PREDICTING ARREST TRAJECTORIES IN MICRO-PLACES:
A TEST OF SOCIAL DISORGANIZATION THEORY

by

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To those who gave their lives for peace and justice.

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DISSERTATION

Presented to the Faculty of

The University of Texas at Dallas

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY IN

CRIMINOLOGY

THE UNIVERSITY OF TEXAS AT DALLAS

December 2016

ACKNOWLEDGMENTS

I would like to first thank my chair, Dr. John Worrall. He spent countless hours guiding me through the process of conducting this study. His dedication and passion for improving knowledge in police research has been my inspiration and motivation throughout my years as a doctoral student. Thanks also go to Dr. Alex Piquero for providing valuable theoretical and methodological advice; he has been a magnificent mentor and model for my academic development. I am most appreciative, too, for Dr. Lynne Vieraitis and Dr. Bruce Jacobs, both of whom provided invaluable assistance in the dissertation process and the classroom. The final member of my committee, Dr. Bryan Chastain, advised me on the geospatial analysis, a critical part of the study; he deserves a heartfelt thank you, as well. Next, I would also like to thank the amazing faculty at UT Dallas; I would not have brought this project to fruition without their help. Thanks also go to the Dallas Police Department and the Caruth Police Institute (CPI) for providing me both the work space and the data. Special thanks go to Corporal Harold Varner, Dr. Mark Stallo, Dr. Steve Bishopp, and Dr. Melinda Schlager, for their mentorship in both education and scientific research, and to Jennifer Davis-Lamm and Shayna Vincent of CPI for being great friends throughout the years. Even my grade school teachers, Mr. Kwong and Dr. Ho, deserve credit; their teachings laid the foundation of my character. Joey Tingsanchali deserves special thanks for his editorial advice and for reading multiple versions of this document. My family also deserves a special note of thanks for all that they gave me. Finally, to

Amy, my wife and my editor-in-chief, thank you for your support and tireless hours editing throughout my doctoral education.

October 2016

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Publication No. ___________________

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The University of Texas at Dallas, 2016

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Although much has been learned about crime in micro-places, their development and continuity over time remains largely misunderstood. In 2006, Weisburd, Bushway, Lum and Yang were the first to develop trajectories of crime at micro-places, but their study was largely atheoretical. In 2012, Weisburd, Groff, and Yang explored theoretical predictors of crime in micro-places, but they did not formally test any one theory. This study builds on both prior efforts by testing whether social disorganization theory predicts Census block-level arrest trajectories in Dallas, Texas, between 2010 and 2014. Results suggest that social disorganization can help explain arrest trajectory group membership, but not completely. While socioeconomic factors, residential stability, and family disruption were significantly associated with trajectory group membership, racial heterogeneity was only significant when it was interacted with other variables. Also, urbanization exerted no discernible effect on arrest trajectory group membership. Finally, social disorganization variables helped predict certain arrest trajectories, but not all of them. Policy implications and research limitations are also discussed.

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CHAPTER 1

INTRODUCTION

The Crime and Place Problem

A few axioms in criminology shed light on the relationship between crime and place (Weisburd, 2010; Braga and Clarke, 2014). First, a small number of people are responsible for most crimes. Second, most crimes take place in a small number of places. Third, these patterns in settings and people seem to remain more or less constant over time. Although these propositions have been tested extensively, researchers have diverged on theoretical explanations for the mechanisms that connect them together. The study of the relationship between them has led to the emergence of the criminology of place (Weisburd, Groff, and Yang, 2012).

Crime theories are essential in examining the causes of crime. Historically, they have been divided into two primary categories: “Development of offenders” and “development of criminal events” (Eck and Weisburd, 1995, p. 4). Development-of-offender theories offer explanations for individual-level offending decisions. While some of these theories explain the behaviors of individual offenders quite effectively, they do not sufficiently discuss the reason crime is concentrated in small-sized settings. This is important because as Eck and Weisburd (1995) wrote, no matter the level of an offender’s motivation, without the occurrence of a criminal event, there is no crime to discuss.

The reason criminal events are concentrated in smaller places deserves careful examination. Early criminal event theories considered larger units of analysis, such as cities and neighborhoods (Pratt and Cullen, 2005). Recently, however, researchers have turned attention to how well these and other theories explain crime at the micro-level. For example, one study argued that households or other highly localized settings might influence the rate of victimization and crime (Smith and Jarjoura, 1989). Despite such observations, there remains a gap in the theoretical and applied research on how well macro-theories can be adapted to explain crime in micro-places with longitudinal studies. The current study works toward filling this gap.

Crime and place in early research.

The relationship between crime and place has intrigued researchers for centuries. Some of the most influential work in analyzing this relationship dates back to the 1800s. As such, this section reviews early work by Guerry (1833, 1864) and Quetelet (1842), who first explored the idea of crime being more likely to occur in specific parts of the urban setting (the causes of this relationship and the theoretical assumptions behind it will be discussed further in the next chapter).

André-Michel Guerry was a lawyer and a statistician who analyzed simple graphic comparisons of semi-graphic table and maps. In his "Essay on Moral Statistics of France," he observed that personal crime was more likely to occur in the southern part of France, but property crimes were more likely to occur in the north. He mapped events such as suicide, illegitimate birth, and welfare needs in relation to crime. He found that crime rates stabilized over time based on place, gender, and age. However, Guerry did not demonstrate why specific crimes were more likely to occur in these regions.

To further the understanding why crime varies according to place, Lambert Adolphe Jacques Quetelet, a statistician and a sociologist, connected the relationship between crime and demographic variations. In his publication, *Of the Development of the Propensity to Crime,* he argued that age and gender are among the most robust predictors of crime. He also argued that crime is affected by socioeconomic determinates such as education and income level, environmental factors such as climate, and individual behaviors such as alcohol consumption. Guerry and Quetelet's work remains among some of the most influential historical works in criminology.

The way demographics influence the settings in which different crimes take place continues to intrigue sociologists. Early researchers began to look for answers in nature. George P. Marsh (1864), in *Man and Nature: Or, Physical Geography as Modified by Human Action*, argued that place serves, as the foundation of the economy of nature, and urban ecology is the result of human-constructed niches. As the human ecology system develops, different groups of people have begun competing for limited resources (Richards, 1907 [2012]). This competition and the ensuing conflict often leads to crime and disorder, and territorial divisions begin to emerge.

To better address these natural territorial divisions, sociologists Ernest Burgess (1925) and Robert E. Park (1925) observed that crime and disorder are most likely to occur in the outer core of the city. Their observations led to the development of concentric zone models that pinpoint areas most at risk for crime. Human ecology directed researchers' attention to gangs, and when Thrasher (1927 [1963]) studied 1,313 gangs in Chicago, he revealed that transient neighborhoods are more vulnerable to criminal activities conducted by gangs.

Clifford Shaw and Henry D. McKay (1942 [1969]) further investigated multiple areas of the city that were more likely to have higher rates of crime. They found that urban areas with newly arriving, underserved immigrants could lead to high rates of population turnover. The instability of this area tended to lead to elevated levels of crime (the next chapter will further discuss the theoretical explanation of why these factors could influence crime).

The study of crime and place has generally been divided in two levels: the macro-level and the micro-level. Macro-level studies may use regions, states, cities, or neighborhoods as the unit of analysis. Researchers usually view social disorganization theory as a macro-crime theory, as it is generally tested within higher-level units of analysis. Micro-level studies, which focus on neighborhood blocks (Perkins and Taylor, 1992), street segments, households, street corners, and intersections, are more difficult to study in the perspective of social disorganization.

Crime in macro-places.

One of the most important steps in studying place and crime is to conceptualize place as a unit. The body of literature generally divides geographical areas using various units of measure. Researchers refer to macro-places as larger geographical areas that often are defined as regions (Ren, Zhao, Lovrich, Gaffney, 2006), states (Legault and Martin, 2005), cities (Baumer, Wolff, and Arnio, 2012), or neighborhoods (Lee, Vaughn, and Lim, 2014; Bradley, Rowe, and Sedgwick, 2011). The major advantage of studying crime at the macro-level is that crime trends can be observed easily, and crime data can be linked to aggregated levels of demographic data sets using, for example, the U.S. Census.

A major disadvantage in studying crime in macro-level places is that the focus on specific crimes can become lost. Crime and victimization is more dynamic at the micro-level because a criminal event usually affects a small number of people in a localized area. The effect of a particular crime at a specific place may be difficult to understand using higher-level units of analysis. As a result, recent research in criminology has shifted its direction to gain a better understanding of micro-level places.

Crime in micro-settings.

The need to study crime in small places is because most crimes occur only in specific areas within a handful of neighborhoods in a city. Researchers have noted that these high-crime locations can be defined as groupings of street blocks, street address clusters, street segments, and intersection sets (Weisburd, Bernasco, and Bruinsma, 2009).

The study of the relationship between crime and the micro setting began with a study of incident calls. Specifically, Sherman and Weisburd (1995) examined 911 calls and found that the majority were sourced from a limited number of places. Their research sought to distinguish the differences between these places and explain variance in calls. Their study opened the door to research on addressing crime at the block level (Bernasco and Block, 2011; Hipp, 2010a), street segments (Curman, Andresen, and Brantingham, 2015), specific places (Braga and Weisburd, 2010), and street corners (Braga, Hureau, and Papachristos, 2011a) that are persistently affected by crime.

Sherman and Weisburd referred to locations of common crime occurrence as crime hot spots. Focusing police efforts on these hot spots has since become a popular tactic in reducing the crime rate. As predicted in a recent meta-analysis, hot spot policing studies have revealed that targeting a small number of high-crime areas can produce a small but significant overall crime reduction effect (Braga, Papachristos, and Hureau, 2011b, 2014). However, hot spot policing is not free of policy and methodological issues and complications (the next chapter will discuss these topics further). Hot spot studies have led criminologists to examine further the concentration of crime in a variety of micro-settings, including the reasons for their formulation (Braga and Clarke, 2014).

Contemporary views of crime and place.

Contemporary studies on crime and place began with urban development (Eck and Weisburd, 1995). After World War II, the demand for low-cost housing increased drastically. High-capacity residential projects became the norm for low-income families. However, researchers soon noticed that high-density housing projects often correlated with crime. The Pruitt-Igoe housing project has become a classic case of early public housing project failure. This housing project in St. Louis, Missouri was designed to house 85,000+ families (Rainwater, 1967), most of whom were low-income minorities. Crime, poverty, and racial segregation soon became prevalent at Pruitt-Igoe, leading to its demolishment in the early 1970s.

Terminating public housing projects is not a viable solution for crime, as this affects low-income families on a large scale; as of 2016, 1.2 million families reside in public housing projects in the United States (Department of Housing and Urban Development, 2016). Instead, a solution can be formed by examining the reason behind the high crime rates within these projects and methods of reducing these causes. Elisabeth Wood explored the relationship between security and natural surveillance for Chicago Housing Authority in 1961 (Jeffery, 1971). Although her work was not published, her findings laid the foundation of Crime Prevention through Environmental Design (CPTED).

Scholars soon realized that crime was more likely to occur in some public housing projects than in others, leading them to seek to understand this phenomenon with the hope of benefitting future housing projects. Ray Jeffery (1971), a criminologist, was among the first to apply modern criminology to urban design. Jeffery argued the physical design of place influences human behaviors enormously. In his book, *Crime Prevention through Environmental Design* (CPTED), he argued that a place often serves as a catalyst for social interactions. A place that discourages social interaction could reduce social control and cause crime prevention to be more challenging. Using experimental psychology as an underpinning, Jeffery described how people could internalize reinforcement and punishment based on environmental structure. He "emphasized material rewards . . . and the use of the physical environment to control behavior," and he suggested that changing environmental structure might influence the perceived risk-reward ratio to achieve the deterrence effect (Jeffery and Zahm, 1993, p. 330). Increasing detection risk in an environment could reduce the likelihood of victimization.

Oscar Newman (1972), on the other hand, approached CPTED with a more social perspective. Newman focused on two important elements: surveillance and social control. First, a defensible space continuously allows both guardians to see and potential offenders to be seen. For example, architectural designs that maximize the use of open space provide guardians with surveillance around the clock. A building must maximize the use of both natural and artificial lighting, and the angle and direction of the building is an important safety element. The second element involves social control. Guardians must be willing to either report or stop a crime. Therefore, considering the ownership of the space is important. Newman identified the four levels of space ownership: public, semi-public, semi-private, and private spaces are based on the level of social control.

Although the early works of Jeffery and Newman argued that crime might be influenced by external controls, the vulnerability of a place also may generate opportunities for violent crime (Stokes, 1981) such as rape (Le Beau, 1988) and property crime (Hannon, 2002). Crime opportunity theory suggests that opportunities to commit a crime could be generated when surveillance is compromised by barriers, lack of clearly defined territorialities, and a deteriorated social climate (Krupat and Kubzansky, 1987). These crime opportunities depend on facility, site features, offender mobility, and target selection (Eck and Weisburd, 1995). However, these vulnerabilities also may be removed or reinforced by potential victims with gates, locks, and surveillance devices in micro-settings (Brantingham and Brantingham, 1995).

Recent studies on crime in micro-places have extended their emphasis to include neighborhoods, as researchers are observing how specific demographics could influence patterns of crime in micro-places. Researchers long have realized that crime is concentrated in specific, small places, and that crime concentration levels remain generally stable over time, making the relationship between crime and place highly predictable (Hawley, 1944, 1950; Shaw and McKay 1942; Weisburd et al., 2004). Because of this, some researchers have shifted their focus to the places in which crime occurs, rather than on the behaviors of offenders. Earlier studies analyzed incident reports, and researchers found that crime incidents occur at concentrated locations (Sherman, Gartin, and Buerger, 1989) known as crime hot spots (Pierce, Spaar, and Briggs, 1986; Sherman and Weisburd, 1995). As a result, the emergence of hot spot studies has generated a new body of literature on crime in micro-places and environmental criminology (Gabor, 1990; Barr and Pease, 1990; Brantingham and Brantingham, 1993; Clarke, 1992, 1993; Eck, 1993; Clarke and Weisburd, 1994; Cozens and Grieve, 2014; Telep, Mitchell, and Weisburd, 2014; Linning, 2015; Weisburd, 2015). Findings from these studies have launched modern policing into a new era.

Stability of crime-at-place.

Prior research has established that (1) crimes concentrated in certain places are known as crime hot spots; (2) crime patterns (frequency and intensity) within hot spots remain relatively stable over time; and (3) the demographic attributes within hot spots can remain constant over a short period of time (Sherman 1989; Sherman and Weisburd, 1995). Consequently, it is possible to theorize that the demographic characteristics of places relate to crime patterns over a length of time (Steadman, Vanderwyst, and Ribner; 1978; Greenberg, Kessler, and Logan, 1979; Chappell, MacDonald, and Manz, 2006). If demographics of micro-place remain stable, they may provide useful predictors of crime outcomes such as arrests and victimizations (Brown, 1978).

To explore the stability of crime in micro-places, Weisburd et al. (2004) used trajectory analysis to test the stability of crime over time. The study used street segments in Seattle as the unit of analysis and linked 14 years of official crime data with specific street segments. The use of trajectory analysis enabled the researchers to observe a distinct developmental trend on the rise and fall in crime rates over time. Unsurprisingly, Weisburd and his colleagues found support that crime events in micro-places remain stable over time. They further found that crime trends in micro-places fell into one of the three categories: increases in crime, decreases in crime, and stability over time. Their study revealed that crime reduction should begin with crime policies that target crime in micro-places.

Recent findings in crime-at-place stability.

Recent studies have provided further insight into crime and place. For example, Weisburd Groff, and Yang (2012) studied crime in the context of specific characteristics of micro-places, as opposed to looking at individual offenders. In *The Criminology of Place,* Weisburd et al.

(2012) argued that there are clearly distinctive crime patterns over time. Using 16 years of crime data, the researchers identified three types of street segments. The first type was low-crime concentration. This type of place consisted of 50 percent of the crime concentration and less than 10 percent of street segments. The second type of street segment consisted of medium concentration, and they are made up of 20 percent of the street segments. The final type of street segment was high-crime concentration, which contained 100 percent of crime incident concentration and 60 percent of the street segments. The authors also concluded that crime trends within these three types of street segments could rise and fall over time.

A crucial aspect of Weisburd et al.'s book discussed how researchers could predict crime trajectories based on relevant theoretical assumptions, particularly with three families of variables: opportunity, social disorganization, and others. In their view, opportunity variables included high-risk juveniles, employment, the number of public facilities, the number of residents, retail sales, the number of bus stops, the number of arterial roads, the number of police and fire stations within a specific distance, and street lighting wattage. Social disorganization variables included property values, housing assistance, mixed land use, racial heterogeneity, urbanization, physical disorder, truant juveniles, and the percentage of active voters. Other variables included the length of street segments and the average number of crimes on neighboring street segments within a specified distance.

Weisburd et al. (2012) found that, with the exception of total retail sales and the number of police and fire station, all opportunity variables were statistically significant predictors of crime trajectories. With the exception of mixed land use and racial heterogeneity, all social disorganization variables were also significant predictors of crime trajectory of micro-places.

Finally, the length of street segment and spatial lag were both significant predictors. Weisburd et al.'s findings suggest that social disorganization and crime opportunity theories can offer valid explanations for crime trends and concentration in micro-places.

Formulation of Theoretical Connections

The law of crime concentration.

Crime concentrated in micro-places is a well-established phenomenon, and this pattern has occurred in large cities around the world, such as in El Salvador (Natarajan et al., 2015), China (Wu, Zhang, and Shen, 2011), Australia (Eastwood, Patton, and Stacy, 1998), and the United Kingdom (Johnson, Summers, and Pease, 2009). Because of the prevalence of this pattern, Weisburd (2015) has argued that crime concentration pattern may be universal, spanning geographical boundaries. He also argued that with enough evidence, formulating a law of crime concentration might be possible.

In the 2014 Sutherland Address, Weisburd argued that crime concentration is comparable to the laws of concentration in the fields of economics and political science. For example, in economics, the Pareto Principle (or the law of vital few) argues that a small number (20%) of investments produces the bulk (80%) of investment results. Another example in natural science is the 10 percent law in computer science and biology. In computer science, for example, the final 10 percent of the coding generally takes up nearly 50 percent of the computational development (Pressman, 2010). In biology, while organisms store 10 percent of food as energy, 90 percent is wasted in heat (Lindeman, 1942). These examples illustrate that most energy, resources, and time are spent on the most complex or rewarding steps in most systems. Weisburd argued that crime follows a similar pattern. He presented crime models from both large and small cities from various regions (Seattle, Sacramento, Brooklyn, Cincinnati, and Tel Aviv-Yafo) to show that the crime concentration pattern is virtually the same (Weisburd and Amram, 2014). However, in order to formulate the law of crime concentration, the body of research should begin to branch out in new directions.

New directions.

For the law of crime concentration to be developed fully, researchers need to analyze longitudinal data on the human developmental process and discern how they affect the attributes of places (Elliott and Huizinga, 1983; Loeber and Stouthamer-Loeber, 1998; Chung, Mulvey, and Steinberg, 2011; Ttofi, Farrrington, Losel, and Loeber, 2011; Warr, 1998; Weisburd, 2012; West and Farrington, 1973; Weisburd and Telep, 2014). This process often encounters social challenges, including poverty, educational shortfalls, and racial/ethnic heterogeneity. Although these problems are not universal, they often exist in places that are prone to crime and disorder. In light of these concerns, Weisburd (2012) and Braga and Clarke (2014) advised that there are five concerns research in this area must address.

First, the law of crime concentration should be formulated on a theoretical platform. For example, most of the crime and place literature explain the mechanism of victim and offender, but these mechanisms generally do not explain those underlying causes of why victims and offenders are there in the first place. In *Criminology of Place,* Weisburd et al. (2012) employed various variables to test for an assortment of social characteristics. However, these findings should begin with a theory (Bernard, Snipes, and Gerould, 2015), and ideally be guided in advance by a specific theoretical perspective

Second, there is a need to expand the law of crime concentration to other micro-levels of analysis. While Weisburd, Bushway, Lum and Yang (2004) and Weisburd, Groff, and Yang (2012) used streets segment as the unit of analysis, generalizing these findings to a higher level of analysis may be beneficial. Indeed, Braga and Clarke warned that it is often dangerous to invoke historically macro-level theories, such as social disorganization, that are not designed to explain crime in micro-places because of ecological fallacy (see pp. 488-490 in Braga and Clarke, 2014). However, micro-level units such as block groups are generally small subsections of neighborhoods. Using these as unit of analysis may be useful to understand crime in micro-places in the context of social disorganization, since macro-oriented theories are more suitable for higher-level units of analysis. Moreover, scholars have also argued that the dividing line between a macro-place and a micro-place could be subjective (Weisburd et al., 2012). Weisburd and colleagues reasoned that the smallest unit of community is family, then street, then a sub-section of a neighborhood, and so on. In other words, each community is nested within another community. Therefore, macro theories may be relevant in micro-communities.

Third, Weisburd raised the question of whether crime concentration across time is stable because social characteristics also remain longitudinally stable. One piece of evidence supports the assumption that the crime concentration level of a street can be varied to compare to adjacent streets even within feet apart (Weisburd et al., 2012). Research therefore needs to focus on addressing demographic variables between places that persistently have high crime rates—again, driven by theory.

Fourth, although the study of crime in micro-places and hot spots is groundbreaking in criminology, its development in regards to the law of crime concentration should connect with real-world application and policy implementation (Braga and Clarke, 2014, pp. 484). Through the years, researchers and police have learned much about hot spots policing (Groff, Ratcliffe, Haberman, Sorg, Joyce, and Taylor, 2015; Koper, 1995, Weisburd and Telep, 2011). However, there is still a shortage of study on how police policy could affect the causes of crime concentration by focusing on street segments instead of a larger area. Researchers need to acknowledge, for example, that police officers are often assigned to arbitrary boundaries, instead of focusing on street segments (Worrall, 2008). The use of higher-level units of analysis may therefore be more suitable to address policy implementation and to direct patrol activities.

Finally, thinking of policy relevance, the studies by Weisburd et al. (2004, 2012) may be improved by using alternative crime data such as arrests. Although incident reports are generally more valid than call-for-service data, they are not as accurate as arrest reports. The use of arrest reports may be another valuable measure of crime because officers must meet a standard before making an arrest.

Current Study

This study attempts to explore each of the aforementioned new directions for crime-at-place research. It begins with the theoretical assumption that social disorganization theory is a possible driving force behind crime hot spots. Using group-based trajectory modeling, it then formally tests the ability of social disorganization theory to explain trends in arrest activity at the Census block group level throughout the city of Dallas.

Sampson and Groves (1989) proposed five measures of social disorganization: socioeconomic status, racial heterogeneity, residential mobility, family disruption, and urbanization. Accordingly, data from the American Community Survey (2014) were gathered and used to operationalize these social disorganization variables. They were then linked with official Dallas arrest data covering the period 2010-2014.

The theoretical cause of crime concentrating in micro-places has yet to be explored fully and has engendered diverging perspectives (these are reviewed more fully in Chapter 2). While a number of studies explained the causes of hot spots through the routine activities theory (Gorr and Lee, 2015; Weisburd, Hinkle, Famega, and Ready, 2011; Weisburd, Morris, and Groff, 2009), others have observed that hot spots contain a higher lever level of social disorganization (Sherman, Gartin, and Buerger, 1989; Weisburd and Green, 1994). Recently, Weisburd, Groff, and Yang (2012) proposed that social disorganization and crime opportunity theories may provide logical explanations for the unusual and concentrated crime rate in hot spots, and further explanation through an integrated theory may be needed.

However, Braga and Clarke (2014) stated that although social disorganization and crime opportunity theories may provide valid explanations on the causation of hot spots, four areas require future study. First, Weisburd, Groff, and Yang's study should be expanded to encompass a broader selection of situational variables. These variables include time of day, day of week, and the year, and they can help further explain the crime pattern theory. Second, future studies should improve the measures of social disorganization and collective efficacy. These studies should focus on variables that are tested significantly in prior research on social disorganization theory. Third, future studies should determine the proper theoretical domain of collective efficacy. Therefore, studies grounded in the social disorganization theory should be restricted to explaining crime only at the neighborhood level. Finally, future studies should test whether collective efficacy could be manipulated at the street level.

In defense of a focus on arrests as the crime variable.

Weisburd (2012) argued that incident data are the best because they are more inclusive than arrest data, yet they are more valid than call-for-service data because officers must decide if each event is significant enough to be recorded. Nevertheless, researchers have argued that arrest data may be equally valid, depending on the study for which they are being used (this concern will be further addressed in the upcoming methodology chapter).

Methodologically, the validity of arrest data is enhanced during the collection process (Rosenfeld and Decker, 1999). First, an arrest is generally a crime event that is a verifiable by all parties involved. Therefore, unlike an incident report, which is inherently an officer's decision that could be influenced by bias and error, arrests can be made only when an officer meets precursory legal requirements. In other words, an arrest report is essentially a confirmed crime event that intrinsically carries a high degree of validity among call-for-service and incident reports.

Another advantage of using arrest data is that they allow researchers to observe arrest patterns. For example, the current body of literature includes many studies on disproportionate minority contacts of low socioeconomic neighborhoods (Kakar, 2006; Leiber, Bishop, and Chamlin, 2011; Werling, 2007). Arrest data most often contain demographic data for the suspects. These demographic data are important for researchers to identify the arrest patterns and behaviors of police officers. Attempting to combat crime in hot spots without knowing the overall demographics of arrestees within micro-places is short-sighted.

A number of studies on crime in micro-places have also used arrest data to measure crime. For example, Weisburd, Morris, and Groff (2009) used longitudinal trajectories in Seattle to understand juvenile arrests at street segments. Their study found that one third of the arrests at hot spots involved juvenile offenders. Their study not only demonstrated that crime concentrates at certain places, but it also supported the notion that peculiar offenders may be concentrated at certain places, as well.

Another recent study conducted by Taylor, Koper, and Wood (2011) also used official arrest data to understand crime and arrest behaviors of 1,400 officers from Jacksonville Sheriff's Office in Jacksonville, Florida. The study sought to understand how officers make arrests in 40 control hot spots, 21 directed patrol hot spots, and 11 problem-oriented policing (POP) hot spots over a 90-day period. Officers were assigned randomly to these hot spots, and researchers found that problem-oriented policing tactics could reduce street violence up to 33 percent over the trial period.

Unit of analysis.

Traditionally, studies on crime and micro-place have used street segments as the unit of analysis. Weisburd et al. (2012, p. 25) argued that studies that use larger levels of analysis have two major problems. First, a higher level of Census data can represent a lower level unit of analysis, but lower-level data do not work in this reverse direction. This study argues that because it is grounded in social disorganization theory, use of block groups such as units of analysis is appropriate because the theory explains problems over larger areas than street segments. Moreover, high arrests are assumed to be nested within block groups that have a higher incidence of crime.

Second, like police boundaries, Census block group boundaries are administratively created, and researchers have argued that these boundaries are meaningless to the study of crime.

However, manmade administrative boundaries may be equally significant because policy decisions are based on these arbitrary boundaries. For example, police resources and personnel assignments are divided based on administrative boundaries, as are such things as home values, insurance rates evaluations, and social service programs (e.g. hospitals and emergency services) (Harris, 2015; Weisburd, 2011; Werling and Cardner, 2011). As a result, block group-level data are useful because other economic predictors are often available at the block group level.

This study does not presume that high-frequency arrest block groups are crime hot spots. However, as Weisburd et al. (2012, p. 14) suggested, the field of study in crime-at-place remains relatively limited. There is a need for these studies to investigate other unit of analysis. This study does, however, argue that a higher number of arrests could be an indicator of high criminal activity, as prior studies have suggested (Greenberg, Kessler, and Logan, 1979). This point will be discussed further in the methodology chapter.

Capitalizing on the power of time.

Many studies have used cross-sectional data to study crime in micro-places. However, cross-sectional studies generally cannot address the dimension of time. Recent studies have tried to capture the time dimension with longitudinal designs such as group-based trajectory modeling (GBTM). However, the use of GBTM in social disorganization studies is highly limited (Stults, 2010; Kubrin and Herting, 2003; Curman, Andresen, and Brantingham, 2015; Deryol, Wilcox, Logan and Wooldredge, 2016).

The novelty of studying crime using longitudinal data in social disorganization theory is that crime in micro-places could fluctuate over time, and trajectory modeling is an excellent tool to model these longitudinal changes since cross-sectional data cannot capture these decisive patterns. As of today, only a handful of theoretical studies of the social disorganization framework have employed trajectory analysis to illustrate these key patterns (Tewksbury, Higgins, Connor, 2013; Yang, 2008; Jennings, Gibson, Ward, and Beaver, 2008; Stults, 2012). Furthermore, while GBTM is a relatively new statistical method, revisiting old problems with new statistical methods may bridge gaps and address limitations reported in older studies. As a result, the generalizability of existing theories may be improved by new research methodologies.

Advancing the study of place using GIS.

Prior studies on crime and micro-places have addressed concerns regarding computational power and map management. For example, they have identified a mapping resolution that could best fit data clustering but also provide sensible data presentations for data to merge (e.g., Fitterer, Nelson, and Nathoo, 2015, Rossmo, 1995).

Data management is often a challenge in dealing with large data sets in geospatial studies, and the emergence of computational criminology enable many studies that was not possible in just two decades ago (Chunn and Menzies, 2006). Advanced geospatial analysis programs now allow researchers to pinpoint crime location accurately on many types of maps. In this study, each arrest is first associated with a Census block group, then recoded as longitudinal data for the trajectory analysis. The accuracy of place is imperative in the social disorganization theory because a place serves as the platform for crime to occur.

Place also is a key component because it influences the criminal decision-making process (Newman and Franck, 1982). While the vulnerability of a place may attract offenders, how each offender perceives such vulnerability is subjective. The causal direction between place and individual decision-making still requires further theoretical and empirical exploration. For example, recent studies have illustrated that the criminal decision-making process of burglars in local neighborhoods may depend both on the physical design of the place and the people who are occupying it (Wright and Decker, 1994; Nagin and Pogarsky, 2001). The question remains as to whether hot spots offer more crime opportunities or if offenders collectively perceive that hot spots are more vulnerable. The place itself may have a higher level of social disorganization with residents who are trapped in a perpetual victimization cycle in which both offender and victim cannot escape due to low socioeconomic mobility. These questions have potential to be highly informative and deserve additional attention.

Summary

Scholars have explored research in crime-at-place throughout history. Crime generally is concentrated in a few places in most cities, and recent scholars have argued that the law of crime concentration may be useful in the context of criminology of place. Recent advances in criminology have also opened the door for the examination of the crime-at-place problem through the lens of social disorganization theory. Such studies may be useful for policy formulation.

While prior studies have used incident reports to examine crime in micro-places, this study uses arrest reports as a measure of crime. Also, unlike traditional hot spot studies that chiefly use street segments as the unit of analysis, this uses Census block groups as the unit of analysis to better fit the context of social disorganization theory and subsequent policy implementation.

The study was conducted in two stages, guided by social disorganization theory. The first stage of this study was to employ trajectory analysis to observe crime (measured by arrests) over time, then use them to identified specific block-group trajectories. The second primary stage utilized multinomial regression to identify which social disorganization variables were significant predictors of high- and low-arrest block group memberships.

The findings from this study offer two contributions to the criminology of place. First, linking arrest trajectories to block group-level units of analysis has never been undertaken in prior research. Second, testing social disorganization, while being guided by crime-at-place literature, takes the field in new directions.

The remainder of the study is organized as follow. Chapter 2 reviews the theoretical literature concerning rational choice, routine activities, and crime patterns that are relevant to crime and place. It also carefully reviews social disorganization theory. Chapter 3 discusses the methodology and the analytical process. Chapter 4 discusses the results of the analysis, and the final chapter synthesizes the findings, implications, and limitations, and discusses how these findings could potentially influence social policies.

CHAPTER 2

REVIEW OF LITERATURE

Theories of Crime and Place

Throughout history, researchers have noted that crime and place share a unique relationship, though the strength and causal order of this connection has been widely debated. As evidence of this, Hirschi (1969) argued that the relationship between place and crime is an indirect outcome of human behavior. For example, young adults are more likely to commit crime, and schools are more likely to have a high concentration of youth. Hirschi's perspective demonstrates that schools are concentrated places for offenders, and research supports that areas around schools have a positive relationship with property crime (Willits, Broidy, and Denman, 2013). However, this association may disappear when school is no longer in session. Thus, the people change a place. Researchers refer to this weak relationship as "loose coupling" (Weisburd et al., 2012).

Other researchers have found that the relationship between crime and place is more direct. Indeed, recent studies have illustrated that applying direct police pressure to micro-places may reduce crime not only at the micro-level, but also in overall crime trends, since the majority of crimes occur in a small number of places (Law, Quick, and Chan, 2014). An example is the connection between crime and places that sell alcohol. Studies have shown that different types of alcohol are associated with different levels (Speer et al., 1998) and types of crime (Toomey et al., 2012), and removing certain risky and poorly managed establishments may help reduce crime

(Franquez, Hagala, and Bichler, 2013). Franquez et al. (2013) observed 87 bars and 17 nightclubs near highways and found that there are significant differences in the types and frequencies of crime between bars and nightclubs. They found that poorly managed bars were associated with internal and external crime issues, and nightclubs were responsible for a wider range of disorders. The study demonstrated that human behavior changes based on the inherent nature of a place and time. Therefore, the preexisting conditions and nature of a place may have a stronger and more direct influence on crime. In other words, the place changes the people. Scholars have defined this reversed relationship as "strong coupling" (Weisburd et al., 2012).

To better describe the relationship between crime and place, Weisburd et al. (2012, p. 5) drew five major conclusions. First, crime is concentrated tightly at certain places, and researchers have described these locations as hot spots. Second, crime hot spots have a high level of stability over time, which may be useful in the long-term prevention and predictability of crime. Third, crime appears to have high levels of variability from street to street. Therefore, it is imperative to keep the unit of analysis to the lowest if possible. Fourth, in addition to crime, social and contextual characteristics also vary from place to place. Fifth, crime and place share a tight relationship, which makes this relationship highly predictable and valuable toward crime prevention. These conclusions have pointed the field of criminology in the direction of attempting to understand why crime is concentrated in certain places. The investigation, however, must begin with the theoretical causes of crime.

This chapter is organized into two parts. The first reviews relevant foundational theories that criminologists have used to explain crime-at-places. These theories include rational choice theory, routine activities theory, and crime pattern theory. It is imperative to review these theories because traditional crime-at-place literature has assumed that crime is a choice and executed with careful calculation, rather than a phenomenon influenced by outside social forces. Reviewing these theories in this order will reveal the notion that crime-at-place is not only a result of individuals' decisions, but is also influenced by other latent sociological constructs.

The second section reviews the key literature in social disorganization theory, focusing on how social disorganization theory may help explain the phenomenon of crime concentration, as Weisburd (2014, 2015) posed. A question is embedded in the context of social disorganization theory: Are the people living in hot spots of crime subjected to a different level of social forces that causes them to be more vulnerable toward a life of criminality and/or victimization? If victims and offenders are trapped in hot spots, the crime concentration problem may continue being perpetuated until the underlying social problems are resolved. If that is the case, it explains why certain police strategies have not been working. These issues are essential not only to the understanding of the causes of crime concentration and prevention policy at micro-places, but also to the identification of the hidden forces that distort the social dynamics of crime.

Theories that explain crime and place.

In general, theorists assess the relationship between crime and place with the help of rational choice, routine activity, and crime pattern theories (Clarke, 1992). First, rational choice theories focus on explaining the decision process of offenders, assuming that offenders are rational and their decision are calculated (Clark, 1992; Clarke and Cornish, 1985). Second, routine activates theory capitalizes on human behaviors and activities in the context of place and addresses victims' vulnerabilities (Cohen and Felson, 1979). Finally, crime pattern, or opportunity theory examines the crime-victim relationship in the context of place and victim susceptibility to offenders (Braga, Weisburd, Waring, and Mazerolle, Spelman and Gajewski, 1999). These theories provide a comprehensive explanation as to why crime occurs at certain places and the types of offenders who commit these crimes.

Although these theories work well to illustrate the process by which criminals make decisions and select their targets, the question of what causes offenders to concentrate in a small number of areas remains (Braga and Weisburd, 2010). Recent advances in criminology have noted that, fundamentally, individual social patterns of both victims and offenders alike could be products of home disruption, racial heterogeneity, and socioeconomic disadvantages. In that sense, social disorganization theory could be an alternative explanation of the reason crime concentrates in smaller places (Weisburd, Groff, and Yang, 2012). Are people who live near crime hot spots underserved within communities that are economically broken? Do they suffer more family problems than their neighbors, who also are plagued by domestic issues? These questions are intriguing to theorists, practitioners, and policymakers.

Underlying assumptions.

Eck and Weisburd (1995, p. 5) argued that while the rational choice, routine activity, and crime pattern theories explain crime-at-place well in a theoretical sense, they possess both strengths and weaknesses in practice. For example, while rational choice best addresses an offender's calculations, it does not address offender motivation because humans often exhibit irrational behaviors (Hollis and Nell 1975; Robbins, Chatterjee, and Canda, 2011; Zafirovski, 2003). These three theoretical perspectives are often grouped as crime opportunity theories because they focus on explaining crimes that are occurring based on the probabilistic encounters between offender, victim, and place (Braga and Clarke, 2014). Overall, the themes of these theories suggest a positive relationship between crime and crime opportunity.

Why crime concentrate.

The phenomenon of crime concentration is well established in criminology. Research has repeatedly shown that some places have higher levels of crime, regardless of whether a city's structure is a concentric, a sector, or a multi-nucleus design (Wikström and Dolmen, 1990). Accordingly, this section will review some of the underlying assumptions of these theories and discuss how recent research in these areas could provide the next generation of literature with a new direction.

Rational choice.

The assumption that crime is a matter of individual choice has dominated criminology for centuries. Beccaria, as one of the earliest scholars on crime, argued that as long as humankind is born free, it has the right to choose (Beccaria, 1764). This notion established that behavior is a matter of individuality, and because crime is a conscious choice, it is assumed that the offender is rational. Beccaria (1764) also believed that for a rational person, punishment is at its most effective when its severity, certainty, and swiftness are proportional to the crime. While the balance between pain and pleasure is relative, offenders generally seek pleasure over pain. Therefore, crime may involve a conception of utility (Bentham, 1780). Because humans are rational, the decision to commit a crime may change when the risk of pain and suffering outweigh the pleasure or profit of crime.

A few centuries later, economists Derek Cornish and Ronald V. Clarke (1986 [2014]) questioned whether the utility of pain and pleasure can be measured and how offenders perceive risk in their decision-making processes. In their book, *The Reasoning Criminal: Rational Choice Perspectives on Offending*, Cornish and Clarke (1986 [2014]) explained that the intricate decision to commit a crime depends on an offender's background characteristics, previous experience and learning methods, and generalized needs. The decision is also governed by the perceived solution, state of readiness to offend, chances, and evaluation of the solution crime would bring. The study became a cornerstone of situational opportunities theory, and it provided the initial understanding of the situational techniques that may help offenders make their decisions (Clarke, 1997; Wortley, 2001).

Rational choice theory offers an economic approach to understanding the criminal decision-making process. However, this theory fails to address three major aspects of crime. First, people often commit crime when they are incapable of being rational (Gold, 2011). This is often happening when a person is committing wrongdoing while under the influence of drugs or duress. People also may lack the psychological or mental capability to make rational decisions due to mental illnesses.

Second, human behaviors and decisions are not always rational even if people are capable of making rational decisions, and deterrence depends highly on an individual's perception. For example, prior research by Decker and Wright found that burglars often break into homes to satisfy emotional distress rather than with the purpose of obtaining economic gains (Kiser and Hecheter, 1998). Additionally, even if the decision to offend is rational, perceptions of severity or swiftness of punishment varies among individuals. Therefore, the generalizability of punishment imposed by macro-level society is quite often disconnected between individual rationality and laws. Consequently, the effectiveness of punishment could be questionable (Kleck, Sever, Li, and Gertz, 2005).

Finally, rational choice theory depends on external and internal deterrence, and studies have found that the effect of deterrence is relatively weak (Pratt and Cullen, 2005; Pratt et al., 2010). Recent studies have explored the concept of bounded rationality, which describes decisions that are based on limited information or offenders that are unable to analyze alternative approaches. Offending decisions may be subjects of anger, uncertainty, and time pressure (Jacobs and Wright, 2010). For example, some people may be committing property crime due to a lack of knowledge of alternatives to overcome their temporary problems, and anger, uncertainty, and time pressure further aggravate their criminal motivations. Recent researchers have also begun to understand how age, life events, and situational choices may affect the decision-making process (Coyne and Eck, 2015).

One of the core elements of rational choice theory is the notion that decision-making hinges on the situation. Regardless of an offender's level of motivation, situational limitations may restrict the ability to execute a crime. In other words, offenders are bounded by both information and physical limitations. Research has shown that situational factors may include travel distance (Verma, Ramyaa, Marru, 2013; Rengert, Piquero, and Jones, 1999), availability of abandoned buildings (Spelman, 1993), knowledge of the police presence (Papachristos, Hureau, and Braga, 2013), and discrete choice on how to maximize rewards (Bernasco and Block, 2009). These limitations of situational factors may restrict an offender's geographic mobility (Hartnagel, 1997).

The limitation of travel distance leading to a restricted zone of offense is a phenomenon known as distance decay (Rengert, Piquero, and Jones, 1999). Researchers have found that in most cases, offenders, such as property offenders, do not travel far to commit crimes (Verma, Ramyaa, Marru, 2013). Researchers have also found that the likelihood of crime decreases as distance between the home of the offender and the place of crime increase. For example, drug offenders generally operate within a few miles of their targets, but rarely live at the place where they operate (Eck, 1992; Shaw and McKay, 1969).

It is important to note that the exact driving force of distance decay remains debatable. Some studies have proposed that distance decay may be caused by limited transportation modality and that the availability of the new public transit systems may redistribute offender-target selection, thereby altering the bounded rationality imposed by situational limitations (Masoumi and Fastenmeier, 2016; Sedelmaier, 2014). Other studies have suggested that geographical restrictions may tie to socioeconomic situations such as low residential mobility, correlating with the concentration of an offending population remaining in one place over time (Pettiway, 1982; Warner and Pierce, 1993). More studies are needed to corroborate this.

These studies call attention to environmental characteristics that may influence situational choice. For example, committing an offense at a place with security cameras, or without security cameras, alters the economic equation of risk versus reward for most people. These points transition the recent body of rational choice literature toward examining human behaviors that may be predicable based on mundane routines, and these routines must be carried out at a place. Rational choice, for the offenders, is to minimize risk. Therefore, it is logical for offenders to choose the least risky places to execute crimes, and the safest places are those that are absent of both formal and informal controls (e.g., abandoned buildings). For instance, Spelman (1993) found that blocks with abandoned buildings were 83 percent more likely to be used by prostitutes, drug dealers, property criminals and other illicit users (later sections will further discuss how environmental factors may influence crime pattern theory).

Scholars also refer to the rational choice of criminal location as discrete choice theory. Humans historically have had a tendency to prefer specific places to hunt and to live (Bhat and Zhao, 2002; Fotheringham, 1985; Shaw and Ozog, 1999). Based on this assumption, offenders also may exhibit this pattern of behavior. In a robbery study conducted in Chicago, Bernasco and Block (2009) has argued that offenders selectively choose a place or a situation to commit an offense, rather than adjust to the situation, thus maximizing economic gains while taking full control of the risk. Instead of asking themselves of what they would do in a specific situation, offenders may choose to commit crimes only under specific situations and at certain places. Bernasco modeled crime at the block level by examining 18 residential units occupied by 40 people. He found that crime at small spatial units is highly linked to the environment instead of victims. In addition, offenders often discretely and deliberately select where to commit crimes. Bernasco concluded that the target and the environment might be spatially independent. Recent research by Wiesburd, Lawton, and Ready (2012) has also reported similar patterns of the distribution of crime that can be highly variable between adjacent streets. However, while crime levels may be varying between street to street, such variation is may be depended on human behaviors, habits, and interactions in the context of social dynamic.

Routine activities.

The pattern of discrete and rational choice often leads to a set of mundane habits for both victims and criminals. How these habits and routine behaviors patterns may be correlated to victimizations and perpetrations of crime may be better explained via routine activities theory. Routine activity theory assumes crime is connected to everyday human activities. In other words, because most people follow a structured routine and lifestyle, human behavioral patterns are somewhat predictable and offenders may exploit these patterns. Subsequently, the causes of crime may be explained through these routine activities (Brag and Clarke, 2014).

While human behaviors may seem individualistic, social and environmental factors also may play a role in their influence. Progress in racial and gender diversity, urbanization, and residential mobility in metropolitan areas, for example, have displaced tradition and created new opportunities for potential offenders in modern society (Marcum, 2008). Indeed, Cohen and Felson (1979) observed that major changes in society affect crime patterns. Since the Second World War, more women have been joining the workforce and pursuing higher education. The process of socialization, urbanization, and the civil rights movement created opportunities for many property offenders because women no longer stay at home, which would allow them to be guardians against in-home crimes. Studies have also found that the gender equality movement in education has created more opportunities for sex offenders (Cass, 2007). As women enrolling in college continued to increase after World War II, sex crime rates continued to rise until the mid-1990s because college campuses might have become a platform for both victim and offender convergence, even if the crime did not occur on campus (Fisher, Cullen, and Turner, 2002; Fisher, Daigle, Cullen, and Turner, 2003; Henson and Stone, 1999).

Based on the idea of human ecology, Cohen and Felson (1979) explained that crime may be a product of routine human behaviors, and the routine interaction between people and place could create vulnerabilities to crime. Cohen and Felson further explained that crime requires three core elements: (1) the presence of a suitable target (opportunity), (2) the presence of a motivated criminal, and (3) a place where victims and offenders interact, which serves as the platform for criminal activities.

The interconnected relationship between target, offender, and place is known as the crime triangle (Eck, 2003). However, Eck (2003) argued that these three elements formed only the inner part of the crime triangle. In his view, the likelihood of a crime occurring also depends on a set of external protectors. These protectors are colloquially referred to as "controllers." According to Felson (1986a, 1986b, 1994), the effectiveness and capabilities of controllers vary, and they influence each specific domain of the crime triangle (See Figure 2.1). Collectively, these controllers form the outer part of the crime triangle (Eck, 2003; Tillyer and Eck, 2011). The three types of controllers include intimate handlers, guardians, and managers. The presence of effective controllers may reduce the likelihood of victimization.

Handlers.

According to Eck (2003), intimate handlers generally share a relationship with victims. That relationship may help prevent a crime, as victims can reduce their vulnerability through intervening in the potential offender's activities. For example, a mother, based on her relationship with her child, could alter her child's vulnerability to drug and alcohol via curfew, surveillance, or by conveying the danger of certain activities. Handlers can include parents, friends, children, and employers, to name a few.

Guardians.

Eck (2003) refers to guardians as controllers who provide direct influence on and protection of the victim. Guardians also increase the risk of apprehension for the offender. This type of controller may include bystanders, traveling companions, and police officers.

Managers.

Managers are the third type of control. They are unique because they do not influence the actions of the victims or the offenders, but they do provide surveillance and denial of access to a place (Eck, 2003). Managers may discourage or inhabit criminal opportunities by enforcing rules and regulations. This type of controller includes teachers, property managers, and park attendants.

Figure 2.1. Felson's Crime Triangle[1]

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[1] Center for Problem Orientated Policing (2016). Felon's Crime Triangle [Electronic image], Retrieved from http://www.popcenter.org/learning/60steps/graphics/step_8.gif

Felson and Cohen (1980) argued that many crimes did not occur until urbanization and modernization of people and place. These unforeseen changes in society, especially in metropolitan areas, opened new windows for crime opportunities. Subsequently, Felson and Steadman (1983) continued that crime may fall into one of four categories: (1) the exploitative or predatory offenses that prey on select, innocent targets, (2) mutualistic offenses in which two individuals both violate a law through a complementary relationship, such as prostitution, (3) competitive violations in which two individuals are each both victim and offenders, such as fighting, and (4) an individualist offense in which an individual violates the law against him or herself. These types of offenses may include suicide or drug abuse. Felson and Steadman further argued that the routine activity theory could be expanded to explain all four types of offenses focusing on the concept of place (also see Felson and Cohen, 1980).

An offender's decision to offend may be affected by external controls (Weisburd, Groff, and Yang, 2014). Routine activity theory argues that the crime rate may be reduced by limiting the availability and the attractiveness of a target, the number of motivated offenders, and the access to a place that lacks the oversight of managers.

Motivation.

In recent micro-level studies, researchers have extensively explored the relationship between guardians, victims, offenders, and places (Baker and Wolfer, 2003; Cullen, Agnew, and Wilcox, 2006; Miller, Schreck, and Tewksbury, 2006; Lilly, Cullen, and Ball, 2006). One important assumption of routine activity theory is that the offender must be motivated enough to commit a crime because the offenders initiate the victimization process. However, the relationship between motivation and vulnerability is not always clear.

A major component of routine activity is the offender's motivation level. The original scope of routine activity argued that the motivation level of an offender is already there, but the decision to offend or not depends on the availability of crime opportunities (Cohen and Felson, 1979). These opportunities are determined by the present of suitable targets (vulnerabilities), capable guardians (reinforcement), and possible rewards. Subsequently, crime-at-place concerns some degrees of rational choice and situational criminal decisions (Clarke and Cornish, 1985; Cornish and Clarke, 1987; Weisburd, et at, 2004). Because situations may change, the actions of the criminal are a result of two factors: the preexisting characteristic of the offender and the contextual features of the event and place (Wikström, 2004).

Some scholars have challenged the idea that the level of motivation among individuals in the context of routine activities varies extensively, and this may be worth additional scholarly attention. For example, Miller, Schreck, and Tewksbury (2006) argued that while offenders with low motivation may be deterred easily, highly-motivated offenders might not be, even with effective controllers.

The measurement of motivation often presents problems for rational and routine activity theorists. The primary problem is that the individual level of motivation is often difficult to measure, and levels of motivation change because of both external and internal factors. Prior studies have attempted to measure offender motivations using vignette studies or situational surveys to observe how respondents react to a particular situation (Carmichael and Piquero, 2004; Worrall, Els, Piquero, and Teneyck, 2014). However, because real-life situations are dynamic, these studies may not capture the true picture when other factors exist in the actual situation (Carmichael and Piquero, 2004). Other studies have therefore attempted to capture the gradient of motivation through participant observation designs. For example, in their books, *Armed Robbers in Action* and *Burglars on the Job,* Richard Wright and Scott Decker noted instantaneous changes in motivation based on changes of environmental factors when offenders engage in crime (Wright and Decker, 1994, 1997).

Other psychological, physiological, and environmental factors may further alter offenders' decision-making processes. Studies have shown that offenders with antisocial behaviors, psychopathy, or damage to their prefrontal cortex may possess levels of motivation that are different from others' when engaging in crime (Farrington, 1995; Paternoster and Pogarsky, 2009; Dolan, Bechara, and Nathan, 2008). For example, studies have found that the Lateral Pre-Frontal Cortex (LPFC) is responsible for analyzing cognitive context-dependent stimuli, and damage to this area could affect one's motivation to obtain reward (Sakagami and Watanabe, 2007; Ballard, Murty, Carter, MacInnes, Huettel, and Adcock, 2011). Resulting psychological and physiological deficits could diminish the ability to evaluate the risk-reward ratio correctly.

Moreover, researchers have found that time, seasonal cycles, and temperature all affect major crime rates, as these variations could influence the social component of crime motivation (McDowall, Loftin, and Pate, 2012). For example, one study found that weather could be a component of such motivation. Specifically, Hipp, Bauer, Curran, and Bollen (2004) found that property crime rates have strong correlations with pleasant weather and are compatible with the routine activity assumptions. On the other hand, violent crimes correlate with the relationship between aggression and temperature. In sum, these studies illustrate that the study of motivation within the context of the routine activity theory can be complex and implicated by factors that are difficult to measure.

Routine activity theory advances in micro-places.

Recent studies have shifted their attention toward how routine activity theory may play a role in the relationship between crime and place at the micro-level. Certain people are more likely to congregate in specific areas, and controllers may affect these congregating behaviors at the block and street levels. Conversely, certain places are more likely to attract specific types of crime. For example, high-capacity housing, retail property, foreclosed properties, problem buildings, alcohol establishments, and public facilities such as schools and banks are more likely to witness felony assaults occur (Caplan, Marotta, Piza, and Kennedy, 2014).

Kopers (1995) was among the first to study crime hot spot treatment. He found that police officers, as controllers, have an effect on crime levels within micro-places. However, the effect of the controller is reduced if the officer remains in an area for a period that is either too short or too long. This observation raised the question that the simple presence of the controller may not be enough, and that controller actions in micro-places play a more significant role in crime reduction (Tillyer and Eck, 2011). For example, in a more recent study, Tillyer and Eck (2011) found that the effectiveness of handlers depended on (1) the social proximity between the victim and the controller, (2) the willingness of controller to intervene, (3) the degree of opportunity and timeliness to intervene, and (4) how much the controller knows about crime prior to the event. These findings suggest that micro-places have low levels of formal or informal social cohesiveness or efficacy, and that they may have less effective guardians or handlers.

Effective crime prevention strategies, in the context of routine activities, as P. J. Brantingham and P. L. Brantingham (1978) wrote, focus on dealing with ordinary behaviors that are responsible for the overwhelming majority of crime. However, a recent study on property crime found that disrupting the routines of offenders could enhance the effectiveness of guardians or handlers in micro-places. One example is target hardening. Hayes (1991) found that placing highly attractive merchandise in lockboxes disrupts the routine of thefts and subsequently reduces the overall risk to victimization.

Clarke (2009) argued that while the routine activity theory generally is designed to address crime in macro-places, its application in situational crime prevention (SCP) is founded upon the rational choice theory (RCT). Routine activity theory could be suitable for addressing specific crime problems and protective measures within the context of micro-places.
Certain places are more attractive based on location, even if all other variables are equal. As Weisburd et al. (2011) pointed out, crime can be highly variable between one street segment to the next, and the physical design of a place may contribute to its vulnerability.

Crime pattern theory.

In contrast to the routine activity theory, which posits that a place is merely a platform where victims and offenders collide, some researchers have noted that crime opportunities are distributed asymmetrically and may be spatially predicted (P. L. Brantingham and P. J. Brantingham, 1999; P. J. Brantingham and P. L. Brantingham, 1991; Wilcox and Eck, 2011). In the simplest definition, crime pattern theory assumes that “something at a place attracts criminal behaviors.” One reason may be that offenders consciously make decisions based on situations, and the environmental design of place of potential perpetration may influence that decision (P. L.

Brantingham and P. J. Brantingham, 1990; P. J. Brantingham, and P. L. Brantingham, 1993). Patterns of space, time, and crime distribution may help predict or forecast crime (Caplan, Kennedy, and Miller, 2010). Indeed, crime pattern theory and environmental criminology are often used interchangeably (Eck and Weisburd, 1995).

Researchers have asserted that crime patterns vary between two types of places: zone of time and space (Giddens, 1984; Hayward and Hobbs, 2007) and zone of patterned liminality (Hollands and Chatterton, 2003; see for example, Hadfield, 2006, Hadfield, Lister, and Traynor, 2009; Hobbs, Lister, Hadfield, Winlow, and Hall, 2000). On the one hand, zone of time and space refers to places where crime occurs based on a natural crime distribution. On the other hand, zones of patterned liminality are man-made places that create higher levels of crime opportunity. An example of this would be the “red light” district. Rethinking physical design of place of within these zones may help reduce crime opportunities.

Crime pattern theory suggests that crime is distributed asymmetrically instead of symmetrically. As such, Brantingham and Brantingham (1999) argued that researchers should first understand why these places are more favorable in offenders’ risk-reward calculations. According to Brantingham and Brantingham, these places are more favorable because they have a weak physical design, and targeting subjects in these areas reduces the risk of detection and apprehension. As a result, the offender-target relationship is based on the specific opportunity presented by the place. Crime prevention programs may be more effective by removing these crime opportunities because “generalized approaches, while popular, are unlikely to have a substantial impact on crime rates because they cannot address the diversity of criminal behavior” (Brantingham and Brantingham, 1990, p. 18).

Oscar Newman (1972) demonstrated that places that suffer high crime patterns generally have physical design traits that attract crime. In his book, *Defensible Space*, Newman illustrated that crime distribution is generally higher for places that have higher population densities. While controlling for population density, crime also is higher at places that have poor surveillance, physical designs that discourage human interaction, and informal social control. Newman hypothesized that those obscure places that have poor lighting and less walkable space discourage residents from serving as natural guardians. Moreover, places that have clearly divided public and private boundaries serve as barriers to potential offenders. Other studies have explored whether denying access to private space by alley gating (Bowers, Johnson, and Hirschfield, 2004; Staunton, 2006), employing closed-circuit televisions (Sivarajasingam et al., 2003; Welsh and Farrington, 2004), and installing streetlights (Farrington and Welsh, 2002) enhances the defensibility of a place.

Another component of crime pattern is the pattern of behavior, which may be associated with offenders' pattern of travel. Prior studies have examined the crime movement patterns of rapists (Warren, Reboussin, Hazelwood, Cummings, Gibbs, and Trumbetta, 1998), serial murders (Canter, Coffey, Huntley, and Missen, 2000), and burglars (Bowers and Johnson, 2004). With rare exceptions, they have concluded that crime patterns are associated with human behaviors. For example, there is often a pattern of proximity between the victim and the offender (Warren et al., 1998; Canter et al., 2000). Bichler, Christie-Merrall, and Sechrest (2011) examined the travel patterns of 2,563 delinquent youth and found that there are significant patterns between place-specific and person-specific distance depending on city, method of mobility, and age cohort, with the exception of age. Their study illustrates that the context of a place includes locality, availability of transportation, and place type.

Other researchers have a different perspective on crime pattern theory. If offenders concentrate in one place because of crime opportunity, then the number of opportunities would be finite because victims would begin to adopt prevention methods. Based on the optimal foraging theory, crime opportunities eventually would be depleted, and offenders would move away (Bowers and Johnson, 2004). Conversely, reality demonstrates that crime hot spots remain stable over time and offenders do not fluctuate. Johnson and Bowers argued that change of preying ground is coherent with geographical changes. Using domestic burglaries as an example, researchers have demonstrated that domestic burglary clusters shift over time to nearby locations successively, in a slippery manner. This finding reveals there may be a gap between the observed and actual stability of crime over time, and longitudinal designs are more suitable for crime-displacement studies.

Advances in crime pattern theory in micro-places.

Crime pattern theory is a relatively new idea and has been modified extensively in recent years, as testing it generally requires massive computational power. However, recent advances in geospatial information system (GIS) have enabled researchers to examine spatial and temporal variation in the context of micro-places, and crime pattern theorists have capitalized this technology to generalize crime patterns based on location and types of crime that are likely to occur (P. L. Brantingham and P. J. Brantingham, 2004; Hiropoulos and Porter, 2014). One theory is that the limitations on offenders' physical mobility may influence the spatial pattern of crime. Using two year of arrest data from 1,632 parolees released from New Jersey prisons, Miller, Caplan, and Ostermann (2016) found that property, drug, and violent crime hot spots generally are within 1,200 feet from the offenders' place of residence. However, the research team found that these relationships are asymmetrical. Although locations of hot spots are within walking distance, the relationship is relatively weak, as offenders do not always walk to hot spots to commit crimes.

Prior research has found that the probability of offender residences being close to crime hot spots is relative to the distance of victims' locations (see Böhm, Kailing, Kröger, and Zimek., 2004 on Euclidean, Chebyshev, and Manhattan distance in cluster analysis). In most cases, the likelihood of finding an offender's residence decreases as the distance from the place of victimization increase. However, the opposite also supports the likelihood that an offender's residence decreases within the immediate proximity to the victim. This suggests that offenders often travel away from their homes to commit crimes, but that maximal range is limited by walking distance. This offending pattern could help law enforcement agencies conduct cluster analyses and triangulate the location of suspects (Rossmo, 1995).

Recent studies on physical designs also provide new insight for crime prevention strategies, and restricting access to private space is one of them. The primary function of gating is to disrupt both crime opportunity and routine activities between offender and target. Prior studies on alley gating in the United Kingdom demonstrated a reduction in theft and property crimes (Bowers, Johnson, Hirschfield, 2004; Rogers, 2007, 2013). However, a more recent study shows that the gating strategy may not work on all types of crime. Jacobs and Addington (2016) found that robbery patterns did not vary between gated and non-gated communities. Researchers have suggested that natural surveillance, collective efficacy, and sanction threats could affect gating and restricted access techniques.

Uncharted territory.

While rational choice, routine activity, and crime pattern theories have addressed the motivation and the relationship between victim and offender, ambiguity remains as to the causes of crime concentration. One question includes how social disorganization may cause people who live in high-crime areas to be more vulnerable to victimization—or more likely to be arrested. Braga and Clarke (2014) have argued that people living in highly disorganized areas are more likely to be victimized because they conduct routine activities within risky areas. Contrarily, people living in non-crime or low-risk areas have a low likelihood of victimization or arrests, even if they engage in risky activities. Therefore, integrating social disorganization into answers on questions regarding crime in micro-places may be possible. For example, the police may know a certain household that is more susceptible to crime, but the underlying question is what causes that house to be more vulnerable than the neighboring house, or one on the next street over. Social disorganization theory may therefore be able to provide insight on these micro-variations of crime in the context of micro-places.

Integrating Place-Based Theories of Crime with Other Theories

Braga and Clark (2014, p. 482) argued that crime-at-place, particularly crime at micro-places, may be both connected directly or indirectly to social disorganization. Likewise, Miethe and Meier (1990) have suggested that integrating social disorganization and routine activity theories could lead to improvement in the literature, as both seek to address the social components of crime. In addition, vulnerability is created by the routine activities of both offenders and victims nested within the same neighborhoods in which they live and work. Research seems to bear these assertions out. For example, Weisburd, Groff, and Yang (2012, p. 153) found that property values, housing assistance, urbanization, physical disorder, truant juveniles, and active voters were all significant predictors of crime at micro-places. However, racial heterogeneity and land usage exhibited no clear effect on crime incidents. Another study of auto theft at the block level demonstrated that integrating social disorganization and routine activity theories improved the predictive power of these events in spatial analyses for a midsized southeastern city in the United States (Rice and Smith, 2002).

Braga and Clark (2014) also argued that some activities are limited to certain groups of people that share the same living space. For example, people living in higher socioeconomic neighborhoods are likely to engage in behaviors and activities that are common among residents of low SES areas due to income, social value, occupation, and informal social control (Braga and Weisburd, 2010). Therefore, researchers should examine the relationship between social disorganization and crimes at place.

However, before integrating social disorganization and opportunity theories (rational choice, routine activities, and crime pattern), the body of research should examine whether social disorganization itself can help explain crime in micro-places alone. In other words, Weisburd et al. (2012) may jump to conclusions too quickly by submitting that social disorganization may be at work in understanding crime in micro-places. In addition, a number of scholars have suggested that there are many overlaps between the two theories and that both traditions can individually predict crime or arrests at micro-places—before theory integration (Kornhauser, 1978; Tittle, 1995). As of today, *no study has tested social disorganization as a stand-alone explanation for* *crime-at-places*. New studies should focus on this distinction so that the body of literature can make better connections between theory and reality. The current study seeks to fill this gap in the literature.

To direct the focus on crime at micro-place and the context of social disorganization, it is imperative to review Weisburd et al.'s (2012) thesis. Weisburd et al. (2012, pg 119) argued that social disorganization may play a significant role in explaining why crimes are likely to concentrate at micro-places. Their assumption was simple: specific locations that have higher crime rates may have sociological problems in common with those traditionally studied at the macro-level.

Wikström and Dolmen (2001) also suggested that these problems might include low SES, problems within the family, or over urbanization, to name a few. These problems could eventually lead to localized failure of informal social control. Logically, higher concentrations of these problems would lead to higher concentration of crime at these localized areas. But before continuing the discussion on how the relationship between crime and place may be connected to social disorganization, it is necessary to review some of the specific seminal works on the social disorganization theory that help inform our understanding of crime beginning from macro-places.

Social disorganization theory.

Few would disagree that early social disorganization research was embryonic for understanding the relationship between crime and place. Early criminologists were quick to note noted that certain places in a country have higher crime rates (Smith, 1937; Shannon, 1954). For example, cities have more crime than rural areas, and place and people of low income are more likely to be associated with crime and disorder. However, the causes of these variations in crime were largely unknown until André-Michel Guerry (1833, 1864), who documented and mapped that crimes-against-a-person's offenses on specific properties follow a distinctive geographical pattern. These groundbreaking observations of commenced the investigation of social causes of crime in the context of place.

In the early 1900s, the Chicago school began to shift its attention to the relationship between crime and place at the community level (Bursik, 1984; Park, Burgess, and McKenzie, 1925 [1967]; Park and Burgess, 1921; Reiss and Tonry, 1986; Shaw, Zorbaugh, McKay, and Cottrell, 1929; Shaw and McKay, 1942 [1969]). In addition to the well-known Burgess model, researchers began to explore other social parameters that may be used to predict crime in the context of place. For example, Wirth (1938) found that areas with large populations and with high population densities are more likely to have higher crime rates. Moreover, places that exhibit high levels of racial and ethnic heterogeneity are more likely to attract crime problems.

On the other hand, Shaw and McKay (1942) argued that economic hardship and population mobility also are significant to crime and disorder. They observed that crime is generally higher at places that are saturated with poor working class populations who cannot move out of these areas due to economic hardship. Ultimately, contemporary scholars defined social disorganization as the failure of a community structure to recognize the common values among its residents around which to establish a functional, informal social-control system (Bursik, 1988; Kornhauser, 1978; Sampson and Groves, 1989). Subsequently, in the second half of the 20th century, debates on the relationship between crime and place were overshadowed by other criminological theories. The idea of social disorganization resurged until scholars reconceptualized the theory of how ecological deterrence could play a role in crime patterns (Bursik, Grasmick, and Chamlin, 1990). Based on this social ecology, Bursik and Grasmick (1993) constructed a systemic model that argues social disorganization is linked to the strength and connection of social control.

To gain a better understanding of how social predictors of crime function in the context of spatial relationships, Sampson, Raudenbush, and Earls (1997) matched survey data from 8,872 Chicago residents to neighborhood structural data from 1990 to observe the effects of spatial interdependence, income inequality, and social processes on homicide. They found that degraded social control due to concentrated disadvantages and low collective efficacy could be associated with homicide. Their research supported the notion that social factors are important variables to account for when studying crime and disorder in terms of spatial context.

Bursik, Grasmick, and Chamlin (1990) found that the neighborhood is the most meaningful level of aggregation for the study of social disorganization theory. However, that study was limited by the ability to analyze micro-level data. The question that remains is whether valid crime predictors that are traditionally examined in macro-theories remain valid at lower levels of aggregation. While Bursik, Grasmick, and Chamlin, (1990) found that deterrence may not have an effect on crime reduction in the context of social disorganization, other scholars have found that over-policing may actually have an adverse effect on crime control at the community level. Over-policing may erode the community structure as well as the valuable police-citizen relationship (Côté-Lussier, 2013; Richards, 1992).

Using social disorganization theory as their framework, Rose and Clear (1998) argued that the overuse of formal controls such as policing and crackdown may reduce the ability for some communities to employ informal controls. They found that discriminatory or saturated policing could further destabilize families and communities that already had a weakened social structure to begin with. For example, arrests and incarceration often result in loss of income, (regardless of whether that income is legitimate or not), loss of capable guardians, and a reduction in labor and productivity at the community level. Likewise, an insight gained from the Rose and Clear's work concerns how similar family disruption may result in elevated crime and victimization at the micro-level. Recent research on hot spots policing also argued that over-policing also could backfire by diminishing police legitimacy, inducing unnecessary fear, and discouraging collective efficacy (Weisburd et al., 2011; Weisburd, Groff, Yang, 2014; Hipp, 2010b).

At the heart of social disorganization is the concept of collective efficacy (Morenoff, Sampson, Raudenbush, 2001). Sampson, Raudenbush, and Earls (1998) defined collective efficacy in terms of cohesion based on trust that establishes shared expectations for control. In time, this trust would grow over time and develop into a sense of cohesion that allows the community or the group to influence an individual's behaviors within the community via informal control mechanisms (Sampson, Morenoff, and Gannon-Rowley, 2002). In addition, these relationships' interconnection become an entity known as social capital, and social capital within the neighborhood often translates into tangible resources that could reduce crime and disorder.

Collective efficacy reduces crime and disorder over time, by instilling a sense of ownership within the community (Sampson and Raudenbush, 2004). A high level of collective efficacy, theoretically, would deter individuals from delinquency since such behaviors would compromise their social capital. However, collective efficacy is difficult to measure and is often subjective. Some researchers have attempted to quantify collective efficacy via alternative measures such as voting behaviors (Bandura, 1997), local friendship networks (Sampson, Raudenbush, and Earls, 1998), and neighborhood size (Stein, 2014). For example, Sampson et al. (1998, 1999) measured the level of informal social control by inquiring how much trust residents have on relying on neighbors to control delinquent children. Recent studies have incorporated the use of multi-level design and latent variable analysis (Matsueda, 2015). In addition, Morenoff, Sampson, and Raudenbush (2001) argued that most studies of human interaction concerning collective efficacy often neglect factors that determine a neighborhood's context: (1) neighborhood interdependence based on spatial dynamics and (2) social-institutional processes. Therefore, Morenoff et al. concluded that routine activities might be essentially an application of social disorganization theory.

In order to evaluate potential correlations between individuals' behaviors and social disorganization, Weisburd and colleagues (2012) focused their research at micro-level crime. This line of research was theoretically grounded on the notion that daily routines (i.e., routine activities) is a product of collective efficacy and informal social control. Informal social control is essential within communities, and this is particularly evident at the street level (i.e. see Anderson (1994) in *Code of the Street*). Hence, if collective efficacy diminishes, behaviors of victims and offenders will likewise change having an impact on crime and disorder.

For example, Taylor (1997) defined street blocks as key mediating social and spatial constructs. In doing so, his research further illustrated Bursik and Grasmicks (1993) three levels of control: private (friends and family), parochial (nearby acquaintance), and public (external agents). These three sources of social control provide the linchpin between one's social environment and their individualistic behaviors. Together, people residing in the local area collectively define the ecological dynamics for their own neighborhood. In all, findings from this line of research suggest that individuals' behaviors and routine activities at the micro-level (i.e., street blocks) are a derivative of the eco-psychology of their social environment.

Such notions are in direct contrast to Wilson and Kelling's (1982) broken windows theory. Wilson and Kelling posited that broken windows occur because of routine activities stemming from poor collective efficacy and lack of neighborhood social capital. Their theory contends that broken windows are the result neighborhood routine activities and social disorganization. In other words, people who commit crime must travel or live in the area for other reasons (Wilson and Kelling, 1982).

Predictors of crime in social disorganization theory.

Clifford Shaw's and Henry McKay's (1942) original model assumed that community social disorganization is associated with: (1) competition of ethnic groups, (2) city centers where urbanization level is high, (3) a lack of supervision among youth within the family, (4) a consistent movement of residents in and out of a community, and (5) communities that struggle with economic hardship. Based on these assumptions, many studies have developed social disorganization variables to test the validity of social disorganization theory (Sampson and Groves, 1993). Over the years, researchers have found that these variables are relatively reliably measure of social disorganization.

Based on these assumptions, Sampson and Grove (1989) conducted a study in the United Kingdom and found that victimization and criminal offence rates correlated with social disorganization variations between communities. Guided by Shaw and MacKay's work, Sampson and Grove (1989) formulated five measure of social disorganization: socioeconomic status, ethnic heterogeneity, residential mobility, family disruption, and urbanization. The following subsections look at each of these in detail.

Socioeconomic status.

Research has consistently demonstrated that crime is associated with socioeconomic inequality, and this effect is much stronger when interracial inequality is accounted for (Logan and Stults, 1999; Macmillan, 2000; Patterson, 1991; Stolzenberg, Eitle, and D'Alessio, 2006; Eitle, D'Alessio, and Stolzenberg, 2006). Studies have reported that crime, especially violent crime, is more likely to occur among underserved populations (Braithwaite, 1989; Messner, 1982). For example, Patterson (1991) studied 57 small areas and found that poverty is associated with both violent and property crimes. Socioeconomic status often is associated with racial inequality, unemployment and employment type, family disruption, and poverty (Hooghe, Vanhoutte, Hardyns, and Bircan, 2011).

However, not all scholars agree that economic deprivation and crime share a direct relationship (Kornhauser, 1978; Tittle, 1983; Bursik and Grasmick; 1993). Dunaway and colleagues (2000) argued, for example, that while most studies conclude that crime is highest in lower class neighborhoods, most studies fail to account for spurious causes (e.g. social and racial inequality) that may interject the relationship between social class and crime (Dunaway, Cullen, Burton, and Evans, 2000). Likewise, Logan and Stults (1999) found that when all other factors are equal, middle-class Black people are significantly more exposed to more violent crimes than their middle-class White counterparts. While the directness of the relationship between SES and crime is questionable, SES has been a robust predictor of neighborhood stability.

Improving the socioeconomic situation at a specific place may reduce crime, but sudden and massive economic disruption could unsettle the normal daily life of the residents and lead to a higher level of disorder. Significant economic development, such as gentrification, could actually elevate crime. Indeed, Van Wilsem, Witterood, and De Graaf (2006) found that the sudden and intensive SES improvement of neighborhoods could lead to higher crime. The study suggested that increased residential mobility in gentrifying areas should be done progressively. However, it failed to support the idea that fluctuations in ethnic and income heterogeneity affect crime. This suggests that socioeconomic status may have a greater effect on communities as a whole.

Ethnic and racial heterogeneity.

Shaw and Mckay (1969) found that crime rates were highest in communities that exhibit high levels of ethnic heterogeneity. This observation led to the conclusion that neighborhood conditions were causal agents of crime instead of individual attributes. Shaw and Mckay assumed that ethnic heterogeneity caused crime as follows:

> immigrant and migrant groups have brought together the widest variety of divergent cultural traditions and institutions, and where there exists the greatest disparity between the social values to which the people aspire and the availability of facilities for acquiring these values in conventional ways, the development of crime as an organized way of life is most marked. Crime, in this situation, may be regarded as one of the means employed by people to acquire, or to attempt to

> acquire, the economic and social values generally idealized in our culture, which persons in other circumstances acquire by conventional means. (p. 319)

J. R. Blau and P. M. Blau (1982) theorized that violent events are more prevalent when there is a higher level of ethnic heterogeneity, as competition between groups leads to more frequent violence. At the macro-level, minority members congregate in groups to face common societal conflicts such as economic, social, and ethnic inequality together. The convergence of individuals based on ethnicity has become an instrument of power, such as street gangs that offer both social competition and mutual protection (Matsueda, Drakulich, and Kubrin, 2006). Nevertheless, these group conflicts lead to aggression that drives hostile impulses that materialize as criminal violence. Because ethnic back group is often associated with racial diversity, Sampson and Groves (1989) argued that such ethnic conflicts may be modeled based on racial differences. To support this finding, Altheimer (2007) conducted a study on ethnic heterogeneity and found that economic inequality, the human development index, race mixture, and the sex ratio are all significant predictors of violent crimes such as homicide. However, Sampson, Morenoff, and Raudenbush (2005) argued that although immigrant populations are correlated with violence, the effect size is relatively small when compare to other powerful social forces.

Residential mobility.

While social control shapes the core of social disorganization theory, residential mobility could supposedly exert a negative effect on social control, as high turnover rates can translate in consistent breaks in social ties, since transient residents have generally lower interests in improving the community (Bursik, 1988; Sampson and Groves, 1989). Similarly, economic deprivation may translate into a lack of resources for purchasing property, leading to higher levels of renters who have a low sense of ownership (Logan and Stults, 1999). Smith and Jarjoura (1988) found that residential mobility has the strongest correlation with crime in low SES areas. Therefore, gentrification may improve local crime rates. Kooi and Patchin (2008) studied six years of residential data on 114 block groups and found that improved resource allocations directed toward gentrification and owner-occupied housing could alleviate crime.

Shaw and Mckay (1969) realized that high levels of residential mobility could be indicative of other attributes, such as a higher likelihood of residents above the poverty line leaving for better neighbors in the suburbia, while those residents lacking special skills and money remain behind. As a result, some studies have found the effect of residential mobility to be marginal (Roh and Choo, 2008). Roh and Choo (2008) argued that it actually could have a negative correlation to crime, as society is no longer undergoing rapid urbanization. Some scholars also have raised the question of whether residential mobility alone is a strong enough measure of social disorganization, since it does not take into account the context of the neighborhood (Gunnar Bernburg and Thorolfur, 2007).

Family disruption.

Family influence serves as a critical crime predictor in many crime theories (Beaver, 2001; Burgess and Akers, 1966; Hirschi, 1969; Hirschi and Gottfredson, 1990). Broken homes and disruptive families have been found to have adverse effects on children and adolescents, and these may extend into adult life (Sampson and Laub, 1993; Laub and Sampson, 2003). Studies have found that family influence has a significant effect on many delinquent behaviors, including drug use, alcohol abuse, and serious violence (Krohn, Hall, and Lizotte, 2009; Kaukinen, 2002;

McNulty and Bellair, 2003; Weisburd, Lawton, Ready, and Haviland, 2012). Social disorganization theory hypothesized that low levels of family disruption in communities could translate to stronger family and community structures that provide youths with quality supervision (Shaw and Mckay, 1969). Moreover, Rice and Smith (2002) argued that such community characteristics could help form a communal supervision system for adolescents when they are in otherwise unsupervised situations, especially when adolescents encounter sudden structural impediments like family disruption and residential mobility. The idea of communities alleviating the stress of broken homes inspired the rise of community centers in many major cities.

Urbanization.

Rapid urbanization and drastic disruption of a place may increase crime levels and lead to the rise of social problems (Shaw and McKay, 1942). These factors may also be indicators of uncontrolled rural-to-urban migration and population growth, which may result in higher levels of poverty, rapid growth of inner-city communities, and crime (Mishra and Patel, 2013). Scholars from other developing countries such as Korea, China, and India have discovered similar phenomena abroad (Roh, Kwak, and Kim, 2013; Chen, Yuan, and Li, 2013; Mishra and Patel, 2013).

Scholars have explored the effect of rapid urbanization on crime for decades. One explanation for this correlation is that urbanization increases the physical proximity of people, leading to an increase in social conflicts. Using data from 4,000 residential city block, Roncek, Bell, and Francik (1981) tested the proximity hypothesis of crime on housing projects. The study supported a correlation between living closer to housing projects and violent incidents, and while this increased chance of violence is relatively small, it is significant for those involved. Another explanation is that rapid urbanization also induces rapid change to norms (see Myers, 1995; Savelsberg, 2002). Savelsberg (2002) argued that sudden changes in urbanization often lead to modernization that redefines cultural norm and resulting in social conflicts. These rapid changes could induce disorder and fear that may jeopardize social cohesion (Markowitz, Bellair, Liska and Liu, 2001). Using the British Crime Survey data ranging from 1988 to 1992, Markowitz and colleagues attempted to extend social disorganization theory and found a positive relationship between disorder and urbanization.

Advances in social disorganization theory.

Social disorganization theory has received more attention in recent years. While one of the major criticisms of it is that it fails to explain crime at the individual level, scholars are revisiting how social disorganization may influence crime in micro-places. Overall, improvement of localized area is one of the recent trends in studies in the relationship between crime and place.

In 1969, Philip Zimbardo examined conformity in Bronx, New York using a disabled automobile with no license plates. A family stopped by seemingly unsupervised care to remove a radiator and battery. Within a day, the vehicle was destroyed. Following Zimbardo's study, Wilson and Kelling (1982) introduced their broken windows theory, which argues that minor collapse in informal social controls signals a deficiency in formal and informal social controls, and this causes crime and disorder to accelerate (Kelling and Bratton, 1998; Kelling and Coles, 1996; Wilson and Kelling, 1982). As a result, effective crime controls prevent minor infractions of social organization. The broken windows theory transformed ideas on the influence of informal controls and led to key policies such as the stop-and-frisk initiative in New York City and the community-oriented policing strategy (COPS).

Nevertheless, the effectiveness of policies driven by the broken windows theory have received much criticism due to perceived racial bias and transgressions against individuals' civil liberties (Harcourt, 2004; Rosenfeld, Fornango, and Baumer, 2005). Moreover, a recent study argued that the broken windows theory failed to generate effective crime control in the context of micro-places and social disorganization. Specifically, Weisburd, Hinkle, Famega, and Ready (2011) conducted a study over a six-month period at 55 street segments and found that the broken windows policing tactic at crime hot spots failed to produce significant effects on crime perceptions, social disorder police legitimacy, collective efficacy, and fear of crime.

Maintaining broken windows-inspired policing tactics at micro-places may be ineffective, but other studies have found more effective alternatives. By comparing Census data between 1990 and 2000, Snipp (2003) found that neighborhood improvements help reduces both violent and property crimes. However, the positive effect of gentrification disappears when the effect of the neighborhood structure is accounted for. Snipp's study suggested that social disorganization may have a stronger effect on crime at the neighborhood level.

Another study found that fostering a sense of community may be another viable approach. Sampson (1993) argued that one way of doing this is to improve community facilities. For example, Foster, Giles-Corti, and Knuiman (2014) demonstrated that walkable communities are more likely to have lower levels of fear of crime. Using data from 1,044 homeowners, the team found that supportive actions such as improving neighborhood aesthetics may augment social interaction between residents and lessen fear of recreational walkers, which may mean an enhancement on natural surveillance and informal social control. While studies have explored fear and crime, fear of crime and fear of disorder appear to be problems unique to micro-places. While perceptions of disorder and crime are highly correlated, Gau and Pratt (2008) realized that people living in high-crime and disorderly areas are more likely to be able to distinguish improvements at the micro-level. Therefore, reducing crime and disorder may be two different localized tasks. In other words, broken window theory and the order maintenance policing strategy it calls for may not have a direct effect on crime reduction at micro-places.

Kurbin and Weitzer (2003) outlined a micro-level unit of measure of social disorganization. They argued that even if researchers control for individual-level factors, higher-level aggregates, such as neighborhoods, could have a direct effect on the offending rate of individuals. In addition, social context may have an effect on the relationship between crime rates and individual factors, and this effect may be shaped by the interactions between neighborhoods and individuals. In other words, although low SES neighborhoods have crime, urbanization could, over time, change the context and structure of neighborhoods and crime, and these changes often begin at the individual level in modern metropolis (Kirk and Laub, 2010).

Social disorganization may affect a place in the dimension of time. In *The Place of Context: A Theory and Strategy for Criminology's Hard problems*, Sampson (2013) expounded on how crime changes (in the longitudinal sense) may be correlated with social disorganization predictors, as human growth and desistance at micro-places may affect crime trends in micro-places over time (Groff, Weisburd, and Yang; 2010). To test this extension of social disorganization and the influence of structural characteristics and mechanisms on crime, Steenbeek and Hipp (2011) conducted a longitudinal study using 10 years of data from 74 neighborhoods in Utrecht, Netherlands. They found that disorder is perpetuated by residential instability and social control, rather than social disorganization. Subsequently, destabilization in social control could cause further disorder. This finding supports order maintenance policing and broken windows tactics, as they could have an indirect effect on crime.

The main feature of longitudinal studies in crime-at-place study is to track a set of place with similar features and observe their change in crime across time. Unlike cross-sectional studies, each observation is made at the same place over a period of time. Therefore, a longitudinal model is more sensitive to a particular influence. However, the key to a longitudinal study is to recognize such influence (e.g. socioeconomic attribute) and how it may affect crime outcomes. Sometimes such influence may be latent. For example, Weisburd et al. (2004) studied the trajectory of police incident reports and found that places can have increasing, decreasing, and stable level of police incidence. Such variation cannot be observed accurately in a cross-sectional study. Therefore, a form of longitudinal study known as group-based trajectory modeling (GBTM) is needed. GBTM may be a useful method of modeling changes over time, and few studies have explored longitudinal crime data using GBTM in the context of social disorganization theory (Groff, Weisburd, and Yang, 2010; Weisburd et al., 2004; Weisburd et al., 2014). The next chapter will further discuss the usefulness of this type of study and how this procedure can further inform social disorganization theory.

Hot Spots Policing: The Policy Side of Crime in Micro-Places

Understanding crime problems in localized areas and how policies can be better informed by these findings is at the heart of crime-at-place research. The disconnection between theory and practice in crime-at-place studies has posed a challenge to policing, and evidence-based policing was implemented only in recent decades (Green, 1995). New empirical studies and findings influenced many once-prominent policing practices.

Traditional policing tactics typically rely on random patrols and field service to operate as a form of deterrence (Kelling, 1978). Kelling et al. (1974) conducted a study on random patrols and found that they were largely ineffective, as crimes are not distributed randomly. Since many crimes are not random events, they are likely to concentrate at certain place within the city. Logically, it would be more productive to study the characteristics of these crime-infested places to understand how and why they are differing from others. Sherman (1989) researched this question and found that a handful of people accounted for most service calls, and the majority of these calls come from a few concentrated places within the city known as crime hot spots.

Researchers have demonstrated that crime hot spots are more likely to be located at communities that have higher levels of racial and ethnic heterogeneity, poverty, and other social problems (Roh, 2006). For example, studies have suggested that communities experiencing problems with prostitution and human trafficking are more likely to have problems with runaways, poverty, poor education, and family violence (Monroe, Kinney, Weist, Dafeamekpor, Dantzler, and Reynolds, 2005; Reid, 2011; Roe-Sepowitz, Hickle, Dahlstedt, and Gallagher, 2014; Scarpa, Hurley, Shumate, and Haden, 2006). As a result, solutions to crime in micro-places may be focusing on not only increasing policing, but also resolving the underlying problems (Payne et al., 2013).

Conclusion

This chapter has provided a brief review of the theories that traditionally have been used to address crime-at-place, including rational choice, routine activity, and crime pattern theories. While each of these provide some explanation of the relationship between crime and place, they generally fall short in explaining the causes of crime concentration. Recent studies on hot spots have pointed toward deeper problems that influence crime rates in specific areas due to variance in formal and informal social control (Weisburd, Groff, Yang, 2014). These problems have social disorganization aspects and can include low socioeconomic status, high levels of racial heterogeneity, family disruption, high residential mobility, and over-urbanization. These factors may negatively affect micro-places and could lead to crime concentrating at specific hot spots, and possibly over time. As such, research needs to follow a new direction, one that aligns the study of crime-at-place with a social disorganization perspective.

CHAPTER 3

METHODOLOGY

Introduction

Although several theories have addressed the relationship between crime and place, few researchers have tested such theories with longitudinal data, specifically in the context of micro-places. Recently, Weisburd, Groff, and Yang (2012) suggested that social disorganization may explain crime trend variations in micro-places. They noted:

> in our view, this neglect of social disorganization theory in the criminology of place has hindered the development of theory and empirical analysis in this area…The street segment in this context can be seen as a type of community, much smaller than that which has focused the interests of social disorganization theories, but nonetheless a social system where social disorganization may have salience for understand crime problems (Weisburd et al., 2012, p. 120).

Consistent with Weisburd et al.'s (2012) research, this study sought to test social disorganization theory in the context of micro-places, but with a focus on arrests rather than crimes. As explained below, this approach offers additional insight into the phenomenon of crime variability at low-level units of analysis.

Research questions.

According to Weisburd, Bushway, Lum, and Yang (2004), micro-places generally exhibit one of three overall crime trends: upward, downward, or stable. In contrast, Wheeler, Worden, and McLean (2015) eight distinct crime trajectory groups in micro-places. These disparities in the literature suggest it is first necessary to determine whether crime (or in the case of this study, *arrests*) increases or decreases over time in the specific area studied. This, therefore, leads to the first research question:

> *Research Question #1: Do arrest trends also increase or decrease over time within micro-places?*

This study is unique in two respects. First, it uses geo-coded arrest reports to develop arrest trajectories at micro-places. The first part of the trajectory analysis partially replicates the work completed by Weisburd et al. (2004), who modeled crimes at micro-places in a trajectory study. Examining arrests, not just crimes, is important because arrest data do not reflect crime rates only; they also allow researchers to observe police tactics and effects of policing activities. For example, Marvell and Moody (1996) found that more arrests are associated with higher crime rates, which could be especially true of departments that measure crime rates based on *prima facie* cases that result in arrest, fines, or criminal charges. As a result, the positive effect of police interventions may be underestimated or countered by over-arrests or over-convictions. Furthermore, the intensity and locations of arrest may be based on micro-level biases. Simply put, certain factors may lead officers to patrol a place more frequently or with less discretion due to saturations of disadvantaged populations, especially minority youth. This phenomenon is sometimes referred to as "disproportionate minority contact" (Piquero, 2008a). Studying arrest data may help advance the understanding of this research gap.

Second, this study uses demographic data from the U.S. Census to test social disorganization theory with specific arrest trajectories. No prior studies have done this, even with crime data. For example, the Weisburd et al. (2004) study, which is most analogous to this one, developed crime trajectories only and did not introduce demographic variables into their models. Although a subsequent study conducted by Weisburd et al. (2012) incorporated a limited number of social disorganization variables, many questions remain because no formal test of the social disorganization theory in micro-places has been conducted since social disorganization is primarily a macro-theory. Understanding how social disorganization interacts with arrests at place may help to (1) gain a better understanding of crime control tactics and (2) reduce crime by first undertaking the underlying social problem (Taylor, Mumford, and Stein, 2015). This, then, leads to research questions two and three:

> *Research Question #2: Can social disorganization variables help predict high arrest-trend and low arrest-trend groups?*
>
> *Research Question #3***:** *Which social disorganization factors are correlated to arrest trends and what are their effect sizes?*

Study setting.

This study analyzed data from Dallas, Texas. The City of Dallas is one of the fastest-growing cities in the United States (with an annual growth rate of 8.54 percent) and is home to more than 1,197,816 people (Census, 2010). Dallas enjoys a relatively low population density compared to other large cities, with a density of 3,645 people per square mile. However, the large population causes Dallas to be the ninth-largest city in the United States, with a growth rate of more than 20,000 people per year (City Mayors, 2015). The median household income was 58,000 dollars in 2015, with a lower-than-average unemployment rate of 4.1 percent at the time of this study (Forbes, 2015). The city resembles a classic concentric model, with its dense city core comprised of a centralized business district, an industrial area in the southwest, and suburbs on the outer rings that extend up to a 10-mile radius. Interstate 635 forms the north and east boundaries of the city; Interstate 20 forms the city's south boundary, and State Highway 12 encloses the west side of the city.

The City of Dallas is located at the heart of Dallas County. The red line on the map depicted in Figure 3.1 represents the city's limit (i.e., the boundaries of this study). The Dallas Police Department is responsible only for the patrol sectors within the city of Dallas and a small area in Collin County in the north, Tarrant County in the west, and Lake Ray Hubbard in the east (Figure 3.2). Highland Park, which is located at the north center of the city, is excluded from the Dallas Police Department's jurisdiction. To aid command and control, the Dallas Police Department divided the city in seven patrol divisions: northwest, north central, northeast, central, southwest, south central, and southwest.

The United States Census Bureau divides Dallas County into 1,669 block groups. However, only 869 block groups fall within the boundary of the City of Dallas, over which the Dallas Police Department has direct jurisdiction (Dallas City Hall, 2015). According to the Dallas Police Department, high-crime areas are concentrated in southwest and south-central areas (Pickett, 2016).

Maps rendered by Google's geospatial data service, which include data collected from the Dallas Police Department, indicate the problematic areas. These high crime areas (or hot spots) also are known as Targeted Area Action Grids (TAAG) (see Figures 3.3 and 3.4). Figure 3.3 shows the "heat map" of crime in Dallas in 2016. The darkest blue shows the lowest level of crime and the lightest gray shows the highest level of crime. In this map, each block represents a

Census tract (a block group is too small to display in this context). Note that the north central, northeast, southeast have lower levels of crime. South central and northeast show more grayish blocks.

Figure 3.1. City of Dallas Mapped State Geospatial service[2]

[2] This map is accessed via google GIS from the University of Texas Perry-Castañeda Library Map Collection. Retrieved on 27 September 2016, from http://www.lib.utexas.edu/maps/texas_cities.html

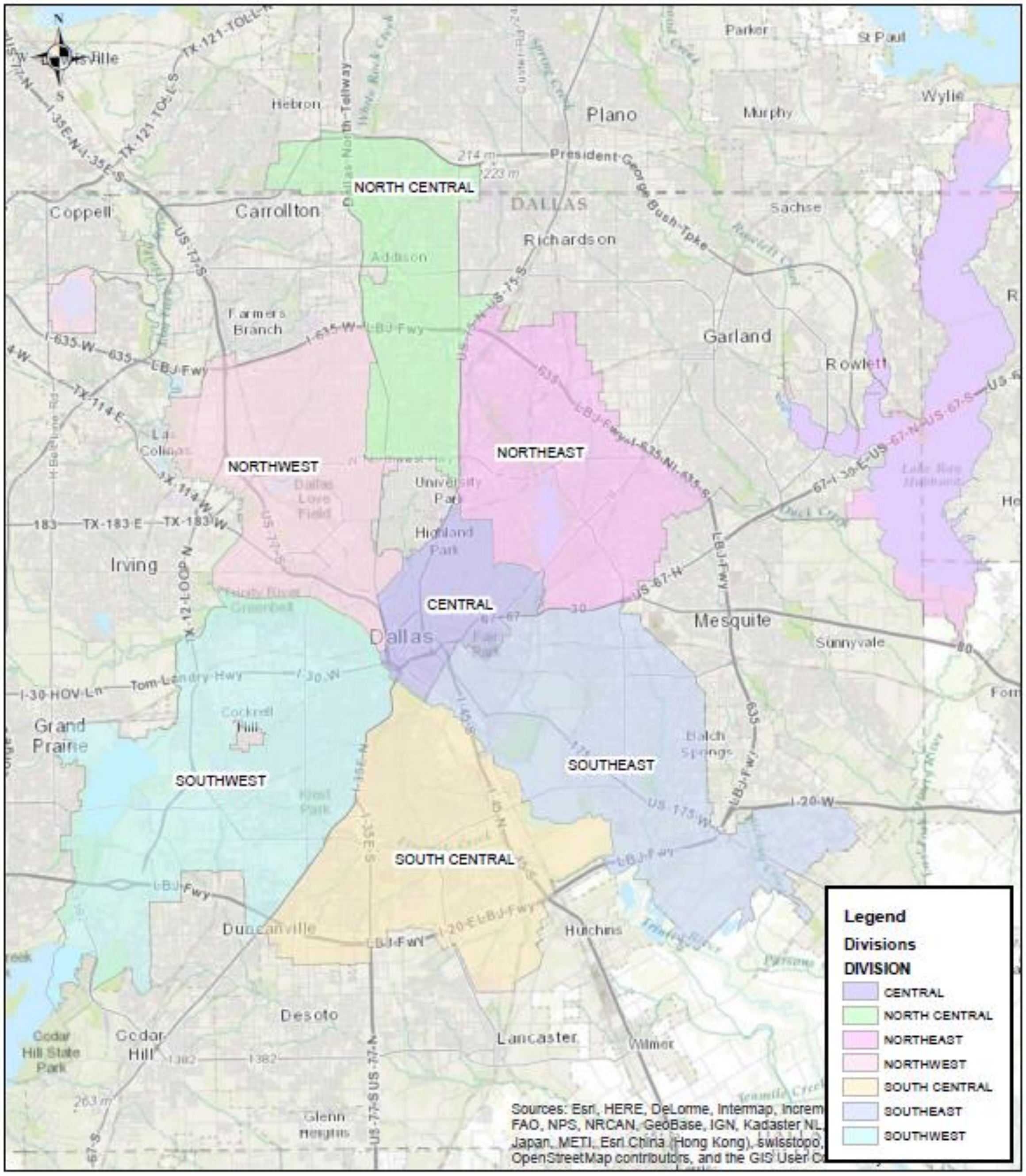


Figure 3.2. Patrol Map of City of Dallas Courtesy rendered by Esri GIS 10.2[3]

[3] Courtesy of Dallas Police Department Crime Data Analyst Unit. Map was provided to this study on 10 July, 2016.

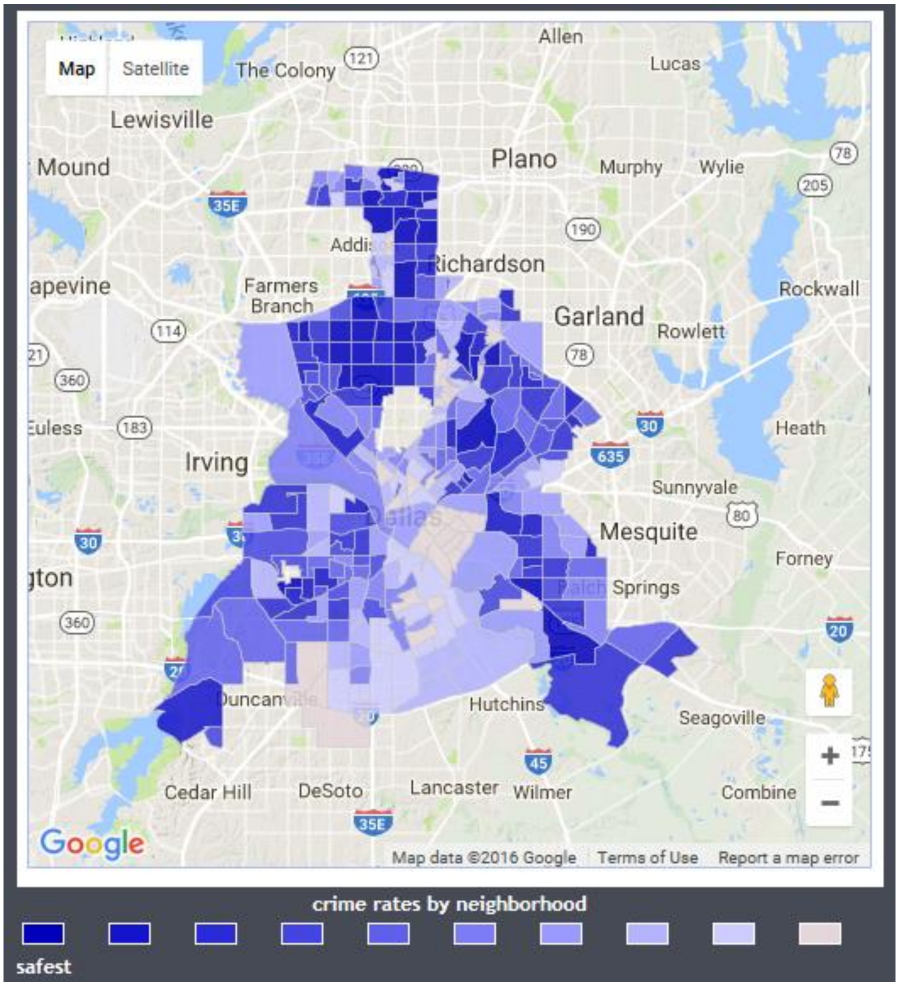


Figure 3.3. Choropleth Map of High Crime Area[4]

Figure 3.4 illustrates the Targeted Action Area Grid. These TAAG locations (green box with red outlines) represent the highest police activities and crime. In other words, these areas represent crime hot spots. Note that these Targeted Action Area Grids are far larger than street segments. As a result, the size and definition of hot areas and cold areas can be quite subjective. These two maps illustrate that using the block group as a unit of analysis may be more functional

[4] Map can be access via https://www.neighborhoodscout.com/tx/houston/crime/ (Location, Inc, 2016).

for practitioners than statistically calculated crime clusters. The following section will further address this point.

The maps describe the socioeconomic distribution in a spatial sense, with most members of the affluent class clustered in the Highland Park area, uptown, and the outer edges of the city, close to nearby Richardson, Plano, and Carrolton (See Figure 3.3 and 3.4). This pattern resembles Shaw and Mckay's concentric model and better highlights the neighborhoods and suburbia that are more likely to be located in the outer ring of the city. Dallas is also composed of a large number of minority and lower-middle-class communities, with spotty and decentralized upper-middle and upper-class neighborhoods.

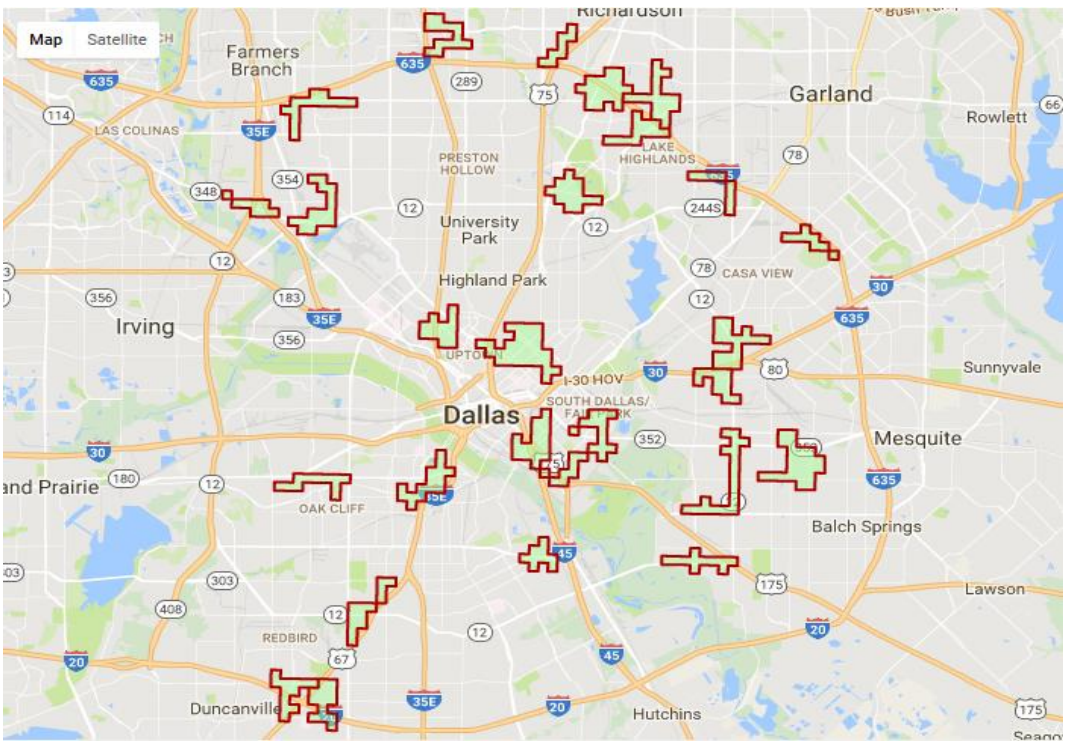


Figure 3.4. Dallas Department Designated Targeted Area Action Grids[5]

[5] Source Map of Targeted Action Area Grids was provided by Dallas Police Department (Safer Dallas, 2016)

Unit of Analysis

One of the challenges of this study was to identify the best unit of analysis. Weisburd et al. (2014) and others (see Hipp 2007, 2010a, 2010b; Taylor, 2015) have pointed out that there is no perfect unit of analysis for research of this nature, as all units of analysis have some advantage and disadvantages. Weisburd and colleagues have argued that using street segments is more suitable than block groups, for three key reasons. First, data can aggregate upward, but not downward. In other words, block-group-level data may statistically represent the attributes of a block face, but a street segment usually is not a good representation of the entire block, nor is a block group a strong representation of a Census tract. This statistical relationship is known as "averaging" (Weisburd et al., 2014, p. 24). Therefore, researchers may refer to higher levels of data to reflect street-segment level attributes without canvasing data street by street. Second, a block group is a subjective boundary, and it does not represent the actual size of a crime hot spot in the sense that a statistically-produced map would. Second, research has also demonstrated that there are often disconnects between the actual location of crime hot spots and *police*-reported hot spots (Ratcliffe, 2010). As a result, many departments shift toward direct patrol to compensate for this difference (Taylor, Koper, and Woods, 2011; Wells, Zhang, and Zhao, 2012). Finally, street segments have well-defined boundaries, and their attributes are a function of local residents' behaviors (Taylor, 1997, 1998). The attributes of a street segment can change drastically from street to adjacent street, so using block groups may not adequately reveal the context of micro-places.

While this study acknowledges these limitations of using block-group data (block-level data for Census 2010 was not yet available from the U.S. Census at the time of study), this study argues that there are nevertheless some valid reasons that make the use of block group data beneficial. First, a Census block group is made up of a number of Census blocks and is a subdivision of a Census tract. A typical Census tract has between one and nine block groups (U.S. Census Bureau, 1994). The number of blocks within a block group varies, with an average of 39 (U.S. Census Bureau, 2014). Although this may seem large, from a geospatial perspective, this is about the size of six blocks by six blocks. Second, block-group data are useful because they provide a functional unit of measurement for police agencies to make patrol-based decisions, as most policies are not designed to focus on a single street (Ratcliffe, 2010). For example, Philips et al. (2015) found that higher levels of calls for service are associated with higher levels of arrest rates at block groups, and it could be possible that patrol districts are not in line with scholar-mapped hot spots. Third, while block groups are relatively large compared to street segments, they are still relatively small compared to Census tracts, neighborhoods, cities, or counties. This means that block groups provide an excellent environmental backdrop for the local ecology, especially when studying social disorganization theory (Deryol et al., 2016). Since this study focuses on micro-places and is guided by social disorganization theory, it may be necessary for research to move gradually toward street segment-level analyses.

Data

This study required three sets of data. All data sets needed to be linked together based on their temporal and spatial relationships. These three sets of data included arrest data, maps and Census block group shape files, and demographic data to test social disorganization theory. While the U.S. Census collects its data via an advanced sampling method, the Dallas Police

Department collects its arrest data through non-random sampling (additional data limitations will be discussed in the concluding chapter).

Arrest data.

Arrest data were provided by the Dallas Police Department via an internal data request. Data were collected for the period from 2010 through 2014 (n = 42,509). Arrest data prior to 2010 and a portion of 2010 arrest data were not fully digitized and, as such, were not included in the study. In addition, data collection was cut off in 2014 because the year 2015 had not yet been compiled when the Dallas Police department provided the data used in this study.

The arrest data contain detailed demographic and personal information for each arrestee, including name, address, race, age, and gender. The data set also contained information concerning where the arrest was made and details regarding victims. Arrest locations were critical for mapping purposes.

Due to the sensitivity of the data, the author sought and secured Institutional Review Board (IRB) approval (see Appendix A). The raw data contained the names of victims and offenders, their addresses, and personal contact information. It was necessary to remove all such personal information to ensure the privacy of the offenders and the victims. All personal data with respect to victims and arrestees were stripped, and the original data copy was then locked in an encrypted data vault at the Caruth Police Institute located within the Jack Evans Police Headquarters in downtown Dallas. The only arrest data variables used in the analyses were the date, time, location, and the type of offense.

Table 3.1 illustrates the distribution of offense types captured by the arrest data set. Overall, 40 percent (n = 16883) of arrests were for Part I crimes and nearly 60 percent (n =

25626) of arrests were for Part II crimes (e.g. drugs, prostitution, disorderly conduct …). Of all Part I offenses, offenses involving property (burglary and robbery) accounted for 66 percent of all arrests in the sample. In contrast, arsons (0.2%) and murders (1.2%) were the rarest offenses. Although this study does not presume that high-frequency arrest block groups are crime hot spots, research does suggest that a higher number of arrests could be indicative of high criminal activity (Chamlin and Myer, 2009). Note that while property crime consists of more than 66 percent of Part I offenses, it constitutes only 26 percent of total crime. Furthermore, the clearance rates of property crime are traditionally low. Therefore, this table reveals that the number of reported crimes may be skewed when compared to incident reports. This study suggests that observing arrest rates may be just as important when exploring crime concentration.

Table 3.1

Distribution of Arrested Offenses

	N	%
Part I Offenses		
Murder	205	1.2
Robbery	1,904	11.3
Assault	2,970	17.6
Burglar	5,457	32.3
Theft	5,620	33.2
Arson	31	.2
Sexual Assault	702	4.2
Part I Total	16883	39.7
Part II Total	25626	60.3
	42509	100

With the use of geospatial analysis software, it was possible to link these arrests to block group level demographic information—for the purpose of testing social disorganization theory, one of this study’s main contributions. Because these data contain date and time, using longitudinal modeling and generalized least square (GLS) regression to examine arrest trends was also a viable analytic strategy.

Geospatial data.

In order for the ArcGIS 10.3 software to pin arrest data on a map, several files were needed: a source map of Dallas, shapefiles for the streets of Dallas, and shapefiles identifying the Census blocks. In addition, a street name database was also needed in order to build a geo-locator to help geo-code street addresses in the arrest reports. ESRI GIS provided a map of Dallas within the mapping software which was downloadable from the enterprise server. The shapefile for Dallas City Streets and the street name database was downloaded from the City of Dallas geospatial information system service (http://gis.dallascityhall.com/ shapezip.htm). The Census block group boundary shapefile was downloaded from Census 2010 TIGER/Line file block group (http://www.census.gov/geo/maps-data/). After all these data were collected, they were then imported to ArcGIS as map layers.

Census data.

The demographic data used in this study came from the American Community Survey (ACS). They were downloaded from the U.S. Census website's American Fact Finder data locator (http://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml), using the advanced search function.

The ACS is an ongoing statistical survey to enhance the decennial Census. City planners, nonprofit organizations, and researchers use it to make predictions on demographic changes at the local level. Because the ACS provides estimates, the lowest aggregate available in the data is the block-group.

The level of accuracy of ASC depends on the number of yearly estimates it includes; its accuracy increases based on one-, three-, and five-year estimates. While the one-year estimate produces the most immediate data, the five-year data provides the most accurate information. For this study, the 2014 ACS was chosen because (1) it is the most accurate estimation for the purpose of this study and (2) it aligns perfectly with the period with the length of trajectories (between 2010 and 2014). A copy of the ASC survey can be downloaded from https://www2.census.gov/ programs-surveys /acs/methodology/questionnaires/2016/quest16.pdf. The final chapter will further discuss ACS disadvantages and limitations.

The ACS is a continuous measurement survey program and is superior to decennial data (Salvo, Lob, and Love, 2002). First, the ACS has a minimal data requirement compared to the long form. Second, the ACS has twice the response rate compared to the long form Census. Salvo, Lob, and Love (2002) argued that these two qualities reduce the level of non-sampling error, even for high-poverty areas that are known to have a very low response rate. Continual estimation also allows researchers to have the most updated snapshot of the demographics of an area without having to wait many years. Although the ACS is based on an advanced sampling technique, it has its unique set of limitations. The lowest aggregate for ACS only exists at the block-group level, and it does not contain block-level or street-segment data. Therefore, it is an estimation based on block-level estimates. This limits researchers' ability to match demographic data to street segments and block levels.

Data handling and transformations.

Once the arrest data were collected from the Dallas Police Department, the greatest challenge was data cleaning. Data cleaning was a lengthy process because the raw data were not in the correct format and could not be used immediately by both ArcGIS and STATA, the software used to estimate this study's statistical models. For example, police officers had input reports in various date-time and address formats, used inconsistent spelling across reports, and sometimes entered wrong information in the forms they were required to use. It was therefore necessary to correct all arrest reports to a uniform date- and address-reporting format that was readable for the geospatial software. Once these corrections were made, the data were then imported into ESRI ArcGIS 10.3, along with its geographical data as a layer.

It is important for the reader to be aware that some arrests are not made at the offense location, and secondary locations are annotated on the report if it is available. Otherwise, it is assumed that the offense location is where the arrest was made.

One of the most powerful features of ArcGIS 10.3 is that this software allows users to join different types of data based on spatial relationships. For example, using the Census block group shapefile as its platform, it was possible to geo-code each arrest and place it within the corresponding polygon that represented the Census block group. A similar process was also completed for the demographic data downloaded from the ACS. However, instead of point data (addresses), the association for ACS was represented by block group polygons.

After mapping the block group boundaries and street layers in the software, individual arrests were matched and aggregated to block group level. Once the matching was completed, ACS data were then combined spatially to each block group using the "joint" command. Once the joint process was completed, the GIS software produced a cross-sectional database. Using a utility program call Stat/Transfer, the database was then converted into STATA format for further analysis.

The final step of the data manipulation was to convert the cross-sectional data into longitudinal data sets so that they could be used in statistical modeling. Initially, the five-year data set was divided into 20 consecutive quarters because doing so would maximize the number of trajectories and groups (see Piquero, 2008b). However, initial analysis found that 20 observation points (quarterly) did not provide enough cases to produce a meaningful resolution for the trajectory plots, as most places reported zero arrests in each quarter. There are two ways to overcome this problem. First, Weisburd et al. (2004) used zero inflated Poisson (ZIP) trajectory models, but there are problems with these types of models when the distribution assumptions are violated (Davies and Guy, 1987). Because Weisburd et al. (2004) had 20 years' worth of data, it was more appropriate for them to model the entirety of the year. However, it makes less methodological sense for this study to count the arrest rate quarterly.

Another way is to aggregate the data into less observation periods to produce a higher count per observation. The final option was to transform the data. However, analysis with transformed data was problematic (see Appendix B). As a result, this study aggregated the number of arrests annually to increase the count in each observation without transformation. The final data set contained 869 block groups and longitudinal arrest data over a five-year period.

Missing data and outlier analysis.

The arrest addresses could not be mapped until they were first geo-coded. Geo-coding is a process of using a geo-locator (a program within ArcGIS) to digitally matching the raw address data to the known-reference address database. While more than 87 percent of arrest addresses were geo-coded by the geo-locator and matched to the reference database, 13 percent (n = 5,318) of arrest locations failed to match successfully. These unmatched cases were caused by missing or misspelled addresses, wrong street names and house numbers, and/or addresses outside the city limits. To reduce lost cases, manual corrections to these addresses were needed to rematch the 5,318 arrest cases. One way to reduce these lost cases was to spell check the addresses or to match the addresses to the nearest block or intersection. The lengthy correction process was able to assign addresses to 2,175 cases. Of the remaining 3,148 unmatched cases, 1,689 cases had completely missing addresses, and 1,454 cases were wrong, incomplete, or outside the city boundary. The total usable arrest data included 39,366 cases. The missing cases (2,175 of 42,509 cases) constituted just five percent of the overall sample.

While data that are missing completely at random (MCAR) or missing at random (MR) do not likely affect the statistical models (apart from a reduction in sample size), data that are missing not at random (MNR) can seriously affect the estimations by introducing bias. One way to ensure that missing cases are MCAR or MR is to conduct a *t*-test on a set of "check" variables (Allison, 2002). In the current study, these check variables were chosen to ensure that the missing data were free from gender, race, age, or even temporal bias. Thus, *t*-test comparisons were conducted on day of the week and time of arrest in addition to the gender, age, and race of the arrestees. The analyses failed to find that there were statistically significant differences on the gender, age, and race variables. Similarly, there were no differences between missing and non-missing cases on arrest time and day. We can generally conclude, therefore, that the missing cases were MCAR or MR.

Another important preliminary inquiry was to identify and reduce the number of "outlier" block groups. One of the GLS assumptions is that both dependent and independent variables must be free of outliers. While many block groups had little to no arrests, a few of them also had a high incidence of arrests, which may have influenced the final statistical outcomes were no steps taken to address the issue. One way to correct this is to conduct an outlier analysis using the Mahalanobis distance score (Mahalanobis, 1936; McLachalan, 1992). Based on geographical attributes and arrests, the analysis identified five outlier block groups (three block groups had super-high population density and two block groups had completely missing demographic data). The final number of usable block groups for the analysis was thus reduced to 864 from the initial 869. However, this study retained all cases for the dependent variable to ensure that the highest arrest block groups were included.

Variables

The crime data used in this study were arrest records. Although Sherman and Weisburd (1995) and Weisburd et al. (2004) argued that incident reports are more appropriate because call-for-service data may be over-inclusive (overestimation) and arrest data may be too exclusive (underestimation), this study expresses different opinions about the importance of using arrest data. In criminology, the reality of crime is often an estimated number in between victim reports (e.g., NCVS and surveys) and official data (arrest data and UCR). Research concerning crime-at-place has largely used call-for-service reports (victim reports) and incident reports (police officers' assessments). Few studies have tried to set the hard numbers (i.e., actual crimes that are associated with an offender). For example, Menard (1987) examined five- to ten-year trends of UCR data on juvenile delinquency, Nation Crime Victimization Survey, and National Youth Survey on self-reported offenses. Where there are disconnects between self-reported victimization data and official crime reports, self-reported delinquency and arrest data share a more similar pattern. This suggests that it is equally important to study official reports to understand the baseline number in the context of crime-at-place. Moreover, a prior study argued that arrest data may be just as valid as other sources of crime data reports (Rosenfeld and Decker, 1999). Indeed, arrest data have a reasonably high degree of validity since they require a crime to be confirmed by officers with suspects who had been apprehended. Moreover, Osgood (2000) suggested that crime and arrests share a positive relationship, even if only a small number of offenses ensue in arrests. It is thus logical to assume that Census block groups that exhibit a higher number of arrests may also have a higher level of crime.

Dependent variables.

This study developed group-based trajectories of arrests in Census blocks throughout Dallas, then modeled them with social disorganization variables. As such, the dependent variable was the outcome of trajectory group membership over a five-year period between 2010 and 2014. Depending on the number of groups and model fit, the dependent variable was either binary (e.g., "1" for a high trajectory group and "0" for a low trajectory group) or nominal (e.g., multiple trajectory groups). For binary models, logistic regression was used; for multiple trajectory groups, multinomial regression models were estimated.

Many prior studies suggest that crime hot spots remain stable over time (Weisburd, 2008; Weisburd and Telep, 2014; Weisburd et al., 2004). Some studies, however, have found that certain hot spots are chronic and others are temporary (Chainey and Ratcliffe, 2005; Gorr and Lee, 2015). This suggests trajectory analysis is appropriate because it allows the study to include the longitudinal aspect of arrest data collected. In other words, using longitudinal data may allow the study to help identify chronically high arrest areas.

Independent variables.

Shaw and McKay's (1942) theory of community systemic structure argued that low economic status, ethnic heterogeneity, residential mobility, family disruption, and urbanization were the leading indirect predictors of crime. These variables were theorized to influence local friendship networks, teenagers' peer group supervision, and organizational participation by residents. In turn, they were presumed to influence both crime and delinquency. This study adopts a similar stance, but with a focus on arrests.

Sampson and Groves (1989) were among the first to operationalize social disorganization variables and test their ability to predict crime. This study extends the work of Sampson and Groves and tests their social disorganization variables in a study design that is analogous to that of Weisburd et al. (2004). The following subsections discuss in the detail the social disorganization variables used in the analyses.

Socioeconomic status (SES).

In Sampson and Groves (1989), the SES measure was constructed by summing the *z*-score of college education, occupation status by percentage of white-collar employees, and income level. The formula was as follows:

$$SES = z\_degree + z\_white\_collar + z\_med\_inc$$

The measure of SES in this study replicates Sampson and Groves' *z*-score summation on the percentage of college educated, percentage of professional or white-collar position, and median household income. The Cronbach's alpha for the three-item measure was 0.9258.

Racial heterogeneity (RH).

This study also implemented Sampson and Groves' racial heterogeneity formula $(1-\sum p_i^2)$, where *p* is the percentage of group and *i* is the number of group to replicate the racial heterogeneity scale. For example, a community made up of a population that is 20 percent black, 20 percent Asian, and 60 percent white is far more heterogeneous than a community that is 40 percent black and 60 percent white. There were four racial groups used in the construction of the heterogeneity variable: white, black, Asian, and other. The Cronbach's alpha for the four-item measure was 0.462. Hispanic was excluded because it is an ethnic group rather than a racial attribute (Sampson and Groves, 1989).

Residential stability (RS).

Residential mobility concerns the flow of residents at one place over time. The ACS estimated this variable based on the length of residence for more than one year. Another measure the ACS collected was the proportion of renters versus homeowners. Indeed, research has found that home ownership is positively correlated with residential stability (e.g., South and Deane, 1993). This study combined the two variables, again using Sampson and Groves (1989) approach, such that z-scores of (1) the percentage of people who live in the same house and (2) the percentage of homeowners residing within the block group were summed together. The Cronbach's alpha for the two-item measure was 0.7736. The formula for operationalizing the variable was as follows:

$$stability\_index = z\_same\_house + z\_owner$$

Family disruption (FD).

Sampson (1986) argued that family disruptions, including parents' marital problems and disruption, may affect informal social controls. Sampson and Groves (1989) operationalized family disruption by using the proportion of divorced and separated families and single-parent households. For this study, family disruption was operationalized as the *z*-score summing divorce and separated families, based on families residing within a block group. The formula was:

family disruption = z_[(divorce + separated households]/total number of families]

Urbanization (U).

Fischer (1982) argued that urbanization could weaken local kinship, weaken peer association networks, and impede socialization in local affairs. However, rapid urbanization does not always have an effect on some countries (e.g., Japan) (see Roberts and LaFree, 2004). Nevertheless, Sampson and Groves (1989) used a binary variable method to indicate either a city center or a rural area. Unfortunately, though, all of the block groups analyzed in this study were located within the city limits, making it difficult to use Sampson and Groves' measure to quantify urbanization. But fortunately, recent studies point out that population density (Kunnuji, 2016) and housing density (Gibbs and Malvin, 2008) may be indicative of urbanization, although the direct relationship between crime and population density is mixed (Rice and Harris, 2006; Baltagi, 2006). This study thus used population density and housing unit density as measures of understanding the level of urbanization. The Cronbach's alpha for the two-item measure is 0.9592. The formula was:

urbanization = z_population density + z_housing unit density

Analytical Strategy

This study used a non-experimental design to understand how social disorganization factors may be connected to arrest trends. Weisburd (2010), however, argued that the study of crime-at place may be conducted using non-experimental methods, so this study's design is consistent with prior research. A randomized trial was not possible given the data, timeframe, and resource constraints.

Trajectory analysis.

Studying arrest data through trajectory analysis generates new questions with respect to place. For example, what causes the elevated level of arrest at a specific place? and Is this due to more officers being present more often? In addition, are police officers practicing objective or subjective views while making arrests among these block groups, as well as in their arrest decision-making processes? These questions have led scholars to believe that police behaviors may affect crime-at-place (Groff et al., 2015).

Group-based trajectory modeling was employed in order to distinguish between arrest trends across block groups. The major advantage of group-based trajectory modeling (GBTM) over manual trend plots is that GBTM uses an advanced statistical method to distinguish membership groups (Nagin and Tremblay, 2005). While some argued that GBTM is a descriptive tool, it is an extremely useful tool for theory testing (Brame, Paternoster, and Piquero, 2012). In addition, GBTM allows the analyst to make such distinction based on a set of addition attributes (Nagin and Land, 2010).

The "Proc Traj" STATA plug-in allows users to model longitudinal data through discrete mixture models: censored normal, zero-inflated Poisson, and logistic. Because the number of arrests is aggregated annually with the absence of negative numbers and a true zero (e.g. all block groups experienced at least one arrest each year), a censored model is required. There are distinct differences between a truncated model and a censored model. Truncation occurs when both dependent and independent variables are missing. On the other hand, censoring occurs only when a dependent variable is lost or limited. For this study, the number of arrests is limited to zero, so censored modeling is the most appropriate approach.

Determining the appropriate number of trajectory groups.

One of the key issues in GBTM is settling on the appropriate number of groups. Brame, Paternoster, and Piquero (2012) pointed out that the number of predicted membership groups may depend on the number of cases and the length of observation available. The shorter the time frame, the more limited the group should be. In addition, researchers often determine what is the most appropriate fit statistics and the number of groups based on theoretical assumptions.

The fit statistics that are used to determine the model of best fit include Akaike's Information Criterion (AIC) (Akaike, 1974), the Bayesian Information Criterion (BIC) (Schwarz, 1978), sample-size adjusted BIC (ssBIC) (Sclove, 1987), and Consistent AIC (CAIC) (Bozdogan, 1987). The most commonly used is BIC, and model fit is determined by the proximity of BIC to zero, average posterior probability, odd of correct classification, and Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) (Lo, Mendell, and Rubin 2001; Jung and Wickrama, 2008).

Because the number of groups and length of trends often vary from study to study, arguments frequently arise in longitudinal studies. For example, Moffitt (1994) proposed three group trajectories to distinguish the latent factors that affect youth offenders based on antisocial behavioral variations among 536 boys. But in a later study that followed 270 males from age 12 to 32 years old, Van der Geest, Blokland, and Bijleveld (2009) found that offenders can be further divided into five distinct classes. Similar findings are also reported by other studies (Maldonado-Molina, Jennings, and Komro, 2010). These discrepancies show the importance of exploring a concept in various contexts. In other words, the classification of latent groups is often based on the sample size, the time period over which data are observed, and other factors.

Researchers must also be careful when interpreting latent constructs, as while statistical distinction may identify many membership groups, groups should also be defined based on theoretical justifications (Diamond, 2013; Nagin and Odgers, 2010). In many cases, statistical packages may distinguish latent variation simply based on statistical significance. However, the researcher must look beyond the numbers and make sense of why and how these differences exist. Hence, the classification of these differences should be based on sound theoretical reasons and not simply by numbers.

Group identification protocol.

Weisburd et al. (2004) identified 18 distinct crime trajectory groups. They were able to do so because their data contained 40 years of crime observation. In comparison, this study's five-year observation period was relatively short, making it unlikely that a dozen or more arrest trajectories could be identified. The appropriate number of group memberships was therefore determined by considering both the proportion of members in each group *and* BIC statistics. In other words, a balance between both considerations was sought (e.g., if just one observation appeared in one group, that information would probably not be useful to policymakers).

To illustrate group membership changes, the analysis explored up to six distinct trajectories. The one-group model displayed the overall trend, the two-group model provided two trajectories, and so on. Results appear in chapter four.

Comparing independent variables across trajectory groups with ANOVA.

Once the appropriate number of groups was determined, the next step was to use analysis of variance (ANOVA) to compare predictor variables across groups (Tabachnick and Fidell, 2007). This step was taken because growth curve modeling essentially "has its roots in analysis of variance" (Nagin, 2010, p. 62). The cornerstone of trajectory analysis is based on the variation of an attribute among trajectory groups. In order to distinguish two groups of subpopulation based on an attribute, such attributes must be varied among the two groups. ANOVA also helps to reduce false negatives (Type II) by accounting for sample size between each group, their significance levels, and the effect sizes. Analysis of variance is useful when a large group is compared to a smaller group of the population, especially when some trajectories could result in a very small number of members.

Regression analysis.

Finally, regression models were estimated to answer the question of whether social disorganization variables can help distinguish between high-arrest and low-arrest trajectory groups—and also the last research question of whether social disorganization factors are correlated with arrest trends (see Menard, 1987 and 2002 in *Applied Logistic Regression Analysis*). Depending on the outcome of distinct groups, the dependent variable was either binary (e.g., only high- and low-arrest trend) or consisted of multiple groups (e.g., high-arrest, mid-arrest, and low-arrest trend groups). Results from these models appear in chapter four.

CHAPTER 4

RESULTS

Descriptive Analysis

Before the trajectory analysis was conducted, descriptive statistics for each block group were calculated, as were box-whisker plots to visualize arrest trends in each year and the distribution of each independent variable. A correlation analysis was also conducted to test for collinearity between independent variables.

Table 4.1 provides the descriptive statistics for all 864 block groups used in the final sample. The mean number of arrests per block group in wave one (2010) was 2.36 (SD = 3.99). In wave two (2011) it was 6.70 (SD = 8.65). In wave three (2012) it was 8.63 (SD = 10.18) arrests, in wave four (2013) it was 11.17 (SD = 14.48), and in wave five (2014) it was 10.52 (SD = 13.11). A box whisker plot is provided in Figure 4.1 to illustrate the distribution of arrests in each of the years studied.

Overall, the number of arrests in Dallas progressively increased over the five-year observation period. The year 2010 had an unusually low number of arrests, which may have been due to incomplete data provided by the Dallas Police Department. This limitation will be further addressed in the next chapter. Overall, however, the arrest distribution pattern varies highly among block groups in Dallas.

Table 4.1

Descriptive Statistics of Block Group

Variables	*M*/%	*SD*	*Min.*	*Max*.
Dependent variable				
Arrests				
Wave 1 (2010)	2.36	3.99	0	68
Wave 2 (2011)	6.70	8.65	0	143
Wave 3 (2012)	8.63	10.18	0	148
Wave 4 (2013)	11.17	14.48	0	229
Wave 5 (2014)	10.52	13.11	0	194
Independent variables				
Socioeconomic status				
Degree holder (%)	27.93	27.4	0	99.46
Median income (USD)	54427.89	41448.83	7961	250000
White collar position (%)	32.77	23.19	0	93.06
Racial heterogeneity				
White (%)	60.67	27.56	0	100
Black (%)	24.01	28.23	0	100
Asian (%)	2.51	5.13	0	58.41
Others (%)	14.82	15.18	0	89.81
Total (%)	100			
Residential stability				
Ownership of home (%)	49.68	31.23	0	100
Live in the same house more than a year (%)	82.45	14.03	27.99	100
Family disruption				
Divorced & separated (%)	18.54	8.11	0	57.26
Urbanization				
Population density (person per sq. mi)	8386.03	12348.05	0	207313
Housing unit density (unit per sq. mi)	3666.79	4908.42	0	71383

Note: N=864

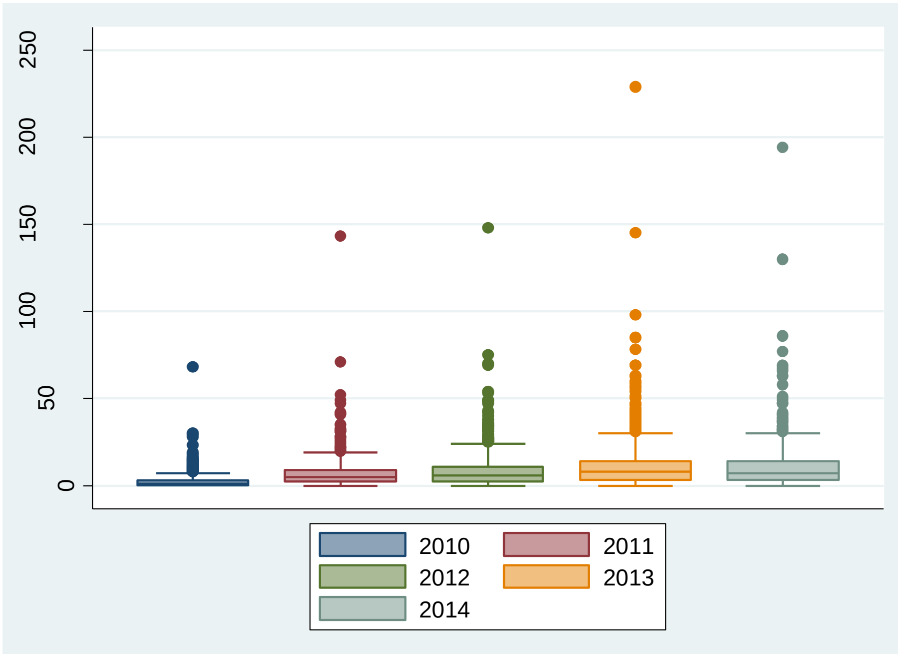


Figure 4.1. Box-whisker Plot for Arrests between 2010 and 2014

Following the work of Sampson and Groves (1989), this study tested social disorganization with five independent variables: socioeconomic status (SES), racial heterogeneity, residential stability, family disruption, and urbanization. The three-item measures of SES included the percentage of degree holders, median income in U.S. dollars, and the percentage of people holding white collar or managerial positions. The median percentage of college graduates who hold a four-year degree was 15.19 percent (n = 861, M = 27.93%, SD = 27.4) (Figure 4.2). The percentage of college graduates in this study's sample was slightly lower than the national average (Dynarski, 2016). In terms of income, the centile median income of the sample was about $40,839 ($n$ = 860, M = $54,427, SD = 41,448). The average median income was slightly higher than the national average median income of $51,759 in 2012 (U.S. Census, 2012). Overall, about one third of the population was employed in managerial positions (see

Figure 4.2). Finally, the median percentage of the population holding white collar or managerial position was 23.19 percent (n = 859, M = 32.77%, SD = 23.19).

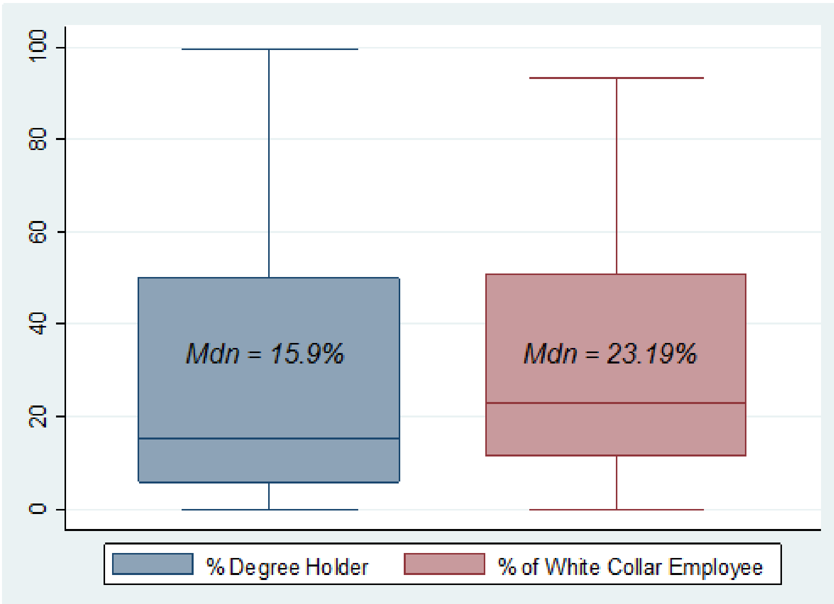


Figure 4.2. Box-whisker Plot for Degree and Occupational Position

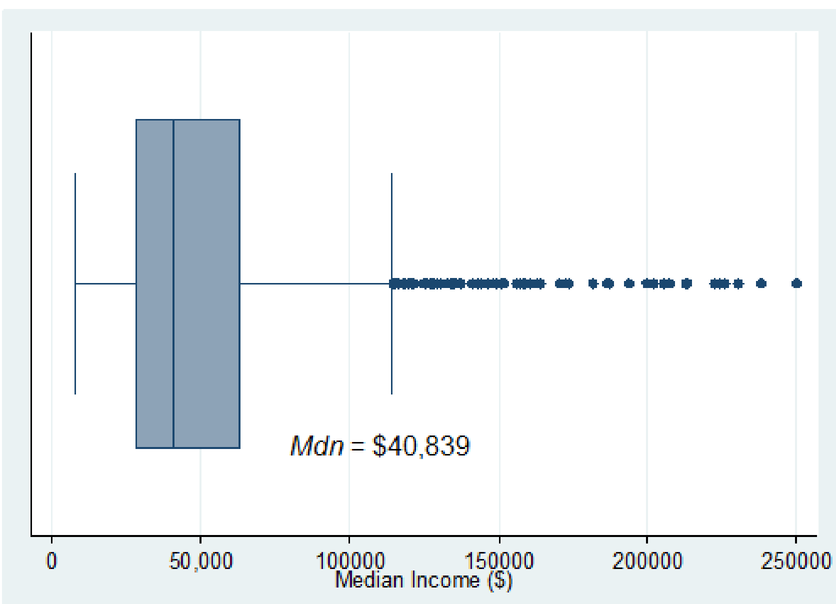


Figure 4.3. Box-whisker Plot for SES Indicators Median Income

Racial heterogeneity was the second measure of social disorganization in this study. The American Community Survey (ACS) reports racial data in four categories: White, Black, Asian, and Other. According to the data downloaded from the U.S. Census ACS 2014 5-year estimate, Dallas is composed of 60.67 percent (*n* = 861, *SD* = 27.56) whites, 24.01 percent (*n* = 861, *SD* = 28.23) blacks, 2.51 percent (*n* = 861, *SD* = 5.13) Asians, and 14.82 percent (*n* = 861, *SD* = 15.18) other (see Figure 4.3).

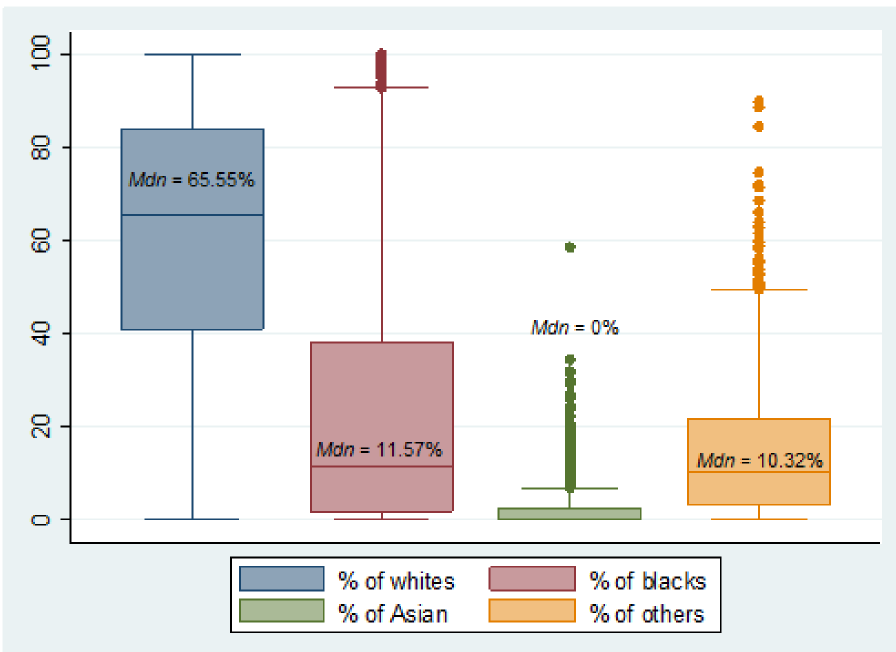


Figure 4.4. Box-whisker Plot for Racial Distribution

A two-item measure was used to measure residential stability: the percentage of home owners and the percentage of the population who have stayed in the block group for more than one year. In the sample, the median percentage of home owners for block groups was 55.89 percent (*n* = 859, *M* = 49.68 *SD* = 31.23). The percentage of households within the block group that reported that they have lived in the same home for more than a year was 82.45 percent (*n* =

861, *SD* = 14.03). This score was then standardized. It is presented in Figure 4.4 (see Figure 4.4). Overall, Dallas residents enjoy a relatively high degree of residential stability.

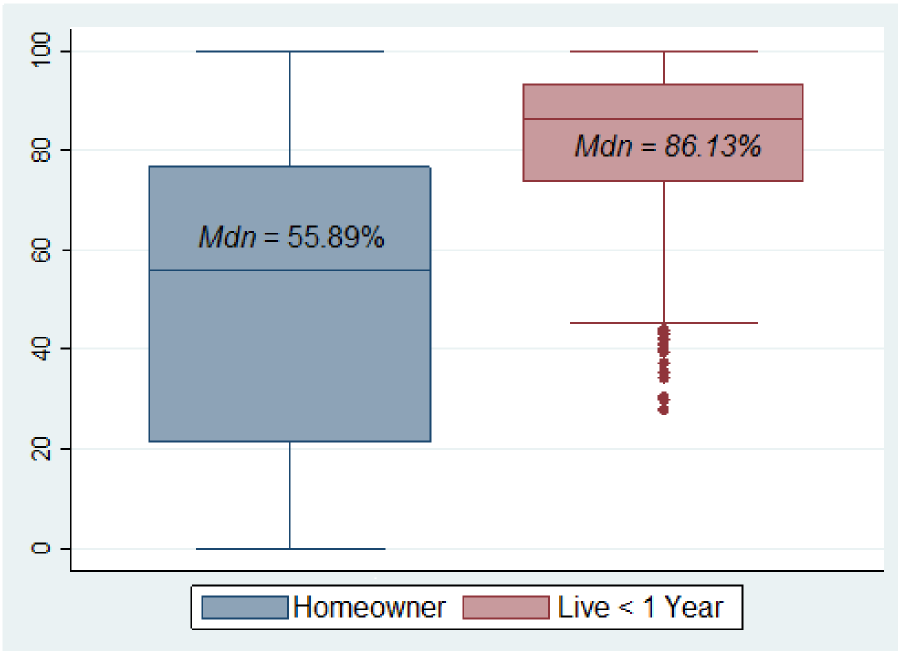


Figure 4.5. Box-whisker for Residential Stability

As for family disruption, the mean percentage of divorced or separated family in the block groups was 18.54 percent (*n* = 860, *SD* = 8.11) (Figure 4.5). This variable combined the percentages of divorced and separated families to ease interpreting the model, because some households may be separated and not divorced or divorced but not separated. This number is lower than the national average of between 40 and 50 percent of families who have experienced disruption (American Psychological Association, 2012) (see Figure 4.5).

Figure 4.6 illustrates levels of urbanization in Dallas for both population density and residential unit density. Based on the data provided from the census, the median population density of the block groups was 5528.5 (*n* = 862, *M* = 8,386.03, *SD* = 12,348.05) persons per square mile. In addition, the median number of housing units per square mile of each block group was 2126.5 (n = 862, M = 3,666.79, SD = 4,908.42) units. While this number appears high, block groups within a small area with many apartments or high rises could drastically elevate this number at the city center (see Figure 4.6).

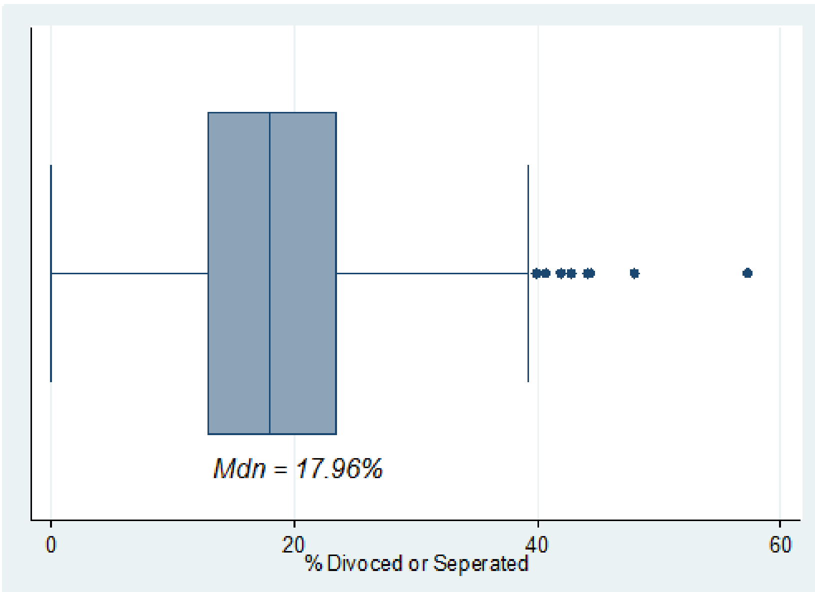


Figure 4.6. Box-whisker Plot for Family Disruption

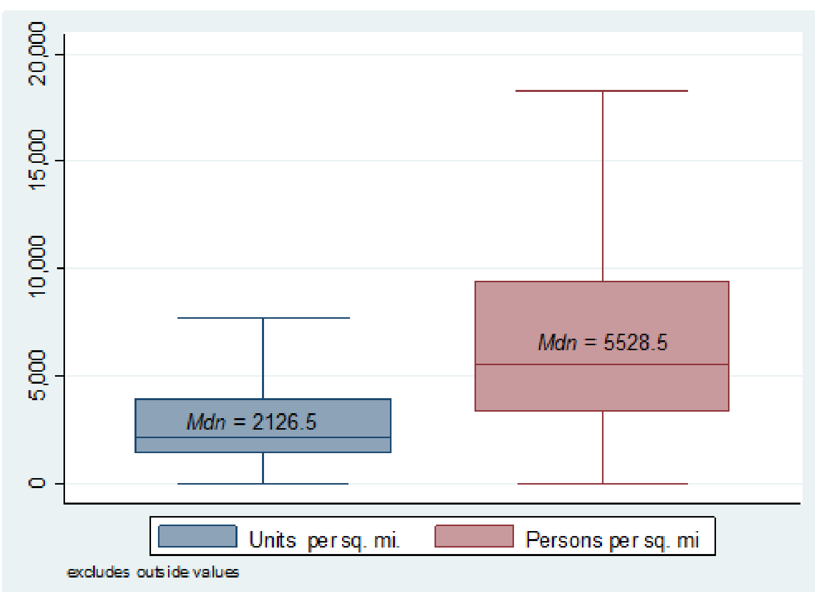


Figure 4.7. Box-whisker Plot for Urbanization

Correlation Analysis

Table 4.2 reports pairwise correlations between each of the independent variables. With the exception of family disruption and urbanization, all variables were correlated as expected (Sampson and Groves, 1989). The socioeconomic variable shares a positive relationship with residential stability, while it has a negative relationship with racial heterogeneity, family disruption, and urbanization. Moreover, SES shares a moderate relationship with racial heterogeneity and family disruption. This means that block groups with low SES levels are more likely to live in a more diversified neighborhood and are more likely to experience divorce or separation. Although the relationship is relatively weak, it appears that those with a higher level of SES are also more likely to be homeowners, enjoying a higher degree of residential stability. This may also reflect that people living in low SES block groups are likely to endure high density housing compactness and population concentration (e.g. apartment or public housing projects). Furthermore, low SES family are more likely to experience a higher degree of urbanization.

The correlation analysis further suggests that racial heterogeneity shares a moderate negative relationship with residential stability. Block groups with higher levels of racial mixtures are more likely to be transient in nature, which means people are less likely to own their home or be able to remain at one place more than a year. In addition, these block groups with higher levels of heterogeneity are more likely to experience family disruption and urbanization.

For residential stability, although the correlation is relatively weak, this study finds that block groups with higher levels of family disruption experience less stability in terms of residency. Families experiencing problems are more likely to move about or are unable to own a home. The correlation analysis also suggests that there is a weak to moderate relationship between urbanization and residential stability. Residents in block groups that have high levels of population density or building unit density are less likely to own a home or are more likely to move in a short period of time. Finally, the correlation analysis suggests that the relationship between family disruption and urbanization is insignificant.

Table 4.2

Correlation Analysis of Independent Variables of Block Groups

	SES	Racial Hetero.	Residential Stability	Family Disruption	Urbanization
SES	1.000				
Racial Heterogeneity	**-0.440*** <0.01	1.000			
Residential Stability	**0.162*** <0.001	**-0.325*** <0.001	1.000		
Family Disruption	**-0.379*** <0.001	**0.193*** <0.001	**-0.261*** <0.001	1.000	
Urbanization	**-0.110*** 0.001	**0.143*** <0.001	**-0.331*** <0.001	0.034 0.325	1.000 <0.001

Note: * *P*<0.05

Trajectory Analysis

Unlike 20 years ago when group-based trajectory analysis was first developed, there are now many statistical packages on the market for model estimation, including Mplus, STATA, and SAS. Some software is free for researchers, but some is proprietary. While Mplus is one of the more popular programs for latent variable models, other statistical packages also offer free GBTM plug-ins for users to conduct trajectory analyses. For example, “Proc Traj” is a free downloadable plug-in for users who already have SAS or STATA.

This study utilized the "Proc Traj" STATA plug-in to conduct the trajectory analyses. The "Proc Traj" plug-in models longitudinal data by using discrete mixture models. It supports many modeling approaches, but the three that are most widely used are: the censored normal model (when the dependent variable is treated as a continuous variable), the zero-inflated Poisson (ZIP) model (when the dependent variable is treated as a count variable or contains many zeroes), and the logit model (when the dependent variable is binary). According to Weisburd et al. (2004), the researcher should make the decision on which "parametric form [Normal, Poisson, or Logit], the functional form of the trajectory over time, and the number of groups" should be included in the model (see Jones, Nagin, and Roeder, 2001; Jones and Nagin, 2013; Weisburd et al., 2004, p. 297).

Occasionally, the model selection process could be a complex and time consuming procedure in trajectory analysis. However, scholars have provided some instructions on simplifying this process. For example, Nagin (2005) advised that it may be helpful to plot the data longitudinally before conducting a trajectory analysis. There are two reasons for this. First, visualizing the data in a plot may help the researcher to recognize the trend, which could aid predicting the direction and the number of trajectories based on theoretical assumptions. Second, visualization allows the researcher to identify the possible number of distinct trajectory clusters (e.g., the number of clusters). Additionally, because the shape of the trajectory may help determine the best-fitted polynomial order (linear versus quadratic, cubic and quantic), visualizing the data may help assess the best fit polynomial order to reduce the time needed for the analysis (Niyonkuru et al., 2013).

A plot for the average arrests of block groups is shown in Figure 4.7, and a profile plot of arrests in each block group over the five years is provided in Figure 4.8. Visual assessments of the annual average of block groups suggest that the overall arrest trend steadily increased between 2010 and 2014. In addition, this curve is also best fitted with a quadratic function. Again, the low number of arrests in 2010 may be due to an incomplete report. It is unlikely that the Dallas Police Department has increased the average number of arrests by 400 percent over a five-year period (this point will be further addressed in the limitations section of chapter five). The profile plot of all 864 block groups in Figure 4.8 tells a different story, namely that there may be at least two or three major clusters of block groups (bundles): low, medium, and high. This plot shows that there are a few block groups that experience a higher level of arrests and increase over time. A middle group experiences some arrests over time. A cluster that enjoys consistently low arrests over time is also apparent. In contrast to the findings provided by Weisburd et al. (2004), the results in Figure 4.11 do not show that the block groups in this study exhibit an increase, decrease, and stability over time (the next section will interpret this model in greater detail). However, this may also suggest that arrest trajectories and police incident report trajectories share an unparalleled pattern over time.

Model selection criteria.

Model selection in a trajectory analysis is based on two main features: the distinct vector of each trajectory (number of possible groups) and the probability of group membership (Nagin, 1995). In addition, a number of other useful model selection criteria were considered. For example, Nagin (2005) advised that the most useful information in the analysis is the group

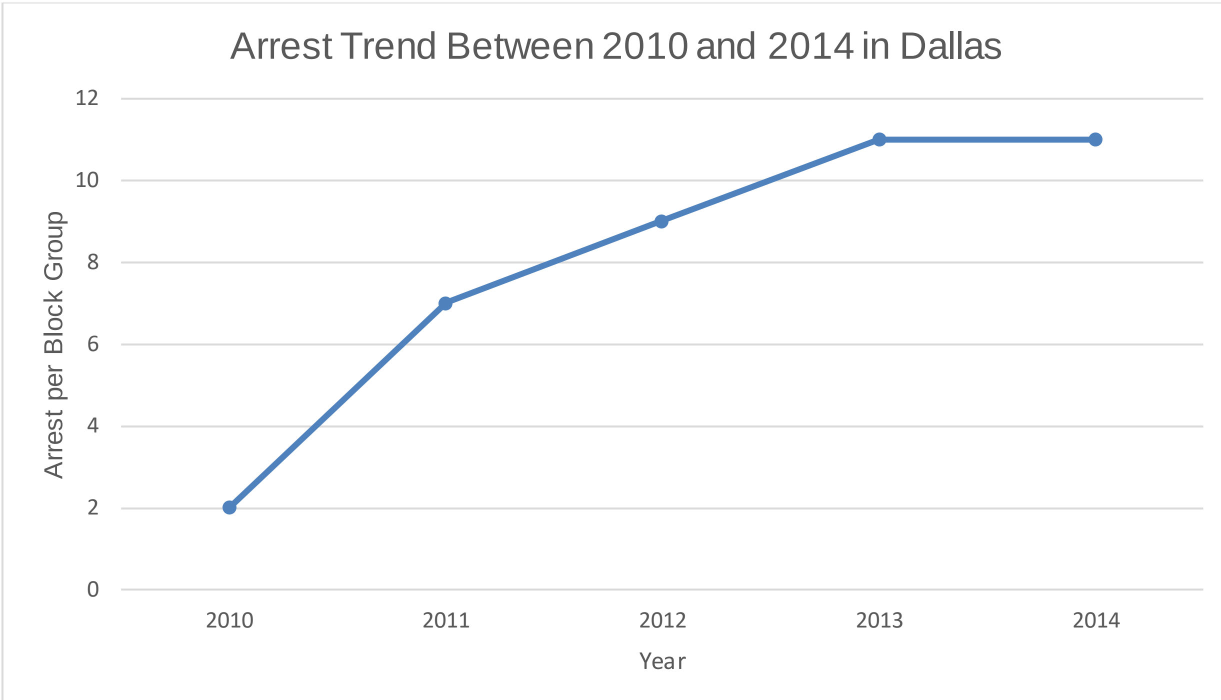


Figure 4.8. Arrest trend of 864 block groups over the five-year period

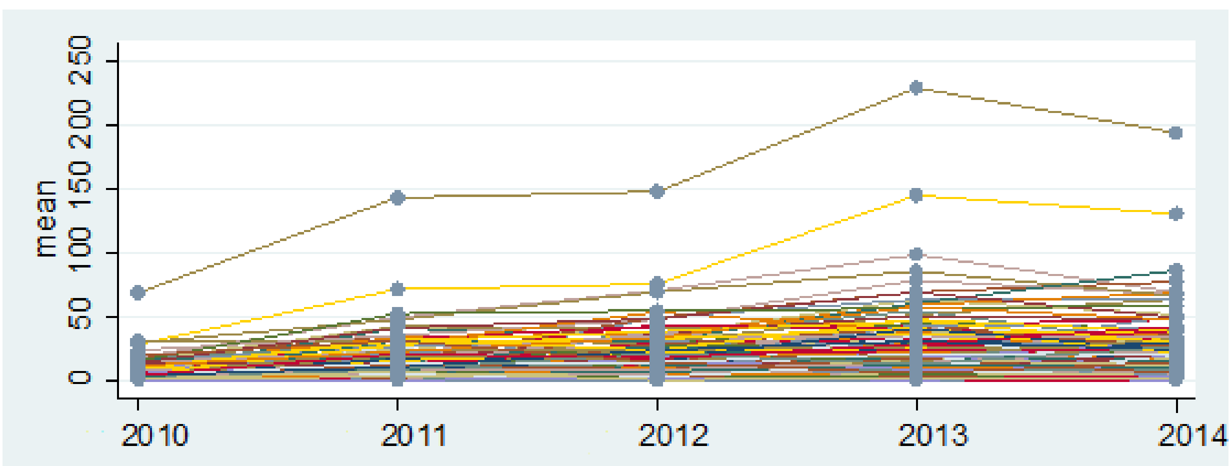


Figure 4.9. Profile plot of arrest trend of all 864 block groups

membership probabilities, as the membership probability may help the researcher estimate the possible number of groups and what these groups mean theoretically. In addition, prior studies may also help compare the number of group memberships grounded on the theoretical significance, contrast the distinctiveness of the group based on statistical variations, and decide which fit statistics to use in order to identify the model of best fit (e.g., Bayesian information criteria, or BIC). Ultimately, however, the researcher must decide what is the most meaningful and logical approach to describe these models.

For the purpose of this study, model selection was based on the following criteria: (1) BIC and Akaike information criterion (AIC) goodness of fit; (2) the probability of each membership group and presence of zero-membership groups; (3) model convergence and the ability of STATA to calculate the standard error to construct confidence intervals; (4) the meaningfulness of classes (e.g., whether a five-class model makes more sense than a three-class model does and how much BIC is different); and (5) a proper distribution of membership probability to permit regression analysis. Concerning the fifth criterion, this may be necessary to reduce the number of groups to increase the sample size of each group to conduct regression analysis. For example, if a group contains two members and the increase in trajectory classes would simply split them into two groups, it may be statistically and theoretically reasonable to keep two groups as one.

The trajectory analysis began with a one-class model and progressively developed into a six-class model (class indicates the categorical distinctiveness of the group). Table 4.3 summarizes all the trajectory statistics for each class. The next section will further discuss these models.

Trajectory modeling.

One-class model.

The analysis began with a one-group solution, with each trajectory plotted by a cubic function (*BIC* = -15,319.74). The one-class model has an extremely wide confidence level (see the dotted line in Figure 4.9). In the one-class model, the probability of group membership is 100 percent. The plot displays an increasingly high arrest trajectory. Cross comparison of both AIC and BIC (only BIC is shown on Table 4.3) with other models shows that the one-class model has the most distant value from zero among all class models (Table 4.3). Therefore, the one-class model has the poorest fit statistics to explain arrest trajectories.

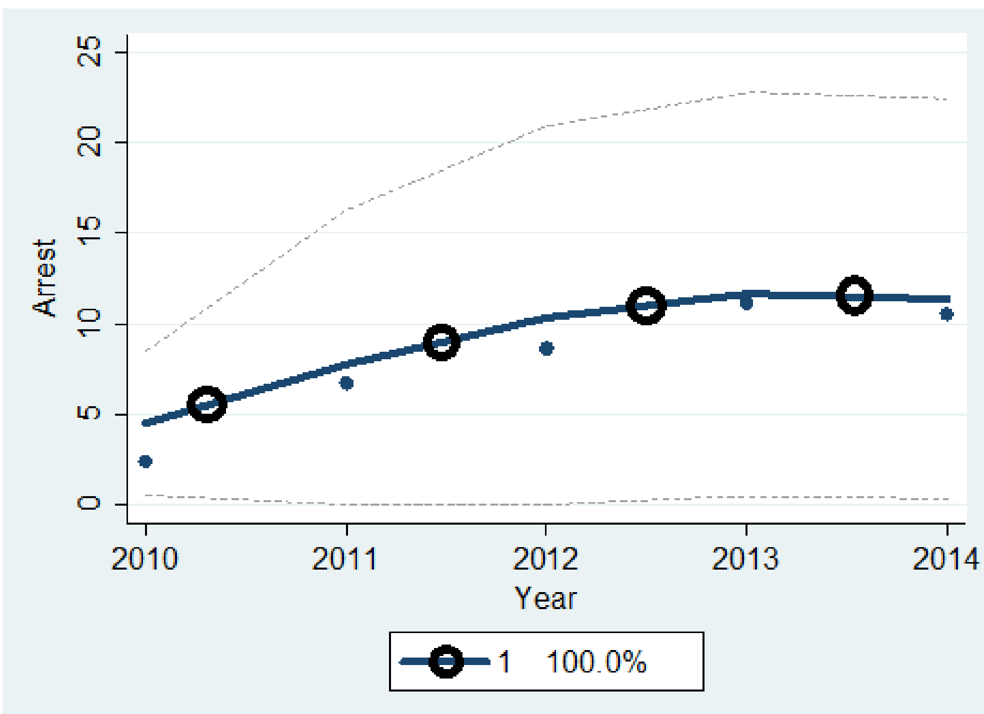


Figure 4.10. One-group trajectory plot

Two-class model.

The two-class model shows two more distinctive vector trajectories. Visually, there is a high arrest group trajectory and a low arrest group trajectory. Both high and low trajectories are fitted with a cubic time function with a *BIC* value of -14,256.60. The BIC value shows that this model has an improved fit over the one-class trajectory model. There is a two-membership distribution of high and low arrest trajectories (See Figure 4.10). The probability of membership fit in the low arrest-risk trajectory is 95.86 percent (95% CI [95.24, 96.64]). Accordingly, the probability of block groups fitting into the high arrest-risk trajectory is only 4.14 percent (95% CI [3.44, 4.84]) (see Table 4.3). In addition, the high arrest trajectory also has a wider confidence interval compared to the low arrest-risk trajectory model. In comparison to the one-group trajectory, which indicates there is a generally high arrest trend, the two-class model shows that there may not be the case. In fact, this model begins to resemble the common criminological theme that a small number of places are responsible for a large number of crime.

Three-class model.

The three-class trajectory model has a BIC value of -13,632.41, which is a slight improvement from the previous 2 trajectories model (see Table 4.3). This model has three distinct arrest patterns: trajectory 1 for low arrest-risk group membership, trajectory 2 for medium arrest-risk group membership, and trajectory 3 for high arrest-risk group membership (see Figure 4.11).

In this model, trajectory 1 is fitted with a cubic function, while the medium (trajectory 2) and high arrest (trajectory 3) trajectories are fitted with linear functions. The model continues to suggest that the probability of high arrest trajectory group membership is very low (n = 2 block groups), while nearly 99.8 percent of all block groups have a better chance of fitting into the medium and low arrest-risk trajectories. Overall, the probability of being classified as a high arrest-risk block group is only 0.2 percent (95% CI [0.07, 0.39]). The probability of a block group being classified as a low arrest-risk block group is 91.3 percent (95% CI [90.25, 92.29]), and the medium arrest-risk trajectory is 8.5 percent (95% CI [7.49, 9.51]. This model also has a much tighter confidence interval for all three trajectories. The three-class model continues to support the hypothesis that a small number of places are responsible for most of the arrests, a few places produce some arrests, and arrests are still a rare event for most places.

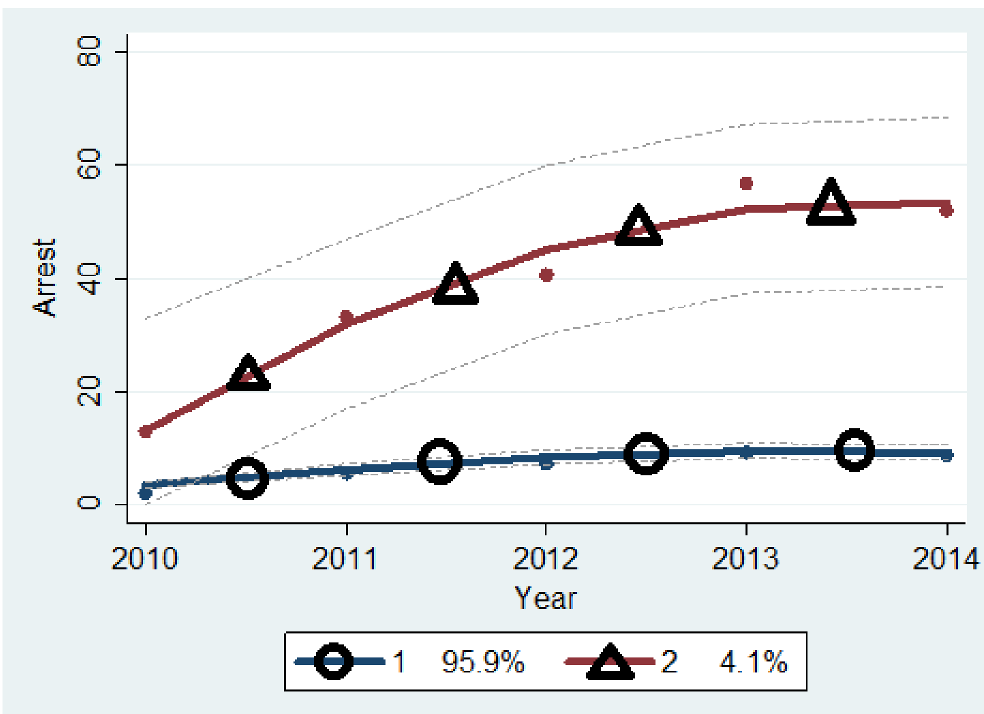


Figure 4.11. Two-group Trajectory Plot

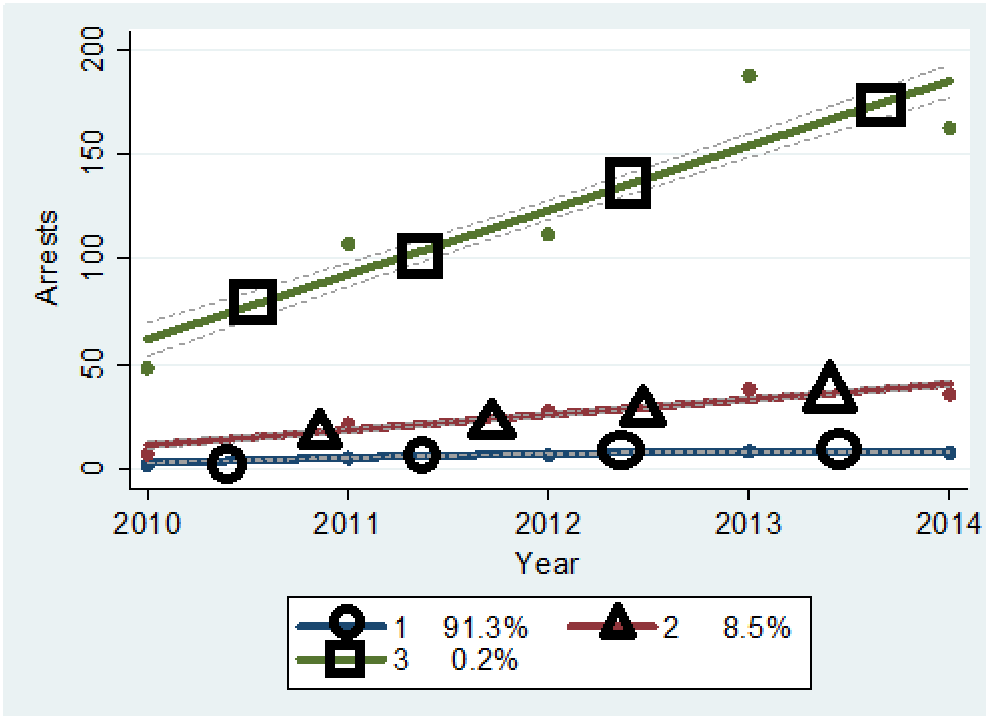


Figure 4.12. Three-group Trajectory Plot

Four-class model.

The four-class trajectory plot continues to reveal a high arrest trajectory, this time with three lower arrest-risk trajectories (see Figure 4.12). The fit statistics (BIC = -13,215.28) for the four-class model also improved from the previous model. In the four-class model, the probability of a block group being classified as very low arrest-risk (trajectory 1) is 72.8 percent (95% CI [71.09, 74.49]), and is fitted with a quadratic function. The probability of a block group being classified as a low arrest-risk trajectory (trajectory 2) is 23.9 percent (95% CI [21.41, 25.5]), and this trajectory is fitted with a cubic function. The probability of a block group being classified into the high arrest-risk membership trajectory (trajectory 3) is 3.1 percent (95% CI [2.51, 3.75]), and it is fitted with a linear function. Finally, the probability of a block group being classified into the very high arrest-risk membership trajectory (trajectory 4) is also 0.2 percent (95% CI [.16, .30]), and it is also fitted with a cubic function (see Table 4.3).

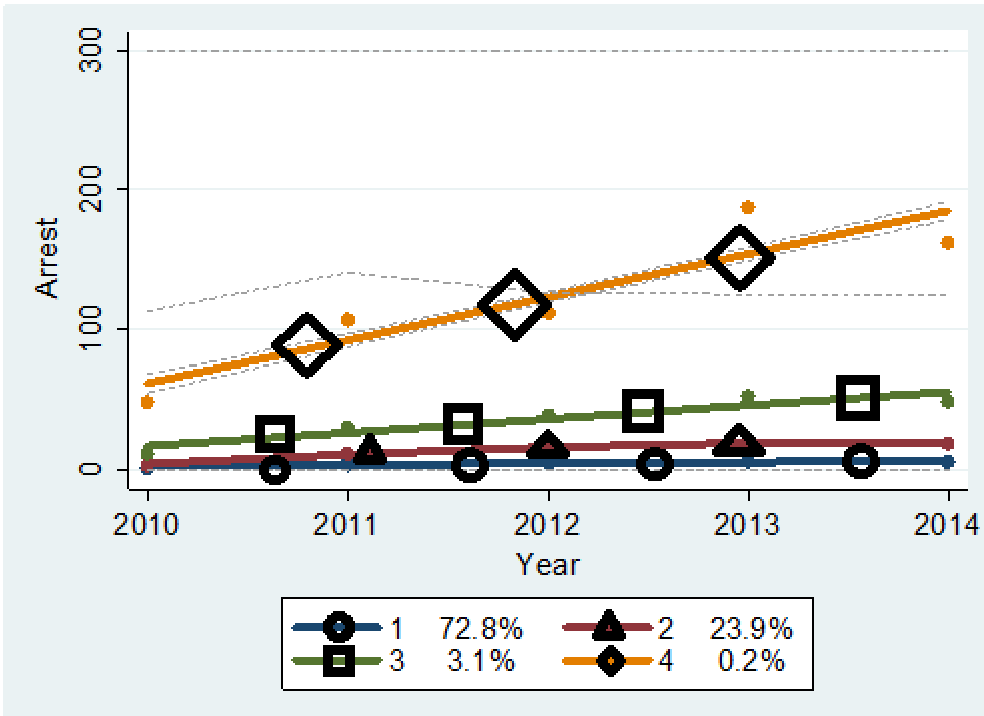


Figure 4.13. Four-group Trajectory Plot

Five-class model.

The next model is the five-class model (See Figure 4.13). The fifth model has a BIC of -12,940.18 in comparison with the other four classes. This model has membership groups of very high risk arrest trajectory (trajectory 5), high risk arrest trajectory (trajectory 1), medium arrest-risk trajectory (trajectory 2), low arrest-risk trajectory (trajectory 4), and very low arrest-risk trajectory (trajectory 5).

The very high arrest-risk trajectory (trajectory 5) has a membership probability of 0.2 percent (95% CI [0.16, 0.30]). The membership contains two block groups that have the highest constant arrest rate. The high arrest-risk trajectory (trajectory 1) has a membership probability of

1.5 percent (95% CI [1.08, 1.92]). The medium arrest-risk (trajectory 2) has a membership probability of 7.80 percent (95% CI [6.83, 8.76]). The low arrest-risk (trajectory 4) has a membership probability of 35.59 percent (95% CI [33.52, 37.65]). Ultimately, the probability of being classified in the very low trajectory (trajectory 3) is 54.88 percent (95% CI [52.77, 56.97]) (see Table 4.3).

This model shows two distinct features: the probability of membership decreases as arrest risk increases, and it continues to suggest that a very small number of places may be responsible for many arrests (0.2% very high arrest-risk membership). This model also suggests that the majority of the arrests are conducted in more than 44.9 percent of the block groups (Trajectory 1, 2 4 and 5 comprise of 44.9 percent of memberships), and nearly half of the block groups enjoy an extremely low rate of arrest (Trajectory3 comprise of 54.9 percent of membership). The membership groups have wide demographic variation.

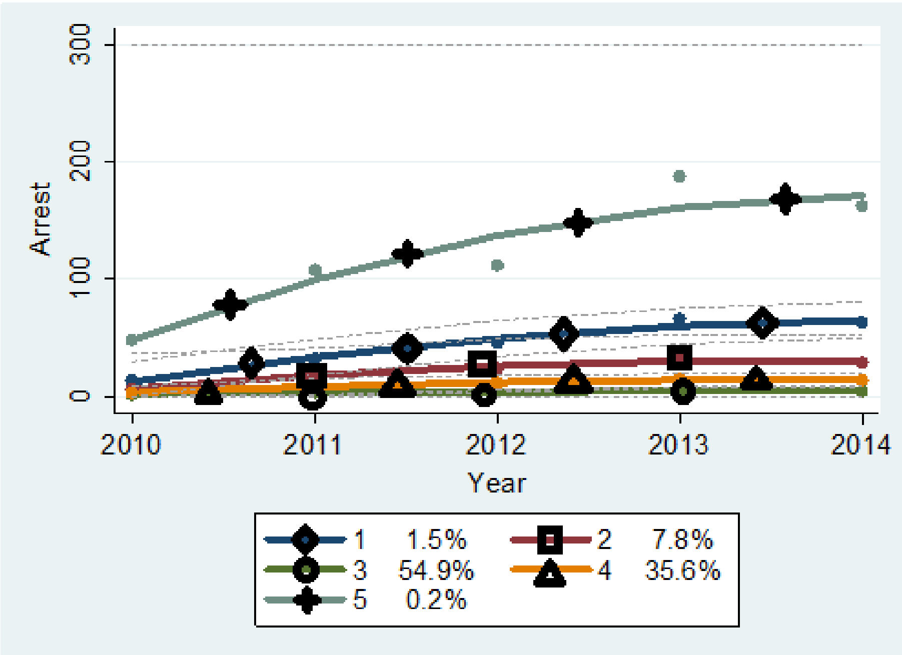


Figure 4.14. Five-group Trajectory Plot

Six-class model.

To identify ideal six-class trajectories, it was necessary to estimate over 5,472 models, and figure 4.14 displays the six-class trajectory plot (see Figure 4.14. The best-fitted time polynomial function configuration is shown in Table 4.3. Based on BIC alone, the six-class model apparently yields the best fit statistics (*BIC* = -12,796.87). However, examination of the membership probability shows the six-class trajectory model simply split the two cases from the highest arrest-risk trajectory in the five-class model into two separate trajectories. There is little theoretical reason that the separation was necessary. In addition, the highest arrest-risk trajectory in the six-class model has a standard error of 0.11, and this would yield a confidence interval range between -0.01 and 0.21. This confidence level interval makes little sense in model interpretation.

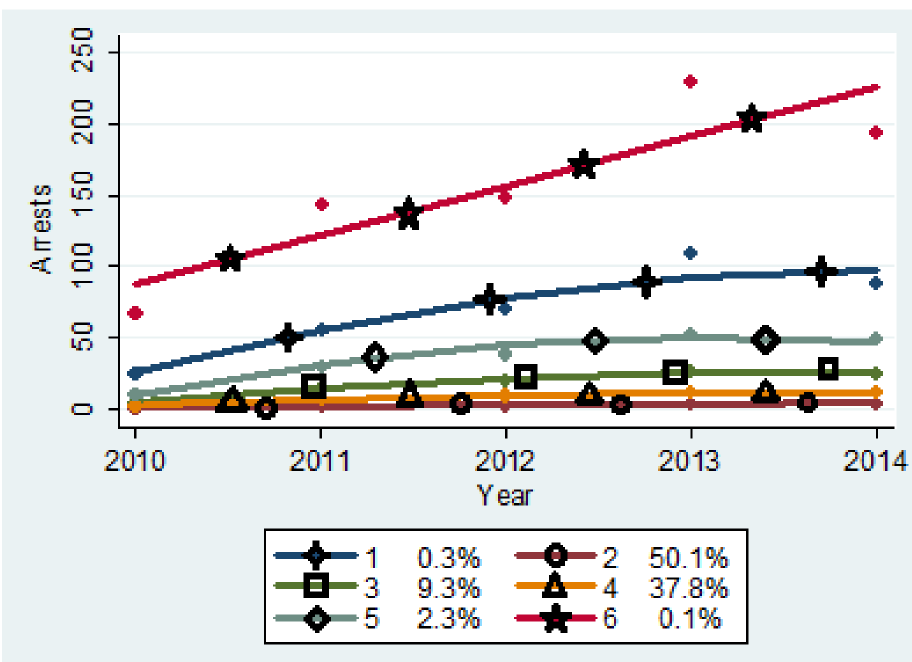


Figure 4.15. Six-group Trajectory Plot

Trajectory model of best fit.

Figure 4.16 illustrates the graphical distribution of the five-group trajectories, and the risk distribution agrees with the crime map presented in previous chapter (see Figure 3.3). In addition, the five-class model provides a more meaningful interpretation of the latent classes (very high, high, medium, low, and very low arrest risk) with reasonable membership probability. The five-class model also has a better BIC in comparison to other classes. As a result, this study retained the five-class model, as it was most appropriate based off the aforementioned model selection criteria. It is imperative to retain the two cases in the very high group trajectory (instead of dropping them as outliers) because of theoretical importance. This will be further discussed in the next chapter.

Comparison of Independent Variables between Groups

After identifying the best-fitted trajectory model of risk, the next step is to perform an analysis of variance (ANOVA) to test if each of the independent variables vary significantly across the five possible risk levels of block groups. This step also helps the multinomial regression analysis by identify potential significant predictors. The comparison is shown in Table 4.4. Note that the ANOVA model cannot be interpreted like the regression model since each comparison is in the absence of other intervening variables. The F-test shows that SES, racial heterogeneity, residential stability, and family disruption vary significantly across the groups. However, urbanization did not vary significantly across groups at the $p < .05$ level.

Tukey's honest significant difference (Tukey's HSD) post-hoc analysis was then conducted (via *tukeyhsd* command in STATA with *sg101* package installed). This post-hoc analysis conducted 10 paired comparisons for each of the five independent variables and concludes with following results. First, differences in sample size between groups generally *do not* affect the significance of the main effect, but only up to the high trajectory group. Second, the very low arrest risk trajectory and the very high arrest risk trajectory are insignificant on heterogeneity due to sample size. Third, family disruption is insignificant between the very high arrest risk trajectory and all other trajectories, and this difference was caused by the small sample size of the very high risk trajectory group. This diagnostic test may help explain the level of significance of predictors in the regression analysis in the next section.

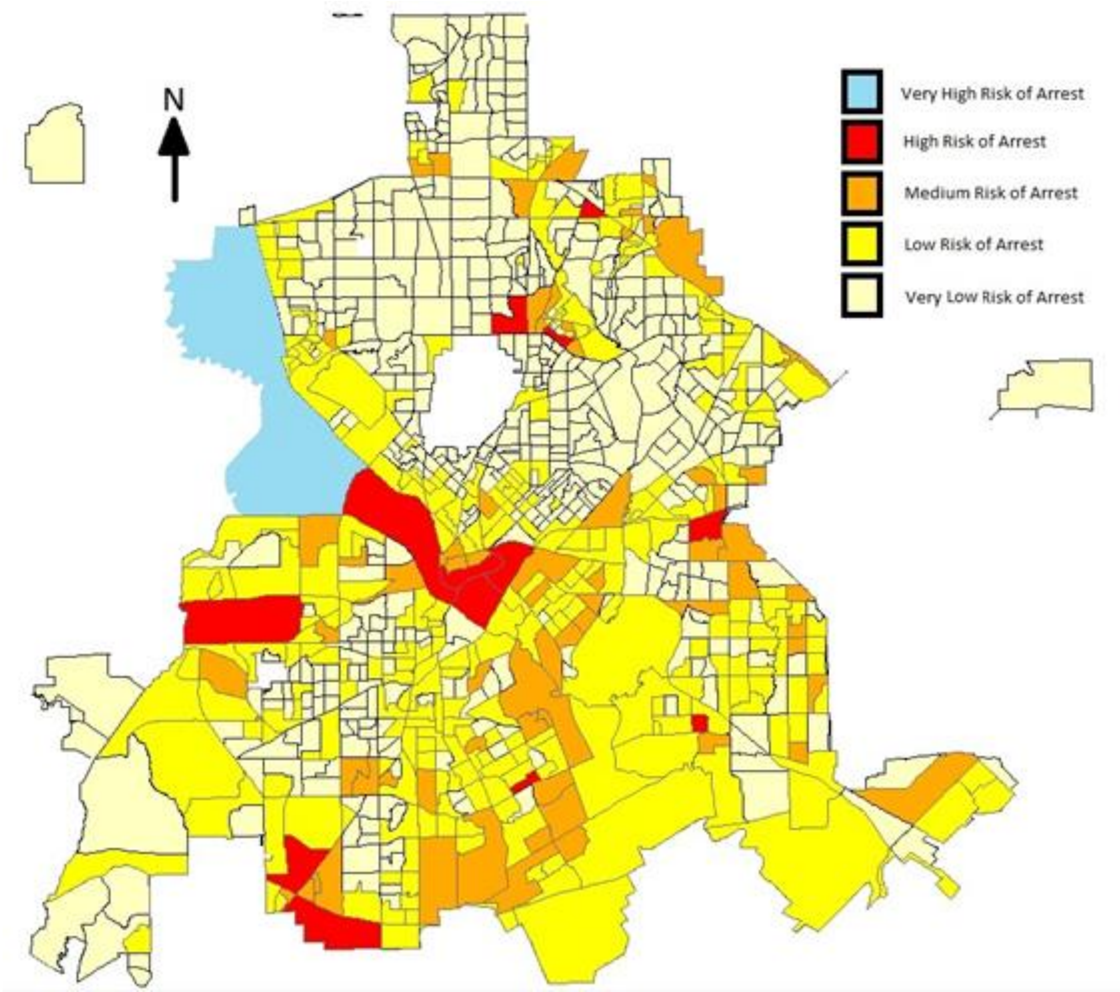


Figure 4.16. Distribution of Risk Trajectories

Table 4.3

Trajectory Analysis for each Class of Trajectory Membership Group

Class	*BIC*	Order	Trajectory	Membership Probability	95% CI
1 Group	-15319.74	Cubic	1	100.00%	-
2 Groups	-14256.60	Cubic	1	95.86%	(95.24, 96.64)
		Cubic	2	4.14%	(3.44, 4.84)
3 Groups	-13632.41	Cubic	1	91.27%	(90.25, 92.29)
		Linear	2	8.50%	(7.49, 9.51)
		Linear	3	0.23%	(.07, .39)
4 Groups	-13215.28	Quadratic	1	72.79%	(71.09, 74.49)
		Cubic	2	23.86%	(21.41, 25.5)
		Linear	3	3.12%	(2.51, 3.73)
		Quadratic	4	0.23%	(0.07, 0.39)
5 Groups	**-12940.18**	Cubic	1	1.50%	(1.08, 1.92)
		Cubic	2	7.80%	(6.83, 8.76)
		Quadratic	3	54.88%	(52.77, 56.97)
		Cubic	4	35.59%	(33.52, 37.65)
		Cubic	5	0.23%	(0.16, 0.30)
6 Groups					
	-12796.87	Cubic	1	0.31%	(0.13, 0.51)
		Quadratic	2	49.72%	(47.64, 51.81)
		Cubic	3	9.40%	(8.35, 10.45)
		Cubic	4	38.41%	(36.28, 40.55)
		Cubic	5	2.04%	(1.93, 2.14)
		Quadratic	6	0.10%	(-0.01, 0.21)

Table 4.4

Analysis of Variance (ANOVA) between Groups

Variable	*Partial SS*	*df*	*MS*	*F*
Socioeconomic (SES)	1352.68	4	338.17	53.66**
Racial heterogeneity (RH)	1.96	4	.49	14.64**
Residential stability (RS)	240.60	4	60.15	20.04**
Family disruption (FD)	63.65	4	15.91	17.02**
Urbanization (U)	10.10	4	2.53	0.66

* *p* = <.05, ** *p* = <.01

Multinomial Regression Analysis

Regression modeling begins with the examination of each basic independent variable and, if theoretically or methodologically important, their interaction effects. Because the dependent variable in this study is the classification of trajectory group membership (with five distinct categorical groups), multinomial regression is the most appropriate regression approach. Multinomial regression (MR) is a special case of Generalized Least Square (GLS). It relaxes the assumption of parallel regression by making stepwise comparisons between classes of the dependent variable.

In this study, the very low arrest-risk trajectory (trajectory 3) is used as the base comparison model. The classification of the lowest arrest trajectory is used from here on as the reference group to compare the effect size of each social disorganization variable. In other words, if the coefficient of SES is -0.25 for low arrest trajectory group and -0.50 for medium arrest trajectory in the regression model, the -0.25 coefficient is only relative between the low versus very low trajectory group and the -0.50 is between medium and very low trajectory group.

According to Tabachnick and Fidell (2007), there are a number of key assumptions in the generalized least square regression model. The researcher must first ensure the number of cases is large enough for the number of independent variables. The regression must also be free of outliers in both independent variables and dependent variables (see previous chapter on data manipulation and data cleaning). In addition, the researcher may have to transform the data to meet the distribution assumption. For this study, the independent variables were standardized and the dependent variable was categorical. As such, no transformations were necessary in this phase of the analysis. Finally, independent variables must be free from multicollinearity.

Based on the correlation matrix, the correlations between each independent variable were low (refer back to Table 4.2). Therefore, there is little to no evidence that the no multicollinearity assumption was violated. With that said, there are other indicators to detect multicollinearity. First, comparing the pseudo R^2 value at the end of the estimate may signal that there is a possible multi-collinearity (Smith and McKenna, 2013). Second, models exhibit very large standard errors for coefficients. Third, test of linear predicted value (*linktest* command in STATA) may be used to test for the problematic variable by regressing the referencing group versus other groups individually via dichotomous variables as the next step. Once the two highly correlated variables are identified, one of them should be dropped from the model.

Model selection in multinomial regression interpretation.

Table 4.5 reports the results of regressions of group membership on each *individual* social disorganization variable (i.e., one per model). This step was taken in order to identify significant predictors. Non-significant predictors were dropped from subsequent models. Model diagnostics are also provided in the final section. Wald tests of simple and composite linear hypotheses were also conducted for each regression model (command *test* in STATA), and fit statistics were used for model diagnostics in the end of this chapter (command *estat ic* in STATA).

Interpreting the results of multinomial regressions is somewhat counterintuitive. Using model one (see table 4.5) as an example, the results show an SES coefficient of -0.44 between low and very low groups on the socioeconomic variable. In straight model interpretation language, this translates as follows: A one-unit increase in socioeconomic status is associated with a 0.44 decrease in the relative log-odds of being in a low trajectory group versus a very low trajectory group. Since this interpretation makes little sense in real world applications, the following subsections seek to report the models in simply language to the fullest extent possible given the research objectives.

Base variables.

Model 1.

Model 1 (Table 4.5) shows that SES is a significant predictor for low (b = -0.44, SE = 0.09) and medium trajectory membership groups (b = -0.55, SE = 0.04). For the purpose of regression analysis, the sample size of the very low arrest trajectory consists of 477 block groups, low arrest trajectory consists of 304 block groups, medium arrest trajectory consists of 68 block groups, high arrest trajectory consists of 13 block groups, and very high arrest trajectory consists of only2 block groups. The negative relationship indicates that a higher arrest-risk trajectory would potentially have a lower SES level. However, contrary to what is expected, the effect of SES progressively increases only up to the medium risk trajectory. The predictive effect of SES is no longer significant for high and very high arrest-risk trajectories. In other words, this model does not support that high and very high arrest-risk trajectories have a significant SES level than the very low trajectory group has. Finally, the Wald test of simple and composite linear hypotheses reports that the overall effect of socioeconomic is significant.

Model 2.

Similar to model 1, the effect of racial heterogeneity in model 2 (Table 4.5) extends only to the medium arrest-risk trajectory, but not to the high and the very high arrest-risk trajectories. Table 4.5 also shows that racial heterogeneity has a positive effect on predicting low (b = 2.80, SE = 0.42) and medium (b = 2.82, SE = 0.74) trajectory group membership. This means that a block group with higher levels of arrest risk is likely to have a higher level of racial heterogeneity in comparison to a very low risk group. However, again, this predictive effect is lost when the high and very high arrest-risk trajectories are compared to the very low trajectory group. This means it is unlikely that the level of racial heterogeneity is significantly different between high and very high arrest locations compared to low arrest locations. Although the coefficients for high and very high arrest-risk trajectories are statistically insignificant (too few n in very high trajectory group), the coefficient continues to be positive and particularly high for the very high arrest-risk trajectory (b = 8.69). It is difficult to dismiss the idea that racial heterogeneity fails to play a role in arrest risk trajectory prediction. Wald test results show that the overall effect of racial heterogeneity is significant.

Model 3.

This model (Table 4.5) shows that residential stability is a strong and significant predictor for low (b = -0.23, SE = 0.04), medium (b = -0.46, SE = 0.07), high (b = -0.66, SE = 0.16), and very high (b = -0.85, SE = 0.41) levels of arrest-risk trajectories. Similarly, the relationship between residential stability and arrest-risk trajectory classification are negative. This indicates that residential stability is likely to decrease for those being classified as high and very high arrest risk group members. This model supports that residential stability could have a robust protective effect on arrest at the block group level. Wald test results show that residential stability has an overall significant effect on arrest trajectory groups.

Model 4.

The fourth model focuses on family disruption. Like residential stability, this model shows that family disturbance is a significant indicator for predicting low (b = 0.46, SE = 0.08), medium (b = 0.72, SE = 0.13), high (b = 0.82, SE = 0.27), and very high arrest-risk trajectory (b =1.68, SE = 0.52). This finding demonstrates how a family-level social network offers a protective effect. Low informal social control at home is a critical factor that could result in a higher risk of arrest, as suggested earlier in the review of literature, and a higher arrest-risk trajectory has a higher likelihood of divorce and separated couples. Wald test results show that the overall effect on family disruption is also significant.

Model 5.

The last model in Table 4.5 confirms the earlier ANOVA finding that urbanization is not a significant predictor of group trajectory membership, at least with the sample of data analyzed for this study. It also suggests a need to drop the urbanization variable from subsequent analyses, which this study does. Interestingly, the Wald test also shows that the overall effect on urbanization is not significant. Since the Wald tests in this model fails to reject the null hypothesis, this means removing urbanization as one of the variable will unlikely affect the model fit as *the coefficient* is far too small to the standard error. As a result, urbanization is unlikely to predict arrests (Fox, 1997).

Table 4.5

Multinomial Regression – Base Variables Models

Variable	Model 1 *b*(*SE*)	Model 2 *b*(*SE*)	Model 3 *b*(*SE*)	Model 4 *b*(*SE*)	Model 5 *b*(*SE*)
Socioeconomic Status					
Very high	-0.53 (.50)				
High	-0.18 (.11)				
Medium	**-0.55 (.09)****				
Low	**-0.44 (.04)****				
Very low	- (-)				
Racial Heterogeneity					
Very high		8.69 (6.38)			
High		2.84 (1.69)			
Medium		**2.82 (0.74)****			
Low		**2.80 (0.42)****			
Very low		- (-)			
Residential Stability					
Very high			**-0.85 (0.41)***		
High			**-0.66 (0.16)****		
Medium			**-0.46 (0.07)****		
Low			**-0.23 (0.04)****		
Very low			- (-)		
Family Disruption					
Very high				**1.68 (0.52)***	
High				**0.82 (0.27)***	
Medium				**0.72 (0.13)****	
Low				**0.46 (0.08)****	
Very low				- (-)	
Urbanization					
Very high					-42.44 (31.40)
High					-0.72 (0.50)
Medium					-0.03 (0.08)
Low					-0.01 (0.04)
Very low					- (-)
Wald χ^2	131.72	52.45	65.23	57.16	4.16
	<.001**	**<.001****	**<.001****	**<.001****	.385

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

Interaction variables.

Model 6.

The first model reported in Table 4.6 is the first full model that incorporates SES and its interaction variables on predicting trajectory membership. The effect of SES, with all other variables accounted for, continues to be a significant predictor of low (b = -0.42, SE = 0.10) and medium (b = -0.82, SE = 0.26) arrest-risk block group trajectory membership. Increases of SES reduce the log-odd of being in low and medium trajectory versus very low arrest group.

Likewise, the effect of SES is not a significant predictor for high and very high arrest-risk trajectory groups. Moreover, residential stability provides a protective effect for low arrest (b = -0.22, SE = 0.05), medium (b = -0.52, SE = 0.11), and high (b = -0.60, SE = 0.18) arrest-risk trajectory group (except the very high arrest-risk trajectory group). Increases in residential stability reduce the log-odd of being in low, medium, and high arrest trajectory versus the very low arrest trajectory group. Lastly, this model shows that there are no significant interaction effects between SES and other base variables with respect to arrest-risk trajectory group membership.[6] Wald test results shows that the effect of the overall model is significant.

Model 7.

Model 7 (Table 4.7) provides a full model, but with the focus on racial heterogeneity rather than socioeconomic status. This model shows that SES is a significant predictor for low

[6] Interaction variables are constructed with main effects. Therefore, they may introduce multicollinearity detectable only by other means since this type of multicollinearity (MC) does not affect the observed pseudo R^2 (Jaccard, Wan, and Turrisi, 1990). One diagnostic test to detect this type of MC is to regress these regressors on a continuous regressend and inspect the variance inflation factors (VIF). If MC exists, it may be corrected by dropping the problematic interaction variable. However, Frost (2013) and P.D. Allison (2012) argued that multicollinearity caused by the product of two independent variables does not necessarily affect model fit. As a result, models with severe multicollinearity can still produce accurate predictions.

Table 4.6

Model 6. Socioeconomic Status

Variables	Very low b (SE)	Low b(SE)	Medium b (SE)	High b (SE)	Very high b (SE)
SES	- -	**-0.42 (0.10)****	**-0.82 (0.26)****	-0.67 (.40)	-0.89 (3.86)
RH	- -	0.29 (0.56)	0.51 (1.24)	-0.15 (1.99)	10.87 (15.32)
RS	- -	**-0.22 (0.05)****	**-0.52 (0.11)****	**-0.60 (0.18)****	-1.22 (1.59)
FD	- -	0.05 (0.10)	0.22 (0.20)	0.53 (0.32)	0.27 (1.55)
SESxRH	- -	-0.19 (0.26)	0.38 (0.58)	1.30 (0.96)	-1.00 (5.35)
SESxRS	- -	-0.04 (0.02)	-0.07 (0.05)	0.01 (0.09)	-0.26 (0.65)
SESxFD	- -	-0.08 (0.05)	-0.06 (0.10)	0.19 (0.17)	-0.60 (0.59)

Note: *Wald* $\chi^2 = 162.05$, $p<.001$
$*p < .05$, $**p<.01$

(b = -0.39, SE = 0.09) and medium (b = -0.62, SE = 0.25) arrest-risk trajectories. This continues to support the idea that SES is a significant predictor for low and medium arrest-risk trajectory block group membership. As expected, the effect of SES is not a significant predictor for high and very high arrest-risk trajectories. Although the coefficient of racial heterogeneity is insignificant, the medium arrest-risk trajectory does have a higher level of racial heterogeneity compared to very low and low arrest-risk trajectories. It is the same for family disruption; the medium (b = 1.68, SE = 0.44) arrest-risk trajectory has a higher level of family disruption compared to the very low level of arrest risk.

Importantly, the interaction between racial heterogeneity and family disruption actually has a significant but negative effect (b = -3.39, SE = 0.97). This counterintuitive relationship indicates that there is a possible inhibiting effect. Specifically, if racial heterogeneity and family disruption each has an individual positive relationship with arrest (although the racial heterogeneity was found to be insignificant, it still has a positive relationship toward arrests), the combined effect of racial heterogeneity and family disruption together will have a negative effect on the arrests. To be sure, a separate analysis was conducted to validate this relationship.

However, such counterintuitive relationship continues to exist even after the multicollinearity variable was removed from the regression model. This relationship and interpretation can be complex, and some models are bound to have such counterintuitive outcome by chance alone. Further research will be needed to confirm this relationship.

Table 4.7

Model 7. Racial Heterogeneity

Variables	Very low *b* (*SE*)	Low *b* (*SE*)	Medium *b* (*SE*)	High *b* (*SE*)	Very high *b* (*SE*)
SES	- -	**-0.39 (0.09)****	**-0.62 (0.25)****	-0.69 (0.41)	-1.24 (6.46)
RH	- -	0.29 (0.54)	1.31 (1.29)	-0.43 (2.48)	6.27 (28.37)
RS	- -	-0.24 (0.14)	-0.35 (0.23)	-0.56 (0.44)	-0.76 (2.91)
FD	- -	0.39 (0.26)	**1.68 (0.44)****	0.27 (0.90)	1.29 (2.73)
RHxSES	- -	-0.15 (0.25)	0.19 (0.55)	1.37 (0.95)	0.06 (11.42)
RHxRS	- -	0.06 (0.30)	-0.25 (0.50)	-0.06 (1.00)	-0.05 (5.13)
RHxFD	- -	-0.68 (0.58)	**-3.39 (0.97)****	0.50 (1.96)	0.51 (5.37)

Note: *Wald* χ^2 = 178.64, *p*<.001
*p < .05, p<.01

Model 8.

For residential stability, the SES variable continues to be a significant predictor for the low (b = -0.46, SE = 0.05) and medium (b = -0.67, SE = 0.14) arrest-risk groups, and this effect is also negative. These results are reported in Table 4.8. However, SES is not a significant predictor for high and very high arrest-risk groups. In addition, this model shows that residential stability has a negative relationship with the medium (b = -0.58, SE = 0.23) level of arrest-risk trajectory membership. The medium arrest-risk trajectory has a significantly lower level of residential stability compared to the very low arrest-risk trajectory. Furthermore, family disturbance is also a significant predictor of the medium (b = 0.40, SE = 0.17) arrest-risk trajectory, and this relationship is positive. Overall, this model does not suggest that residential stability has an interactive relationship with other socio-disorganization variables.

Table 4.8

Model 8. Residential Stability

Variables	Very low *b* (*SE*)	Low *b* (*SE*)	Medium *b* (*SE*)	High *b* (*SE*)	Very high *b* (*SE*)
SES	- -	**-0.46 (0.05)****	**-0.67 (0.14)****	-0.24 (0.19)	-2.38 (2.29)
RH	- -	0.08 (0.09)	-0.04 (0.17)	-0.13 (0.42)	1.50 (2.75)
RS	- -	-0.21 (0.13)	**-0.58 (0.23)***	-0.36 (0.39)	-2.37 (2.96)
FD	- -	0.13 (0.09)	**0.40 (0.17)***	0.01 (0.41)	2.79 (1.71)
RSxSES	- -	-0.03 (0.02)	-0.06 (0.05)	-0.07 (0.07)	-0.36 (0.55)
RSxRH	- -	-0.01 (0.29)	0.01 (0.48)	-0.36 (0.87)	0.04 (4.60)
RSxFD	- -	0.03 (0.05)	0.12 (0.09)	-0.23 (0.14)	0.53 (0.56)

Note: *Wald* χ^2 = 165.06, *p*<.001
*p < .05, p<.01

Model 9.

Model 9 (Table 4.9) investigates how family disruption may affect arrest-risk trajectory classification. Foremost, SES continues to be a significant predictor for low (b =-0.46, SE = 0.05) and medium (*b* = -0.057, *SE* = 0.10) arrest-risk trajectories, but not for the high or very high trajectory group. Increases in SES also reduces the log-odd on being in low and medium arrest trajectory.

However, residential stability becomes a more stable predictor for low (*b* = -0.21, *SE* = 0.05), medium (*b* = -0.51, *SE* = 0.09), and high (*b* = -0.52, *SE* = 0.19) arrest-risk trajectories. Increased residential stability reduces the log-odd of being in higher level of arrest trajectory, and the effect size also continues to increase steadily as the arrest risk increases (with the exception of predicting the very high arrest-risk trajectory). In addition, family disruption is a significant predictor for medium (*b* = 1.78, *SE* = 0.48) risk trajectory group membership. Finally, referencing model 7, the interaction relationship between family disruption and racial heterogeneity continues to have a negative effect only with the medium arrest-risk trajectory group (b = 1.78, SE = 0.48). The possible inhibiting effect of family disruption and racial heterogeneity continues to be significant in model 9 (b = -3.30, SE = 0.97).

Table 4.9

Model 9. Family Disruption

Variables	Very low b (SE)	Low b (SE)	Medium b (SE)	High b (SE)	Very high b (SE)
SES	- -	**-0.46 (0.05)****	**-0.57 (0.10)****	-0.18 (0.16)	-0.80 (0.84)
RH	- -	0.53 (0.51)	1.21 (1.00)	-0.66 (2.07)	8.28 (14.91)
RS	- -	**-0.21 (0.05)****	**-0.51 (0.09)****	**-0.52 (0.19)****	-1.40 (1.24)
FD	- -	0.31 (0.25)	**1.78 (0.48)****	0.52 (0.84)	1.22 (4.65)
FDxSES	- -	-0.08 (0.05)	-0.01 (0.10)	0.17 (0.15)	-0.62 (0.53)
FDxRH	- -	-0.67 (0.58)	**-3.30 (0.97)****	-1.01 (1.87)	-0.09 (6.13)
FDxRS	- -	0.04 (0.05)	0.12 (0.09)	-0.25 (0.15)	0.46 (0.70)

Note: *Wald* χ^2 = 188.05, p<.001
*p < .05, p<.01

Model 10.

The final model (Table 4.10) is a full model to examine which of the independent variables continue to be significant when all the variables are included (urbanization is still left out, however, as it was not significant in the results reported in Table 4.5). The final model shows that when all the independent variables are accounted for, only SES and family disruption are significant. In addition, the interaction variable between racial heterogeneity and family disruption continues to be significant for the medium arrest-risk trajectory membership.

Post-estimation and diagnostics.

A final step in multinomial regression analysis is to explore post-estimation model fit. Pseudo R^2 (McFadden's R^2 command *fitstat* in STATA), information criteria (AIC and BIC), and tests of irrelative alternatives and combining alternatives are used for post estimation diagnostics in this study (Ray, 1973; Long and Freese, 2014). While R^2 is often used to describe variance explained in ordinary least square (OLS) regression, the interpretation of R^2 in GLS is often

Table 4.10

Model 10. Social Disorganization (full model) between Arrest Risk Trajectories

Variables	Very low b (*SE*)	Low b (*SE*)	Medium b (*SE*)	High b (*SE*)	Very high b (*SE*)
SES	- -	**-0.38 (0.10)***	**-0.68 (0.28)***	-0.57 (0.39)	-1.65 (5.23)
RH	- -	0.24 (0.56)	1.25 (1.39)	-0.07 (2.32)	8.79 (24.81)
RS	- -	-0.17 (0.14)	-0.49 (0.26)	-0.43 (0.47)	-1.38 (3.54)
FD	- -	0.42 (0.27)	**1.90 (0.50)****	0.41 (1.03)	1.04 (5.48)
SESxRH	- -	-0.30 (0.28)	-0.01 (0.61)	1.19 (0.99)	0.86 (8.11)
SESxRM	- -	-0.05 (0.03)	-0.08 (0.09)	0.01 (0.09)	-0.13 (0.80)
SESxFD	- -	-0.10 (0.05)	0.01 (0.11)	0.14 (0.17)	-0.62 (0.64)
RHxRS	- -	-0.12 (0.31)	-0.19 (0.53)	-0.07 (1.05)	-0.39 (5.10)
RHxFD	- -	-0.89 (0.62)	**-3.50 (1.01)****	-0.77 (2.29)	0.16 (7.32)
RSxFD	- -	0.01 (0.06)	0.07 (0.09)	-0.26 (0.15)	0.40 (0.75)

Note: *Wald* χ^2 = 184.92, *p*<.001
*p < .05, **p<.01

problematic since GLS relaxes many assumptions that are restrictive in OLS models (e.g. variance explained). As a result, the pseudo R^2 can be used as one of the supplemental tools to assess model fitness in conjunction with both AIC and BIC (unlike AIC and BIC, higher the pseudo R^2 the better). The pseudo R^2 in this study may help diagnose if there are too many independent variables that were entered into a multiple regression equation but without significant cases. The low pseudo R^2 suggests that it is unlikely that the number of independent variables that were entered inflated the variance explanation (Cohen, Cohen, West, and Aiken, 2002).

Another important diagnostic step is to ensure model fit. While each of the models explores a concept within the social disorganization domain, some models may better explain what is happening in reality than others do. AIC and BIC are more appropriate tools to assess such goodness of fit as they impose penalties on unfitted models. The fit statistics in Table 4.11 show the cross comparison of each of the model. While model 1 through model 5 are most parsimonious since these models regress on a single predictor, AIC and BIC suggest that they may not be the most fitted model (with the exception of model 1).

Assessment of models 6 to 10 has improved both AIC, BIC, and pseudo R^2. Comparing models 6 through 10, fit statistics show that while Model 10 has the highest pseudo R^2, Model 9 actually has the model of best fit based on AIC and BIC. This suggests, therefore, that model 9 best explains the relationship between social disorganization and arrest-risk trajectory. Moreover, Hausman and Small-Hsiao test of independent of other alternatives was conducted for all of the model (via *mlogtest, iia* command in STATA) (Cheng and Long, 2006; Fry and Harris, 1998). Post-hoc diagnostics shows that these the odds of these models are independent of other alternatives (Hausman and McFadden 1984; Small and Hsiao, 1985).

Finally, there are post-hoc diagnostic tests that can be used to verify the significant level of the parameters. Some of these tests include the Wald test, likelihood ratio tests, and score tests. These three tests are commonly known as tests for differences among nest models. While the nested effect of one variable may influence the overall effect size of coefficient in the model, Wald tests can be used to test the significance of these parameters. For the purpose of this study, the Wald test is used and the Wald χ^2 value is provided in each model (the Wald tests is an approximation of the likelihood test, but only having to estimate one model instead) (Fox, 1997; Menard, 2002). The only model where the parameter is statistically insignificant is in model five which is urbanization (see rightmost column in Table 4.11).

Table 4.11

Post-estimation and Goodness of Fit Analysis

Model	*pseudo R^2*	*AIC*	*BIC*	Wald χ^2
1	0.1246	1475.087	1513.133	**131.72****
2	0.0342	1628.132	1666.197	**52.45****
3	0.0432	1610.747	1648.793	**65.23****
4	0.0376	1621.225	1659.28	**57.16****
5	0.0123	1665.813	1703.887	4.16
6	0.1778	1434.383	1586.568	**162.05****
7	0.1799	1430.865	1583.05	**178.64****
8	0.1762	1437.079	1589.263	**165.06****
9	0.1848	1422.79	1574.975	**188.05****
10	0.1887	1440.227	1649.481	**184.92****

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

Chapter Summary

This chapter first provided a descriptive analysis of the demographic attributes of 864 block groups in Dallas. Next, trajectory analysis was used to distribute these block groups into five classes: very low arrest-risk, low arrest-risk, medium arrest-risk, high arrest-risk, and very high arrest-risk. Third, ANOVA was used to check whether key predictors varied across trajectory groups. Finally, multinomial regression was used to test what factors within the social disorganization domain may be best to predict these arrest-risk trajectory groups. Individual and interaction effects were explored, as well.

In general, the results suggest that social disorganization theory may be useful to explain arrest-risk trends at small-level units of analysis (i.e., Census blocks). More specifically, the results support that socioeconomic indicators, residential stability, and family disruption are more robust predictors than racial heterogeneity for low and medium arrest-risk trajectories. The analysis also found that social disorganization is a good predictor of medium arrest-risk trajectory membership. Additionally, this study found that the interaction between racial heterogeneity and family disruption is a consistent and robust predictor for the medium arrest-risk trajectory.

The analyses failed to find that the social disorganization variables Sampson and Groves (1989) suggested are significant in predicting high and very high arrest-risk trajectories. In the end, only residential stability is a significant predictor for the high arrest-risk group, and no social disorganization variable is significant to predict a very high arrest-risk trajectory.

Given that very low arrest risk (54.88%), low arrest risk (7.8%), and medium arrest risk (35.59%) constituted 98.27 percent of block groups in this study, the explanatory power of social disorganization theory cannot simply be dismissed. Although, social disorganization is useful in predicting arrest risk in general, it is not useful in predicting arrests in high arrest-risk trajectory membership groups (which in the boarder assumptions of hot spot). This finding suggests that using social disorganization variables to explain crime at a place, as proposed by Weisburd et al. (2014), which much limitations.

CHAPTER 5

DISSCUSSION

Summary of Findings and Comparison to Prior Research

Many criminological theories state that a small number of people and places are responsible for a large number of crimes (Wolfgang, Figlio, and Sellin, 1972; Sherman, Gartin and Buerger, 1989). This pattern has led to the question of which factors make these places or people unique. While criminology has long fixated on how social, environmental, and biological features may affect an individual's likelihood to commit a crime, crime-at-place research has generated a new genre of questions on why crime congregate in specific places.

Research in the past two decades has argued that criminogenic areas may differ from other places, and targeting such crime hot spots may yield dramatic crime reduction results. Although researchers understand that crime is a rare event for the majority of the population, there remains a missing link in determining the reason criminogenic populations congregate in high-crime areas. This linkage is essential for criminology because criminologists understand that controlling crime with police at hot spots treats only the symptom; the underlying "disease" cannot be cured without identifying its root causes.

This study was concerned with one central question: *What causes hot spots*? While rational choice theory, routine activities theory, and crime pattern theory describe how these places are saturated with crime, these perspectives fail to address adequately why crime concentrates in specific locations. As such, this study adopted a social disorganization perspective to work toward explaining crime at hot spots.

Weisburd et al. (2014) argued that criminals congregate in specific places due to unobserved social forces, and such influences may be generated by social disorganization. Specifically, places that are affected by higher levels of social disorganization are expected to experience lesser degrees of informal social control, and crime naturally concentrates in these pockets. Crime concentration may thus be the consequence of fundamental social problems, including socioeconomic disparity, racial heterogeneity, residential instability, family disruption, and over-urbanization, as prior scholars have highlighted (Sampson and Groves, 1989; Bursik and Grasmick, 1993).

Weisburd's (2014) article on the law of crime concentration went beyond overviewing overlooked aspects of the literature to shed light on a new direction within the field: Social disorganization may be a platform for developing classical criminology (rational choice, routine activities theory, and crime pattern theory) through the crime-at-place concept. However, before integrating rational choice, routine activity, and crime pattern theory to social disorganization theory, testing whether social disorganization theory can serve as a stand-alone theory in explaining crime-at-place is necessary.

To continue in the vein of Weisburd et al. (2012), this study began with the question: *Do arrest trends also increase or decrease over time within micro-places in similar patterns to criminal offending*? Weisburd et al. (2012) identified 18 trajectories of crime in micro-places and argued that three general trends exist in police incident reports at street segments: some street segments witnessed reductions in offending, some witnessed increases, and some saw neither increases nor decreases.

This study used arrest reports acquired from the Dallas Police Department as raw crime data to map five years of arrests into GIS, replicating the work of Weisburd et al. (2012). Interestingly, the analysis failed to replicate their findings. Instead, the trajectory analysis in this study revealed that there are various levels of arrest trajectories in the City of Dallas. While the analysis revealed that the City of Dallas had experienced an overall increase of arrests between 2010 and 2014, not all places experience arrest equally. The author was able to identify five distinct arrest trajectories—very high arrest risk, high arrest risk, medium arrest risk, low arrest risk, and very low arrest risk—based on the collected data. While only two percent of block groups fell into the category of medium, high, and very high arrest-risk trajectory, 98 percent of them fell into the low and very low arrests risk trajectory categories. The result not only coincides with the Dallas Police Department's Target Action Area Grid provided in Figure 3.4, but is also consistent with the fact that a small number of places are responsible for a high number of criminal activities.

One reason this study yielded different findings than the Weisburd et al. (2012) study may be the different measures of crime. While this study used arrests as the measure of crime, Weisburd et al. (2012) used incident reports. These two data sources bear some inherent differences because the decision of a police officer to execute an arrest depends on many factors, including victim/offender relationship (Bouffard, 2000; Hindelang, Gottfredson, Garofalo, 1978), rules and procedures (Whitebread and Slobogin, 2000), the strength and standard of evidence (Hirschel and Faggiani, 2012), and the expectation of increasing clearance rates driven by political motivations (Davis, Jensen, and Kitchens, 2011).

Another possible reason for the disparate findings is that there are qualitative differences between arrest and filing an incident report. Police officers usually have more freedom in filing incident reports, as these reports are not legally restricted in the way arrests are (e.g., arrests require probable cause, compliance with the Fourth Amendment, etc.). However, officers do face important legal constraints in making arrests. Such requirements often depend on the type of offense and the level of harm inflicted on the victim. As Weisburd et al. (2012) wrote, incident reports are records of possible criminal activities only, and these activities may or may not involve an actual criminal offense. On the contrary, an arrest is a chargeable offense that generally results in jail time and court proceedings.

Along with using two different data sources, the two cities studied in this and Weisburd et al.'s (2012) study possess several differences. Specifically, the demographic composition of Dallas compared to Seattle is quite different as Seattle is composed of much larger non-Hispanic white population (US Census, 2012). As a result, placing these two studies in the same context is concerning. Research on how arrests could be varied based on location specificity deserves additional research.

This study also sought to answer the question: *Can social disorganization variables help predict high arrest trends and low arrest trajectory groups*? Trajectory analysis has been widely employed in life-course criminology (Nagin and Piquero, 2010). Recent scholars have extended the use of this tool in other crime studies and theoretical research to include crime clearances (Worrall, 2015), domestic violence (Richard, Jenning, Tomsich, and Gover, 2013), and self-control (Higgins, Jennings, Tewksbury, and Gibson, 2009), to name a few. Trajectory analysis served this study well because it allowed the author to map data over time and observe the probability of block groups, and how social disorganization variables may play a role in distinguishing among the identified trajectories. The research found that the social disorganization theory explains crime well, with some limitations.

Overall, this study found that social disorganization variables help explain arrests for very low, low, and medium arrest trajectories. However, the theory may be inadequate in explaining the causes of arrest at high and very high arrest trajectory block groups. However, a new question is why the effect of social disorganization does not explain places that have high crime. Firs, one possible cause may be there are very few samples in the high and very high arrest group. Naturally, because the number of block group belong to high arrest trajectory will be small (therefore, it is important to test the variation of independent variables between group using ANOVA). Comparing large group to small group may cause the effect of social disorganization to become insignificant. Second, there is a lack of variability of the independent variables within groups. All of the high and very high arrest trajectories experience high degree of social disadvantages (see ANOVA analysis).

Three specific theoretical implications flow from the research. First, social disorganization may be irrelevant to block groups that have very few to no arrests. Second, it may be only relevant to block groups that have some arrests and are affected by social disorganization. Finally, social disorganization may be no longer relevant to block groups that are experiencing high to very high arrests. Social disorganization can explain arrests in smaller places only up to certain point, but its effect on arrests is robust for most places and cannot be dismissed. Future research should focus on addressing other theoretical causes that could influence the level of arrest for high and very high arrest trajectories.

Which of the social disorganization variables were most associated with arrest-risk trajectory group membership? Using model nine as the final model, among the exogenous variables in social disorganization cited by Sampson and Groves (1989), this study found that the effects of socioeconomic stability, residential stability, and family disruption were most consistently able to predict arrest-risk trajectory group members. Among these variables, family disruption exhibited the greatest overall effect size, but the effect of SES and residential stability are more consistent.

Interestingly, racial heterogeneity and urbanization were not reliable predictors of arrest trajectories. Racial heterogeneity affected arrest only in terms of its relationship with family disruption in the full models. Moreover, the multinomial regression analysis suggests that this relationship is counterintuitive. Whereas both racial heterogeneity and family disruption had a positive relationship with arrest, their interactions actually produced a negative effect on arrest. The cause of this contradictory result is not quite understood and should be further investigated because it may be important to social policy. However, one may speculate that the effect of divorce or separation is different on arrests among races. For example, a divorce occurring in a white family may have a different consequence compared to a divorce in a black family. Finally, this study suggests that urbanization has no effect on arrest at all in this study. Urbanization was found repeatedly to be insignificant in this study. One reason for this is that all of the block groups are within the city limits.

Social disorganization theory does not appear to be well-equipped to explain block groups that belong in high and very high trajectories, but it does seem to assist in explaining crime (as measured by arrests) in most places. While social disorganization theory does not explain arrests for all trajectory groups, it does explain them for more than 98.3 percent of the block groups (very low = 54.9%, low = 35.6%, and medium = 7.8%). Although social disorganization is a useful theory, it is not useful in the context of crime-at-place. Maybe future studies should incorporate time-varying covariates that may influence trajectory paths. Although social disorganization factors may not fluctuate over a short time, capturing changes in the social dynamic over a longer time period may be useful in understanding how these social forces may affect arrest trends.

Another point is that this form of study should be replicated in other cities and by employing differing levels of aggregation (e.g., something different than Census blocks). Different levels of the community aggregation may react to social disorganization in various ways. Moreover, social disorganization variables may not affect all types of places the same way. As Nagin (2005) noted, it is nonsense to suggest that psychological depression affects everyone in the same way. In a similar vein, this study found that socioeconomic factors do not affect every *place* the same way.

Policy Implications

Pratt and Cullen (2005) found that places with concentrated disadvantage are most susceptible to crime. These social disadvantages include racial heterogeneity, poverty, and family disruption. The empirical relationships between crime and these social problems are not only robust, they are persistent and consistent over time. Subsequently, this social disorganization and economic deprivation attracted much attention in policy research, as the key to an effective crime reduction program may begin by alleviating these social problems.

Scores of criminological studies have demonstrated how social problems cause crime. For example, the effect of socioeconomic deprivation, as one of the most robust variables, has been examined by learning theories (Sutherland, 1947; Sutherland and Cressey, 1955; Freeman and Temple, 2010), classical and general strain (Botchkovar, Tittle, and Antonaccio, 2013; Cloward and Ohlin, 1960; Merton, 1938), and institutional strain theory (Chamlin & Cochran, 1995; Messner and Rosenfeld, 2007), among others. However, transforming these theoretical understandings into functional social programs is a far more challenging task (Pratt and Cullen, 2005).

An important aspect of social research is to inform policy so that lawmakers are able to make informed decisions (Anderson, 2003). As the previous section argued, some social disorganization variables are useful in predicting arrest trends, while others are not. This study is useful to policy because it identifies which factors may be relevant, which may be irrelevant, and how they may impact citizenry (Weisburd, Lum, and Yang, 2003). Yet policymakers should interpret these findings with caution, as not all factors affect every place the same way or with the same magnitude. This study, however, may contribute to the field by pointing out that attention should be paid toward programs that are capable of reducing socioeconomic disparity, residential instability, and family disruptions.

Improving the socioeconomic situation.

While this study found that economic variables may have an effect on predicting arrests among certain block groups, improving socioeconomic disparity to reduce arrests may be more complex in practice. First, the results of this study suggest that socioeconomic factors are significantly associated with low, very low, and medium arrest trajectory member groups. Consequently, improving the job prospects, education levels, and income situation for these block groups may help reduce arrests. On the other hand, SES is not a significant predictor of high and very high arrest trajectories. The question of whether investing in massive financial socioeconomic improvements would reduce arrests has no easy answer.

While investing more money into these high and very high arrest block groups may not have a significant impact on arrests, it is important to recognize that very low, low, and medium arrest trajectories constituted 98 percent of the block groups in Dallas. As a result, policymakers should not forego reducing poverty in socioeconomic disadvantaged neighborhoods. Moreover, strong empirical evidence supports that SES is a robust correlate of crime, although the causal link between the two continues to be debated (Tittle and Rowe, 1974; Kennedy, Silverman, and Forde, 1991; Tonry, 2004). For example, LaFree (1999) found that socioeconomic inequality could lead to violent crime, particularly homicide, and that death and violence caused by firearms is more likely to occur in low SES neighborhoods (LaFree, 1999; Kennedy, Kawachi, Prothrow-Stith, Lochner, and Gupta, 1998).

In their book *The Crime Drop in America*, Blumstein and Wallman (2000) demonstrated that improvements in the economy and job prospects are tied to crime reductions because many policies are both directly and indirectly connected to socioeconomic deprivation. One way to reduce poverty is to enable job skills at an early age (Heckman, 2006). Meaningful job training that begins in high school, such as that provided by Career Academy, may lead to improvement in income and an increase in job satisfaction, which can serve an informal social control function (Cullen, Levitt, Robertson, and Sadoff, 2013).

Providing job skills to youth also may reduce their chances of falling into gangs. Krohn, Ward, Thornberry, Lizotte, and Chu (2011) demonstrated that joining a gang increases the risk of economic hardship later in life. In addition, heavy policing may sustain a negative socioeconomic impact. Increasing policing levels is likely to increase arrests that may ultimately lead to conviction and imprisonment among a population that already is economically deprived (David Brown, Dallas Chief of Police, personal communication, December 10, 2015). Former Dallas Police Chief David Brown's comments coincide with Clear's (2009) argument that mass incarceration could put local residents into perpetual poverty for multiple generations, as imprisonment often translate into the removal of income and economic productivity for low SES neighborhoods and families. As a result, increasing arrests in low socioeconomic neighborhoods may reduce crime, though only in the short-term; prolonged arrest policies may drastically weaken the long-term health of these neighborhoods. A policy that aims to reduce arrests or find an alternative to them may help reduce poverty in crime hot spots.

Policymakers and practitioners should determine where to invest the money required for reducing arrests. They may choose programs that focus on justice reinvestment and evidence-based policing, where money that funds punitive punishment is rechanneled to disadvantaged communities (see Maruna, 2011; Clear, 2011; Davies, Harvell, and Cramer; 2015). In short, unless massive gentrification is taking place to remove crime-causing agents, such as apartments, abandoned homes, or drug houses, which are generally exorbitant, local governments could be more creative in their fiscal expenditures to increase the crime-reduction effect (Spelman, 1995).

Residential stability.

While this study found that residential stability is a significant predictor of arrest trajectory group members, part of this variable may be linked to socioeconomic disadvantages. Indeed, the pairwise correlation analysis presented in an earlier chapter illustrated that there is a significant correlation between socioeconomic status and residential stability.

Ideally, SES improvements may increase residential stability by increasing the likelihood of homeownership, which may promote collective efficacy. Conventional wisdom suggests that homeowners are more likely to have a higher level of social capital by engaging in social and political affairs, such as in homeowners' associations and community organizations. Rohe and Stegman (1994) found that homeowners are more likely to engage in neighborhood and block associations, but are less likely to participate in neighborly activities or other community organizations. As a result, residential stability, collective efficacy, and arrests may help to explain social control mechanisms.

Braithwaite (1989) demonstrated that offenders are more likely to have high residential mobility (or instability). This is especially true for those who have been incarcerated (Drakulich, Crutchfield, Matsueda, and Rose, 2012). Offenders returning to society face challenges in obtaining employment and a stable income, and without a steady paycheck, many revert to their lives of delinquency. Whether such residential instability causes delinquency or delinquency leads to residential instability remains unknown (Muruna, 2001; Pager, 2003). However, "coercive mobility," the displacement of large numbers of residents from a poor community, is known to occur, and it could destabilize community dynamics and social networks. These disruptions may lead to further social disorganization and destroy the fragile, informal social control system (Clear, 2009).

A recent longitudinal study on social disorganization theory and social control mechanisms further supports that such disruption may reduce subsequent levels of social control, leading to further residential instability (Steenbeek and Hipp, 2011). One approach that policymakers could take to increase residential stability is to reduce drug problems in housing areas, and a number of the drug-reduction programs have indicated promising results. For example, the Drug Abatement Response Team (DART) has helped reduce drug marketing and illicit transactions in rental property, and High Point Drug Market Intervention also has reduced overt drug distribution points in residential areas (Eck and Wartell, 1998; Hipple, Corsaro, and McGarrell. 2010; Kennedy and Wong, 2009).

Family disruption.

While family disruption was found to have a significant effect on arrest trajectory, family cohesion is probably the most important component within the context of informal social control (Hirschi, 1969; Gunnar Bernburg, and Thorlindsson; 2007). Abundant evidence supports that reducing family disruption may have an effect on crime (Bruinsma, Pauwels, and Weerman, 2013; Sampson, 1986; Shihadeh and Steffensmeier, 1994). This study found that family disruption is a significant predictor of low and medium arrest trajectories, with family disruption possibly affecting arrest for over 95 percent of the block groups within Dallas. While attempting to resolve family problems house-to-house may neither be a feasible nor a suitable course of action in reducing arrests, some family projects, such as the behavioral couples therapy for substance abuse, may be a worthwhile investment.

Previous studies have shown that more functional housing projects and family counseling programs could reduce family disruption (Bagarozzi and Giddings, 1983; Winters, Fals-Stewart, O'Farrell, Brchler, and Kelley, 2002). These studies found that family counseling can teach couples conflict resolution by modifying internal and external behaviors. Participants must remain drug and alcohol free by entering into a binding sobriety contract. Moreover, participants are pledged to help their partners successfully complete the program. Over a course of 24 weeks, with 60 to 90 minutes per session, participants learn to internalize and externalize their behaviors through active listening, feeling expression, and cognitive behavioral therapy skills. These skills help participants resist drug addiction and avoid high-risk situations. Patients who undergo the treatment program have reported positive changes in relationship satisfaction, decreased alcohol consumption, and higher marital adjustment test scores.

Study Limitations

Although this study has yielded significant findings that social disorganization variables may be useful in predicting arrest group trajectory membership, some limitations concerning analytical techniques and data must be addressed. While some of these limitations are common, a few are unique to this study.

Analytical technique limitations.

Although group-based trajectory modeling is a useful tool for modeling longitudinal data, like many statistical techniques, it has its limitations (Nagin and Odgers, 2010). For this study, the first limitation concerns the number of trajectories restricted by the number of cases and observation periods available. Weisburd et al.'s (2012) study included 15 years' worth of crime data, which enabled them to produce 18 trajectories with an abundance of cases in each group.

For this study, the number of trajectories was limited because of a shorter five-year observation period. This study analyzed just 38,000 cases, whereas some others have been able to analyze data on more than 100,000 cases (e.g., the study of Wheeler, Worden, and McLean (2015) included 190,000 cases from 2000 to 2013 and Weisburd, Morris, and Groff (2009) analyzed 2,028, 917 incident reports). Consequently, the ability of this study to generalize crime situations over time is limited. Future studies could overcome this shortfall by collecting more cases over a longer period of time.

The second limitation concerns the GBTM methodology. GBTM assumes that each observation is independent of others or free of temporal autocorrelation (Nagin, 2009). Ideally, the number of arrests in 2011 is independent from the number of arrests made in 2010. However, this may not be the case in reality. Indeed, some studies have illustrated that the increase or decrease of police effort to make arrests often depends on crime rates reported the year prior and locations (Seidman & Couzens, 1974; Brown, 1978; Sheley & Hanlon; 1978).

GBTM may also lack spatial generalizability. Weisburd et al. (2004, 2012) identified 18 trajectories in their Seattle research, but they noted that to extrapolate the same outcome for all cities may not be practical because each city is unique. In other words, while the 18-trajectory rule may yield the best fit for Seattle, it may not do the same for Dallas. This study selected its models based on best fit criteria, using BIC value and consistency of results. The outcome was five trajectories, far less than 18. This limitation restricts the results of this study because it similarly cannot be generalized to other cities.

Fourth, this study did not account for possible spatial autocorrelation of individual arrest trajectories. In a recent study, Wheeler and Worden (2016) found that crime trajectories may be spatially correlated, meaning, for example, that low arrest trajectory block groups may be near those that have medium near-high arrest trajectories. However, GBTM does not assume such spatial correlation. As a result, this study may not be able to extrapolate arrests patterns accurately.

Fifth, this study does not account for the temporal and seasonality aspect of arrest patterns. Recent studies of crime trends suggest some locations have high crime (and by extension arrest) only during certain parts of the day— "burning time" (Brantingham and Brantingham, 1981). This study does not account for this level of temporal correlation, as pointed out by Verma and Lodha (2002). Spatial regression and time series analysis are more appropriate to account for this limitation.

Another GBTM limitation includes situational determinants (Nagin, 2005). Unlike in a time-series analysis, in which the introduction of variables may cause a break in trend, trajectory analysis does not model situational determinants. For example, heavy gentrification may change the arrest trajectories within a short period of time. Accordingly, a block group that belonged to the high or very high trajectory in 2010 may not in 2014. Changes in the social attributes of a block group influence changes in its arrest trajectory. Moreover, while the social dynamics of higher geographic aggregates, such as Census tracts and block groups, are more static, block and street segments may be more dynamic and are sensitive to change. Therefore, block-group trajectory studies may be insufficient in generalizing street-segment trajectories.

Perhaps one of the most significant statistical limitations of this study is its modeling approach, with which other scholars have expressed similar challenges (Curman, 2012). The occurrence of arrests is technically a count variable, and because count variables are bounded at zero, the most preferable model for count data are either the Poisson model or a more general zero-inflated Poisson model. Treating arrest occurrence as a continuous variable thus violates the linear model assumption (Davies and Guy, 1987).

Fortunately, though, the zero-inflated Poisson modeling approach within "Proc Traj" in Stata limits the maximum number of cases to 50. Any observation with more than 50 cases would cause the model to become unstable or unable to converge. One solution is to truncate the maximum cases to 50 (a right-censored model). However, doing so may introduce another serious limitation in that the high and very high trajectories would be lost. A solution for this would be to treat the count variable as a continuous variable only if certain conditions are met (Davies and Guy, 1987; Martin-Grace, 2012). According to Martin-Grace (2012), a count variable may be treated as a continuous variable if: (1) there are very few zeros, and (2) the intuitive interpretation of non-integer outcome is acceptable. Consequently, this study aggregates the quarterly arrests into annual data to avoid the zeros in the observation in order to analyze the data using a censored normal model, but at the expense of shorter length of observation. This limitation could have reduced the possible number of trajectories.

Finally, the measure of racial heterogeneity in this study may be questionable. This study acknowledges the weaknesses in Sampson and Groves' (1989) heterogeneity equation, $1-\sum p_i^2$. While this equation is intended to measure variances in race, it disregards specific ethnic backgrounds (such as Hispanic, Japanese, and Haitian), which could have an impact on the context of social conflicts. Steenbeek and Hipp (2011) also pointed out that using this equation does not contribute a meaningful measure of racial variations. For example, a block group containing a 100 percent black population will have the same heterogeneity score as a block group containing a 100 percent white population. However, the social and cultural contexts of the two groups is drastically different. This limitation may be the reason racial heterogeneity is insignificant in the final model.

Data limitations.

The data utilized in this study were limited in several respects. First, Dallas County is comprised of more than 1,600 block groups, but this study included only block groups located within Dallas city limits. There were just 864 of these. The results thus may not be generalizable to other locations in Dallas County. It is doubtful, too, that they are generalizable beyond Dallas County or the State of Texas.

Structural data limitations.

Structural data limitations concern collection methods and non-sampling errors. Non-sampling errors may be difficult to identify, as they can occur in many ways. For example, certain police officers may have failed to turn in their reports to the crime data unit, causing these cases to be excluded in this study. Researchers have few means of identifying these types of errors. In addition, since the data were secondary, their quality (including their reliability and validity) depends completely on the police officers who collected them.

Another structural problem in the data included the length of observation and large portion of possible missing data from 2010. First, a five-year period may be too short to represent the actual longitudinal arrest pattern for some block groups, especially those that had recently undergone gentrification and community improvements. Second, the data also contains numerous cases for the year 2010. Although missing data analysis did not find that these missing cases were systematic, loss of these data may affect the overall slope of each trend, resulting in inaccurate trajectory vectors. Having a longer period of observation in future studies may help to reduce this type of single-year sampling error, as it is the only measured portion of arrests in the year 2010.

There was also a missing address problem. The author corrected problematic address data to the fullest extent possible, but future studies may wish to use a primary data collection method to reduce missing data.

This study also assumed that demographic variables are constant over the observation period. A study shows that while localized demographic changes depends on long term growth in population (Leistritz, Murdock, Toman, and Hertsgaard, 1979). The growth of population may be affected by migration of population from rural area and economic prospect. While it is difficult to observe demographic changes in days, weeks, or months, the slope of change becomes far more visible over a longer period of time. Because the American Community Survey is a multi-year estimate, this study can only assume that demographic attributes remain static. Future studies may model social disorganization factors as a dynamic variable by collecting a multitude of demographic information over time to alleviate model specification errors.

Omitted variables.

Another data limitation was that fewer than all of the known social organization variables were specified in the statistical models. For example, factors such as organizational participation and local friendship networks were not included. Such information was not available in the Census data analyzed, so future studies should make a better effort in incorporating collective efficacy data, particularly in the context of a longitudinal design (Matsueda & Drakulich, 2016).

Arrest decisions are often based on police discretion. This study also lacked the data to conceptualize and operationalize why police officers made more arrests in some block groups relative to others. Many factors, including changing of police leadership, implementation of localized policy, and command-directed policing tactics, may influence policing discretion, so future studies may want to consider improving in this area.

Another theoretical limitation is that the offending populace may consist of both transient and local populaces. Unfortunately, there is little data on transient offenders who travel to high arrest areas to commit crimes in the sense of crime-at-place and routine activities. This information is important because prior studies on offender patterns have suggested that most offenders do not travel too far to commit an offense (Brantingham and Brantingham, 1981). Knowing if offenders travel to these high-arrest block group may shed light on social learning and peer association.

Finally, this study assumes that all variables have equal influences on arrests, but the levels of influences of each variable may be different based on the context of place which makes the variables unequal. For example, residential stability may not be an important factor for the wealthier rental properties (e.g. Uptown and North Park).

Limitations of Unit of Analysis.

Scholars have agreed that a street block or a street segment is the most suitable unit of analysis for crime-at-place research (Weisburd et al., 2004; Weisburd, Groff and Yang, 2011; Groff, Weisburd and Yang, 2010; Braga, Hureau and Papchristos, 2011a; Bernasco and Block, 2010). However, to study the actual socioeconomic situation of a place, it is usually necessary to move to a higher level of aggregation. Using a higher level of aggregation, such as the block-group level in this study, leads to the common limitation of overgeneralization. For example, while the study of micro-places aims to address a particular hot spot (usually a street segment) that is "bad," this study may unintentionally label the entire block group as "bad" when in fact that is not the case (Groff et al., 2010).

Using block groups as a unit of analysis may also pose measurement issues, as statistics observed at block-group levels may not be indicative of what is occurring at, for example, the street or household level (Jacobs, 1999). Indeed, quantitative approaches cannot capture the same street-level information as an ethnographic approach. And even if ACS produced block-level data, they may not fully capture how socioeconomic and related variables affect residents at levels beneath the Census block.

Future Directions for Studies of Crime and Place

In his article, "Damned If You Don't, Damned If You Do: Crime mapping and its implications in the real world," Ratcliffe (2002) pointed out that labeling a place as a crime hot spot can help police departments pinpoint problematic areas and help officers to concentrate operational focus and reduce logistical demands. However, labeling a place as a crime hot spot also intensifies its policing activities, reduces home value, increases fear of crime, and discourages land developers from investing in these areas. In other words, hot-spot policing tactics could backfire (Haberman, 2016; Weisburd et al., 2011). Future studies should focus on how hot-spot labeling could destroy the already weakened collective efficacy and social capital among these locations.

Though demographic factors and social context may not fluctuate over a short period, they do change progressively over decades (Cohen and Felson, 1979; Steenbeek and Hipp, 2011). Future studies may also wish to consider the use of using multi-decennial census data to employ time-dynamic models and regress on the time covariates to capture how change in demographics can affect change in crime trends over time. A multi-level design can also help to reduce the measure gap. Crime activities of a street segment may be nested at the block level. When a police officer is deployed to a hot spot, the officer also is patrolling the nearby area within the block group. Essentially, the benefit of crime control is likely to spill over to the nearby street and cause the block group to have an elevated level of arrest (Green, 1995; Lawton, Taylor, and Luongo, 2007; Sorg, Wood, Groff, and Ratcliffe 2014).

While social disorganization may help to explain arrests in areas with low and medium arrest-risk trajectories, it does not do so for areas with high and very high arrests. This disconnect may indicate that police officers are arresting more people of these block groups, regardless of their social disorganization situations. This study unearths some of the potential problems that require resolution before being integrated in the social disorganization theory and into crime-at-place research.

When resolving social problems in block groups that belong to low and medium arrest trajectories, policymakers should keep in mind that social disorganization variables may interact with each other. This study concludes that, together, racial heterogeneity and family disruption create an inhibiting interaction effect. Future studies could further examine this counterintuitive relationship, since these latent effects may cause well-designed policies to fail. As such, policy should be multidimensional and address these interrelated social issues, as targeting one or two dimensions of the issue only may not be as effective (Anderson, 1993).

Finally, this study demonstrates that the social disorganization theory may be used to explain arrest trends, but not all core social disorganization factors are important in this regard. While socioeconomic, residential stability and family disruption variables were consistent predictors of arrest trends in areas with very low-, low-, and medium-level arrest trajectories, they did not perform well in other domains. And although the effect of racial heterogeneity itself was an insignificant predictor in arrest trends, the inhibiting effect on arrest is worthy of further investigation. This study also found that urbanization does not seem to play a key role in predicting arrest trends. Block groups with high to very high arrest trends may not be experiencing these trends due to social disorganization. The elevated arrest trends may be influenced by other factors, again suggesting the need for more research.

APPENDICES

Appendix A (Institutional Review Board Approval)

THE UNIVERSITY OF TEXAS AT DALLAS

Office of Research Compliance

800 W Campbell Road AD15 Richardson Texas 75080-3021
972-883-4579 Fax 972-883-2310

Date:	**May 11, 2016**
To:	**Ivan Wong** **John Worrall, PhD** **Criminology**
From:	**Sanaz Okhovat, Assistant Vice President** **Amanda Boone, Assistant Director** AB **Institutional Review Board** **Office of Research Compliance**
Re:	**Approval of IRB 16-29** **Title: Trajectory of Crime in Micro Place**

This letter is notification of approval of the research project referenced above. IRB approval of this research begins as of **May 4, 2016** and ends on **May 3, 2017.**

The IRB requires that you report as soon as possible any unexpected adverse events (including non-serious and serious events) that occur during the study. If the research is expected to continue beyond 12 months, you must request Continuing Review and re-approval of the project least 6 weeks prior to the date of expiration date noted above.

If you plan to change the research project (number of participants, title, procedure, payment, consent form, etc.), you must submit a request detailing the proposed changes and receive IRB approval before the changes are implemented except when prompt changes are necessary to eliminate apparent and immediate hazards to the participants.

The IRB requires that all personnel who interact with research participants or who have access to research data be trained in research ethics and practices concerned with the protection of the welfare and rights of research participants. These ethical principles are outlined in the Belmont Report.

All investigators and key personnel involved with this protocol must have documented training with this office. The training can be found at: http://www.utdallas.edu/research/orc/irb/required_training/

If you have any questions related to this approval, please call 972-883-4575 or send an email to amanda.boone@utdallas.edu.

Appendix B

Growth mixture models.

While the most basic form of modeling is the growth mixture model (GMM), an alternative approach is the longitudinal latent class growth analysis (LCGA) (Jung and Wickrama, 2008). The basic from of the growth mixture model is:

$$Y_{it} = \beta_0 + \beta_{1j}(T_t) + \beta_{2j}(T_t^2) + \beta_{3j}(T_t^3) + \ldots + e$$

In this equation, Y is the dependent variable (block group), where i is the individual case and t signifies a polynomial function of time, β_{1j} are the different latent classes, and T_t reflects the period of observation of Y. The number of latent class is defined by the researcher based on BIC, AIC, and other model selection criteria. Muthén and Muthén (2000) explained that the appropriate approach as depending on person-center (place-center in this study) or variable-center analysis. Conventional growth model provides a single-average growth estimate to determine what the average is. GMM demonstrates this assumption and "allows for differences in growth parameters across unobserved subpopulations estimate" (Jung and Wickrama, 2008, p. 304). Lastly, latent class growth analysis (LCGA) is a special type of GMM that fixed-variance and covariance estimates for the growth factors of each class to zero. Nagin and Land (1993) and Jones, Nagin, and Roeder (2001) pointed out that doing so would homogenize all individual growth trajectories within a class. This study will analyze the data from both the GMM and LCGA approaches.

Analytic rationale.

The researcher acknowledges that using censored normal modeling approach with count data may potentially violate the trajectory modeling assumption. Two solutions were suggested to address this violation. The first option is to standardize the dependent variable or transformation. However, it makes little sense to try to turn discrete variables into continuous variables using statistical manipulation. This become problematic because discrete variables have their limitations when is fitted an analytical approach that is designed for continuous variables. Doing so may be a serious error.

Another alternate solution to fit data into the Poisson trajectory modeling is by truncating the maximum cases to 50, but doing so will exclude the high and very high trajectories. This alternate solution defeats the intent of this study of identifying the high and very high trajectory, because many block groups that have high number of arrests will be dropped from the analysis.

Trajectory model diagnostics.

An important step in trajectory model selection is to inspect the average posterior probability (AvePP) to see how well each street is fitted into a particular trajectory because trajectories are built on errors. While most block groups may fit well into a trajectory, some may be straggling between trajectories. The average posterior probability of each trajectory is generated by the sum of posterior probability of each block group divided by the number of block group.

The average posterior probability also helps calculate odds of how well the trajectory is correctly classified (OCC). In this equation, k indicates the particular trajectory and π is the estimated proportion of the assignment. Nagin (2005) suggested a trajectory is correctly classified and precise when the average posterior probability is above .70 and a OCC value greater than 5. The following formula is used to calculate the OCC.

$$OCC_k = \frac{AvePP_k / (1 - AvePP_k)}{\hat{\pi}_k / (1 - \hat{\pi}_k)},$$

Odds of Correct Classification (OCC) by Trajectory for a five- trajectories model

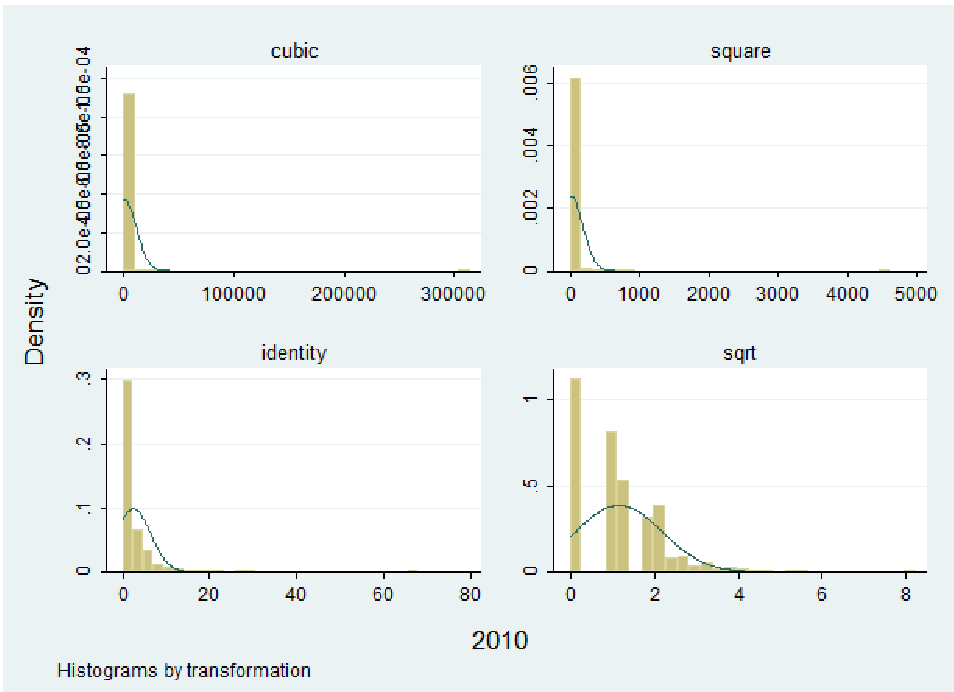
	n	%	AvePPk	OCC
Very Low arrest	477	55	.95	15.55
Low arrest	304	35	.90	16.71
Medium arrest	68	9.9	.94	142.58
High arrest	13	1.9	.99	5111.53
Very High arrest	2	.2	1.00	369.00

Because all trajectories have an Average Posterior Probability of greater than .90 with an OCC > 5 (Nagin, 2005), this analysis reflects the five-trajectory model has good classification precision and adequate separation.

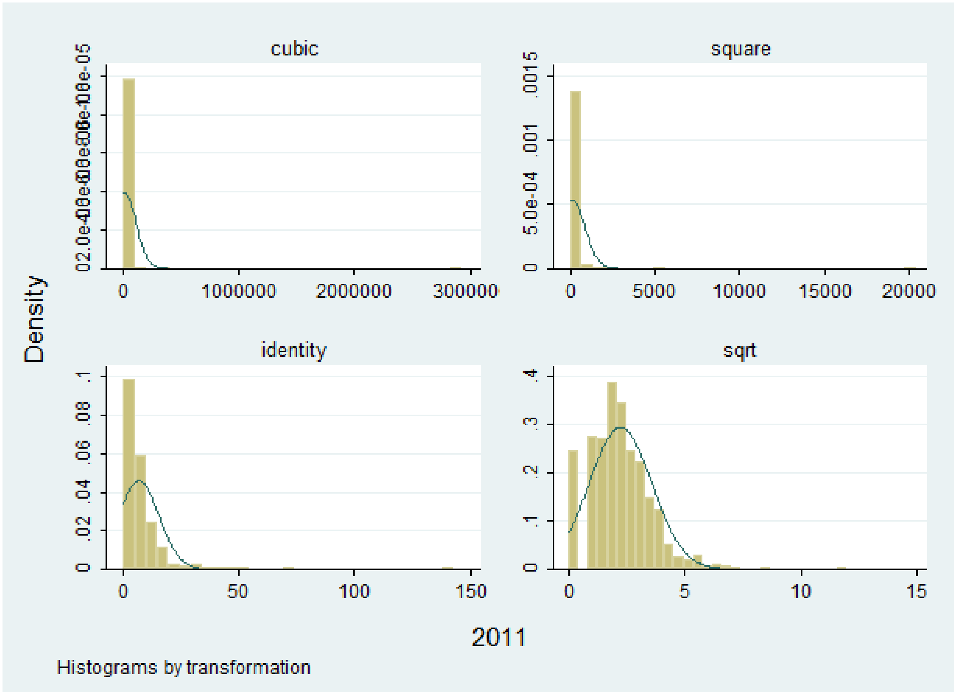
Arrest distribution.

The researcher had also checked the dependent variable for normality and post transformation distribution. Graphical analysis is listed here (via *gladder* command in STATA).

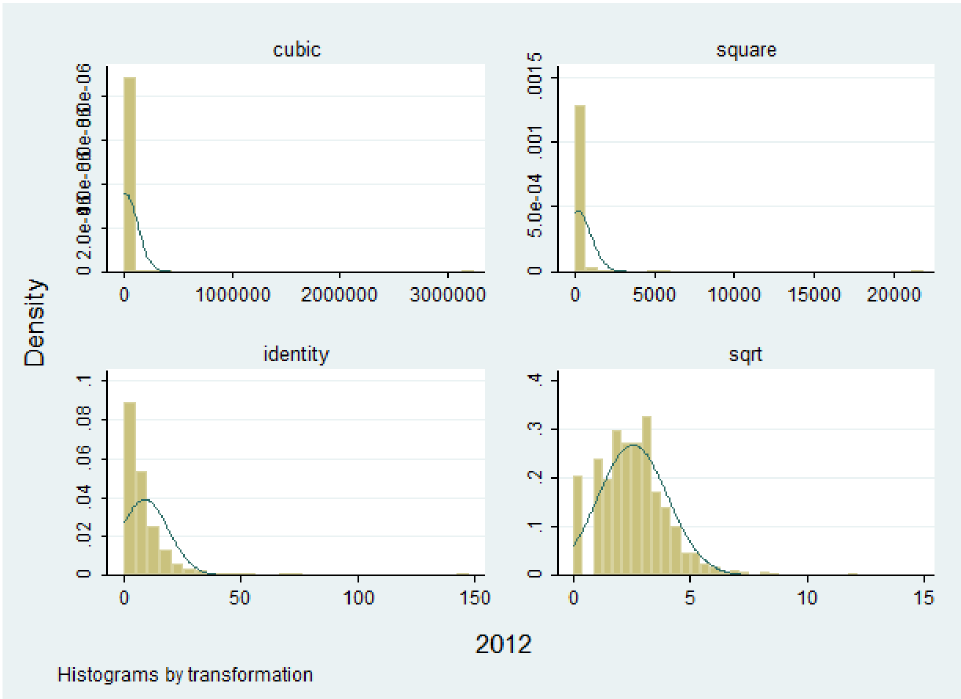
Arrest distributions of block groups.



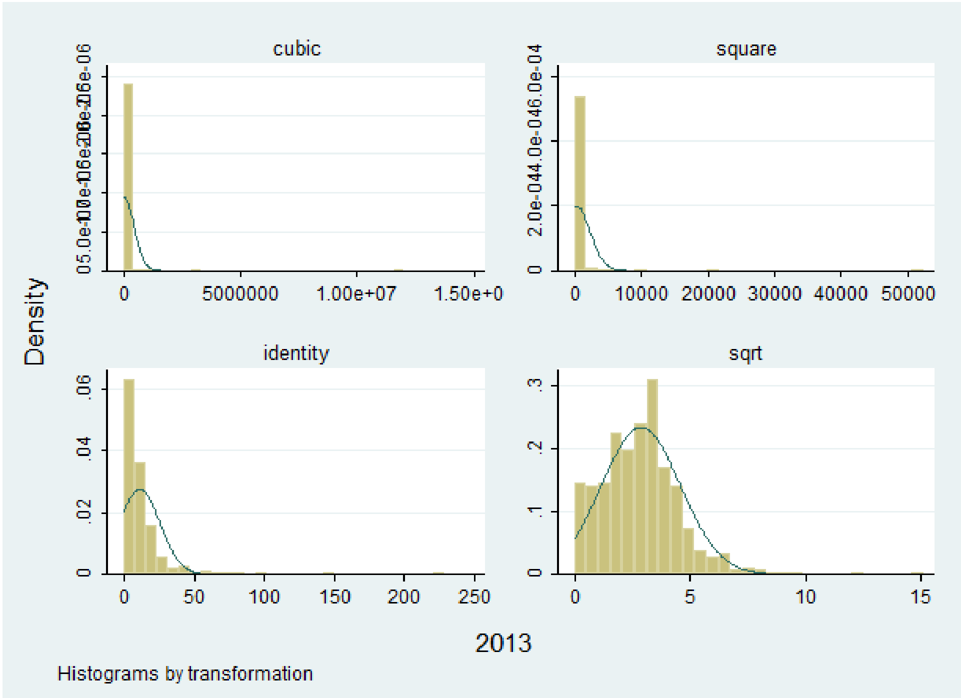
Transformation	Formula	$\chi 2$	p
cubic	a_2010^3	.	
square	a_2010^2	.	
identity	a_2010	.	0.000
square root	sqrt(a_2010)	.	0.000
log	log(a_2010)	.	.
1/(square root)	1/sqrt(a_2010)	.	.
inverse	1/a_2010	.	.
1/square	1/(a_2010^2)	.	.
1/cubic	1/(a_2010^3)	.	.



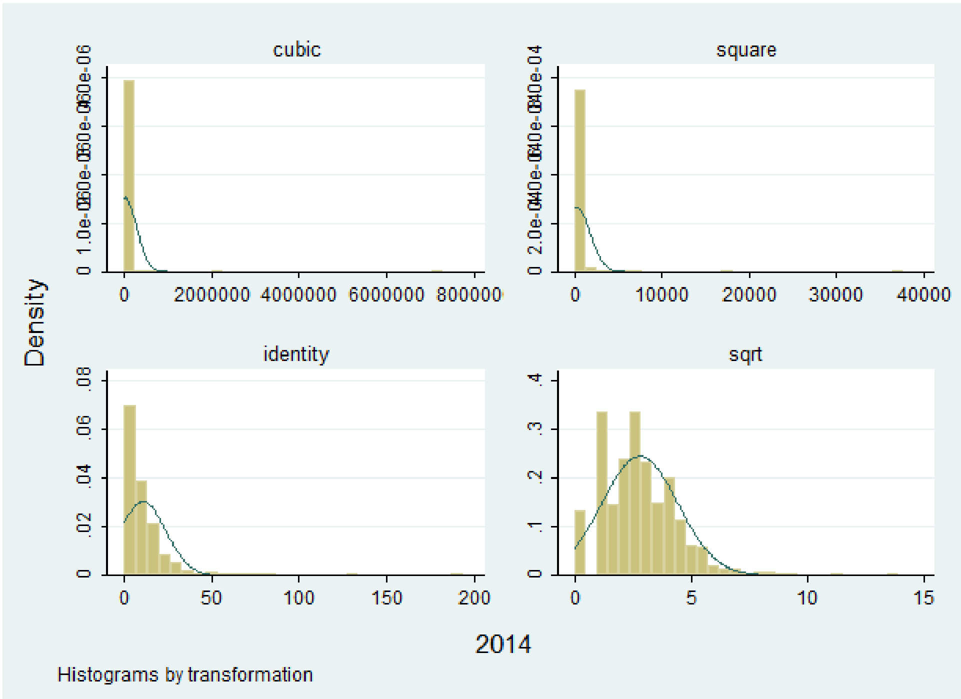
Transformation	Formula	$\chi 2$	p
cubic	a_2011^3	.	.
square	a_2011^2	.	.
identity	a_2011	.	0.000
square root	sqrt(a_2011)	.	0.000
log	log(a_2011)	.	.
1/(square root)	1/sqrt(a_2011)	.	.
inverse	1/a_2011	.	.
1/square	1/(a_2011^2)	.	.
1/cubic	1/(a_2011^3)	.	.



Transformation	Formula	$\chi 2$	*p*
cubic	a_2012^3	.	.
square	a_2012^2	.	.
identity	a_2012	.	0.000
square root	sqrt(a_2012)	.	0.000
log	log(a_2012)	.	.
1/(square root)	1/sqrt(a_2012)	.	.
inverse	1/a_2012	.	.
1/square	1/(a_2012^2)	.	.
1/cubic	1/(a_2012^3)	.	.



Transformation	Formula	$\chi 2$	p
cubic	a_2012^3	.	.
square	a_2012^2	.	.
identity	a_2012	.	0.000
square root	sqrt(a_2012)	.	0.000
log	log(a_2012)	.	.
1/(square root)	1/sqrt(a_2012)	.	.
inverse	1/a_2012	.	.
1/square	1/(a_2012^2)	.	.
1/cubic	1/(a_2012^3)	.	.



Transformation	Formula	$\chi 2$	*p*
cubic	a_2014^3	.	.
square	a_2014^2	.	.
identity	a_2014	.	0.000
square root	sqrt(a_2014)	.	0.000
log	log(a_2014)	.	.
1/(square root)	1/sqrt(a_2014)	.	.
inverse	1/a_2014	.	.
1/square	1/(a_2014^2)	.	.
1/cubic	1/(a_2014^3)	.	.

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