CRIME CONCENTRATIONS IN ATLANTA: TESTING THE LAW OF CRIME CONCENTRATION AT PLACE

by

Zachary M. Drake
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DEDICATION

This is dedicated to my loving girlfriend Kathryn, my parents Ron and Diane, and to the citizens of the City of Atlanta

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A great deal of gratitude is expressed to Dr. Charlotte Gill whose guidance and input on this project were remarkably valuable. Dr. Gill's mentorship made this thesis a piece to be proud of and taught me a great deal along the way. Many thanks to Dr. Sue-Ming Yang whose mastery of methodologies helped refine this analysis. To Dr. David Weisburd, apart from his thought leadership in the field of crime and place, his teaching of the subject allows for students like me to form new ideas and contribute to the field as I hope to have done here. This committee deserves the utmost of thanks for their oversight of my master's thesis.

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LIST OF ABBREVIATIONS

Atlanta Police Department .... APD
Group Based Trajectory Analysis .... GBTA

ABSTRACT

CRIME CONCENTRATIONS IN ATLANTA: TESTING THE LAW OF CRIME CONCENTRATION AT PLACE

Zachary M. Drake, M.A.

George Mason University, 2017

Thesis Director: Dr. Charlotte Gill

In this study, I explore the law of crime concentrations using Atlanta, GA. The goal is to add a new data point to the growing literature of crime concentrations as well as begin the academic discussion on urban layout as it relates to crime concentrations. Using data provided from the Atlanta Police Department, I use similar group-based trajectory analysis as previous studies in the crime concentration literature. I use the street segments, and the number of crimes occurring there per year, as the unit of my analysis. Crime in Atlanta is more concentrated than in other cities, and seems to follow patterns attributed to suburbs by other authors. Most streets show no crime across 8 years and the clear majority of streets are stable in their amount of crime. The increased concentration found in Atlanta could contribute to the study of urban layouts previously believed to be safer by Defensible Space scholars. Further research can use Atlanta as a basis to test the connection between crime concentration and urban layout.

INTRODUCTION

Crime and place is a growing field of study that is having great impact on both research and practice in crime fighting. Crime and place examines crime as a geographic phenomenon, and attempts to shift the conversation about crime away from offenders and more to context. Landmark studies have begun to reveal applicable trends in crime distribution that will benefit both research and practice from here to come. However, this field of criminology comes with new territory to be explored. Even simpler, the newness of many of the ideas means they have not been succumb to the rigor of time and science. In the book *The Criminology of Place*, the authors encourage researchers to confirm their theories and results and help “build a science of the criminology of place” (Weisburd et al., 2012, p. 193). In this study, I attempt to lend a hand to this task by replicating and enhancing existing work in this field using Atlanta, GA as a focal point.

LITERATURE ANALYSIS

Concentration of Crime at Place

The past decade of research has shown that crime is highly concentrated when examined at microgeographic levels, or "places". These "places" can be measured as anything from addresses, to buildings, to street blocks. While it has long been the notion that crime occurs more in some places as opposed to others, this modern line of research is showing remarkable reliability in the way crime is distributed. These patterns in findings have culminated in what David Weisburd has termed "The Law of Crime Concentration at Place" (Weisburd, 2015). "For a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015, pg. 138). The notable findings of this line of work are broken down over the next few pages.

One of the first studies to reflect crime concentrations at microgeographic places was by Sherman, Gartin, & Buerger (1989) in Minneapolis, MN. In this study, Sherman et al. found that 50.4 percent of police service requests in one year called officers out to just 3.3 percent of the addresses in the city of Minneapolis. These results reflected aggregated crime rates and when robbery alone was separated out, it was concentrated at only 2.2 percent of addresses. It is important to note that this analysis used calls for service to the police, therefore it is based solely on reported crimes. This study serves as one of the initial observations of crime concentrations at microgeographic place.

Weisburd, Bushway, Lum, and Yang (2004) examined Seattle, WA, using street segments instead of addresses and incident reports instead of calls for service. Weisburd et al. defined a street segment as two block faces on both sides of a street (Weisburd et al., 2004). Their data spanned 14 years from 1989 – 2002. The researchers found that half of all crime in Seattle occurred on 5.1 percent of street segments and a quarter of all crime occurred on 1.6 percent of street segments. This study was the first of its kind to incorporate a time component into the concentration of crime across the city. Using an 18 group, group-based trajectory analysis (GBTA), Weisburd et al. compared changes in crime rates over 14 years for the individual street segments. They found that not only was crime concentrated at few places, but crime concentrations were largely stable over the years, with only a small proportion of street segments showing sharp increases and decreases in crime rates.

Weisburd, Groff, and Yang reexamined Seattle in detail in the 2012 book entitled *The Criminology of Place* (Weisburd, Groff, and Yang, 2012). The purpose of this work was to detail precisely what factors were contributing to the concentration of crime and how changes in the urban landscape affected crime rates on individual street segments. Weisburd et al. developed a multi-variate model that attempted to analyze why street segments were classified into their respective trajectories. Primarily, the authors were concerned with factors related to opportunity theories (*see next section*) and how high crime street segments demonstrated several risk factors defined by theories of environmental criminology. Overall, the authors concluded that factors such as an increased number of bus stops, vacant lots, and increased residential population all contributed to the assigned trajectory of the street segment. Environmental factors did affect the amount of crime and the crime trends over time for individual street segments, and the resulting concentration of crime in specific segments.

Few other studies have used trajectory analysis to examine the stability of crime trends over time. Curman, Andresen, and Brantingham (2014) replicated Weisburd et al. (2004) in Vancouver, BC, Canada. Curman et al. implemented both 7-group GBTA and 4-group k-means approaches to trajectory analysis. Curman et al. used 16 years of crime data from 1991 to 2006. They found looser concentrations of crime in Vancouver than Seattle with 60 percent of calls for service going to 7.8 percent of street segments. The authors found levels of stability even higher than Seattle. Vancouver had zero increasing trajectory groups and 4 decreasing groups (Curman et al, 2014).

Gill, Wooditch, and Weisburd (2017) used the trajectory analysis approach to test the concentration of crime in a suburban setting in Brooklyn Park, MN. Using 15 years of crime data, from 2000 to 2014, the authors used a similar 18-group trajectory analysis to examine crime concentrations. As hypothesized by the authors, crime concentrations were significantly tighter in a suburban environment with 50 percent of the crime incidents occurring at just 2 percent of the street segments. Just as with Seattle and Vancouver, there was considerable stability in the crime concentration. Notably, the authors conclude that in a sprawled, suburban setting, street segments may not serve the same behavior setting function they do in cities. (Gill et al., 2017; Weisburd et al., 2004).

Wheeler, Worden, and McLean (2016) also used trajectory analysis to examine Albany, NY. With data from 2000 to 2013, they used an 8-class trajectory analysis and found that all the trajectories matched the overall decline in crime across the city, similar to Vancouver. The authors raise two important points regarding trajectory analysis and crime. First, both Vancouver and Albany have significantly fewer street segments than Seattle (though far more than Brooklyn Park). This could result in a lack of statistical power to detect trends in crime concentration change. Second, Albany showed significant clustering of street segments, different from those found in other sites. Wheeler et al. (2016) assert that perhaps the unique socioeconomics of each city alter the spatial distribution of crime hotspots.

Table 1 shows the historical data for each of these sites. The number of street segments, crimes, and population estimates are as reported by the authors. I included this table for the comparison of the studies in their own context. While some authors have done this level of comparison in their work (Curman et al., 2014; Wheeler et al., 2016), the comparisons were done using contemporized data, that is the data for each city at the time of comparison as opposed to the time of the original study. It is less relevant to use 2014 Seattle to explain results of 2004 Seattle. The significance of the crime concentration findings must be reviewed within their own historical context. Cities are ever changing. Populations change, residents come and go, streets are built and torn down and redesigned.

Table 1: Trajectory Based Crime Studies

City	*Years of Study*	*Population*	*Crimes*	*Street Segments*	*Total Crime Concentration*
Seattle, WA	14 (1989 – 2002)	563,374	1,490,720	29,849	50% of crime at 5% of street segments
Vancouver, BC	16 (1991 – 2006)	578,041	1,080,000	12,980	60% of crime at 7.8% of street segments
Brooklyn Park, MN	15 (2000 -2014)	78,000	222,585	2937	50% of crime at 2% of street segments
Albany, NY	14 (2000 – 2013)	100,000	189,595	10,212	Not reported

I believe this is a caveat to be made to the longitudinal studies of crime and place. As cities become more modernized, change becomes more rapid. If opportunity theories are to be used to explain the concentration of crime at place, then researchers must also consider the pace at which these opportunities are adjusted. Crime concentrations may in fact remain stable, but it should not be seen as a guarantee and inversely, newer studies finding less stability should consider the changing dynamics of a city as an explanation for the inconsistency before throwing out the theories and arguments already made by researchers.

There have been other examinations of crime concentrations using simpler methods. Table 2 shows a summary of several studies done to date which test the law of concentration and provide comparable data (Curman et al., 2015; Sherman et al., 1989; Weisburd & Amram, 2014; Weisburd et al., 2004; Haberman et al., 2017; Weisburd, 2016, Gill et al., 2017). While I have included recent population estimates for each of these sites, I adhere to my previous point that crime concentration levels must still be taken within their own temporal context, which was not identifiable for many of these data points. The examination of these sites is observational. Trajectory analysis is not used in many of these studies and the data ranges vary widely. However, each reports the percentage of microgeographic locations to which half of all the crime in the respective cities concentrates. While these sites do not show the same exact levels of concentration, Weisburd summarizes several of these examples together to produce a "bandwidth" of concentration where about half of the crime in a city can be expected to concentrate at around 4 percent of places and a quarter of all crime should occur at less than 2 percent of places (Weisburd, 2015). When including some extra sites that were not included in Weisburd's argument (Vancouver, Philadelphia, Minneapolis), we see that crime concentrations are still very close to this 4 percent mark, with over half of the sites being between 3 and 5 percent concentration. I included these sites that Weisburd has not, but these are not perfectly relatable. I denote the unit of analysis and the types of crime used. Weisburd (2015) argues that crime concentrations can only be compared for the same measure of crime and the same unit of analysis. For instance, in Philadelphia, Haberman et al. (2016) used street blocks and only examined street robberies. The 3.9 percent concentration the authors found can't simply be compared to the 3.3 percent concentration found in Minneapolis. In Minneapolis, Sherman et al. (1989) found different concentrations when they examined different crimes individually as opposed to the general crime level across the city. Nonetheless, I included these as demonstrations of crime concentrating at place, and not as data points to be taken to define a bandwidth of crime concentration between the two test sites.

Table 2: Crime Concentrations Across Various Cities

City	***50% Crime Concentration***	***Unit of Analysis***	***Population Estimate (Estimation Year)***	***Type of Crime***
Vancouver, BC, Canada	7.8% (60%)	Street Segments	631,486 (2016)	General Crime; Calls for Service
Cincinnati, OH, USA	6.0%	Street Segments	298,165 (2014)	General Crime; Incident Reports
Tel Aviv-Yafo, Israel	5.6%	Street Segments	432,892 (2015)	General Crime; Incident Reports
New York, NY, USA	5.5%	Street Segments	8,491,000 (2014)	General Crime; Incident Reports
Seattle, WA, USA	5.1%	Street Segments	668,342 (2014)	General Crime; Incident Reports
Sacramento, CA, USA	4.2%	Street Segments	485,199 (2014)	General Crime; Incident Reports
Philadelphia, PA, USA	3.9%	Street Blocks	1,560,000 (2014)	Street Robberies; Incident Reports
Ventura, CA, USA	3.5%	Street Segments	109,484 (2014)	General Crime; Incident Reports

Minneapolis, MN, USA	3.3%	Addresses	407,207 (2014)	General Crime; Calls for Service
Redlands, CA, USA	2.1%	Street Segments	70,622 (2014)	General Crime; Incident Reports
Brooklyn Park, MN, USA	2.1%	Street Segments	78,728 (2014)	General Crime; Incident Reports

Theoretical Framework of Crime Concentrations

There are two major perspectives used to explain why crime concentrates heavily in some places as opposed to others: opportunity theories and social disorganization. The primary explanation is done from the perspective of routine activities theory (Cohen and Felson, 1979; Sherman et al., 1989; Weisburd et al., 2012). Both perspectives find their roots in the early work of Chicago school scholars, who were the first to show that human behaviors vary across a city and at the same time crime rates occur in some concurrence to these human behavior patterns (Park & Burgess, 1925; Shaw & McKay, 1942). The concept of social disorganization asserts that the "ecology" of human life is dependent on the environment on which it is cast, and that environment plays a major role in the behavior patterns of humans (Hawley, 1950; Wilcox et al., 2004; Park & Burgess, 1925).

Barker (1978) later developed this perspective. Humans' interactions with their environments lead to consistent patterns of behavior that are not unique to each individual, but are the result of the mass web of human behaviors interacting with other humans, things, places, times, and most important the "nonverbal context or milieu" (p.26). Schools, work, home, restaurants, and even places of entertainment like cinemas have “normal” modes of behavior. These “milieus”, as Barker argues, are the social norms of behavior in a certain time and space, that help form the web of behavior patterns. Directly building from the work of Barker, Cohen and Felson developed the concept of routine activities theory (Cohen & Felson, 1979; Clarke & Felson. 1993). Routine activities theory claims our daily lives, composed of a near uncountable number of actions, reactions and interactions, create opportunities for crime to occur. The key to this theory is that crime occurs when there is the most opportunity. An opportunity for crime exists when a motivated offender, a suitable target, and infective guardianship meet in space and time (Cohen & Felson, 1979).

A very important aspect of routine activities theory is that this convergence of a motivated offender, a suitable target, and ineffective guardianship in time and space is not the result of strictly illegal activates, but is directly affected by all human activities (Cohen & Felson, 1980). As humans go throughout their daily lives, the seemingly unconnected decisions and movements cause this opportunity structure of crime to occur in limited amounts in limited space. Changes in human behavior patterns, because of various factors and reasons (i.e. weather, disasters, economics, and even crime itself), directly result in changes to the opportunity for crime to occur in either positive or negative directions.

In 1993, Brantingham and Brantingham laid out a framework for thinking about offender target selection and the phenomenon of why crime occurs in some places and not others. Their system of “nodes, paths, and edges” can be broken down and applied to understand crime concentrations at place. Brantingham and Brantingham posit that while routine activities may in fact explain how crime events are able to occur, the offender themselves does at some level impact this through their own routine activities, knowledge and assumptions about the location, and what they call the offender's "readiness potential".

Readiness potential is the ability or subjectability of a would-be offender to be "activated" into criminal behavior (Brantingham and Brantingham, 1993). It is assumed that most offenders are not spending their days committing criminal activity full time. Offenders are not in 24/7 pursuit of the best opportunities to commit crime, an important assumption in the use of opportunity theories like routine activities to explain crime concentrations. This is the phenomena of activation the Brantinghams describe. Something takes a person walking down the street with "readiness potential" and motivates them to act. This activation is proposed to be a result of stimulation from the environment and/or the offender's beliefs about the environment.

This is an explanation for what authors have historically noted to be "patterns of criminal behavior" (Taylor & Nee, 1988; Brantingham and Brantingham, 1993). While Barker describes expected behavior in certain behavior settings, scholars have also applied criminal behavior to normal criminal behavior settings. This is one explanation as to why offenders are activated in some places and not others. Indeed, this is a necessary assumption for the law of crime concentration at place. It is highly unlikely that in large cities, the street segments showing none or low numbers of crime are all high in guardianship or low in suitable targets. Anywhere there are cars, buildings, stores, or homes there is something worth targeting for theft or destruction and times where these targets are left unattended. The answer must then lie in the lack of offenders (Cohen and Felson, 1979) or the lack of offender activation (Brantingham and Brantingham, 1993). These two ideas work in interaction. Routine activities theory posits guardianship as a major driver in reducing criminal opportunities, which can also be seen as reducing the activation of offenders with high readiness potential. Conversely, the need for external activation for an offender to commit crime could also be seen as a lack of motivated offenders in an area with little factors to activate criminal activity.

How then do offenders find and select targets for criminal activity? Is it by chance that activated offenders randomly select targets nearest them when they are activated? Brantingham and Brantingham posit the notion of “awareness spaces”. “Offenders seem to use similar strategies in finding criminal targets: look where you are; look in areas you know well or at a specific site you know; or look in the areas that are understandable and predictable” (Brantingham and Brantingham, 1993, pg. 9). Drawing upon routine activities theory, the authors assert that would-be offenders find targets through their highly patterned daily activities. This is called an “awareness space” (Brantingham and Brantingham, 1991). The pinnacle of this theory, which will be explored in the next section’s concepts is this: offenders commit crimes according to their own routine activities and in very limited places that are easily explored from their known spaces.

Urban Layout and Crime Concentration

The above frameworks make up the field of environmental criminology. The implementation of this mode of thinking spans across cities from police departments to zoning offices. The main questions that stem from the environmental approach to criminology is what kinds of environments (streets, residences, zoning, etc.) have higher rates of crime, and how can we understand criminal opportunities (routine activities, target selection, etc.) in these environments. This line of research is important for analyzing the law of crime concentration and why these small number of streets have so much more crime than other streets. Is there something about the physical streets themselves that make targets more accessible and selectable by activated offenders?

Research testing this kind of environmental criminology spans decades and predates all literature supporting the law of crime concentration directly. In 1977 for example, Bevis and Nutter examined crime rates on different types of streets in Minneapolis. Their inquiry was whether crime occurs more or less on complicated street networks as opposed to straightforward grid connections. Initially, the authors found no connection across the entire city. However, they reexamined their results isolated to neighborhoods that were already known to have high amounts of crime. At this level of analysis, it was confirmed that complex road networks had less burglary than straightforward grid networks. The authors propose that city wide, the overall lack of crime in most neighborhoods hid the distinction. However, in neighborhoods that are already criminally attractive, criminals seem to select targets on grid layout streets more than complex networked streets, especially dead-end streets and cul-de-sacs (Bevis and Nutter, 1977).

Studies like this support a theoretical framework known as “defensible space”. The concept originates from Oscar Newman’s 1972 book titled *Defensible Space.*

Newman's approach was for buildings and cities to be designed in such a way that individual locations rest on impermeable streets (Newman, 1972). This creates an environment where residents and regular inhabitants of these streets can provide "natural policing" of who is and is not supposed to be there. Proponents of defensible space argue for cul-de-sacs and dead-end streets since these types of road networks would theoretically limit traffic and create such an impermeable street.

Fast-forwarding through decades of research and the questions of exactly how urban layouts affect crime are still largely unsettled. There is evidence that the defensible space approach can be used in many applications to understand crime concentrations (Shu and Hillier, 2000; Hillier, 2004). In a 2004 review, Hillier showed in one London borough that permeability, without any kind of use or added integration to the rest of the city, increased the risk for crime (Hillier, 2004). The author asserts that defensible space is correct in that permeable streets face a threat of criminal activity that is not present in non-permeable, defensible space type streets. However, Hillier also echoed previous findings that secondary access points to closed streets defeated much of the effect of "defensible space". Hillier further emphasized that traditional streets, with residences facing each other on either side of the street, are shown to be just as safe as "defensible streets" when no other points of access (alleys, parks, paths, etc.) connect to the buildings on this street. This would again imply that the concept of a safe street layout is much more about access and visibility than the actual type of street layout.

Beyond street layouts, there is also evidence suggesting different housing types are safer compared to other housing types. Hillier and Shu (2002) build on the work of

Tracy Budd (1999) to examine this issue. Budd (1999) used data from the British Crime Survey for a multivariate analysis and found that, when social and economic factors are considered, apartments were indeed safer than houses. In fact, detached houses were shown to be the least safest form of housing. Hillier and Shu (2002) confirmed the finding and said that in order of safest to most at risk, the more sides of a house that are exposed the more the risk of being the target of crime. Townhouses seemed to vary in their safety with those in the middle being least likely to be targeted and those on the ends of the development at most risk. This echoes early work in the field of environmental criminology which observed that corner houses tend to be targeted for crime more often (Taylor and Nee, 1983).

In a 2008 piece, Hillier and Sahbaz revisit the concept of street layouts and crime rates. In their review, the authors note that evidence to date on the concepts of population density, limited number of dwellings, and reducing movement patterns to certain streets, as they all relate to crime, is mixed and inconclusive (Hiller and Sahbaz, 2008). The authors attribute this largely to the problem of methodology. Measuring the impact of density, both population and dwelling, on the street level of crime requires methodology that can somehow account for or proxy the minute differences between urban environments. Hillier and Sahbaz used an analysis known as Space Syntax, which is used to identify the underlying patterns of urban streets as they pertain to land use and movement. The authors assert that because Space Syntax can take into account population density (in form of residences), street level activity, and land/zoning use, it can be used to examine street by street crime distributions and link these destructions back to the aforementioned measures.

Hiller and Sahbaz performed this analysis on streets in a London borough with data spanning 5 years of crime. The street syntax index was used to drive a logistic regression which also considered several social and economic factors (like tax values). Their results showed that compact dwellings (i.e. apartments) had the lowest crime rates and the rates fell as the socioeconomics became more affluent. Houses showed a u-shaped curve with more crime in low affluence and high affluence neighborhoods. As for density (measured through residences as a proxy for population), single dwellings showed a crime decrease of over 27 percent on average across the wards studied as density increased. The authors noted that when measured separately, ground level dwellings showed a 38 percent decrease, and multi dwelling buildings showed a mixed and fairly neutral change (Hillier and Sahbaz, 2008).

The most notable result from this study was the impact that movement had. The authors defined two types of movements for streets. “To-movements” are the accessibility of a street and the traffic going to the street. “Through-movements” are the permeability of the street and the traffic moving through it to another destination. The authors control for local movement of within 300 meters to determine the values of these movement levels. When doing so, the authors find that higher “through-movement” resulted in a decrease risk for crime of 15.3%. The authors also find that the more connections to a street (number of streets with access to the street) the more at risk for crime the street. This suggests that the safest streets were those with few connections and ample movement (i.e. main roads) and the most dangerous were those with many connections and light movement (i.e. grid streets with less development).

The idea of offender target searching (Brantingham and Brantingham, 1993) connects back very well here. If Hillier (2008) has shown that the more secluded a house the safer, while at the same time the more through traffic the safer, than many would see this as a paradox. Nonetheless it can be explained as the process by which offenders search for targets within their known areas and along their routine activities (Brantingham and Brantingham, 1993). Residences that are hidden and out of sight, yet easy to get to, are simply more likely to be found by motived/activated offenders when target searching.

The Present Research in Context

This study will test the law of crime concentration in Atlanta, GA, using similar trajectory analysis as in previously discussed studies. While the law of crime concentration has shown to be valid across many existing studies, the number of studies testing the law over multiple time periods is still very small. Further, 2 of the studies done so far use data dating back to pre-millennium years. The two studies who have measured concentration over time using more modern data found results somewhat different than the existing studies, although the differences were explained by other factors.

In addition, the concepts of urban layout as they relate to crime concentration have largely been ignored in previous literature. While existing studies have connected crime concentration to routine activities and environmental criminology, none to date have discussed crime concentrations over time to offender target selection. To do this, a data point with a diverse set of street layouts is needed for comparison.

In this study, both questions will be attempted. First, a new trajectory analysis of the law of crime concentration will be done with data within the current decade. Second, Atlanta, as argued later in the paper, can serve as the data point needed to make initial inferences about urban layout, street layout, and how crime concentrates along them. Both of these themes in the literature can be explored by answering the question: does crime concentrate in Atlanta the same way it has in previous cities measured when using microgeographic places and temporal analysis?

METHODS

In the present study, I measure crime concentration in Atlanta, GA, using similar longitudinal methods as other major crime concentration studies. There are several purposes to this study. The primary purpose is to add a new data point to the growing literature of study sites regarding crime concentration (Weisburd et al., 2012, Weisburd et al, 2015). With every new data point surrounding a scientific concept, there is potential for more nuances and detail to be revealed as well as opportunity to solidify existing knowledge. Second, I hope to use the Atlanta data point as a step toward connecting trajectory analysis of crime concentrations to the discussion of crime and urban layout.

Study Site

Atlanta, GA, (hereafter referred to as Atlanta) is the economic center of the ninth largest metropolitan statistical area (MSA) in the United States (U.S. Census, 2016). Atlanta is a useful and novel addition to the list of tests of the law of concentration. First, no city in the southeastern United States has yet to be tested for crime concentrations using trajectory analysis. While the concept of regional culture is not discussed in this paper, a drastic change in crime concentration levels would demand a theoretical and analytical exploration into the possibility that crime might concentrate differently in different culturally similar geographies.

Second, Atlanta is a uniquely sprawled out city. With a population of 456,002 and a land area of 134 square miles, Atlanta's population density is a mere 3,403 people per square mile. This is not much denser then Brooklyn Park, MN, whose population density is 2,906 people per square mile and is classified as a suburb by the authors (Gill et al, 2017). As previously discussed, there is evidence that increased density at the street level decreases the risk for crime (Hillier and Sahbaz, 2008). While these densities represent the city-wide totals, an aggregation of the street level densities, they provide a solid starting point for which to examine the law of crime concentration as it relates to density.

Atlanta's low density for such a major city is in part because of its large land area, but also largely because of its unique layout. Atlanta is comprised of a large amount of single-family housing as opposed to flats and apartments. 43.6 percent of Atlanta residents own their own home. Across 2011 to 2015, 77.6 percent of residents lived in their existing home for over a year. This shows a high level of consistency amongst residents in their neighborhoods as opposed to constant resident turn over, which many social disorganization scholars argue contributes to crime (Wilcox et al., 2004).

In 2010, Atlanta was 38.4 percent White, 54 percent Black, 5.2 percent Hispanic, 3.1 percent Asian, 2.0 percent multiple race, and the remaining made up of other racial groups. From 2011 to 2015, 47.9 percent of adults age 25 and older held a bachelor's degree and 89 percent held a high school education. 8.6 percent under the age of 65 are disabled. Between 2011 and 2015 the median household income was $47,527 and 24.6 percent of city residents were considered below the federal poverty line.

Data

The data set comes from the Atlanta Police Department (APD). APD maintains a free and publicly available dataset of reported crimes from 2009 to the present on their website. This dataset is updated monthly with the reported crimes from the previous month. APD claims that the data is the raw file from their data collection that is used by their district commanders and crime analysis units. If this is the case, we can assume that the data is sufficiently reliable to be used by a trained researcher or analyst. Because these are based on incident reports and not calls for service, any duplication in report has been filtered by APD and only unique incidents remain.

The dataset provided by APD includes all UCR Part 1 crimes reported to the police. This is an important note for two reasons. Primarily, the UCR Part 1 is limited to only certain crime categories. These categories are aggravated assault, criminal homicide, forcible rape, robbery, assault, burglary, larceny, and motor vehicle theft. I must adhere that arson is considered a UCR Part 1 crime, but in Atlanta arson is investigated by the fire department and therefore arson data are not tracked by APD. Second, because this is only crimes known and reported to the police, there is the accepted fact that crime occurs without the knowledge of the police department.

There is a natural limitation in the crimes excluded from this dataset. For example, simple assaults and drug crimes are large numbers of crimes in most cities, but are excluded from this data set. However, past research of crime concentrations using trajectory analysis has not entirely distinguished between different types of crime (Weisburd et al., 2004; 2012). On the contrary Andresen and Lining (2012) assert that examining crime concentrations without separating into individual crimes runs the risk of losing resolution due to aggregation. As mentioned previously, this does limit the ability of my study to be joined with other crime and place studies to support a singular bandwidth of crime concentration. The studies included by Weisburd (2015) all used general crime for their assessments. The use of strictly Part 1 crimes may produce results different than if all crime was included. Nonetheless, the sample of crimes that are available, are in my opinion enough to assess the general concentration patterns of crime in Atlanta.

In the original data set, there are a total of 270,969 crimes that occurred from January 2009 through December 2016. These are confirmed incidents of crimes and not calls for service alone. It is important to note APD records both the date of the report and the date the crime occurred. Not all reported crimes have known dates of occurrence and many crimes are discovered and/or reported to the police sometime after the occurrence of the crime. In my view, measurements of crime concentration are much more accurate when done by sorting crimes on their date of occurrence rather than the date of reporting. When aggregating to the yearly level, this has very little impact as only a handful of crimes around the New Year holiday would affect the summations if sorted in either way. The main impact is on crimes reported years after their occurrence date. To avoid these crimes being considered into the analysis, the crimes were sorted on the date of occurrence before analysis. All those crimes whose occurrence was outside of the years being studied, or had no occurrence date recorded, were removed before analysis. This amounted to 4,574 crimes.

The crimes are broken down to the totals in Table 3. As expected, property crimes severely outnumber violent crimes. Larceny from vehicles occurs at the highest rate and homicide at the lowest rate. I want to make a special note of the rather low rate of commercial and residential robbery as opposed to the high numbers of burglary and larceny. This an evident example of routine activities theory at work in aggregate crime numbers as a robbery involves some level of guardianship over the property being stolen as opposed to burglary and larceny (Cohen & Felson, 1979).

Table 3: Atlanta Part 1 Crimes by Type 2009 - 2016

Type of Crime	***Number of Crimes***	***Rate Per 1,000 Residents***
Auto Theft	37,619	82.5
Non-Residential Burglary	8,345	18.3
Residential Burglary	42,423	93.03
Larceny	63,658	139.6
Larceny from Vehicle	75,927	166.5
Residential Robbery	1,859	4.08
Commercial Robbery	1,824	4
Pedestrian Robbery	14,249	31.2
Aggravated Assault	18,850	41.3
Forcible Rape	935	2
Homicide	706	1.5
Total	***266,395***	***584.20***

Table 4 shows the number of crimes broken down by year. The crime rate in Atlanta fell overall by 26.5 percent over the course of the 8 years included in this study. However, this trend was not uniform to all crimes. Rape and Homicide increased 34 percent and 39 percent respectively. The largest decreases were in crimes targeting residences. Residential burglary fell from 7,394 incidents in 2009 to 3,393 incidents in 2016, a decrease of 54 percent. Residential robbery declined from 309 incidents in 2009 to 206 incidents in 2016, or 33.3 percent. All property crime decreased from 34,180 incidents in 2009 to 24,746 incidents in 2016, or 27.6 percent. Violent crime decreased from 5,477 incidents to 4,311 incidents, down by 21.3 percent.

Table 4: Crimes Per Year by Type

	2009	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*
Auto Theft	5,646	5,009	5,235	5,097	4,449	4,135	4,221	3,827
Non-Residential Burglary	1,682	1,273	994	774	885	968	812	957
Residential Burglary	7,394	6,713	6,409	5,255	4,892	4,446	3,921	3,393
Larceny	8,440	8,710	8,911	8,535	7,975	7,406	7,088	6,593
Larceny from Vehicle	11,018	9,225	8,630	8,822	9,290	9,429	9,537	9,976
Residential Robbery	309	233	268	245	199	213	186	206
Commercial Robbery	282	208	214	179	284	221	235	201
Pedestrian Robbery	2,019	1,660	1,760	1,810	1,863	1,917	1,722	1,498
Aggravated Assault	2,591	2,591	2,515	2,459	2,232	2,185	2,111	2,166
Forcible Rape	100	79	134	94	100	146	148	134
Homicide	76	88	89	82	83	92	90	106
Total	***39,557***	***35,789***	***35,159***	***33,352***	***32,252***	***31,158***	***30,071***	***29,057***

The crimes described above were geocoded using the public geocoding server maintained by the Georgia Department of Transportation (GDOT). The GDOT database divides all streets and roads into segments, with descriptive information of each segment, which will serve as the unit of analysis in this study. The number of street segments within the city limits of Atlanta (and service area of APD) totaled 19,884 (n=19,884). The average length of a street segment is 0.1426 kilometers (467.92 feet). The geocoding process found a 92.84% match rate of crimes (247,319 crimes) which is well above the standards defined for crime and place studies (Andresen & Malleson, 2011; Ratcliffe, 2010). Using a geographic information system (ArcGIS Pro 2.0), the sum of crimes that occurred along each street segment (each crime was only mapped to one street segment, the nearest one) was calculated for each year (i.e. 2009, 2010, etc.). The resulting data, which was used for the analysis, contained crime counts for each of the 19,884 street segments for a total of 8 observation points.

The geocode only matched real addresses, and automatically removed intersections and undefined locations. Of these 19,076 crimes that were removed, 15,828 occurred at known intersections (82.97 percent). The remaining were removed as a result of the geocoder specifics. Many scholars have debated the inclusion of intersections in crime and place analysis (Weisburd et al., 2012; Curman et al., 2014). Crimes at intersections are arguably contextually separate from the crimes that occur on street segments, especially if the purpose of using the street segments is as a proxy for human behavior settings (Weisburd, 2004). For this study, I am leaving intersections removed from the analysis.

Analysis

The first level of analysis was to calculate the level of crime concentration based on the number of crimes per street segment per year. This analysis was very straightforward. Taking the number of crimes counted on each street segment, 100 percent, 50 percent, and 25 percent of the sum were calculated for each year. Within the same year, the smallest number of street segments needed to sum to each of these percentages was calculated based on the counts per street segment within said year. Finally, the number of each street segments summing to the percentage of the crimes respectively was divided by our total number of street segments (n=19,884) to arrive at the smallest percent of street segments that can be summed to equal each percentage of the crime count for each given year. The results from this first wave of analysis will yield the general levels of crime concentration in Atlanta. The outputs will be summarized in simple charts that are reported in the next chapter.

In order to use Atlanta as a new data point in the crime concentration literature, I also tested the stability of high crime areas over time using the same methods as previous studies (Weisburd et al., 2004; Wheeler et al., 2016; Gill et al., 2017; Curman et al., 2014). I use a group-based trajectory analysis to compare the level of crime across street segments over the 8 years of the study. This analysis was conducted using the *traj* plug-in for Stata 15. Trajectory analysis is useful for examining large numbers of observations and comparing their trends over time. The alternative way to come to these conclusions would be to map the year by year trajectory of each street segment (n=19,884), and compare them all side by side to qualitatively arrive at conclusions. For obvious reasons, this is practically impossible for any human to compute without some sort of statistical formula or proxy. By creating trajectories that represent the mean trajectory of a smaller number of observations, researchers can define qualitative conclusions about large data sets over time.

Group-based trajectory analysis (GBTA) has been widely used in criminology for some time, predominately in the measurement of criminal career/developmental trajectories (Nagin, 2005; Nagin & Odgers, 2010). The original development of the method was intended for the examination of the criminal career in longitudinal data across age. Many other scholars have since applied GBTA to the analysis of crime at place (Weisburd at al., 2004, 2012; Wheeler et al., 2016; Gill et al. 2017). For crime concentration, GBTA is useful for two predominant reasons. First, GBTA provides a sufficient way to classify high crime streets with a count and time component. Alternatively, researchers would be able to classify streets as high and low crime with some fair amount of ease, but would then have to re-classify for each given time point they were wishing to observe. With GBTA, street segments can be classified on their crime trends over time resulting in a simple but more in-depth comparison. Second, GBTA reveals underlying trends in crime rate changes. The single trajectory of a city's overall crime rates will miss underlying phenomena affecting smaller groups of street segments. By using GBTA, any phenomena affecting small groups of street segments can be seen in context to the changes over time across the city.

Group-based trajectory analysis accomplishes this task using growth mixture models (Nagin, 2005). The trajectories are calculated by estimating the maximum likelihood of each observation for a set number of growth coefficients. Crime data is collected as counts, meaning that all values are assumed to be independent of both each other and the mean. The number of “zeros” is not random or arbitrary, since the streets without crime are not null but very much an important point with a value of zero, and in fact significant to the level of concentration. Therefore, models are adjusted to the assumptions of a zero-inflated Poisson distribution.

The most difficult part of using this methodology is the selection of the number of classes, since these must be set by the researcher before analysis. Nagin (2005) offers an effective and widely utilized approach to determining the best number of groups and the polynomial order of the mixture models. The primary selection criteria for Nagin’s process is the Bayesian Information Criterion (BIC), which produces a coefficient based on the logarithm of the maximized likelihood of the model, the model parameters, and the sample size (Nagin, 2005; Kass & Raftery, 1995). According to Nagin, the BIC serves an adequate criterion for two reasons. First, the BIC increases as the number of groups increases. Second, BIC is penalized with the addition of superfluous groups. The group with the lowest BIC (by absolute value) should be selected.

Nagin offers other criteria to be considered. GBTA provides the probability of group membership for each observation for each group trajectory, known as the posterior group probability. A measure of a model’s fit is the mean posterior probability of group membership for each group. The mean posterior probability of each group is calculated by averaging the probability of group membership for each observation within its respective assigned group. The result is the likelihood that the observation would be assigned to its own trajectory group over other groups. There is no established benchmark for posterior probabilities, but Nagin suggests that .70 (70%) is adequate to determine model fit (Nagin, 2005). In addition to BIC and posterior probabilities, researchers must also consider the statistical significance of group membership as well as the models themselves. Other scholars have recommended also using cross tabulation to see the changes in group membership as different group numbers are used (Yang, 2010). Cross tabulation can be helpful in determining whether an added group represents something new or simply divides other groups to create an only slightly different trajectory.

Nagin attests that there is a level of qualitative craft in selecting the model that best fits data (Nagin, 2005; Nagin and Odgers, 2010). There is no fool-proof method or stone-written criteria. Instead, researchers are left to determine which number of groups is best for drawing qualitative conclusions from the analysis. In general, the smallest number of groups that can adequately be used to understand the trends in a data set is preferred.

Nagin's process is to test multiple numbers of groups on a data set and determine the group with the best BIC and posterior probabilities. Nagin then recommends testing multiple polynomial orders to examine the effects of different model types using the same number of groups (Nagin, 2005). I followed this process starting with the 5 group – quadratic model and continually increased the groups until a decrease in BIC was found. The *traj* plug in for Stata allows users to set a predefined polynomial for observations with no data (street segments with zero crimes for each year). I set these observations to run with a flat model since streets with no crimes for any of the 8 years would be guaranteed to be their own, flat trajectory. Because GBTA does not handle outliers well, as they distort the mean trajectories, I truncated the crime counts at 60 for the trajectory assignment (Gill et al., 2017).

Table 5 and Table 6 show results of my model outputs. When testing all the group assignments with a quadratic polynomial, I determined that the 16-group model was the best selection. The 16-group model could provide the highest BIC, while maintaining a lowest posterior probability above the .70 threshold. The BIC calculation does continue to decrease in absolute value up until the 20-group model before it starts to increase again. This increase is a sign that the additional group added in the 20-group model (that was not present in the 19-group model) is unnecessary. The posterior probabilities also fell below .7 starting at the 13-group model, but then seem to rise at the 16-group model only. This is evidence of the appropriateness of the fit for the 16-group model as compared to the next closest number of groups. I then tested the various polynomial orders for the 16-group model, using the same criteria for selection. Here, the BIC for the quadratic was the lowest absolute value. The posterior probabilities for both the linear and the cubic models fell below .70. Ultimately, using these criterion, the 16-group, quadratic model was selected.

Table 5: Model Statistics for Quadratic Equations

Number of Groups	***Log-likelihood***	***BIC***	***AIC***	***Lowest Posterior Probability***
5	-173163.46	-173262.43	-173183.46	.9234273
6	-170001.60	-170120.37	-170025.60	.9336981
7	-168198.47	-168337.04	-168226.47	.8894541
8	-167176.95	-167335.32	-167208.95	.8698651
9	-166658.44	-166836.59	-166694.44	.8630452
10	-166378.20	-166576.15	-166418.20	.8159727
11	-165946.84	-166164.59	-165990.84	.7174913
12	-165688.04	-165925.59	-165736.04	.7007099
13	-165494.71	-165752.05	-165546.71	.7201539
14	-165309.21	-165586.34	-165365.21	.6959432
15	-165231.27	-165528.20	-165291.27	.6553154
16	**-164578.49**	**-164895.22**	**-164642.49**	**.7008854**
17	-164454.91	-164791.43	-164522.91	.6350114
18	-164402.11	-164758.43	-164474.11	.5658738
19	-164167.19	-164543.30	-164243.19	.6333865
20	-164222.93	-164618.83	-164302.93	.5423864

Table 6: Various Polynomial Order of the 16-Group Model

Polynomial Order	***Log-likelihood***	***BIC***	***AIC***	***Lowest Posterior Probability***
Linear	-164880.22	-165117.77	-164928.22	.6987646
Quadratic	**-164578.49**	**-164895.22**	**-164642.49**	**.7008854**
Cubic	-164859.22	-165255.12	-164939.22	.6428444

RESULTS

I found the crimes in Atlanta concentrate at higher levels than other crime and place studies. 100 percent of the crime across 2009 to 2016 was found on average at only 34.52 percent of the street segments for the year. 50 percent of the crime was found at an average of 3.12 percent of the street segments. Finally, 25 percent of the crime was found at 0.67 percent of street segments. These numbers can be seen in the table and graph below. Table 7 shows the number of street segments making up the concentration levels for each year.

Table 7: Crime Concentration Results from 2009 to 2016

Year	***100% Concentration***	***100% of Crime - Street Segments***	***50% Concentration***	***50% of Crime - Street Segments***	***25% Concentration***	***25% of Crime - Street Segments***
2009	37.58%	7472	3.35%	666	0.67%	133
2010	35.24%	7007	3.11%	619	0.64%	127
2011	35.80%	7118	3.28%	652	0.67%	134
2012	34.75%	6910	3.01%	599	0.67%	133
2013	34.50%	6859	3.23%	643	0.72%	144
2014	33.74%	6708	3.05%	606	0.66%	132
2015	32.32%	6427	2.94%	585	0.65%	129
2016	32.28%	6418	2.98%	592	0.70%	140
Mean	***34.52%***	***6865***	***3.12%***	***620***	***0.67%***	***134***

Table 8 shows the percetage of street segements that had no crime throughouth the year for each year. I include this here with the results of the concentration analysis as an inverse comparison to the 100 percent concentration numbers. The number of crime free streets increases over the years by over 5 percent. As stated earlier, Atlanta saw over a 12 percent increase in population from 2011 to 2015. These are the same years where the increase in the number of crime free streets is greatest. This could be hinting at a correlation betweent the new residents moving in and streets losing what little crime they contributed originally.

Table 8: Number of Street Segments with Zero Crimes by Year

Year	***Percent of Street Segments with No Crime***	***Number of Street Segments with No Crime***
2009	62.42%	12,412
2010	64.76%	12,877
2011	64.20%	12,766
2012	65.25%	12,974
2013	65.50%	13,025
2014	66.26%	13,176
2015	67.68%	13,457
2016	67.72%	13,466

As evident in Figure 1, the number of street segments contributing to total number of crimes declined over the period of the study. In 2009, 37.58 percent of street segments contained 100% of the crimes. By 2016, only 32.28 percent of street segments contained 100% of all crimes. However, this roughly 5 percent decrease is not proportionately matched in the 50 percent and 25 percent analysis. In fact, there is some fluctuation at the 50 percent and 25 percent levels with inconsistent variation across years. This is evidence of the crime rate drop across Atlanta that was seen in the original crime totals. The relatively flat 50 percent and 25 percent in comparison to the 100 percent line might be assumed by some that the high crime streets are staying relatively high crime and only streets with historically low crime rates are changing.

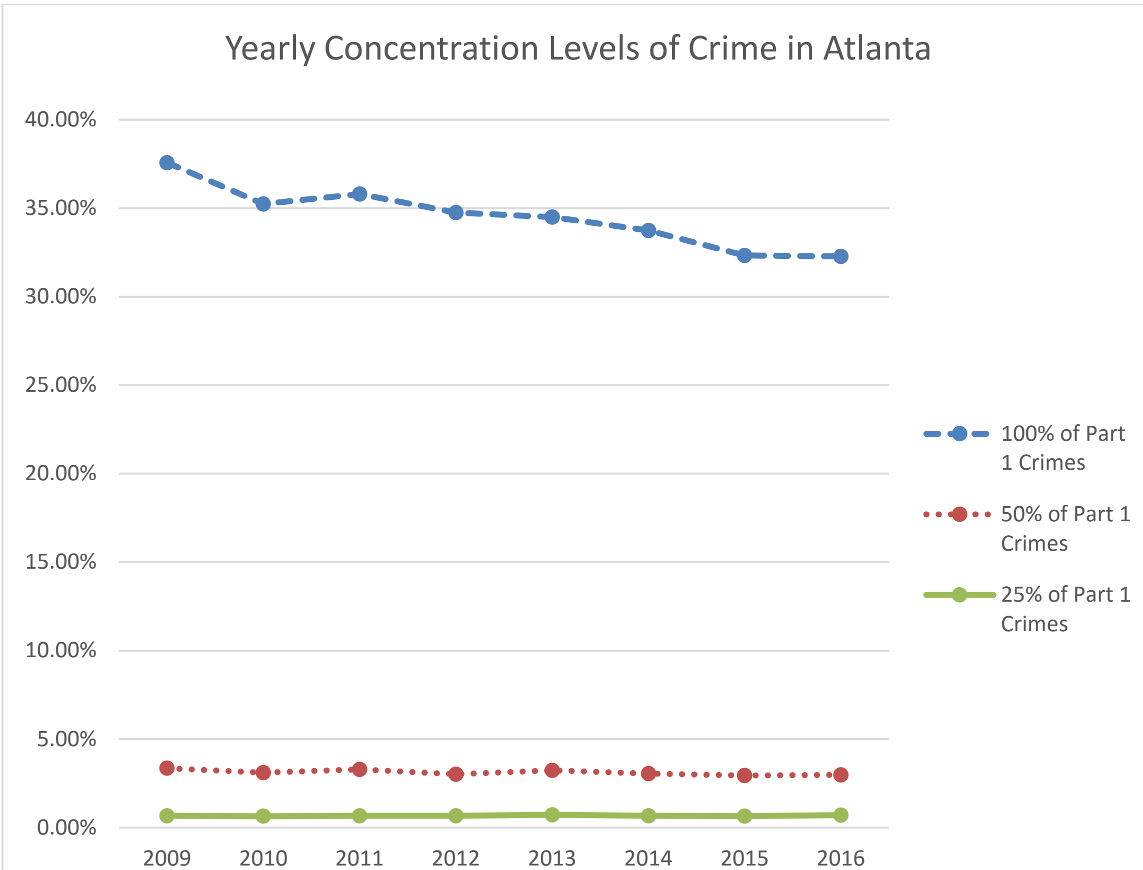

Figure 1: Crime Concentrations from 2009 to 2016

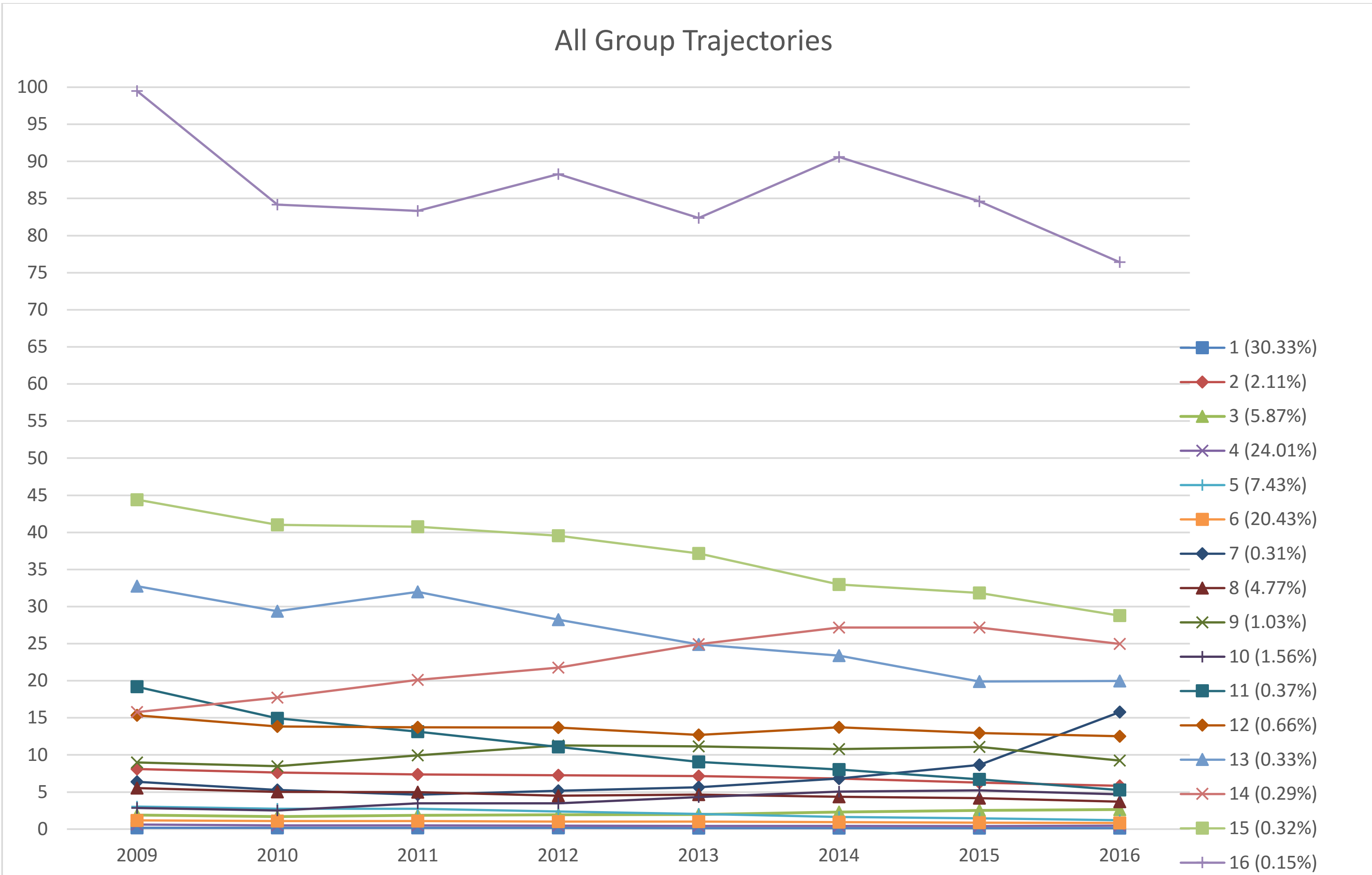

Figure 2: All 16 Group Trajectories in Atlanta

Figure 2 shows the results of the 16-group trajectory models. These line graphs represent the true average number of crimes for each group, as well as the percentage of street segments the group represents. Overall, the crime rates on street segments in Atlanta have been highly stable year to year. Categorizing these groups required a definition as to what is considered stable. In my opinion, any fluctuation of 1 to 2 average crimes per year is relatively stable. One extra crime per year is not a drastic change to even streets with only one crime for the year.

Groups 1, 3, 4, 5 and 6 are stable with very little changes over the 8-year period. These groups are crime free or low crime, and make up what I call the "low stable" category. These five groups represent 87.89% of street segments (approx. 17,476) in Atlanta. Their trajectories are seen in Figure 3.

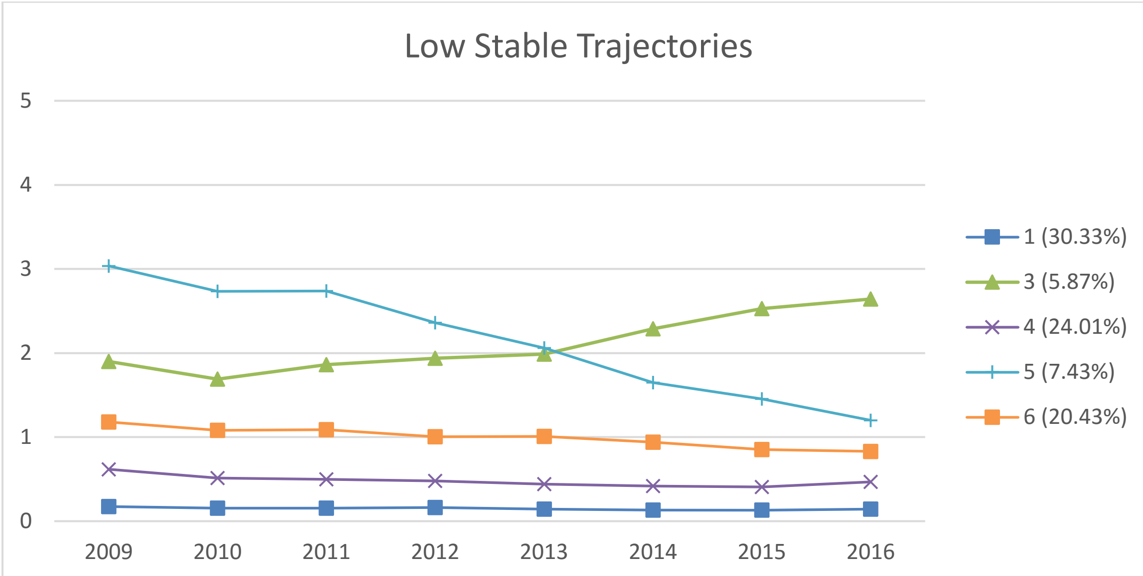

Figure 3: Low Stable Crime Trajectories

Groups 2 and 8 seem to maintain relatively medium levels of crime across all 8 years. These groups see a small reduction in crime rates but always have some level of crime. These groups are defined as “medium stable.” Group 2 represents the largest number of this category with 2.11 percent of street segments or 419 streets. Group 8 is 4.77 percent or 948 streets. These trajectories are shown in Figure 4.

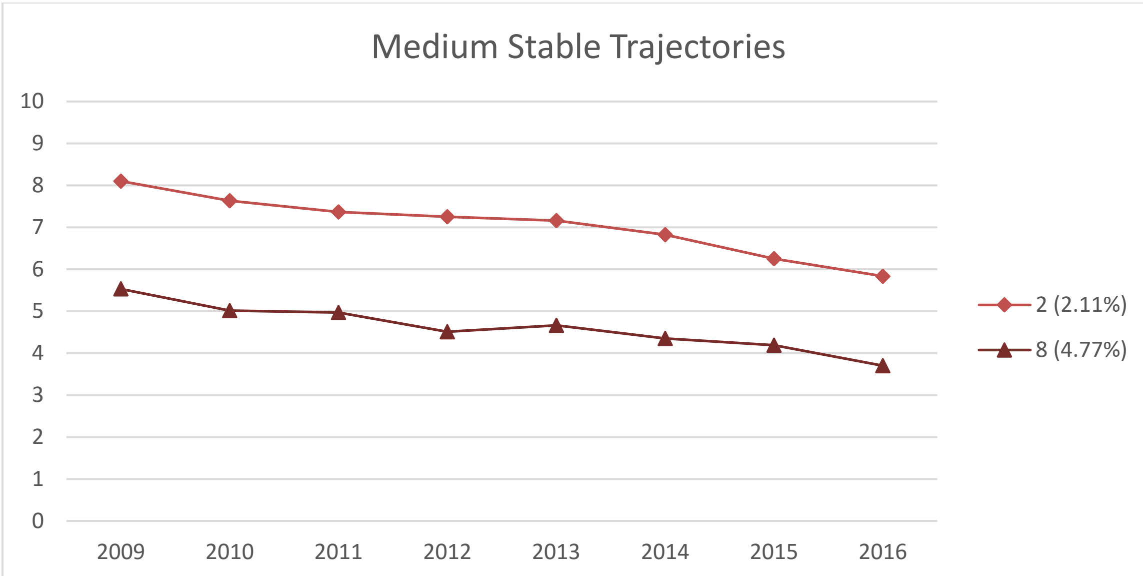

Figure 4: Medium Stable Trajectories

Three trajectories showed increases in crime rates. While these rise at different paces and at slightly different rates, these groups only marginally increase compared to their original crime totals. Group 7 makes up .31 percent and 61 street segments. Group 7 has very low crime right up until 2016. While group 7 does not go a year without any crimes, it was medium to low crime until 2016, in which it became high crime. Groups 9 (1.03 percent) and 10 (1.56 percent) increase by small amounts overall but do so in a way that I believe is different enough from other trajectories to be included in the subtle risers group.

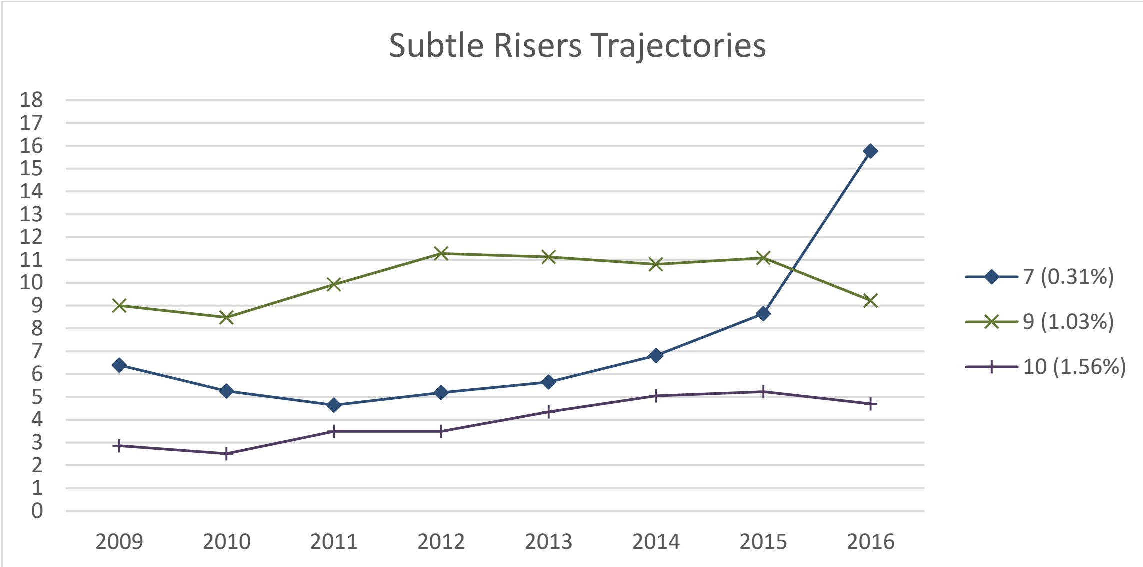

Figure 5: Subtle Risers Trajectories

The next three categories are all classified as "high crime", but span a large range of crime levels. Group 16 starts at 100 crimes in 2009, whereas group 11 starts at only 20 crimes. While this is a huge difference between the two numerically, they are both high crime compared to the rest of the street segments in the city. There is little value to determining them to be different as both are high crime and both decrease over the years of the study. Groups 15, 13, and 11 seem to show trends that match the crime rate of the city. Group 15 makes up .32 percent (63), group 11 is .37 percent (74), and group 13 represents .33 percent (65) of street segments. The shape of these 202 streets seems to follow the shape of the 100 percent concentration line in Figure 1 very closely. Group 11 gets very low, as these street segments eventually become what I would consider low crime at an average of 5 crimes per year. Group 16 is a bit less like the 100 percent decline but is still representative of very high crime streets that seem to be declining.

Group 16 makes up .15 percent of street segments, about 30. These groups I consider to be “high declining.”

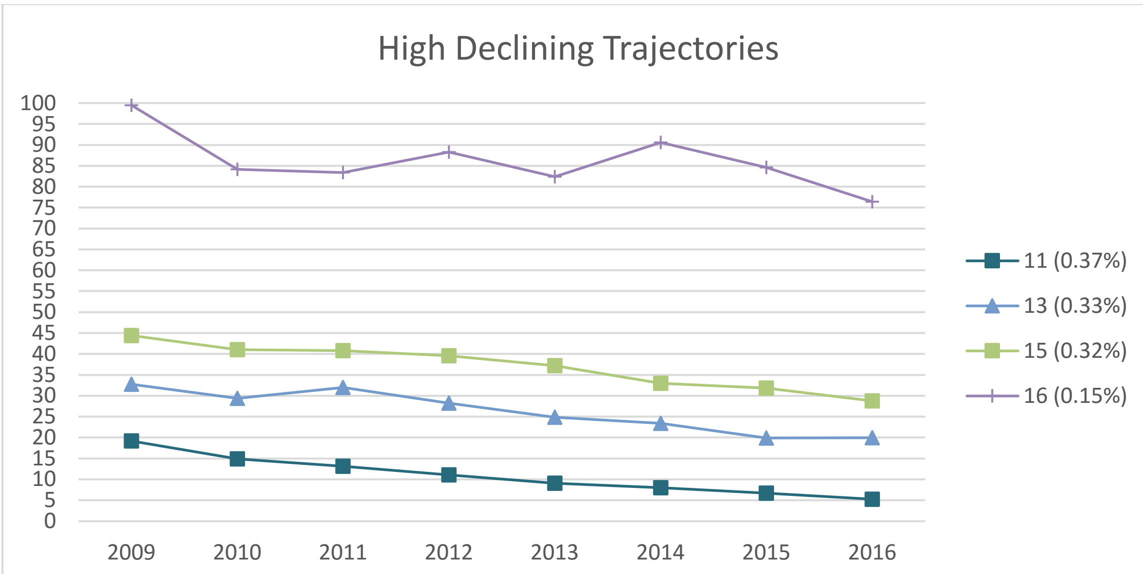

Figure 6: High Declining Trajectories

Groups 14 and 12 are respectively their own categories. Group 14 is the only “High Increasing” group as these streets average 16 crimes in 2009 and over 25 crimes in 2016. Group 14 makes up only .29 percent of streets, 58 individual segments. Group 12 is high crime, but remains stable across the 8 years of the study in the same way the “low stable” and “medium stable” groups maintain stability. Group 12’s average start at about 15 and drops to about 13. While this is a decrease, a 2 crime drop from 15 is proportionally smaller than the changes in other groups considered to be non-stable. Group 12 is .66% of street segments (131).

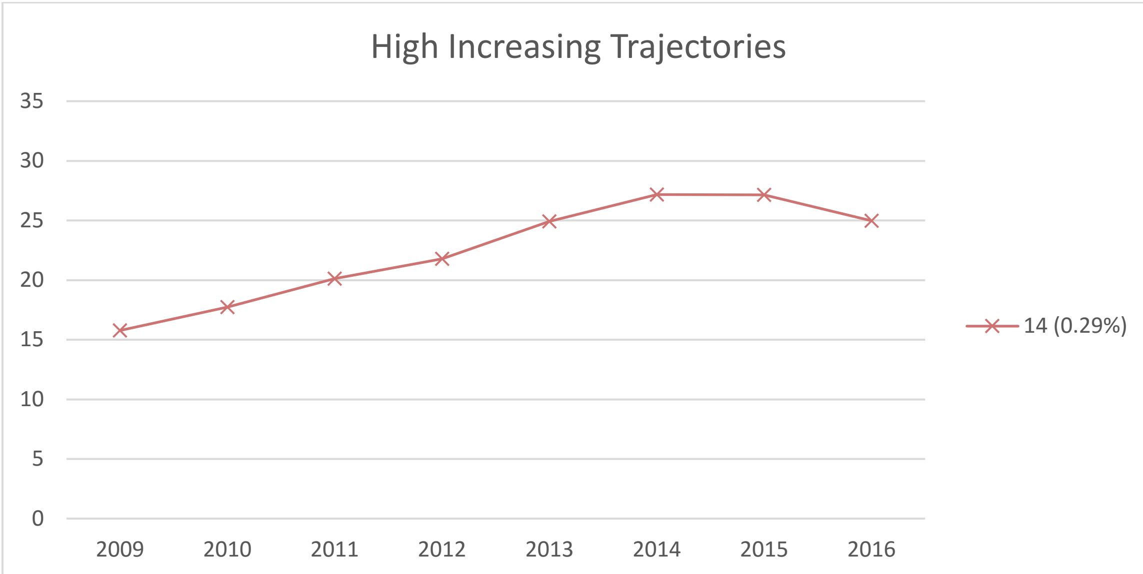

Figure 7: High Increasing Trajectories

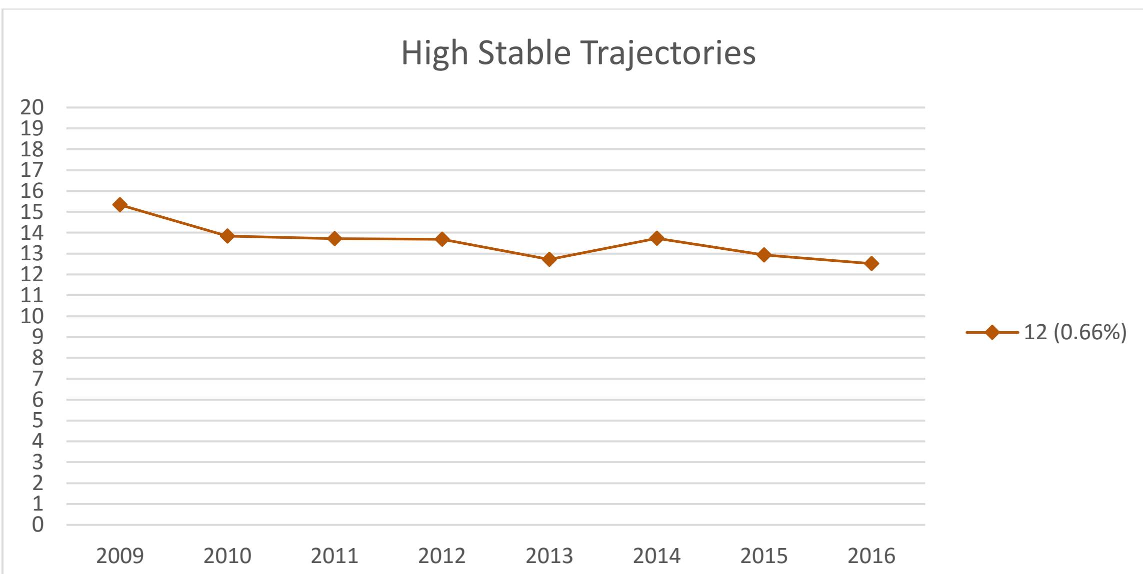

Figure 8: High Stable Trajectories

Table 9 compares the categories and their total number of streets. Again, the "low stable" group makes up the clear majority of the streets in Atlanta. This is evidence of the stability of the crime concentrations in Atlanta. The medium stable group and the low stable group together are well over 90 percent of streets. This is surprising given the growth Atlanta has seen during this analytical time frame. It would be assumed that there would be a bit more turmoil and therefore a little less stability.

Table 9: Categories of Trajectories for Street Segments in Atlanta

Name	***Groups***	***Percent***	***Street Segments***
Low Stable	1, 3, 4, 5, 6	88.07%	17,512
Medium Stable	2, 8	6.88%	1,368
Subtle Risers	7, 9, 10	2.9%	577
High Declining	11, 13, 15, 16	1.17%	233
High Increasing	14	0.29%	58
High Stable	12	0.66%	131

Figure 8 shows the geographic distribution of the categories of trajectories. It is very apparent that the downtown and midtown corridors are made up of a little bit of each group, while the northwest and southwest quadrants of the city, which are predominantly residential, are also predominately low stable. The most "dangerous" group, the high increasing, is extremely spread throughout the city. For the large part, these street segments are located independently of each other. The subtle risers however are much more commonplace throughout the city. As indicated by blue on the map, there is a heavy concentration of these along the midtown corridor. This area has seen heavy development during the period of the study and therefore much of this could be changes to the environment and social organization.

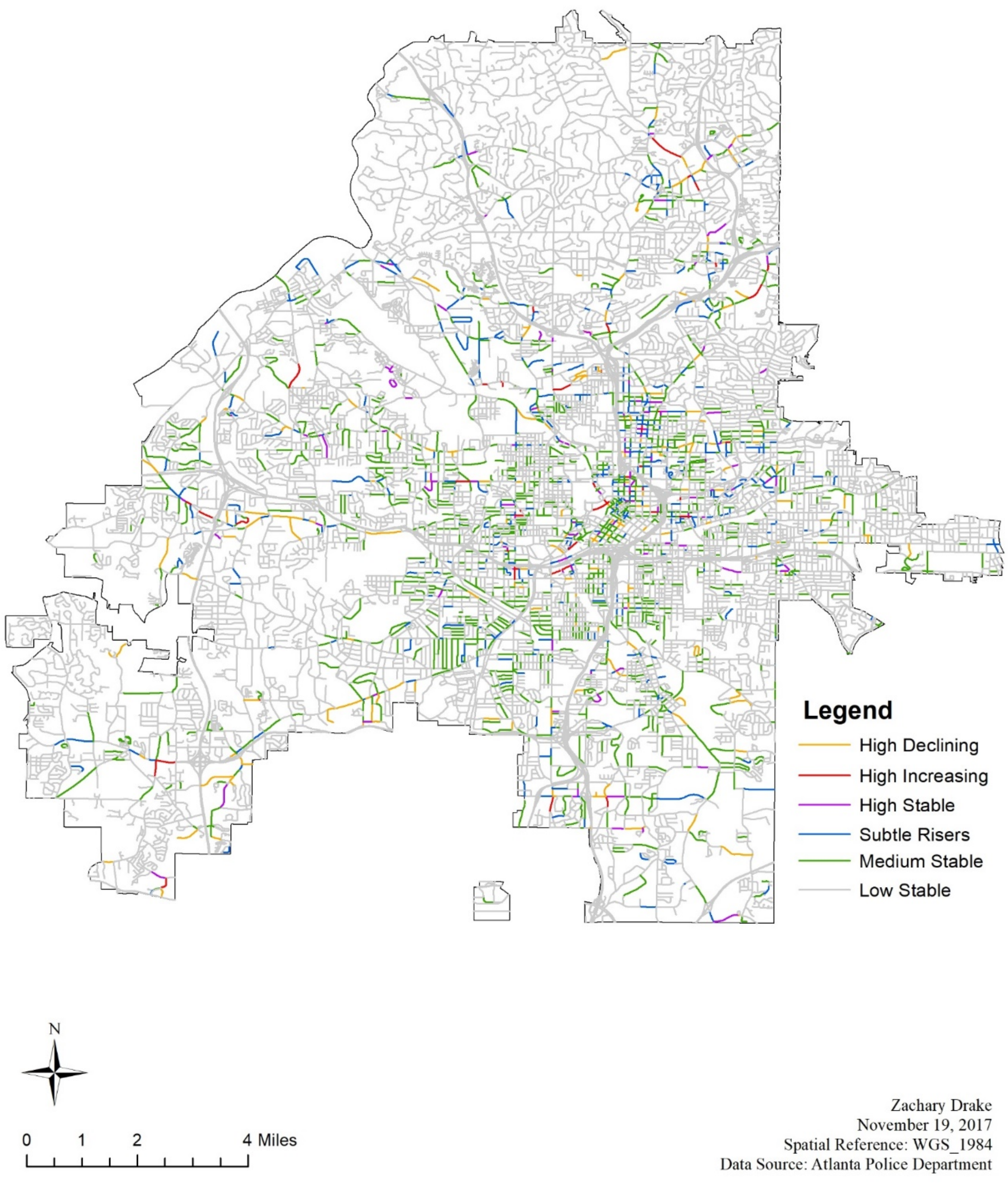

Figure 9: Map of Crime Concentrations in Atlanta

DISCUSSION

It is clear from these results that the remarkable evidence of the law of crime concentration at place is only continued by studying Atlanta. Atlanta does in fact see consistent levels of crime concentration at the 50 percent and 25 percent crime counts. However, there are a few important conclusions that can be drawn from this analysis that are useful for future research and adaptation by practitioners.

Table 10: Crime Concentrations Including Atlanta

City	***50% Crime Concentration***	***Unit of Analysis***	***Population Estimate (Estimation Year)***	***Type of Crime***
Vancouver, BC, Canada	7.8% (60%)	Street Segments	631,486 (2016)	General Crime; Calls for Service
Cincinnati, OH, USA	6.0%	Street Segments	298,165 (2014)	General Crime; Incident Reports
Tel Aviv-Yafo, Israel	5.6%	Street Segments	432,892 (2015)	General Crime; Incident Reports
New York, NY, USA	5.5%	Street Segments	8,491,000 (2014)	General Crime; Incident Reports
Seattle, WA, USA	5.1%	Street Segments	668,342 (2014)	General Crime; Incident Reports
Sacramento, CA, USA	4.2%	Street Segments	485,199 (2014)	General Crime; Incident Reports
Philadelphia, PA, USA	3.9%	Street Blocks	1,560,000 (2014)	Street Robberies; Incident Reports

Ventura, CA, USA	3.5%	Street Segments	109,484 (2014)	General Crime; Incident Reports
Minneapolis, MN, USA	3.3%	Addresses	407,207 (2014)	General Crime; Calls for Service
Atlanta, GA, USA	***3.1%***	***Street Segments***	***456,002 (2014)***	***Part 1 Crime; Incident Reports***
Redlands, CA, USA	2.1%	Street Segments	70,622 (2014)	General Crime; Incident Reports
Brooklyn Park, MN, USA	2.1%	Street Segments	78,728 (2014)	General Crime; Incident Reports

First and foremost, Atlanta comes in amongst the most concentrated cities in the chart presented previously. Table 10 shows Atlanta in comparison to the same table featured in the beginning of this paper. Atlanta is on the very low end of the scale that most of these studies fit into. Again, the units of analysis and types of crime vary, so the comparisons between crime concentration levels are not perfect. However, with some certainty we can say that crime is much more concentrated in Atlanta than most cities.

Gill et al. (2017) labeled Brooklyn Park, MN as a suburb, though Atlanta's density is almost identical and their concentrations are very similar. By all intents and purposes, Brooklyn Park, MN, is a suburb according to the authors of that study (Gill et al., 2017). Brooklyn Park serves as a home for commuters coming in and out of Minneapolis during the week. From a theoretical standpoint, it seems that there would be a lack of guardianship for many residences in Brooklyn Park during the day (Cohen and Felson, 1979). Atlanta is the opposite, as it serves to be the economic center of its metro area. Most people are commuting into Atlanta daily and then leaving at night. While routine activities theory can be used to draw conclusions about both, the concentration rates being similar is what is interesting to me. The dynamics of routine activities theory is wildly different for these two cities, yet the outcomes are similar. In Brooklyn Park, the researchers found that the crime tended to center around busy roads and in Atlanta I find the grid-like areas away from the highways to have the most crime (as evident by color on the map). It may be that Atlanta's residential neighborhoods are far more spread out like traditional suburbs, where as Brooklyn Park is close enough to Minneapolis and dense enough in its own right that it behaves more urban. The similarity between these two jurisdictions is really a demonstration about the diversity of what is a city and what is a suburb. Trends in crime concentration may not be able to be defined along city/suburb distinctions, especially if routine activities theory is used as the foundation for the explanation of concentration.

Atlanta resembles Vancouver and Albany in the fact that there is an overarching decline in crime rates across the city and the highest crime trajectory groups tended to follow a similar decline. (Curman et al., 2014; Wheeler et al., 2016). Curman et al., found 4 of their 7 trajectories to be decreasing. I find in Atlanta only 4 of 16 are substantially decreasing. Vancouver found that decreasing trajectories made up 30 percent of their street segments. Here, I have found that less than 1 percent of the street segments are declining. Yet both Atlanta and Vancouver see overall trends in decline. How can this be? It is likely that because Vancouver's crime is less concentrated than Atlanta's, that the change in crime rates overall was accomplished by crime reductions at many different sites. This would be why so many more street segments were declining. On the other hand, Atlanta had very tight concentration of crime. This means that the crime numbers were generated by a handful of very crime ridden street segments. Any change to these streets will see drastic impact to the overall crime rates, where in Vancouver changes at individual streets are less significant and therefore more changes are needed to make the impact.

This is a great demonstration of why trajectory analysis, or similar methods, are needed to truly examine the underlying trends of crime concentration. Simple analysis at the city-wide level would make one assume both Atlanta and Vancouver were experiencing the same thing. They did both experience large drops in crime with Vancouver’s around 40 percent (Curman et al., 2014) and Atlanta’s about 26.5 percent. But there is a very big difference in a few streets having a lot less crime and a lot of streets having a little less crime.

If crime is already evenly distributed, then normal changes over the years will alter the crime rates in small amounts. One would expect the crime trends to fall in this set up as modern life improves across the city on average. The police get a little better at prevention, place managers maintain newer buildings, technology catches up to security risks. In essence, guardianship is extended more easily (Cohen and Felson, 1979). These are normal progressions that should happen in a city like Vancouver or Atlanta. These changes will never be drastic but they may be enough to prevent a small number more crimes a year. If the crime problem is a result of a lot of streets with a few crimes, these changes reducing their respective streets crimes by small numbers add up to big changes in the city-wide totals.

However, for a highly concentrated city like Atlanta, a decline in crime rates could signal something a bit more drastic. This is most likely the result of a serious change on one of the high crime streets. It could be the building of new properties and corresponding changes in social and cultural factors (gentrification), change in the economic climate, etc. However, it is unlikely that a drop-in crime rates is just business as usual. Incremental changes to a city like this will see incremental changes to very high crime areas and incremental changes to very low crime areas, which sum to something very incremental.

Atlanta did have increasing groups as well though. This is something that Vancouver and Albany did not show. In Seattle, Weisburd et al. (2004) found three increasing trajectory groups. One of the groups increased by nearly 20 average crimes, one by approximately 15, one with subtle increases. This is similar to my findings in Atlanta. Only groups 7 and 14 showed real significant increases with 10 and 9 reflecting similar shapes to the least rising group in Seattle. Gill et al. (2017) also found two increasing groups, with only one being a significant change. One explanation for this is posed by Wheeler et al. (2016) when they argue the statistical power of the number of groups. Seattle, Brooklyn Park, and Atlanta are all done using more than 15 groups while Vancouver and Brooklyn Park are done with less than 10. The number of groups selected depends quite a bit of course on getting the models to converge at the higher numbers in a meaningful way, but there may be something to be said that the higher number of groups allows the detection of these subtly increasing trajectories. As for the sites themselves, it may also be possible that Vancouver and Albany simply did not have an increasing street.

The finding of increasing trajectories in these sites does reflect the benefit of microgeographic analysis. Vancouver and Albany find trajectories which closely follow the overall crime trends of the cities. The purpose of the trajectory analysis is to detect underlying trends in longitudinal data (Nagin, 2005). If overall crime is decreasing, and all trajectories are decreasing, then there is little reason to examine crime at a micro-geographic level. However, the finding of diverse trajectories like those found in Seattle (Weisburd et al., 2004) and now Atlanta demonstrate the multitude of patterns that can be occurring street by street, even when the overarching crime trends for the jurisdiction are decreasing. These underlying patterns are precisely why micro-geographic analysis of crime concentrations over time are important.

For the selected number of models there does not seem to be an initial pattern to the size of the city and the number of groups selected. This makes sense given that the number of groups used in a model reflects the underlying trends more than the data itself. Simpler models may be possible when crime distributions are more even. Since Seattle, Brooklyn Park, and Atlanta are all much tighter concentrations than Vancouver, and have over twice as many groups, it could be that high crime streets have more variability and therefore more groups are needed.

Table 11: Trajectory Studies Including Atlanta

City	*Population*	*Number of Groups in Model*
Seattle, WA	563,374	18
Vancouver, BC	578,041	7
Brooklyn Park, MN	78,000	18
Albany, NY	100,000	8
Atlanta, GA	456,002	16

As stated in the beginning of my paper, I only hope to begin the discussion of urban layout and crime concentrations. We can visually see in Figure 8 evidence of Hillier's (2008) argument. It seems that the more grid like streets of Atlanta's downtown have more crime and the more complex networks of the residential parts of Atlanta are low and stable in crime. There are key nuances here that maybe only one from Atlanta would recognize; specifically, the location of different types of residences. It is apparent from the map that the northwest and southwest Atlanta are predominantly housing subdivisions with complex single-entry roads and cul-de-sacs. This supports the defensible space argument quite well. These areas have the highest amount of low crime streets and therefore once could argue that the intricate street networks lead to the reduced crime (Newman, 1972).

However, what is less known is that the area east of downtown, where the indention on map points out, is also almost exclusively single family detached homes—a type of home that research has claimed should be at a greater risk (Hillier and Shu, 2002). These homes are laid out in a grid that defensible space theorists would argue is less safe.

But this region is still predominantly comprised of low crime streets. This then supports the argument made by Hiller and Sahbaz (2008) that traditional streets can be made just as safe if access points are limited and visibility is high.

Negating Hillier's argument, the downtown area is known for being the most densely populated and built up area. Hillier (2008) asserts that multi-dwelling buildings and more street level density should create safer streets. To be fair, the downtown and midtown sections of Atlanta contain mostly subtle risers; however, they are still very green with stable amounts of crime. Based on Hillier's argument, we would expect these places to be the safest. This reminds me that the human component of routine activities theory is equally as important as the environmental characteristics, and the interaction between people and their environment is key. For example, the downtown area likely attracts large numbers of people for different activities during the day, and a more transient population who may provide less consistent guardianship. Furthermore, the much larger population is moving in and out of the downtown area itself generates more opportunities for crime.

CONCLUSION AND FUTURE RESEARCH

The findings of my study provide strong evidence that Atlanta's crime concentrates in very similar manners to previous research in this field. In this study, I have added a new data point to the existing literature of trajectory analysis on crime concentrations. It is also more evident now that this method is necessary to detect underlying differences in crime concentrations between test sites. Future research should ensure to include temporal components in measuring crime concentrations which many do not.

I have also begun to scratch the surface of connecting urban layout to crime concentrations. This study has simply shown that there is room to incorporate environmental and urban layout theories at much deeper levels into crime and place research. Future analysis must consider more aspects of the physical city such as parcels, zoning, and street specifics to connect high crime streets to the concepts of urban layout and crime prevention.

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