113	0.00133	***	0.00482	0.000821	***
	%15-24	-0.00148	0.00323		0.00870	0.00167	***
block	%50+	-0.00585	0.00152	***	-0.000584	0.000893	
	%vacant	0.000507	0.00110		0.00237	0.000694	***
	%publicassistance	0.0151	0.00520	**	-0.0123	0.00410	**
	%newres	-0.00928	0.00259	***	0.0133	0.00137	***
	%poverty	0.00669	0.00236	**	-0.000355	0.00149	
	%hsged	0.00504	0.00388		-0.00862	0.00221	***
block group	%usepubtransit	0.00498	0.00282		0.00865	0.00190	***
	%k-12	0.00880	0.00361	**	-0.00531	0.00185	**
	#paydaylenders	0.113	0.323		-0.611	0.353	
segment	#hospitals	1.57	0.510	**	2.48	0.134	***
	#bars	0.472	0.0373	***	0.423	0.0111	***
	Land Use Category						
	BIPA	-0.217	0.394		0.0178	0.183	
	IPDA	1.06	0.305	***	1.28	0.158	***
	NCA	1.53	0.296	***	1.59	0.155	***
	NDA	0.883	0.302	**	0.0746	0.190	
block	NPA	1.27	0.288	***	0.911	0.152	***
	OA	0.830	0.337	*	1.01	0.178	***
	RCA	1.63	0.353	***	3.17	0.157	***
	ROSPDA	1.02	0.337	**	0.745	0.174	***
	SMUA	1.44	0.325	***	1.51	0.159	***

Table D.4. Zero-Inflated Negative Binomial Regression Results – Violent and Property Crime

	Observations	13.136			13.136	13.136	
	LR chi2(25)	2455.02			1780.94		
	Prob< chi2	0.000			0.000		
	Log likelihood	-20345.914			-34657.4		
	Pseudo R2	0.0569			0.025		
	N hot months	20,470			67,279		
			violent			property	
		b	*SE*	*P<|Z|*	*b*	*SE*	*P<|Z|*
block	%fhh	0.000389	0.00150		1.34E-05	0.00140	
block	%rent	0.00600	0.000731	***	0.00493	0.000655	***
block	%black	0.0110	0.000735	***	0.00670	0.000673	***
block	%15-24	0.00151	0.00181		0.00814	0.00179	***
block	%50+	-0.00387	0.000781	***	0.000138	0.000728	
block	%vacant	0.00216	0.000594	***	0.0000230	0.000535	
block	%publicassistance	0.00513	0.00318		0.000865	0.00287	
block	%newres	0.00577	0.00120	***	0.00615	0.00104	***
block group	%poverty	0.00394	0.00120	***	-0.00216	0.00108	*
block group	%hsged	0.0125	0.00189	***	0.00482	0.00170	**
block group	%usepubtransit	0.00616	0.00160	***	3.32E-05	0.00147	
block group	%k-12	-0.00303	0.00173	~*	-0.00547	0.00150	***
segment	#paydaylenders	-0.164	0.198		-0.00444	0.178	
segment	#hospitals	1.23	0.469	**	1.38	0.442	**
segment	#bars	0.666	0.0473		0.703	0.0452	***
	Land Use Category						
	BIPA	-0.0652	0.104		-0.0307	0.0785	
block	IPDA	0.904	0.0963	***	0.767	0.0783	***
block	NCA	1.44	0.0929	***	0.993	0.0764	***
block	NDA	0.523	0.102	***	0.334	0.0862	***
block	NPA	0.832	0.085	***	0.773	0.0676	***
block	OA	0.774	0.114	***	0.404	0.0935	***
block	RCA	1.40	0.140	***	1.16	0.123	***
block	ROSPDA	0.564	0.107	***	0.129	0.0858	
block	SMUA	1.22	0.104	***	0.753	0.0856	***
	%fhh						

Table D.5. Cox Proportional Hazard Model – Violent and Property Crime (Zeros Out)

	Observations	14,217			16,655		
	Failures	1081			3519		
	Time at risk	27113280			27113280		
	Wald Chi2	750.68			304.15		
	Prob<Chi2	0.000			0.000		
	Log pseudo	-12533.6			-31611.1		
	nhotmonths	violent			property		
		b	*SE*	*P<|Z|*	*b*	*SE*	*P<|Z|*
block	%fhh	0.00346	0.00222		-0.00184	0.00195	
	%rent	0.00390	0.00135	**	0.000949	0.00115	
	%black	0.0105	0.00140	***	0.00335	0.00109	**
	%15-24	-0.00114	0.00334		0.00394	0.00193	*
	%50+	-0.00494	0.00178	**	-0.000570	0.00206	
	%vacant	0.000858	0.00112		0.00151	0.000948	
	%publicassistance	0.0123	0.00563	*	0.000734	0.00973	
	%newres	-0.007605	0.00274	**	0.00636	0.00314	*
block group	%poverty	0.00687	0.00240	**	-0.00254	0.00284	
	%hsged	0.00894	0.00333	**	-0.00917	0.00388	*
	%usepubtransit	0.00433	0.00295		0.00765	0.00474	
	%k-12	0.00468	0.00340		-0.00221	0.00339	
segment	#paydaylenders	0.0821	0.207		-0.357	0.169	*
	#hospitals	1.34	0.420	***	0.969	0.337	**
	#bars	0.358	0.0425	***	0.0884	0.0319	**
	Land Use Category						
	BIPA	-0.237	0.396		0.0603	0.303	
block	IPDA	1.03	0.319	***	0.831	0.253	***
	NCA	1.48	0.316	***	1.09	0.275	***
	NDA	0.841	0.319	**	0.173	0.273	
	NPA	1.19	0.303	***	0.657	0.257	**
	OA	0.825	0.360	*	0.727	0.284	**
	RCA	1.54	0.392	***	1.88	0.308	***
	ROSPDA	0.977	0.369	**	0.521	0.318	
	SMUA	1.35	0.350	***	1.00	0.292	***

APPENDIX E: IRB DOCUMENTATION

Office of Research Administration

One University Boulevard
St. Louis, Missouri 63121-4499
Telephone: 314-516-5899
Fax: 314-516-6759
E-mail: ora@umsl.edu

DATE:	August 5, 2016
TO:	Michael Deckard, M.A.
FROM:	University of Missouri-St. Louis IRB
PROJECT TITLE:	[892458-1] Policing Microgeographic Areas: Is Temporal Stability Important?
REFERENCE #:	
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	August 5, 2016
REVIEW CATEGORY:	Exemption category # 4

The chairperson of the University of Missouri-St. Louis IRB has APPROVED the above mentioned protocol for research involving human subjects and determined that the project qualifies for exemption from full committee review under Title 45 Code of Federal Regulations Part 46.101b. The time period for this approval expires one year from the date listed above. You must notify the University of Missouri-St. Louis IRB in advance of any proposed major changes in your approved protocol, e.g., addition of research sites or research instruments.

You must file an annual report with the committee. This report must indicate the starting date of the project and the number of subjects to date from start of project, or since last annual report, whichever is more recent.

Any consent or assent forms must be signed in duplicate and a copy provided to the subject. The principal investigator must retain the other copy of the signed consent form for at least three years following the completion of the research activity and they must be available for inspection if there is an official review of the UM-St. Louis human subjects research proceedings by the U.S. Department of Health and Human Services Office for Protection from Research Risks.

This action is officially recorded in the minutes of the committee.

If you have any questions, please contact Carl Bassi at 314-516-6029 or bassi@umsl.edu. Please include your project title and reference number in all correspondence with this committee.