UNDERSTANDING THE SPATIAL CONCENTRATION OF FATAL AND NON-FATAL SHOOTINGS THROUGH SOCIAL DISORGANIZATION AND COLLECTIVE EFFICACY THEORY

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Criminal Justice – Doctor of Philosophy

2018

ABSTRACT

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Firearm violence continues to plague American cities across the United States. For example, the overall homicide rate was 5.3 per 100,000 in 2016 (Federal Bureau of Investigation, 2016). More simply stated, over five people become victims of lethal violence per 100,000 people across the country. Research demonstrates that firearm violence is higher in areas of social disadvantage and clusters in neighborhoods with high levels of socioeconomic disadvantage (Cohen & Tita, 1999; Rosenfeld, Bray, Egley, 1999). Neighborhood and crime researchers have historically focused on the macro level of analysis when studying crime within and across neighborhoods, but more recent research displays that crime spatially clusters at the micro level (Braga et al., 2010, Weisburd et al., 2004). It is still unclear if specific measures of neighborhood characteristics, such as collective efficacy influences crime at the street segment level (Braga and Clark, 2014). Similarly, much firearm research is based on homicide incidents and omits more common non-fatal shootings. This study addresses these limitations by including both the macro (i.e., census tract) and micro (i.e., street segment) levels of analyses and includes both fatal and non-fatal shootings. Using the theoretical framework of social disorganization theory and collective efficacy theory, this research seeks to examine how fatal and non-fatal shootings cluster across neighborhoods, examine the patterns of disorder and disadvantage across neighborhoods and street segments, and improve the construct of collective efficacy through a unique measurement system.

The study examines over 1500 fatal and non-fatal shootings in Indianapolis, Indiana, over a three-year time period. Independent measures of neighborhood disadvantage are drawn from the US Census Bureau, as well as a unique dataset from the City of Indianapolis. The data measures for disorder and collective efficacy allow for analyses at the neighborhood and street segment level. Descriptive statistics explain where fatal and non-fatal shootings cluster across the city and generalized hierarchical linear modeling was conducted to explain how disorder, social disadvantage and collective efficacy correlate with firearm violence.

Results suggest fatal and non-fatal shootings cluster at both the neighborhood and street segment level and including non-fatal shootings into the study of gun violence gives a more robust picture of where firearm violence is occurring within the community. Additionally, community level measures vary at the street segment level when accounting for neighborhood levels of poverty. These findings have both methodological and policy implications that contribute to the study of communities and crime and firearm violence.

This dissertation is dedicated to Elena.
May you always believe in yourself and follow your dreams.

ACKNOWLEDGEMENTS

First, I want to thank my parents for always providing me endless love and support as I have pursued many dreams and goals throughout my life. From an early age you instilled in me that I could do anything I wanted in life with hard work and a positive attitude and that has proven true. I also want to thank my sister for being a wonderful supportive friend and listening to way too many research conversations over family dinners.

Secondly, I would like to thank my dissertation committee; Steve Chermak, Sheila Maxwell, and Sue Grady. Your thoughtful questions and guidance throughout my graduate years has made me a better scholar. There are not enough words to begin to thank my adviser, Ed McGarrell. I am forever grateful for your belief in me from day one, guidance throughout the dissertation process and unwavering support through some challenging times.

Lastly, none of this would have been possible without the love and support of my husband, Matt. Thank you for the countless drives to Michigan, numerous pep talks and for never letting me quit. And to my beautiful daughter, Elena – may this dissertation show you that anything in life is possible with hard work, persistence and a wonderful support network.

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Chapter 1: Introduction

Over the last three decades firearm-related violence has seen both dramatic increases and decreases that has left scholars searching for answers. The level of firearm related homicides reached an unprecedented high of 17,075 incidents in 1993 (Cook and Laub, 1998; 2002). Since the mid-nineties the number of firearm related homicides has steadily deceased with only 9,600 firearm homicides occurring in 2015 (Braga, Papachristos, & Hureau, 2010; Federal Bureau of Investigations, 2015). Although the number of firearm related homicides is still lower than the number in the early nineties, the number of gun related homicides in 2016 increased by 1,500 from the previous year (Federal Bureau of Investigations, 2013; 2016). Additionally, a report from the National Institute of Justice stated the homicide rate increased from 4.4 to 4.9 homicides per 100,000 citizens from 2014 to 2015, an 11.4 percent increase, and the largest increase over a one-period since 1968. The homicide rate has continued to increase by 8.2 percent from 2015 to 2016 (Rosenfeld, Gaston, Spivak, & Irazola, 2017). Over the years some scholars have attributed the increase in homicides to young minority males, areas of highly concentrated disadvantage, and places with high levels of crime, known as "hot spots" (Cook and Laub, 2002; Sherman et al., 1989; Weisburd, 2004). Undoubtedly, the variation in homicides and firearm related violence over the past two decades has kept scholars searching for theoretical explanations, methodological advances, and improved measures of key contextual variables that are known predictors of firearm and community violence.

Unfortunately, few studies have examined the spatial distribution of both fatal and non-fatal firearm violence, and when they have, they have not typically compared where fatal and non-fatal shootings cluster at the micro level of analysis. Little research exists on non-fatal shootings due to the lack of available data sources, and because homicide data are considered more reliable (Wellford 2003; Hipple, McGarrell, O'Brien, Huebner, 2016; Papachristos, Hureau

& Braga, 2013). Despite the dearth of literature on non-fatal shootings, Braga et al. (2010) found that gun assaults in Boston followed a similar pattern to homicide incidents over a 29-year period, but gun assaults were almost five times as prevalent as homicides. Similar results in Indianapolis suggest that non-fatal shootings are approximately four times as common as gun homicides (Hipple et al., 2016). Furthermore, Papachristos and colleagues argue that non-fatal shooting data are similar to homicides, and therefore are typically of higher quality than other official police data, since non-fatal shootings are more likely to be reported to police or emergency services (Papachristos et al., 2013). These findings suggest that a better understanding of both fatal and non-fatal shootings, and where they spatially cluster may provide better tests of theory and help improve policies and practice in the fight against firearm violence.

Criminologists have extensively studied neighborhoods and communities and found that place has an important role in understanding crime patterns (Shaw and McKay, 1942; Sampson, 1985; Bursik and Grasmick, 1993). Much of the place based research has been conducted at the neighborhood level due to the availability and access to official records (e.g., U.S. Census, registered voters, UCR data), that tend to be collected at the macro level. Typically, these represent administrative boundaries such as, U.S. Census tracts and block groups, police districts, and voting districts (Bursik and Grasmick, 1993; Weisburd et al., 2012; Braga and Clarke, 2014).

Although census blocks are considered administrative boundaries, and do not truly represent neighborhoods (Tienda and Stier, 1991), some previous research suggests census block groups make an appropriate unit of analysis due to their reasonably small size, and homogeneity (Klinger, Rosenfeld, Isom, and Deckard, 2016; Rosenfeld, Bray, and Egley, 1999; Taylor, 1997). In contrast and increasingly, other scholars suggest disaggregating the data into small micro places or street segments (Sherman and Weisburd, 1995; Braga, Papachristos, Hureau, 2010; Weisburd, Morris, and Groff, 2009), as there is strong evidence that crime concentrates in a small number of micro places, such as clusters of street segments, groups of street blocks, and intersections (Sherman, et al., 1989; Weisburd, Bernasco, and Bruinsma, 2009). Conversely, Sampson, Morenoff, and Gannon-Rowely (2002) suggest that unit of analysis may not be all that important as one can understand patterns of social class, race, and family in local communities at multiple geographic levels of analysis (i.e., political districts, census tracts, or other neighborhood areas).

Notwithstanding the research scholars have conducted on communities and crime, there are still unanswered questions regarding the best conceptualization of neighborhood, the appropriate level of analysis, and the appropriate measures of social disorganization theory. Weisburd and colleagues demonstrated that crime concentrates on a few street segments in both high and low disadvantaged neighborhoods, and that the high crime street segments possess different characteristics than the low crime street segments (Weisburd et al., 2012). These findings suggest that exclusively studying neighborhoods at the macro level can miss certain crime drivers that vary from street to street. Further, it is still unclear if specific measures of neighborhood characteristics, such as collective efficacy can adequately explain clusters of crime over time at the micro level, and if increasing collective efficacy can reduce crime concentrations on street segments (Braga and Clarke, 2014). This study seeks to close these gaps by examining improved measures of collective efficacy at <u>both</u> macro (i.e., census tract) and micro levels (i.e., street segments) of neighborhoods.

Linking firearms research with advances in the spatial dimensions of crime and violence is at the core of this study. Specifically, this research seeks to make contributions to our understanding of firearms violence as well as to our understanding of the relationship between community characteristics and firearms violence. This research examines the spatial clustering of fatal and non-fatal shootings to determine if they follow similar patterns of previous research that analyzed homicides in social disadvantaged neighborhoods. These spatial patterns are then examined using multiple community characteristics and measured through multiple levels of analysis (e.g., macro and micro).

The next chapter will review the historical context of research on a number of relevant concepts that will be examined during this study. The chapter will begin by reviewing pertinent literature on firearm violence, by discussing individual characteristics, of both victims and offenders, the importance of the victim-offender overlap, and the level of increased risk of victimization based on lifestyle behaviors and social network. The chapter will also review relevant studies that examine the spatial patterns of firearm violence that are conducted at the macro level of analysis (e.g., community level), and progress down Taylor's cone of resolution (1997) to the micro level of analysis (e.g., the street segment). Chapter 3 will review the theoretical foundations of the study and key concepts. The section will begin by reviewing social disorganization theory; the historical context of the theory, the strengths and weaknesses of the theory, and a number of applicable empirical studies will be discussed. Lastly, the chapter will review how the key theoretical concepts of physical disorder, social disorder, and collective efficacy are commonly measured in empirical studies. The strengths and weakness of social disorganization, the key concepts of the theory, and how this study expands the current understanding of firearm violence, social disorganization theory, and collective efficacy will also be discussed.

Following Chapter 3, Chapter 4 will present the current study. An overview of the study site will be presented, a description of the data sources, along with research questions and the methodological design for addressing these questions. Chapter 5 will describe the data that comprise each measure, and the analytic strategy that will guide this study. Chapter 6 displays the results from the analyses and Chapter 7 will include a discussion of the findings, methodological and theoretical implications, limitations, and future research directions.

Chapter 2: Firearms Violence

Not all homicides are committed with a firearm, and furthermore homicides are considered rare events (Wellford et al., 2005). As Wellford et al. (2005) stated in the report of the Committee on Improving Research Information and Data on Firearms, “no authoritative source of information exists to provide representative, accurate, complete, timely, and detailed data on the incident and characteristics of firearm-related violence in the United States (p.20).” Recent studies in Chicago, Boston, Newark, Rochester, and Indianapolis, that examine non-fatal shootings, obtain their data from a specific shooting database kept by the individual police department or prospectively collected their own data. This is not a common practice across police departments and obtaining these data from police records management systems has proven problematic, labor intensive, and time consuming (Hipple, McGarrell, O’Brien, and Huebner, 2016).

There are national databases that collect data on gun violence. The Federal Bureau of Investigation (FBI) Uniform Crime Reports (UCR) is the most commonly used. The problem with using UCR data to study non-fatal shootings, is that non-fatal shootings are not an official crime category within the reporting measures. UCR data has very specific definitions for each crime category and operates under the UCR Hierarchy Rule, which indicates that each crime incident can only have one label, and that label must be the more serious crime that occurred (Federal Bureau of Investigation, 2004). This is problematic in measuring non-fatal shootings, because if a person is shot during the act of a robbery, the incident according to UCR standards needs to be categorized as a robbery, not an aggravated assault, and that non-fatal shooting is therefore “lost” since UCR is based on incident titles. For example, if you were to go to the FBI’s website to obtain data on robberies, you would have no idea that person was shot during that incident. Further, since non-fatal shootings are not a stand-alone crime category in UCR, one cannot measure non-fatal shootings from the category aggravated-assault gun either, as a person could simply point a gun at the victim for it to count as an aggravated-assault gun. The National Crime Victimization survey (NCVS) and National Incident-Based Reporting System (NIBRS) are other national databases of victimizations but the NCVS has its own measurement issues and NIBRS only covers 16 percent of the population (Wellford et al., 2005).

Due to the lack of data sources on non-fatal shootings, there is a dearth of research surrounding the topic. This is mostly due to the ease of access to homicide data, and that homicide data are considered more valid than other crime types, as police are more likely to be notified about a dead body (Black, 1970; Jackson, 1990), and homicide data are not plagued by the "dark figure" of crime (i.e., unreported), as are other offense types. However, homicides do not tell the complete picture of violence, much less firearm violence. Not all violent encounters are fatal, for example, research out of Boston suggest that non-fatal shootings are almost five times as prevalent as homicides (Braga, Papachristos, and Hureau, 2010). In other cities such as Galveston, Texas and Seattle, Washington, the ratio of fatal to non-fatal gun injuries was as high as 8 to 1 in Galveston, and as low as 3 to 1 in Seattle, respectively (Kellerman, 1996). More recent research by Hipple and Magee (2017) in Indianapolis, report almost four times the number of non-fatal shooting victims, as homicide victims. A goal of the current research study is to better understand the difference and relationship between fatal and non-fatal shootings, therefore, this section will begin by highlighting previous research on homicide victimization, the victim-offender overlap, the level of increased risk of victimization based on lifestyle behaviors and social networks, situational characteristics and spatial patterns of homicides, and recent work on non-fatal shootings. The section will end by describing the limitations to the current firearm violence literature, and how this research will expand the current theoretical and empirical understanding of firearm violence.

Demographic Characteristics

One of the classic studies in criminology is Marvin Wolfgang's (1958) revolutionary study on homicides in the 1940s. He analyzed approximately 600 homicides in Philadelphia and concluded that many of the homicides victims are of low socioeconomic status. His results also revealed that young, African American males, appeared as both victims and suspects, at disproportionally higher rates than other demographic groups. Other studies explored individual demographics and behaviors when examining patterns of criminal victimization. Research by Blaser and colleagues (1984) examined the arrest histories of homicide victims and found that victims of homicides were over 10 times more likely to have a previous encounter with law enforcement than victims of non-fatal violence. Kellerman and colleagues (1993) also found that homicide victims were more likely to have a previous arrest record than non-fatal victims, but the effect was only 3.5 times higher. Another study by Dobrin (2001) examined a sample of homicide victims and non-homicide victims through a case control study in Maryland. He found that homicide victims are ten times more likely to be arrested than non-victims, and that each arrest increases an individual's odds of getting killed by almost two times.

When examining the victim-offender overlap, Broidy and colleagues (2006) examined demographic, structural, and behavioral measures in homicide victims and offenders in New Mexico over a six-year time period. Their results suggest there is a significant overlap of offenders and victims, as both groups engage in similar lifestyle activities. However, their findings also indicate that the majority (54 %) of homicide victims do not have a prior arrest history, and nearly half of the homicide offenders (43%) also do not have a prior arrest history.

These findings suggest that there are differences within homicide victim populations. In a post hoc subgroup analysis of victims without an arrest history, they found the victims to be older, less likely to be male, and more likely to be white, compared to victims in the victim-offender group. The authors suggest these differences are due to a variation in risk based on lifestyle choices, behaviors, and neighborhood context. Additional research, by Pizarro, Zgoba, and Jennings (2011) examined the interaction between victims and offenders using homicide data over a ten-year period in Newark, New Jersey. The results suggest the majority of both homicide victims (75%) and offenders (87%) are engaged in a criminal lifestyle, and there are two types of victims and offenders – less criminally involved and more criminally involved. These findings suggest that victims and offenders are similar and are perhaps at the same level of risk in regards to violent victimization.

To summarize this section on the demographic makeup of homicides, victims and offenders tend to be young, minority males, who have past involvement with the criminal justice system. Over the years, scholars have attributed the increased risk to young, minority males to specific lifestyle measures, and behavioral situations that place these individuals at a greater risk of being involved in violence compared to similar populations. In criminology, scholars have attempted to explain and understand who is at a greater risk based on lifestyle measures, network exposure (i.e., who you hang out with), and an individual's risk based on location (i.e., neighborhood). The following sections will review key theoretical themes and empirical research that examines risk of involvement in firearm violence.

Lifestyle and Network Measures

Lifestyle measures help explain the risk factors that increase a person's likelihood of being involved in a crime. Hindelang, Gottfredson, and Garofalo (1978) developed lifestyle theory, and argued that certain individuals and groups are more at risk for victimization than others based on exposure to high-risk places and people. The theory contends that the way individuals spend their time can have a direct effect on their risks of victimization. They found that the more time a person spent in public places, especially in the evening, the more at risk they were to victimization (Hindelang et al., 1978). They also found that individuals who were more likely to be involved in a crime, as either a victim or suspect, hung out with others who shared a similar lifestyle. Therefore, individuals who associate with people who live a high-risk lifestyle increase their odds of victimization based solely on their contacts and their activities. The key tenets of lifestyle theory are supported in the victim-offender overlap research previously discussed by Broidy et al. (2006) and Pizzaro et al. (2011).

Other scholars have examined an increased risk to firearm violence using social contagion theory, which like lifestyle theory connects people based on social behaviors and peer influence. Social contagion theory contends that violence is transmitted much like a disease through a social process due to its reciprocal natures (Loftin, 1986), and that peers within the same network have influence over each other, and will follow each other's social cues (Burt, 1987). Papachristos and colleagues have pioneered this area of research by examining fatal and non-fatal shooting victimizations in Boston, Chicago, and Newark, New Jersey using social network analysis. The results resoundingly suggest that firearm violence is highly concentrated within networks of people who are engaged in illegal activities and participate in risky lifestyle behaviors.

For example, research by Papachristos and colleagues in Boston's Cape Verdean community examined the social network of victims of firearm violence. They studied 763 individuals who were documented together through police field interview cards over a year period, and then coded which individuals were victims of fatal or non-fatal gunshot wounds. Results display that 40 individuals, approximately five percent of the total network were victims of gun violence. Their findings suggest that 85 percent of all the firearm injuries are connected in a single network, and a person's risk of becoming a gunshot victim decreases with every "handshake" or connection away from a shooting victim (Papachristos et al, 2012). Additional research in Chicago, examined co-arrest data over a six-year time period, and found that non-fatal firearm injuries are highly concentrated. Additionally, approximately 70 percent of all gun violence victims are identified within these co-offending networks, and 89 percent of those victims are all contained within a single component (i.e., subgroup) of the entire network (Papachristos, Wildeman, Roberto, 2015). These results suggest that individuals who are engaged in criminal lifestyles (i.e., become arrested) are more at risk of becoming victims of firearm violence, and supports previous research that demonstrates that victims and offenders are one in the same, and that victims often become offenders, and offenders often become victims (Broidy et al., 2006; Pizzarro et al., 2011). Furthermore, the majority of individuals within these networks are young, minority males, who are known to be most at risk for firearm victimization based on previous research (Wolfgang, 1948; Dorbin, 2001; Pizzaro et al., 2011).

More recently, researchers examined the social proximity of a gang member within a co-offending network to determine the risk of gunshot victimization. Using co-arrest, quality of life violations, and field interrogation records, researchers created a co-offending network of 10,531 individuals in Newark, New Jersey, over a one-year time period. Approximately seven percent of the network was identified as gang members through official police records, and less than four percent of the network were victims of fatal or non-fatal gun violence. The results suggest an individual's risk of gunshot victimization increases the closer one is to a gang member or decreases the further away one is to a gang member. More specifically, being directly connected to a gang member increases an individual's risk of victimization by 94 percent (Papachristos, Braga, Piza, Grossman, 2015). Although the current study does not examine gang membership or gang members, previous studies do suggest that gangs are a form of social disorder within a neighborhood (Skogan, 1990), therefore gangs could be an important factor when examining social disorganization and firearm violence.

Situational Factors

In addition to individual demographics, behavioral characteristics, and social networks, scholars have examined the contextual and social characteristics of firearm violence through an adversary effects hypothesis. The adversary effects model contends that victim and incident characteristics can determine if an offender chooses to use lethal force during an assault. They further argue that violence is purposive, lethal outcomes are related to the offender intent, and that the offender intent can be systematically related to other features of the incident (i.e., neighborhood) (Felson and Messner, 1996). Therefore, the spatial location of the firearm incident can be extremely important in understanding contextual factors of firearm violence.

Research by Lauritsen and White (2001) contends that an individual's risk for violence can be influenced by neighborhood disadvantage. They found that people who lived in disadvantaged neighborhoods, no matter their race (Blacks, whites, and Latinos), had a greater risk of being a victim of stranger and non-stranger violence. Work by Fagan and Wilkinson (1998) suggest that the number of individuals carrying firearms increased due to the high number of gun assaults in urban, disadvantaged neighborhoods. Additional research by Baumer and colleagues suggest assaults that occur in socially disadvantaged neighborhoods are more likely to be committed with a firearm (Baumer, Horney, Felson, & Lauritsen, 2003), and that adversary effects in urban settings can lead to more lethal outcomes (Felson and Pare, 2010).

Anderson (1999) argues that violence may be more prevalent in socially disadvantage neighborhoods, due to a need for respect, and a feeling of hopelessness and alienation among the African American community, mostly due to unemployment and racism. Anderson (1999) extended lifestyle theory when he observed the social context of an inner city African American community. He argued that inner city violence is due to a search for respect, and this search often leads to committing acts of violence, to ensure a person does not feel disrespected. This lifestyle, or "code of the street" may lead to more violence, since residents adopt a no snitching, aggressive lifestyle to potentially prevent future victimization (p.10).

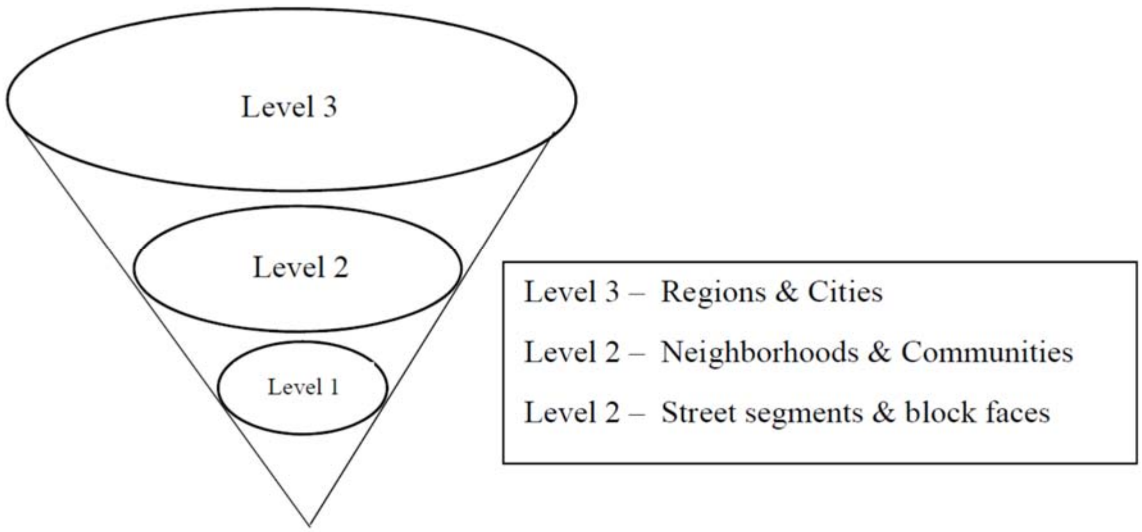
Previous research aligns with Anderson's theory, and demonstrates that homicides are commonly retaliatory in nature, individuals involved in homicides know one another (Block, 1977; Reiss and Roth, 1993), and that a homicide in one neighborhood may result in a homicide in another neighborhood due to retaliation (Morenoff et al., 2001; Braga et al., 2010). Further, the number of retaliatory shootings that cross neighborhood boundaries may be even greater regarding non-fatal shootings, as a non-fatal shooting leaves behind a victim, who is likely motivated to engage in violence, in order to retaliate their victimization (Huebner, Martin, Moule Jr, Pyrooz, and Decker, 2016). The research on retaliatory shootings suggest the importance of extending this spatial analysis to both fatal and non-fatal shootings and is important in order to break the continuous cycle of violence in socially disadvantaged neighborhoods.

Spatial Patterns of Crime

Historically, scholars began studying the relationship between crime and place in the 1830s, when Andre-Michael Guerry examined crime across France, and determined that certain social behaviors (i.e., education and income), and crime occurred disproportionately across place and time (Sampson, 2012). Over the years scholars have studied communities and crime (Shaw and McKay, 1942; Bursik and Grasmick, 1993; Sampson et al., 1997; McGarrell, Giacomazzi, & Thurman, 1997), and have examined the relationship between crime and place at multiple levels of analysis. It has only been over the last two decades, through a number of empirical studies, that scholars began to demonstrate how crime clusters at smaller - micro places, and that crime remains fairly stable over time.

Taylor (1997) describes a 'cone of resolution' to understand the relationship between crime and place at different levels of analysis. He argues that the spatial patterns can vary as you move down the cone to smaller units of analysis. He explains the cone, as more of a funnel, moving from larger macro levels of analysis (e.g., regions), to smaller units of analysis (e.g., communities or neighborhoods), down to micro units of analysis (e.g., hot spots within communities). He argues over the last century scholars began focusing more on smaller units of analysis out of frustration, due to a lack of results at a larger unit of analysis, the development of better computer systems (e.g., crime mapping), and a better theoretical understanding of the link between crime and place. The following sections will describe previous research following Taylor's funnel of analysis and begin by reviewing region and community level studies of crime, and move to smaller, more micro area studies of violence. The review of the micro place research is not isolated to those studies that examine firearm violence, as there is limited research in this area. It is important to discuss the historical context of micro place-based research, that examines other outcome measures, such as; violent crime, all crime incidents, 911 calls for service, and arrests, as they have important theoretical and empirical understandings that lay the ground work for the current study. The current research study hopes to build a better understanding of how firearm violence varies at smaller levels of analysis and contribute to the ever-growing empirical research on crime and place.

Figure 1: Framework for theories of crime and place



Macro-Level Studies of Crime

As noted in the previous section, homicide incidents are known to affect people of lower socioeconomic status, and minorities, therefore, a number of scholars have attempted to understand the spatial patterns of homicides across counties, cities, and neighborhoods. Bullock (1955) examined homicides in Houston, Texas over a four-year time period during the 1940s. He found that over 40 percent of homicide incidents occurred within a city block of the offender's home, and almost 75 percent occurred within two miles of the offender's residence.

Much more recent research by Messner and colleagues (1999) examined the spatial diffusion of homicides across 78 counties in, or around, the city of St. Louis. Their results revealed that homicides were not randomly distributed across counties and displayed evidence of diffusion across counties. They also suggest that affluent and rural counties may serve as barriers that prevent homicides from dispersing into an area (Messner, Anselin, Baller, Hawkins, Deane,

& Tolnay, 1999). Further research by, Cohen and Tita (1999) examined the spatial diffusion of homicides in Pittsburgh, over a four-year time period. They explored the movement of homicides across neighborhoods using U.S. census tracts. Similar research by Rosenfeld, Bray, and Egley (1999) examined the distribution of gang homicides across U.S. census blocks in St. Louis. Both studies found strong spatial associations between high levels of disadvantage, minority populations, and higher rates of homicides (Cohen & Tita, 1999; Rosenfeld et al., 1999).

Additional research by Morenoff, Sampson, and Raudenbush (2001) confirmed previous findings and demonstrated that homicides were not randomly distributed across the city of Chicago. They found that concentrated disadvantage combined with low collective efficacy, predicted a higher number of homicide incidents, and that there is a strong spatial association between collective efficacy and homicides. They concluded that neighborhood organizations and informal friendship networks promote collective efficacy.

Other scholars have sought to understand the movement of homicides across space, and over extended time periods. For example, recent research by Zeoli and colleagues (2014) examined the spread of homicides as an infectious disease, over a 26-year time period, in Newark, New Jersey. They used firearms and gangs as the infectious agents, and census tracts as the unit of analysis. The results suggest firearm and gang homicides spread in spatial and temporal patterns across the city, and other areas remained untouched by homicide clusters. Their findings also suggest that the spread of homicides is aided by economic disadvantage and racial isolation (Zeoli, Pizarro, Grady, Melde, 2014).

Zeoli and colleagues (2015) extended this research by examining the spatiotemporal patterns of homicide clusters by motive in Newark, over a ten-year period. They found homicide incidents motivated by non-intimate familial conflict, escalating disputes, revenge, and drugs displayed significant clusters, but gang motivated homicides were the only incidents that displayed spatiotemporal movement. They did find a spatiotemporal overlap of gang, drug and revenge motivated homicides, which were the most likely categories to be committed with a firearm.

Micro-Level Studies of Crime

Criminologists began examining crime and place at smaller geographic areas such as street segments and addresses, due to advances in technology and theoretical understandings of crime and place (Taylor, 1997). Revolutionary research in Minneapolis, Minnesota examined calls for service across 115,000 places (streets and addresses) and found that only five percent of the city addresses were responsible for over half of the city's police calls for service. They concluded that crime was concentrated in specific areas, and not randomly distributed across place, as previously thought (Sherman, Gartin, & Buerger, 1989).

Following this groundbreaking study, a series of place based studies began exploring the distribution of crime at places, and over time. Weisburd, Bushway, Lum and Yang (2004), examined street segments over a 14-year period using group-based trajectory models using official crime data from the city of Seattle. They found that crime within these concentrated areas remained fairly stable over time. Additional research by Weisburd and colleagues (2009) explored the patterns of juvenile offending. They conducted a longitudinal study of juvenile arrests in Seattle over a 14-year time period. Using the street segment as the unit of analysis, they found that juvenile arrests are highly concentrated, and just 86 street segments produced 1/3 of the crime incidents when a juvenile was arrested (Weisburd, Morris, Groff, 2009). Recently, scholars have replicated the study of crime and place using group-based trajectory models in Vancouver, British Columbia (Curman, Andresen, & Brantingham, 2015), and Albany, New

York (Wheeler, Worden & McLean, 2016). Both studies found a disproportionate number of street segments contributed to the total level of crime, as previously found by Weisburd et al. (2004, 2009), but the temporal trends decreased over time (Curman et al., 2015; Wheeler et al., 2016). These results suggest more research is needed in regards to concentrations of crime at the street segment level of analysis over time.

Research in Boston extended the findings of micro-places over time to violent crime. Braga and colleagues examined trends in gun assault incidents and robberies at the street segment and intersections over a 29-year period (Braga, Papachristos and Hureau, 2010; Braga, Hureau, Papachristos, 2011). Their findings demonstrate over half of the commercial robberies, and two-thirds of streets robberies occurred on only eight percent of the street segments. Gun assaults were even more concentrated with 75 percent occurring on 5 percent of the city's street segments (Braga et al., 2010, 2011). Koper and colleagues also examined shootings at the micro level and found approximately eight percent of the street segments accounted for 64 percent of the shootings in Minneapolis. Higher numbers of shootings were even more concentrated, for example, only 2.8 percent of the city's streets experienced more than ten shootings over the 24-year period, accounting for more than 30 percent of the total number of shootings (Koper, Egge, and Lum, 2015).

Some scholars have examined street segments nested within larger geographic units. For example, Andreson and Malleson (2011) used a spatial pattern test that identifies the similarity in spatial point patterns and to test the stability of crime patterns from census tracts, to census blocks, down to street segments, which is similar to Taylor's (1997) cone of resolution concept. Using police calls for service over a 10-year time span, the authors find that the spatial pattern of crime is stable over time when using the street segment as the unit of analysis. However, an ecological fallacy is present when data are aggregated to the census level, and the problem street segments are what is driving the change for the higher geographic units. Therefore, the authors argue that when using social disorganization theory, the neighborhood is no longer the appropriate unit of analysis to understand the spatial distribution of crime (Andreson & Malleson, 2011).

More recently, Schnell and colleagues replicated a study by Steenbeek and Weisburd (2015) from The Hague, Netherlands, which demonstrated that street segments, accounted for the largest proportion of spatial variability in violent crime, compared to the neighborhood unit of analysis. Schnell, Braga, and Piza (2017) analyzed violent crime incidents across street segments, nested within neighborhoods across Chicago. They found similar results to Steenbeek and Weisburd and suggest that over 50 percent of the total variability in violent crime incidents can be attributed to street segments. They conclude that scholars interested in studying crime and place should focus on micro places and utilize a hierarchical method to understand the variation within different levels of analysis (Schnell et al., 2017).

To summarize the section on spatial patterns of violence, research demonstrates that there are strong spatial associations between higher levels of disadvantage and racial isolation at the macro level of analysis (Cohen & Tita, 1999; Rosenfeld et al., 1999; Zeoli et al., 2014). Additionally, micro level research reveals that crime concentrates on a disproportionate number of street segments and remains fairly stable over time (Weisburd et al., 2009, 2014), although recent research finds temporal trends decrease over time (Curman et al., 2015; Wheeler et al., 2016). Of the few studies that examined street segments nested within larger neighborhood units, they found that the majority of the variability of violent crime and overall crime can be attributed to street segments, and that the problem street segments are what drive the crime rates when aggregated to the neighborhood level (Andreson & Mallenson, 2011; Schell et al., 2017). These findings suggest future research needs to explore how micro places attribute to the variation of crime across neighborhoods, which is one of the main objectives of this dissertation research.

Non-fatal Shootings

The above sections highlight the demographic characteristics, lifestyle and network characteristics, situational characteristics, and spatial patterns of homicides, of those at greatest risk of firearm victimization, based on lifestyle behaviors and neighborhood context. As previously stated, the majority of the current firearm research surrounds homicide data, which occur much less frequently than non-fatal shootings (Kellerman, 1996; Hipple & Magee, 2017). Despite the dearth of historical research on non-fatal shootings, there has been an increase in empirical research over the past few years. The recent work has integrated concepts from the public health field and has explored individual and situational factors of non-fatal shootings, specifically examining the location and severity of the gunshot wound.

For example, Grommon and Rydberg (2015) examined a sample of non-fatal shooting victims, utilizing a unique dataset that measured multiple indicators of the severity of the firearm injury. They measured individual and incident characteristics (victim demographics, number of offenders, victim-offender relationship, incident type, time of day, and private or public), and medical response characteristics (multiple gunshot wounds, method of transport and distance to hospital).Their findings suggest that older victims, known suspects, and victims who refused to cooperate with police were more likely to suffer from critical firearm injuries, than other victims of non-fatal shootings (Grommon & Rydberg, 2015). This research highlights the importance of the victim-offender relationship and suggest that victims who know their attacker are more likely to suffer a more severe gunshot wound. This finding is similar to the research by Papachristos and colleagues that examine individuals increased risk of a firearm injury based on one's associates (Papachristos et al., 2012, 2015).

Additionally, two studies out of Rochester, New York and Indianapolis, Indiana examined both fatal and non-fatal shootings across a number of contextual, social and individual characteristics. The study in Rochester examined 580 shooting incidents over a four year period. They measured how shooting outcomes can vary by the number of shots fired, where and how the victim was hit with a bullet, and if the shooting was fatal. The findings suggest the number of times the victim is hit, the number of shots fired, and other adversary effects contribute to lethal gun violence. For example, fatal outcomes were higher in black victims who were carrying a weapon, but this positive effect on fatality was lost when the weapon was removed (Altheimer, Schaible, Klofas, Comeau, 2016). Their results also suggest that younger victims are more likely to survive a gunshot wound, even when controlling for wound location. Additionally, drug-related shootings increased the odds of a victim being shot in the head, shot multiple times, and fatally being shot (Altheimer et al., 2016).

The Indianapolis study examined 776 fatal and non-fatal shooting victims over an 18-month period. The findings demonstrate that fatal and non-fatal shooting victims differ based on age, the severity of their injuries, and incident motive. Specifically, non-fatal victims are almost five years younger than gun homicide victims, and victims of retaliation/revenge and drug related shootings were more likely to suffer a more serious injury (Hipple & Magee, 2017). These findings are similar to those from the Rochester study (Altheimer et al., 2016), and suggest that age and motive are important in understanding and predicting fatal and non-fatal outcomes. Both studies argue that younger victims are physically more resilient and are able to survive gunshot wounds simply due to being stronger and healthier. Additionally, both studies speak to the situational factors (i.e., motive), as an important factor in understanding fatal and non-fatal firearm violence (Altheimer et al., 2016; Hipple & Magee, 2017).

Although these studies have important developments in examining both fatal and non-fatal shootings, they still leave a number of unanswered questions. Specifically, none of these studies examined the spatial location or pattern of fatal or non-fatal shootings, as it is plausible that individual and situational characteristics may vary based on neighborhoods. Therefore, this study seeks to close this gap by examining the spatial distribution of both fatal and non-fatal shootings across an urban environment.

Limitations of Previous Research

There are several limitations to the research described above. One – the majority of studies only examine homicides, due to the lack of available data on non-fatal shootings. However, the majority of this research lacks information on victims who do not die as a result of their injury, which as previously stated, non-fatal incidents can be as high as five times the number of victims who perish. Additionally, these homicide studies include all methods of death (e.g., stabbing, blunt object), and are not isolated to firearm related homicides.

The second limitation is in regards to examining the spatial distribution of firearm violence. The majority of studies that examine the spatial patterns of homicides, have been conducted at the macro level of analysis (Messner et al., 1999; Cohen & Tita, 1999; Rosenfeld et al., 1999; Zeoli et al., 2014, 2015). The studies that have examined crime at a more micro level of analysis, have generally used calls for service, crime incident, or arrest data (Sherman et al., 1989; Weisburd et al., 2004, 2009), which does not isolate where specific firearm violence is occurring. Of the two studies (Braga et al., 2010; Koper et al., 2015) that do examine shootings at the micro level of analysis, only one includes fatal shootings. Recently scholars have examined crime across multiple units of analysis (i.e., neighborhood and street segment) using hierarchical modeling (Andreson & Malleson, 2011; Steenbeek & Weisburd, 2015; Schnell et al., 2017), but these studies have used broader violent crime categories, which does not isolate the spatial distribution of fatal and non-fatal shootings. This research study closes that gap in knowledge by utilizing spatial analyses to understand the variation in fatal and non-fatal shootings at multiple levels of analysis.

Due to the limited availability of non-fatal shooting data and the dearth of literature on the topic, this research study adds valuable insight into both firearm homicides and non-fatal shootings, to help expand the current theoretical understandings and policy implications. As it is plausible that better gun violence prevention policies are missing from current knowledge due to the lack of research on non-fatal shootings. Therefore, this study examines the differences and similarities of firearm homicides and non-fatal shooting incidents, how the incidents spatially cluster across space, and their relationship to the neighborhood context of collective efficacy and disorder. Additionally, this research on fatal and non-fatal shootings extends the current understanding of firearm violence by linking this to theoretical and methodological research on communities and crime, which will be outlined in the next chapter.

Chapter 3: Theoretical Foundations and Measuring Key Concepts

Social disorganization theory developed through the work of Shaw and McKay in the 1940s, and their research draws heavily from the Chicago School theorists. Shaw and McKay advanced the research of Park and Burgess (1925) on human ecology, and the concentric zone theory to include crime. The concentric zone theory contends that cities are divided into five areas or zones that correspond with levels of social organization and disorganization (Park and Burgess, 1925). Shaw and McKay's primary interest was to understand if neighborhood demographics or the structural characteristics (e.g., poverty, residential stability, low education) explained variation in juvenile delinquency. Their results displayed the ethnic makeup of the neighborhood was not associated with delinquency rates, but high residential mobility, poverty, and population heterogeneity were positively associated with crime (Weisburd et al., 2016). Therefore, Shaw and McKay concluded through their theory of social disorganization, that neighborhoods with physical disorder, poverty, and heterogeneity typically are also the neighborhoods with the highest levels of violence (Tibbetts, 2015). The theory further contends that neighborhoods with high levels of poverty often lacks resources for citizens to invest back in to their community, and therefore disorder is prevalent (Bursik and Grasmick, 1993; Sampson and Groves, 1989). Additionally, residents are unable to form informal networks due to residential instability, and therefore are not able to regulate neighborhood behavior themselves, due to the lack of social control. Lastly, neighborhoods with high levels of ethnic heterogeneity make it hard for residents to identify with each other, and consequently informal friendships are not developed (Bursik and Grasmick, 1993; Sampson and Groves, 1989).

The theory further developed post Shaw and McKay's work to contend that the difference between a socially organized community and a disorganized community is dependent on community solidarity, cohesion, and integration, as these constructs either cultivate or inhibit informal social control (Kubrin, Stucky, and Krohn, 2009). Informal social control is when a neighborhood collectively comes together to address local problems (Shaw and McKay, 1942). Consequently, communities with strong informal social control care about their communities and come together to take social action, whereas, socially disorganized communities lack this collectiveness among residents, are less able to regulate behavior, and therefore experience higher rates of crime.

Social disorganization theory further developed into the systemic model, which is a complex model of "friendship and kinship networks and formal and informal associational ties rooted in family life and on-going socialization processes" (Kasarda and Janowitz, 1974, p. 329). Additional work by Bursik and Grasmick (1993) identified formal and informal relationships of social control into three categories; private (e.g., close friendships), parochial (e.g., informal peer groups), and public (e.g., groups and formal institutions outside the neighborhood). They suggest it is through these networks that individuals within communities are able to come together and organize their neighborhood.

Support for the interactional network notion (Bursik, 2000) of social disorganization theory was found through Sampson and Groves' 1989 study using data on 238 communities from the British National Crime survey. This was the first true test of social disorganization theory and their results supported the theory and indicated that neighborhoods with higher levels of informal social control experience lower levels of crime, and structural characteristics (e.g., poverty, residential stability, heterogeneity) of neighborhoods have a direct effect on the rate of crime within a neighborhood. They further contend that social disorganization theory can explain variations in neighborhood crime rates at the macro level (Sampson and Groves, 1989).

Social disorganization theory is not without its flaws and critiques from scholars though. Many early scholars of the theory, defined disorganization with crime data or levels of delinquent youth to explain neighborhoods with higher levels of crime - which presents an issue of tautology. Scholars attempted to move away from this definitional issue and began to study neighborhood constructs using measures of social and personal ties, but conceptual issues remained (Sampson, 2012). For instance, some neighborhoods with strong personal ties hinder the community's ability to establish social control. Whereas, Wilson (1996) argues that in some poor neighborhoods, residents are connected through personal networks that do not produce social control and can in fact impede social control. Other scholars argue that networks can connect drug dealers and gang members (Pattillo 1998; Venkatesh, 1997), therefore suggesting social ties can be both positive and negative, and it is important to determine what is being connected (Sampson, 2012).

In an attempt to address these conceptual issues, Sampson and colleagues proposed the construct of collective efficacy. They propose there are two fundamental mechanisms – social cohesion (collective part), and shared expectations for control (efficacy part), that comprise the construct of collective efficacy. They formally define collective efficacy, as "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good" (Sampson, Raudenbush, Earls, 1997, p.918). They contend that a community's level of collective efficacy depends on community trust, social interaction, and residents' willingness to exercise informal social control, and take action to address issues facing the wellbeing of the neighborhood (Sampson, 2012). Much like Bursik and Grasmick's (1993) notion of public ties (e.g., formal institutions outside the neighborhood), Sampson (2012) contends that when social cohesion and trust are high, residents are able to collectively come together and take action to garner external resources, for example, when neighborhood resources and public services are cut (e.g., garbage collection, police patrols, etc.).

Sampson (2004) contends the connection between social cohesion, working trust, and shared expectations for action is captured through the concept of collective efficacy. Other scholars suggest these concepts are independent of each other and are two distinct measures. For instance, Uchida, Swatt, Solomon, and Varano (2013) define collective efficacy as, “the ability of residents to produce social action to meet common goals and preserve shared values” (p.2). They argue that collective efficacy refers to residents’ willingness to intervene for the betterment of the neighborhood if a problem occurs. They suggest that intervening can include calling the police, questioning unfamiliar faces, forming social groups, addressing delinquent youths, or “at a higher level”, attend city council meetings to request assistance from government organizations (p.3).

Whereas, they define social cohesion as, “an emotional and social investment in a neighborhood and sense of shared destiny among residents”, therefore, in neighborhoods with high levels of social cohesion, residents are more likely to own homes, trust each other, develop deep social ties and connections within the community (Uchida et al., 2013, p. 3). Their results suggest studying social cohesion and collective efficacy as separate concepts can demonstrate distinct neighborhood processes. For example, they found both perceptions of social cohesion and collective efficacy were statistically significant and associated with perceptions of incivilities and satisfaction with the police. However, their results also suggest there is no statistically significant relationship between perceptions of collective efficacy and fear of crime, although they did find a statistically significant relationship between social cohesion and fear of crime. These results suggest that higher levels of social cohesion are associated with lower levels of fear of crime. The authors argue these results display that social cohesion and collective efficacy are distinct constructs and should further be studied across neighborhoods (Uchida et al., 2013).

Along with differences in the conceptualization of collective efficacy, scholars have also differed on the correct level of analysis that social disorganization theory should be operationalized. For instance, in his study of Chicago neighborhoods St. Jean (2007) presents the notion of pockets within neighborhoods. He argues that certain behaviors that impact crime occur in small, immediate areas, and are not applicable across an entire neighborhood. This idea suggests that people are influenced by their immediate surroundings. Whereas, Sherman, Gartin, and Buerger (1989) argue that theories such as social disorganization may be appropriate at the community level, but are "inappropriate for small, publicly visible places with highly transient populations" (p.30).

Other scholars follow St. Jean's thinking (2007), and argue that micro places (i.e., street segments) have their own behavior settings (Taylor, 1997), and function as small "micro communities", which have similar traits of communities that are crucial to social disorganization theory (Weisburd et al., 2012; Weisburd et al., 2016, p.53). Recent research by Weisburd and colleagues (2014) propose social disorganization theory can help explain why crime concentrates in crime hot spots. They argue that people who spend time on the same street segment together, get to know each other, and each other's routines. Neighbors therefore, develop certain roles and may gain mutual trust that enables them to engage in informal social control.

Additional research in Seattle by Weisburd and colleagues (2012) examined social disorganization theory and crime, by exploring the social processes that occur at the street segment level. They found that physical disorder is the strongest predictor of social disorganization, specifically, a key indicator is the presence of truant juveniles, which more than doubled the likelihood of a street having crime related problems. Another key measure of social disorganization is socioeconomic status, which was measured using a combined variable of public housing and Section 8 vouchers, termed public housing assistance. Although they determined that over 50 percent of the city's public housing assistance was concentrated on less than one percent of the city's street segments, it was an indicator of crime. They also measured collective efficacy at the street segment level using the percentage of active voters, and results display the street segments where residents are more involved in civic engagement are less likely to have chronic crime problems. These findings suggest that social disorganization, levels of informal social control, and collective efficacy vary at the micro level. Consequently, they argue that changing the characteristics at the micro level could impact levels of crime, and that better understanding the behavioral characteristics at the street segment level could help address policies that aim to end unemployment and income inequality, which are known to lead to higher levels of crime (Weisburd et al., 2012; Weisburd et al., 2014).

To summarize these sections, the above passages discuss the historical context and development of social disorganization theory, definitional and conceptual issues with the theory, and how the theory has been tested from macro and micro units of analysis. The following sections will discuss how two key elements of social disorganization theory – disorder and collective efficacy have been measured within empirical studies over the years, and the limitations of prior research. The following section will also address how this research study offers an alternative measure of collective efficacy.

Measuring Key Theoretical Concepts

Disorder

Neighborhood disorder is not known to cause crime itself but can indicate that a neighborhood lacks informal social control, and therefore act as a crime facilitator. Wilson (1975) was one of the first scholars to examine residential fear of crime within urban neighborhoods. His findings demonstrated that residents' fear increased due to daily hassles they encountered on the street. Examples of daily hassles include homeless individuals, panhandlers, and rowdy youth, in addition to physical signs of disorder. Wilson and Kelling (1982) extended work on neighborhood residential fear. They found that neighborhood decay demonstrated a weakened community and increased the likelihood of offenders choosing such neighborhoods to victimize others. Further, they argued that disorder weakened informal social control, and therefore increased crime.

Skogan (1990) examined changes in the neighborhood structure and found that visible signs of disorder in neighborhoods is a sign that the neighborhood may have lost its capacity to solve problems on its own. He further suggested that disorder can foster social withdrawal from residents, inhibit support between neighbors, and discourage residents from taking steps to protect themselves and their community. He also argued that neighborhood disorder increases residential fear, concerns about public safety, and fosters a negative neighborhood reputation across the city (Skogan, 1990).

Further, Skogan (1990) classified disorder into two types - social and physical. He defines social disorder as, "a matter of behavior: you can see it happen (public drinking, or prostitution), or experience it (catcalling or sexual harassment)" (p.4). Whereas, physical disorder is defined as, "visual signs of negligence and unchecked decay: abandoned or ill-kept buildings, broken streetlights, trash-filled lots, and alleys strewn with garbage and alive with rats" (Skogan, 1990, p.4). He argues that small signs of disorder will begin a downward spiral of decay, and lead to neighborhood residents feeling as they have lost their space, therefore, increasing fear and decreasing informal social control.

The measure of disorder has been conceptualized differently over the years, and many scholars have measured disorder through survey data. For example, McGarrell, Giacomazzi, and Thurman (1997) examined the disorder model, while also examining the victimization model and community concerns model in terms of their relationship with fear of crime. Using survey data gathered from citizens of Spokane, Washington, they measured disorder by asking residents perceptions of: social disorder (e.g., public drinking, groups of youths in public spaces, etc.) and physical disorder (e.g., vandalism, physical decay, trash on streets, etc.). They found that perceived neighborhood disorder had the greatest influence on fear, and that disorder was significantly related to fear. Their final conclusion suggests that all three models- community concerns, victimization, and disorder models need to be included to better explain fear of crime (McGarrell et al., 1997).

The main critique of measuring disorder through survey data is that it is measuring individual perceptions of disorder, which could potentially be biased based on the specific neighborhood and people responding (Sampson & Raudenbush, 2004; Hipp, 2010; Yang & Pao, 2015). Additionally, studies using survey measures of resident's perceptions of physical and social disorder have produced conflicting results (Gault & Silver, 2008; Sampson & Raudenbush, 2004; Skogan, 1990, Xu, Fiedler & Flaming, 2005).

Other scholars have examined disorder through systematic social observations (SSO). This data collection method entails researchers drive each street block segment, and code the presence or absence of physical disorder (e.g., trash, litter, graffiti), and social disorder (loitering, public drinking, drugs, etc.) on each street block (Sampson & Raudenbush, 1999; Braga & Bond, 2008, Uchida et al., 2013). For example, Sampson and Raudenbush (1999) conducted this data collection method in their neighborhood level study in Chicago. They found that disorder significantly predicted robbery rates across census tracts and concluded that disorder fosters a conducive environment for robbery offenders. They also suggest that disorder and crime are the results of the same social processes. More recently, Uchida and colleagues assessed physical and social disorder through SSO and conducted their observations on different days of the weeks and time to avoid systematic biases. They measured instances of vacant buildings, litter, and graffiti as physical disorder, and observed people, and their behaviors as indicators of social disorder (Uchida et al., 2013). This data collection method does account for objective measures of disorder, compared to subjective views of a resident's perceptions, but this data collection method is time consuming, and only observes disorder at one specific place and time (Wheeler, 2017).

A number of scholars have utilized citizen calls for police service, also known as computer aided dispatch (CAD) data to measure disorder and police response to disorder. For example, Sherman and Weisburd (1995) measured disorder using soft crime calls for disturbances, drunks, noise, and vandalism, and Weisburd and Green (1995) measured disorder type calls using categories of nuisance, suspicious persons, public morals, and assistance. Although CAD data do have limitations, such as under and over reporting, call data are suggested to be a more reliable measure of crime, compared to crime incident or arrest data (Sherman et al., 1989).

Other scholars have used administrative data, and official police records to measure disorder. For example, Weisburd et al., (2012) used data provided from the Public Utilities department in Seattle to measure physical disorder. They used reported incidents of illegal dumping, litter, graffiti, weeds, abandoned vehicles, and housing issues as indicators of physical disorder at the street segment level. They found that physical disorder was the strongest indicator of social disorganization, and that there is a strong relationship to crime trajectories at the street segment level (Weisburd et al., 2012). In her longitudinal study of violent crime and disorder, Yang (2010), used police incident reports to measure social disorder and utilized the same measures of physical disorder as Weisburd et al. (2012) described above. Using police incident reports, social disorder measures included reports of disorderly conduct, noise, public intoxication, and drug related incidents. She found that areas with no disorder, had no violent crime, and areas with disorder predicted violent crime occurring 30 percent of the time, and concluded that future studies need to include other contextual factors to better understand the relationship between disorder and violent crime (Yang, 2010).

Further work by O'Brien and Sampson (2015), utilized Boston's Constituent Relationship Management (CRM) system to measure physical and social disorder. They measured two aspects of physical disorder; private neglect (e.g., calls for animal issues, illegal rooming and parking), and public denigration (e.g., public graffiti, and improper trash disposal). To measure social disorder and violent crime they constructed five measures; public social disorder (e.g., panhandlers and loud disturbances); public violence (e.g., fight); private conflict (e.g., domestic violence); prevalence of gun violence (e.g., shootings or gun involved incidents); and, alcohol (e.g., public intoxication). Their results suggest the violence emerges from private conflicts within the community, and they conclude that administrative records are a valid measure of disorder (O'Brien and Sampson, 2015).

Collective Efficacy

The concept of collective efficacy was first introduced into the social disorganization model by Sampson, Raudenbush and Earls (1997) as a mediating variable between concentrated disadvantage, residential instability, ethnic heterogeneity, and violence. As mentioned above they define collective efficacy as "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good" (p.918). Sampson and colleagues measured collective efficacy using survey data. The data were collected during the Project on Human Development in Chicago Neighborhoods (PHDCN) through a representative community survey of more than 8,000 residents in 1995 (Sampson, 2012). Using a five-item Likert-type scale, respondents were asked if they strongly agreed that "people around here are willing to help their neighbors", "this is a close-knit neighborhood," "people in this neighborhood generally don't get along with each other," and "people in this neighborhood do not share the same values" (Sampson et al., 1997, p. 920). The questions aimed to measure the social cohesion and trust within the community. They argue that individuals must trust each other before willingly intervening for the good of the community. Their study results suggest that communities with higher levels of collective efficacy, display lower levels of violent victimizations and homicides (Sampson et al., 1997).

A series of subsequent research studies ensued and examined the effect of collective efficacy on a variety of different outcome measures (e.g., perceived violence, burglary, homicide, intimate partner violence). Results from these studies suggest that neighborhoods with higher levels of collective efficacy have lower rates of crime, no matter the outcome of choice (Sampson & Raudenbush, 1999; Morenoff et al., 2001; Browning 2002, 2004). All of the previously mentioned studies utilize the same data set from the PHDCN survey in Chicago, and therefore measure collective efficacy using the same survey questions. As shown in Table 1, eight other studies operationalize and measure the construct of collective efficacy using the PHDCN community survey data (Sampson et al., 1997; Sampson & Raudenbush, 1999; Morenoff et al., 2001; Browning 2002, 2004, 2009; Kirk, 2008; Rhineberger-Dunn et al., 2009).

Other studies examining the construct of collective efficacy (see Table 1) conducted their own community surveys and employed the same or similar five-item Likert-type scale of questions to measure neighborhood social cohesion and social control (St. Jean, 2007; Mazerolle et al., 2010; Wickes et al., 2013; Armstrong et al., 2015; Hipp, 2016; Yuan and McNeeley, 2017). Each study found support that collective efficacy is strongly related to levels of crime across neighborhoods, but using different measures of collective efficacy did produce slightly

Table 1: Measurement of Collective Efficacy

Study	Collective Efficacy Measurement Variable	Unit of Analysis	Outcome Variable
Sampson, Raudenbush & Earls (1997)	Project on Human Development in Chicago Neighborhoods Community Survey (PHDCN-CS) – two five-item Likert-type scale questions measuring social cohesion and social control were combined into a summary variable	Neighborhood Clusters (N=343)	Perceived Violence, homicide and victimization
Sampson & Raudenbush (1999)	Same as above	Neighborhood Clusters (N=196)	Burglary, homicide, robbery, victimization
Morenoff Sampson, Raudenbush (2001)	Same as above	Neighborhood Clusters (N = 343)	Homicide
Browning (2002)	Same as above	Neighborhood Clusters (N = 343)	Intimate partner violence and homicide
Browning, Feinburg, Dietz (2004)	Same as above	Neighborhood Clusters (N=343)	Homicide and violent victimization

Table 1 (cont'd)

St Jean (2007)	Same two five-item Likert-type scale questions measuring social cohesion and social control were combined into a summary variable, as the PHDCN-CS study (above)	One police district	Official crime incidents and perceived crime incidents
Kirk (2008)	PHDCN-CS data– two five-item Likert-type scale questions measuring social cohesion and social control were combined into a summary variable	Neighborhoods (n=80)	Youth Arrests
Rhineberger-Dunn & Carlson (2009)	PHDCN-CS data (same as above) – two five-item Likert-type scale questions measuring social cohesion and social control were combined into a summary variable	Neighborhood Clusters (N=343)	Social cohesion, informal control, police-citizen relations, and formal control
Browning (2009)	Same as above	Neighborhood Clusters (N=343)	Property crime and perceived disorder
Mazerolle, Wickes, McBroom (2010)	Same two five-item Likert-type scale questions measuring social cohesion and social control were combined into a summary variable, as the PHDCN-CS study (above)	Local communities across Brisbane, Australia (N=82)	Violent victimization
Weisburd, Groff, Yang (2012)	Total number of registered voters	Street segment	Crime incidents
Wickes, Hipp, Sargeant, Homel (2013)	Same two five-item Likert-type scale questions measuring social cohesion and social control were combined into a summary variable, as the PHDCN-CS study (above)	Local communities across Australia(N=148)	Collective Efficacy

Table 1 (cont'd)

Uchida, Swatt, Soloman, & Varano (2013)	Community survey using Likert-type scale questions measuring willingness to intervene, social cohesion and capacity for social control, extending the PHDCN-CS survey questions	Neighborhoods across Miami-Dade county (n=8)	Collective Efficacy

Armstrong, Katz, & Schnelby (2015)	Community survey using same two five-item Likert-type scale questions measuring social cohesion and social control were combined into a summary variable, as the PHDCN-CS study (above)	Census tracts across Mesa, Arizona (n=86)	Perceived neighborhood violence (assault and robbery)
Hipp (2016)	Four-point Likert scale survey question asking how likely their neighbors would step in to help during specific situations	Census block groups (N=113)	Perceived crime
Yuan & McNeeley(2017)	Seattle Neighborhood and Crime Survey – eight questions measuring respondents trust in their neighbors and perceptions as to their willingness to intervene	Census tracts (n=123)	Perceived risk and emotional fear of violence and burglary

different findings. For example, Armstrong et al., (2015) found that collective efficacy did predict violent crime but was not the only factor. They also found that measures of social cohesion and willingness to intervene were also predictors of neighborhood violence and concluded that these concepts should be treated as distinct constructs (Armstrong et al., 2015).

Uchida and colleagues (2013) argue the scale used by Sampson et al. (1997) to measure collective efficacy has strong content validity but displays weakness in the measurement of the latent variable. Therefore, Uchida and colleagues expanded Sampson et al.'s (1997) measurement of collective efficacy to include additional questions surrounding the three domains within the original Chicago measure; willingness to intervene, social cohesion, and capacity for social control. The additional questions were added to expand the original questions included in the PHDCN community survey (Sampson et al., 1997), and were collected through an in person resident survey of 1,227 residents across eight neighborhoods in Miami-Dade County, Florida (Uchida et al., 2013). They found both perceptions of social cohesion and collective efficacy were statistically significant and associated with perceptions of incivilities and satisfaction with the police, but only social cohesion was associated with neighborhood levels of fear of crime. Collective efficacy did not reach the level of statistically significant in regards to levels of fear of crime. This led Uchida and colleagues to conclude that social cohesion and collective efficacy are distant constructs and further research is needed to develop these two separate concepts across neighborhoods (Uchida et al., 2013).

Traditionally, collective efficacy has only been measured using community surveys, which can take a large amount of time, and community surveys are expensive to administer (O'Brien et al., 2015). Therefore, Weisburd and colleagues expanded the measure of collective efficacy by using administrative, publicly available data. For instance, in their 2012 study in Seattle, they measured collective efficacy by the number of active voters on each street segment. They argued that if a citizen is willing to participate in a public election, then it is plausible they would be willing to engage in other aspects of public affairs. They defined active voters as people who participated in voting at a higher rate than the average Seattle voter, and then calculated the proportion of active voters on each street segment, to avoid measurement issues with overall population density per street segment (Weisburd et al., 2012). As discussed in previous sections, their findings suggest that collective efficacy varies at the street segment level, and they conclude that a better understanding of neighborhood behavior at the street segment level may help address community inequalities and community levels of violence (Weisburd et al., 2012; Weisburd et al., 2014).

Limitations of Previous Research

Although there is an abundance of previous research on the study of crime and place, there are still a number of limitations. There is a vast amount of evidence that the best way to study spatial patterns and concentrations of crime, is at the micro (e.g., street segment) level of analysis (Sherman et al., 1989; Weisburd et al., 2004; Braga et al., 2010 Weisburd et al., 2012), compared to more traditional macro level neighborhood studies (Sampson et al., 1998; Rosenfeld et al., 1999), but some scholars still differ in their opinions when examining other contextual variables such as – social class, race, and family, as to the most optimal unit of analysis (Sampson et al., 2002). Therefore, this study adds to the current understanding of the variation in disorder, collective efficacy, and crime at the micro and macro levels of analysis.

Another limitation is the lack of clear and consistent measures when examining social disorganization theory. Over the years, measures of disorder and crime have changed, crime has been both an independent and dependent variable, leaving unclear conceptualizations of social disorganization (Braga and Clarke, 2017). A more specific limitation is the measurement and conceptualization of collective efficacy. The majority of studies utilize a community survey, which are known to be costly and time consuming. Weisburd et al. (2012) sought to expand the measurement of collective efficacy by using the number of active voters per street segment to show civic engagement. However, research by Sampson (2012) suggest that individual voting behaviors are not a good measure of collective civic engagement. Weisburd et al.'s (2012) work received further criticism from Braga and Clarke (2017), who offer four specific criticisms to Weisburd and colleagues research on collective efficacy and suggest these areas need future research. In regards to Weisburd et al., (2012) study out of Seattle, which was discussed previously, Braga and Clarke (2017) argue (1) the situational variables are not clearly presented, (2) their measure of social disorganization does not clearly establish the importance of collective efficacy in relation to the relationship between crime and street segments, (3) they lack a clear theoretical background to argue that collective efficacy operates at the street segment and neighborhood level, and (4) there is a lack of understanding if collective efficacy can be impacted and therefore reduce crime at the street segment level. This study expands the current understanding of collective efficacy by introducing an alternative measurement of the construct and by examining how collective efficacy varies at both the macro and micro level of analysis.

Lastly, there is a limited understanding of the spatial distribution and patterns of non-fatal shootings. Previous research has examined homicides (Cohen & Tita, 1999; Morenoff et al., 2001; Zeoli et al., 2014, 2015), but research also suggests that non-fatal shootings occur at a higher rate than gun homicides (Hipple et al., 2016; Hipple & Magee, 2017). Currently, Braga et al.'s, (2010) study in Boston is the only known empirical work that has examined the spatial patterns of both homicide and gun assaults over an extended period of time. Therefore, this study expands the current understanding of the spatial distribution of both gun homicide and non-fatal shooting incidents. The following chapter will discuss the current research study.

Chapter 4: Description of the Current Study

Purpose of Study

The purpose of this project is to advance the understanding of firearm violence and social processes within communities at both the neighborhood and street segment level of analysis. This study has multiple objectives; (1) to examine how fatal and non-fatal shootings cluster across space, (2) to examine the patterns of social disorganization and disadvantage across neighborhoods, (3) to improve the current measurement of collective efficacy, and (4) to understand the relationship between social disorganization, disorder, collective efficacy, and firearm violence. Previous research displays strong evidence that high levels of social disorganization and disadvantage are associated with higher levels of crime (Shaw and McKay, 1942; Sampson et al., 1989; Sampson et al., 1997), and that crime clusters within micro places across time (Weisburd et al., 2004; Braga et al., 2010), but there are still unanswered questions as to the best conceptualization of neighborhood, and if specific measures of neighborhood characteristics can adequately explain crime at the micro level (Braga and Clarke, 2014). Therefore, this research builds on previous macro and micro place research, by extending the current understanding of spatial clustering of firearm violence by including both fatal and non-fatal shootings. Additionally, this study adds to the current understanding of social disorganization and collective efficacy, at both the macro and micro level, and examine a new outcome measure of fatal and non-fatal shootings.

The study takes place in Indianapolis, Indiana. Indianapolis spans 361 square miles, and as of 2016 has an estimated population of 855,164 people (United States Census Bureau, 2016). According to the Federal Bureau of Investigations (2016), in 2015, Indianapolis was ranked the tenth most violent city in the nation for cities with a population over 200,000 people, with a homicide rate of 17 per 100,000 population, and a violent crime rate of 1,288 per 100,000 population. The city of Indianapolis experiences approximately 120 fatal shootings and 400 non-fatal shootings each year, and non-fatal shooting incidents are almost four times more frequent than firearm related homicides. Consequently, the city of Indianapolis has one victim of firearm violence each day producing a rate of 48 per 100,000 population each year (Indianapolis Non-Fatal Review Board, 2016).

The current research study draws data from multiple sources; the Marion County Non-Fatal Shooting Review Board, the Indianapolis Police Department, the Indianapolis Mayor's Action Center, the City of Indianapolis, and the U.S. Census Bureau. Indianapolis is an ideal city for this research due to the level of firearm violence that occurs annually, and the unique number of available data sources that allows for measurement of different physical and social constructs. This study seeks to answer the following research questions:

RQ1: What are the characteristics of neighborhoods associated with high levels of fatal and non-fatal shootings?

RQ2: Is there a relationship between social disorganization, collective efficacy, disorder, and geographic patterns of fatal and non-fatal shootings?

RQ3: What are the micro-place geographic patterns of fatal and non-fatal shootings at the street segment level?

Data Sources

Outcome Measure

The outcome measure in this study is fatal and non-fatal shootings. Non-fatal shooting data will be obtained from the Marion County Non-Fatal Shooting Review Board database, which is generated using information from both police incident reports and internal police documents (Hipple, McGarrell, O'Brien, and Huebner, 2016). Local researchers enter, code, and clean data by hand, and the data only include victims from non-fatal shooting incidents that are classified as an aggravated assault by the FBI's Uniform Crime Report (UCR) definition, "as an unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury' (Federal Bureau of Investigation, 2004). Therefore, self-inflicted and accidental non-fatal shootings were excluded from this study. Additionally, in order to capture all incidents where a person was shot, the UCR Hierarchy Rule[1] was not applied, guaranteeing each non-fatal shooting victim is captured in the data.

Fatal shooting data were obtained from the police department homicide records management database. Data in the homicide record management database are entered and maintained by the lieutenant of the homicide unit. All incidents that were classified as a criminal homicide, and the cause of death was categorized as a gunshot wound were gathered. Self-inflicted, accidental, and justifiable homicides were excluded from this study, as they do not meet the FBI's definition of a criminal homicide, "murder and nonnegligent manslaughter: the willful (nonnegligent) killing of one human being by another" (Federal Bureau of Investigation, 2004).

Independent Measures

Social Disorganization

This study employs a theoretical framework, drawn from social disorganization theory, which contends that poverty, residential instability, and ethnic heterogeneity are structural factors that are associated with neighborhood crime (Shaw and McKay, 1942). The main theoretical premise is that socially disorganized communities lack organization, and crime is therefore able to thrive due to the absence of informal social control within the neighborhood. The theory contends that impoverished neighborhoods often lack resources available to the

[1] The UCR Hierarchy Rule "requires that when more than one Part I offense is classified, the law enforcement agency must locate the offense that is highest on the hierarchy list and score that offense involved and not the other offense (s) in the multiple-offense situation" (Federal Bureau of Investigation, 2004, p. 10).

citizens to invest into their community, therefore fostering the breakdown of the neighborhood structure (Bursik and Grasmick, 1993; Sampson and Groves, 1989). Further, residential instability often occurs in lower income neighborhoods, and is an indicator that citizens are unable to foster informal social control. Therefore, communities are not able to regulate neighborhood behavior themselves because informal networks fail to ever develop (Bursik and Grasmick, 1993). Lastly, ethnic heterogeneity within a neighborhood makes it harder for citizens to identify with each other, consequently, citizens do not develop informal friendships that can strengthen informal social ties (Bursik and Grasmick, 1993; Sampson and Groves, 1989). All three measures are important in understanding the structural relationship of neighborhood and crime.

Poverty, residential instability and ethnic heterogeneity will be measured using data obtained from the United States Census Bureau. *Neighborhood poverty* will be measured as one measure, using four socioeconomic measures; percent unemployment, median household income, percent living in poverty, and percent of female-headed house hold. Previous research has utilized similar measures; the percent of unemployed adults, percent living in poverty, female-headed households, and percent minority, median family income and developed a composite variable of concentrated disadvantage using principal components factor analysis (Sampson et al., 1997; McGarrell, Corsaro, Hipple, & Bynum, 2010; Corsaro & McGarrell, 2010). The measure of *residential instability* will be operationalized, using the percentage of population residing in the same residence for last year, percent of owner occupied homes, and the percent moved within the last year. Lastly *ethnic heterogeneity* will be measured using the total population, and the percentage of the population that is foreign, and Hispanic. Following previous work, the key measures of social disorganization theory; *poverty, residential instability*, and *ethnic heterogeneity* will be measured as separate variables, constructed from census data (Sampson et al., 1997; Morenoff et al., 2001; Swatt, Varano, Uchida, 2013).

Social Disorder

Social disorder has proven to be problematic for neighborhoods and can indicate a weak social structure within the community (Skogan, 1990). Social disorder can increase neighborhood fear, weaken informal social control, and foster a disorganized environment, which can cultivate crime. Previous research studies have used police calls for service data to measure social disorder, utilizing police calls for public intoxication, panhandlers, loud disturbances, suspicious persons, and drugs as indicators of social disorder (O'Brien & Sampson, 2015; Boggess & Maskaly, 2014; Sherman & Weisburd, 1995; Weisburd & Green, 1995). Therefore, this study will measure *social disorder* with data obtained from 911 computer aided dispatch (CAD) calls for service, from the Indianapolis Metropolitan Police Department. Citizen calls to police for public intoxication, narcotics, disturbances, and noise complaints will be used to measure social disorder at both the macro and micro level of analysis.

Physical Disorder

Along with social disorder, physical disorder displays a weakened neighborhood structure that can foster delinquent youths and crime (Skogan, 1990). Previous studies have used administrative data to measure physical disorder (Branas, Cheney, MacDonald, Tam, Jackson, & Have, 2011; Spelman, 1993; O'Brien & Sampson, 2015). Vacant lots, illegal dumping, vandalism, and abandoned homes are indicators of physical disorder, and signs that the community lacks the ability to prevent or improve the neighborhood conditions. This study will measure signs of *physical disorder* using abandoned housing data obtained from the OpenIndy Data Portal, which is maintained by the City of Indianapolis. The OpenIndy Data Portal is an open access website that allows scholars and citizens to download and use a variety of data sources. A database of all known abandoned homes according to the City of Indianapolis as of 2016, will used to measure physical disorder. In addition to the abandoned house data, this study will use the police 911 calls for service, CAD data, to also measure physical disorder. Calls for police service for illegal dumping, abandoned vehicles, and vandalism will be used as indicators of physical disorder at the macro and micro levels of analysis.

Collective Efficacy

The mediating variable of *collective efficacy* will be operationalized using data from the Mayor's Action Center. The Mayor's Action Center (MAC) is an office within the governmental agency of the Mayor's office of Indianapolis and serves as a central repository in which citizens are able to submit requests for city services. Former Indianapolis Mayor Stephen Goldsmith created the MAC in 1992, as a way to centralize all call for service requests for the city of Indianapolis. In the 25 years that the MAC has been in existence, the city has never formally marketed its services to the community. The community becomes informed about the MAC as a resource through a completely organic process, neighborhood leaders inform citizens, and a word of mouth practice continues to pass the message to the community that the MAC is the best method to contact the city, and request city services.

Citizens are able to submit requests through the mail, over the phone and through an online portal. The online portal application, RequestIndy online, offers citizens the ability to request city services, monitor the status of their request, and be notified when the request is completed or closed. If the citizen provided an email address when submitting the request, then they receive an email with their service request number, which allows the status of that specific request to be monitored. The system is based on geographic location, and a specific address must be entered when submitting the request. This is done through an online mapping system within the RequestIndy application. If an individual does not have a specific address, for example, for a pothole, then the requestor is able to zoom into a map of Indianapolis, select the problem location, and the mapping program will assign a specific geographic location to the request. When a citizen calls a request in, it is answered by the MAC call center, where a staffer will talk to the citizen, listen to their issue, and enter the request into the system. Once a request is submitted, the MAC sends the specific information to the appropriate government agency, and it is their responsibility to complete the request and notify the MAC when the service has been completed. For example, a request for a pothole is referred to the Department of Public Works.

Requests are completed as they are received, depending on urgency of the problem, and staffing within the responsible agency. For example, a pothole on a major thoroughfare may be filled before a pothole on a neighborhood street, even if the neighborhood street request was entered first. Otherwise, all requests are handled in a queue like process. The system is also set up to track duplicate requests. For example, if an individual enters their neighbor's home address and identifies high grass as a problem, they will only be able to submit that specific request once. The program searches that type of request for spatial proximity (feet) and time (days) to all previously submitted requests, to determine if the MAC has already been notified. Therefore, if an issue was not handled by the MAC center in an ideal timeframe to a requestor, and they choose to submit another request for the identical problem, the RequestIndy application will prevent this from occurring. There are limitations to this process, and a determined citizen could directly call the appropriate city agency to follow up or submit an additional request, but this not likely as the common practice is for citizens to contact the MAC.

I conducted a set of informal interviews to gage the perceptions and usage of the MAC by the community. I spoke with the Director of the MAC, a district commander with the Indianapolis Metropolitan Police Department, who routinely interacts with neighborhood community groups, and community members themselves who are involved with multiple neighborhood groups. The overall consensus is the community uses the MAC to request city services and accomplish whatever issues they want to address within their community. With any city service there was also discussion of unsatisfied citizens, and even a reference to the "Mayor's Inaction Center", but as one of the community members stated, "I don't usually hear when things are working as they should, I only hear about the problems" (personal communication, 12/14/17). The IMPD commander stated he has witnessed citizens speak up for the MAC when another neighbor was complaining about the lack of follow up, by giving their own positive experience during a neighborhood meeting. Even if the MAC is not handling a citizen's request within their desired timeframe, the community is still calling the MAC about issues within the community.

Citizens calling the MAC allows for a unique dataset of the community's perceptions of issues with their neighborhood and as a measure of civic engagement, or as I argue, as a measure of collective efficacy, because the individual is making the choice to call a governmental agency to help solve a specific problem within their community. I am following Uchida et al.'s (2013) definition, "the ability of residents to produce social action to meet common goals and preserve shared values" (p.2), which differs from Sampson's classic definition, and separates collective efficacy from social cohesion. Although social cohesion could be assumed from residents caring enough about their community to call a government agency to improve conditions within their neighborhood, as the MAC data is not an appropriate measure of "an emotional and social investment in a neighborhood and a sense of shared destiny among residents" (Uchida et al., 2013, p. 2).

Other cities such as Boston, New York, and Baltimore refer to MAC center calls as 311 data. From a historical perspective, 311 calls for service originated in 1997, when the Community Oriented Policing Office (COPS) requested the Federal Communications Commission to reserve the 311 number nationally for non-emergency calls (COPS, 2007; Wheeler, 2017). Since many calls for service that police receive are related to issues of public disorder and not crime, the 311-program intended to reduce the number of calls the emergency 911 dispatch received (Rogers, 1999), and provide the police with information regarding quality of life issues to be addressed through community policing approaches (Wheeler, 2017). Therefore, 311 calls are another form of police calls for service data, that have expanded into a measurement of community engagement and neighborhood issues.

O'Brien, Sampson, and Winship (2015) examined Boston's constituent relationship management (CRM) system (i.e., 311 call data) over a 16-month time period. They utilized three ecometric analyses to assess the validity of large administrative data for research purposes, and conclude it is a valid reliable source, at no cost to the researcher. Although the aim of their study was to validate the use of 311 calls as a measure of physical disorder, they do suggest the calls measure a level of civic engagement. They argue that reporting rates for public issues has two distinct elements, (1) the knowledge of the system and the willingness to use it, and (2) the decision to take action and responsibility for a public space. Therefore, the sum of the 311 calls can be described as civic engagement, because when a person calls to report an issue, like trash or graffiti, that person is taking responsibility for that public space (O'Brien et al., 2015).

When utilizing the MAC data, it is important to understand the variation in calls across neighborhoods, as individuals may have different motives for seeking governmental services. Differences across neighborhoods may be due to differences in the perception of disorder, homeowners may feel more responsible for public space compared to individuals who rent, and the accumulation of disorder may become “normal” and residents see reporting issues useless (O’Brien et al., 2015). O’Brien and colleagues suggest there are two types of calls that can be deciphered from the data, calls for public space (graffiti or illegal dumping), and calls that address more personal motivations (i.e., bulk pick up or snow removal). Therefore, general requests, bulk item pickups, and snow removal requests can be used as general measures of a neighborhood’s engagement and use of the MAC data. They argue that if it is snowing, there will be a common need for city services, and therefore a good measure of a neighborhoods use of the call centers (O’Brien, Sampson, & Winship, 2015).

The measure of *collective efficacy* will be operationalized as a continuous variable, displaying the number of calls citizens made to report indicators of nuisance issues in their neighborhood. Nuisance issues will be measured by calls residents make regarding; abandoned vehicles, high weeds or grass, debris and illegal dumping, and graffiti. These calls will be summarized into one continuous variable to measure collective efficacy at the neighborhood and street segment and suggest that residents are concerned about the wellbeing of their neighborhood and neighbors (Sampson et al., 1997; Weisburd et al., 2012). Since all neighborhoods across the city do not have the same level of nuisance issues, another variable will be used to measure neighborhood engagement across the city. The number of calls the MAC receives for trash service issues and all general calls will be operationalized as a continuous variable to measure neighborhood engagement. As O’Brien et al., (2015), suggest all citizens need to utilize city trash services. As previously stated, previous research has measured collective efficacy using survey data, where citizens were asked about the likelihood they could count on their neighbors or their willingness to intervene to help a neighbor (Sampson et al., 1997; Morenoff et al., 2001), and more recently Weisburd and colleagues (2012) gathered official data through voting patterns. The use of MAC data will be an alternate measure, as it demonstrates an individual's willingness to engage an outside community group to help improve their neighborhood. As Sampson argues collective efficacy needs to focus on the actions that are generated "on the ground" and not from the top, and such actions include the ability of residents to obtain resources from outside the neighborhood, and respond to cuts in public services (Sampson, 2012, p.156). Although the MAC data do not measure the success of residents in obtaining resources for the neighborhood, they do reflect the extent to which residents attempt to bring resources to the neighborhood in response to perceived problems.

Chapter Summary

This chapter describes the objectives of the current study, the specific research questions, and the data sources that will be utilized. As previously discussed, the purpose of this dissertation research is to examine the spatial patterns of fatal and non-fatal shootings and examine the relationship between social disorganization, disorder, collective efficacy, and firearm violence. Data from the Marion County non-fatal shooting database, the IMPD homicide database, IMPD 911/CAD data, the City of Indianapolis, and U.S. Census data will be used to answer the research questions and objectives. Each data source, minus the U.S. Census data will be aggregated to both the macro (e.g., census tract) and micro (e.g., street segment) level of analysis. The next chapter provides specific details regarding the operationalization of the dependent and independent variables that will be used in this study.

Chapter 5: Data Description

The research design for this study is based on a cohort design, which relies on data from the Marion County non-fatal shooting database, the IMPD homicide database, IMPD 911/CAD data, the City of Indianapolis, and U.S. Census data. This research will study fatal and non-fatal shootings at the incident level, and not examine individual level demographics. The use of the data sources in this study are consistent with prior research that examines fatal and non-fatal shootings, social disorganization theory, disorder, and collective efficacy across multiple levels of analysis (Hipple et al., 2016; Sampson et al., 1998; Weisburd et al., 2012; O'Brien & Sampson, 2015). This chapter describes the each of the dependent and independent measures used in this study.

Outcome Measure

The outcome measure was gathered from the Marion County Non-Fatal Shooting Review database[2], which is generated using information from both police incident reports and internal police documents (Hipple et al., 2016). As previously mentioned in Chapter 4, local researchers enter and code data that only includes victims from non-fatal shooting incidents that met the FBI's UCR definition of an aggravated assault[3]. A non-fatal shooting is also defined as a gunshot wound as a penetrating injury caused by a projectile weapon with a powder discharge (Beaman, Annest, Mercy, Kresnow, and Pollock, 2000). Therefore, injuries caused by air guns or pellet guns are not included in this study. During the study time period, January 1, 2014 – December 31, 2016, there were 1,226 non-fatal shooting incidents.

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[2] Some of the data collection for this project was supported by Award No. 2013-R2-CX-0015, awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. The opinions, findings, and conclusions or recommendations expressed in this publication/program/exhibition are those of the author(s) and do not necessarily reflect those of the Department of Justice.

[3] "An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury" (FBI, 2017).

Fatal shootings were obtained from the police department records management database. To be admitted into the study the incident had to meet two levels of criteria; (1) it had to be classified as a criminal homicide by UCR standards, and (2) the cause of death had to be labeled as a gunshot wound. During the study time period there were 367 criminal homicides, where the victim dead from a gunshot wound. Overall, there were 430 criminal homicides committed during the study time period, and over 85 percent were committed with a firearm. Table 2 displays the breakdown of fatal and non-fatal shootings, as well as the total number of shooting incidents during the study time period.

Table 2: Fatal and Non-Fatal Shooting Incidents

Incident Type	N	%
Non-fatal shooting	1,226	77
Fatal shooting	367	23
Total	1,593	100

Independent Variables

As previously discussed, this study employs three theoretically grounded measures in order to examine firearm violence and social processes within communities at both the neighborhood and street segment level of analysis; social disorganization (i.e., poverty, residential instability, and ethnic heterogeneity), social and physical disorder, and collective efficacy. Each measure is described below.

Social Disorganization

Consistent with prior research and to measure social disorganization, U.S. Census data are used to create factor variable measures of neighborhood poverty, residential mobility, and ethnic heterogeneity. To ensure the U.S. Census data are measuring the correct meaning of each variable (neighborhood poverty, residential mobility, and ethnic heterogeneity), confirmatory factor analysis was performed to find existing commonality between variables (Kim and Mueller, 1978). Factor variables can be created when variables have similar, high loadings.

To capture neighborhood poverty four census variables are used and were included in a principal component factor analysis; percentage of individuals living below the poverty line, percentage of individuals unemployed, the median household income, and the percentage of female-headed households. Table 3 shows the communalities for the factor variable of neighborhood poverty. The standardized communality loadings in the principal component were relatively similar across all four census measures and explains 75 percent of the co-variance in these four measures. Therefore, the factor variable measuring neighborhood poverty is statistically and theoretically appropriate for further statistical testing.

Table 3: Factor Analysis for neighborhood poverty

Variable	Communalities
Percent below poverty line	0.93
Percent unemployed	0.79
Median household income	-0.88
Percent female-headed households	0.86

To capture residential instability three census variables were used and entered into a principal component factor analysis; percentage of owner-occupied residents, the percentages of individuals that have lived in the same house for the last year, and the percentage who have moved in the last year. Table 4 shows the communalities for the factor variable of residential instability. The three communalities each have high loadings (0.8) and explains 70 percent of the variance. The percent moved in the last year is negative, which suggests that people are less likely to move and aligns with the percent owner-occupied, and percent of individuals who have lived in the same house for a year. Therefore, the factor variable measuring residential instability is also statistically and theoretically appropriate for further statistical testing.

Table 4: Factor Analysis for residential instability

Variable	Communalities
Percent owner-occupied	0.83
Percent lived in same house 1 year	0.87
Percent moved in last year	-0.83

To capture the measure of ethnic heterogeneity, two census variables were entered into a principal component factor analysis; the percentage of Hispanic residents and the percentage of individuals who are foreign born. Table 5 shows the communalities for the factor variable of ethnic heterogeneity. The variables of percent Hispanic and percent foreign born both have high loadings of 0.92 and explains 85 percent of the variance. This factor variable is theoretically and statistically appropriate to measure ethnic heterogeneity.

Table 5: Factor Analysis for ethnic heterogeneity

Variable	Communalities
Percent Hispanic	0.92
Percent foreign born	0.92

Social Disorder

Social disorder for this study is measured using data obtained from the 911 computer aided dispatch (CAD) calls for service. Following previous studies (O'Brien & Sampson, 2015; Boggess & Maskaly, 2014; Sherman & Weisburd, 1995; Weisburd & Green, 1995) this study will use police 911 calls for narcotics, public intoxication, disturbances, and loud noise complaints as indicators for social disorder. All call types will be combined into one variable to operationalize social disorder. The variable will be measured at the continuous level and be a sum of all 911 calls for narcotics, public intoxication, disturbances, and loud noise calls. For the study time period, there were 11,457 police runs that dealt with narcotics, these could be citizen complaints about narcotics in the neighborhood or narcotic investigations conducted by law enforcement personnel. Both complaints and investigations are indicators that narcotics are present or perceived to be present within the community. Public intoxication runs indicate that there are individuals drinking and loitering in public spaces, which is a sign of social disorder (Skogan, 1990). There were 5,243 police runs for public intoxication within the study time frame.

Disturbances between individuals and within neighborhoods received the highest need for police response and intervention. There were 179,506 disturbance calls during the three-year study time frame. Disturbances indicate there are arguments, fights, and other instabilities occurring within a community that require police intervention. Similarly, loud noise complaints indicate disorder within a community, and show residents cannot deal with loud music, parties, neighbors, etc. without police intervening. For the study time period there were 24,564 loud noise calls for police service. When all 911 calls for narcotics, public intoxication, disturbance, and loud noise complaints are combined into one continuous measure of social disorder, there are a total of 220,770 calls for police service. Table 6 displays the breakdown of each call type. The measures of social disorder, as well as subsequent measures of physical disorder and collective efficacy, will be measured at both the neighborhood and street segment levels.

Table 6: Social Disorder Measures

Call Type	N	%
Narcotics	11,457	5.2
Public Intoxication	5,243	2.4
Disturbance	179,506	81.3
Loud	24,564	11.1
Total	**220,770**	**100**

Physical Disorder

The measure of physical disorder for this study was gathered from two different data sources; police 911 CAD data and the Indianapolis abandoned home dataset, obtained from the OpenData Portal. Citizen calls for police response for illegal dumping, vandalism, and an abandoned vehicle are indicators that a neighborhood is un-kept and are cues that there is a breakdown of social order within the community (Skogan, 1990). There were 687 calls about illegal dumping, 3,152 reports of vandalism, and 1,214 reports of an abandoned vehicle during the study time frame. Abandoned properties are also a cue that a neighborhood is not well maintained (Skogan, 1990), and as of 2016 the City of Indianapolis reported there were 3,248 abandoned homes within the city limits. Police calls for illegal dumping, vandalism, abandoned vehicles within Indianapolis will be combined into one continuous variable to measure physical disorder. The calls for illegal dumping, vandalism, abandoned vehicles and abandoned homes will be combined into one continuous measure, for a total of 8,301 indicators of physical disorder, the breakdown is displayed in Table 7.

Table 7: Physical Disorder Measures

Call Type	N	%
Illegal Dumping	687	8
Vandalism	3,152	38

Table 7 (cont'd)

Abandoned Vehicle	1,214	15
Total	5,053	
Abandoned Homes	3,248	39
Total	**8,301**	**100**

Collective Efficacy

The variable of collective efficacy will be operationalized by combining the number of calls the Mayor's Action Center (MAC) receives from concerned citizens. The MAC receives calls about; trash, tall weeds/grass, graffiti, zoning concerns, pot holes, broken traffic signals, and illegal dumping that citizens want the city to address. This operationalization builds upon previous work out of Boston that has used and validated large administrative data sources (e.g., 311 data) for research purposes (O'Brien et al., 2015). The measure of *collective efficacy* will be a continuous variable, displaying the number of calls citizens made about their neighborhood (i.e., census tract), and street segment, suggesting that citizens are concerned about the wellbeing of their neighborhood and neighbors (Sampson et al., 1997; Weisburd et al., 2012). The calls will be divided into three sections to better understand citizens' needs and usage of the MAC data system. Public issues will be measured by calls residents make regarding; abandoned vehicles, high weeds or grass, debris and illegal dumping, and graffiti. For the study time period there were 14,168 calls to the MAC for abandoned vehicles, 596 calls for graffiti, 16,585 calls for trash, and 28,334 calls for weeds and/or high grass, for a total of 59,683 calls for public space type calls.

Since all neighborhoods across the city do not have the same levels of nuisance issues, another variable will be used to measure neighborhood engagement across the city. The number of calls the MAC receives for trash service issues and all general calls will be operationalized as a continuous variable to measure neighborhood engagement. As O'Brien et al., (2015), suggest all citizens need to utilize city trash services. For the study time period there were 33,695 calls for trash service issues (i.e., city trash collection issues), and 91,918 other general calls for city services to the MAC. Examples of other calls types that are captured in the general calls are; calls for issues with animals, environmental concerns (i.e., chemical spill), city park maintenance, traffic signals, and street repaving.

The two largest calls categories within the general calls were for animal services and street maintenance. There were 27,196 calls to the MAC relating to stray animals, abandoned/sick/injured animals, and dangerous animals. Street maintenance issues were the second largest call type with 24,572 calls for potholes, street erosion, and street line painting. Calls for animal services and street maintenance were not included in the nuisance call category as citizens may be more likely to call about these issues while driving to work, or out running errands, and these calls may not represent issues isolated to a resident's neighborhood. Table 8 displays the breakdown of MAC call types.

Table 8: Mayor's Action Center Measures

Call Type	N	%
Abandoned Vehicle	14,168	7.6
Graffiti	596	0.32
Trash	16,585	9
Weeds/High Grass	28,334	15
Total Public Space Calls	**59,683**	**32**
Trash Services	33,695	18
General Calls	91,918	50
Total MAC Calls	**185,296**	**100**

Analysis Plan

To answer the research questions guiding this study, several separate analyses will be conducted.

RQ1: What are the characteristics of neighborhoods associated with high levels of fatal and non-fatal shootings?

RQ2: Is there a relationship between social disorganization, collective efficacy, disorder, and geographic patterns of fatal and non-fatal shootings?

RQ3: What are the micro-place geographic patterns of fatal and non-fatal shootings at the street segment level?

This study is interested in examining if there are spatial patterns of fatal and non-fatal shootings, and how fatal and non-fatal shootings vary across neighborhoods at both the macro and micro level of analysis, when examining social disorganization, collective efficacy, and disorder.

Unit of Analysis

It is important to define the unit of analysis for this study and understand what will be measured at both the macro and micro level, as neighborhoods have been defined and measured differently in previous research. For this study the macro level of analysis will operationalize neighborhoods using census tracts. This follows research conducted by Klinger and colleagues (2015), Rosenfeld et al. (1999), and Taylor (1997), who argue that census groups are appropriate measures of neighborhoods due to their size and homogeneity.

The micro place unit of analysis will be the street segment and build off the previous research of Weisburd et al. (2004) in Seattle and Braga et al. (2010) in Boston. A street segment is defined as "the two block faces on both sides of a street between two intersections" (Weisburd et al., 2004), and is a small enough area to allow social trends to be noticed, whereas common aggregation methods may hide such trends (Braga et al., 2010; Taylor, Gottfredson, & Brower, 1984).

Each of the independent measures for social and physical disorder, collective efficacy, and the outcome measures of fatal and non-fatal shootings will be operationalized and measured at both the macro and micro level of analysis. The data were collected at the individual address level; therefore, each measure can be aggregated to the street segment and census tract. The independent measures for social disorganization uses U.S. Census data, which are only available at the macro level. Therefore, poverty, residential instability, and ethnic heterogeneity will only be measured at the census tract level of analysis.

Analytic Strategy

To accomplish the above analysis all data measures were geocoded through ArcGIS 10.4.1, which involves assigning X and Y coordinates to each individual address[4]. Next, using a street centerline file, a database was developed to identify and maintain all street segments within the city of Indianapolis, not just those that have a reported fatal or non-fatal shooting, indicator of social or physical disorder, or call into the MAC center (Wheeler, 2017). Each measure was then spatially joined to the corresponding street segment and census tract in which it aligns. There are 53,922 [5]street segments within Indianapolis and mean length of 391.5 feet long (SD=380.9).

This study only includes arterial and residential streets, and highways[6] are excluded due to the lack of human activity that occurs on such segments (Weisburd et al., 2012). Intersections, also known as street corners are locations where multiple streets cross. Intersections have been

[4] All measures were automatically matched with a 90% minimum candidate and match score. If measures did not automatically match at 90%, then records were matched by hand. Unknown addresses and addresses where an exact location could not be determined (e.g., 3567 Bennett – unknown if Drive, Court or Street) were dropped from the analysis.
[5] There were originally 72,148 street segments but all non IMPD jurisdiction areas (Beech Grove, Speedway, Lawrence) were removed from the analyses (n= 3,157). Next, all street segments that cross boundaries with a census tract (n=5,547) were removed to ensure spatial interdependence (Groff et al., 2009). This follows prior work by Schell et al., 2017) and still includes 96% of all street segments within Indianapolis.
[6] Highways are also State Police jurisdiction; therefore this study does not have those data.

included (Braga et al., 2010), and excluded (Weisburd et al., 2004) in previous studies, but this research follows the work done in Boston and includes intersections, as police usually record non-fatal shootings to the nearest intersection (e.g., 10th St and Rural Ave), if no crime scene can be located at a specific address (e.g., 1020 N Rural St). Similarly, research suggests that street corners commonly serve as hang out locations for gang and drug activities (Tita et al., 2003; Weisburd and Green, 1994). For the analyses, two study data sets were created: one for the individual street segment-level and one for the census tract-neighborhood level.

Preliminary analysis first examines the rate (per 10,000) for fatal and non-fatal shootings by census tract, to help determine the extent in which adding non-fatal shootings changes the picture of firearm violence. The analysis first examines each measure at the census tract level, and then moves down to the street segment. Descriptive statistics for each independent measure and the outcome measures are displayed at both the macro and micro level of analysis. These analyses will also determine which street segments possess the most fatal and non-fatal shootings in the city and establish if firearm related shootings cluster on a small number of street segments as found in previous cities (Braga et al., 2010; Koper et al., 2015).

The next step was to run a univariate and bivariate local Moran's I, to test the spatial association of each individual measure, and to examine the spatial relationship between each community measure and fatal and non-fatal shootings. These analyses were conducted in Geoda, which is a free software that can be obtained at: https://geodacenter.asu.edu/ (Anselin, 1995; Grady et al., 2017). The Moran's I test produces a scatterplot, significance map, and cluster map, which classifies each neighborhood based on a weighted average of adjoining neighborhoods, a given value, and a spatial lag term. That is, neighborhoods that are higher than the mean are considered to have "high" values, and neighborhoods below the mean have "low" values" (Anselin, 1995).

Next, a series of bivariate and multivariate regression analyses were conducted to understand the characteristics and associations between social disorganization, social and physical disorder, collective efficacy and firearm violence at both the census tract and street segment level of analysis. Geographically weighted regression analyses were performed in GWR4.0, which is a free software developed at the National Centre for Geocomputation, National University of Ireland Maynooth, and was download from (http://gwr.maynoothuniversity.ie/other-gwr-software/).

Lastly, generalized hierarchical linear modeling (GHLM) was conducted to examine effects at multiple levels of analysis. The utility of this method is simply stated by Raudenbush and Bryk (2002), "with hierarchical linear models, each of the levels in this structure is formally represented by its own sub-model. These sub-models express relationships among variables within a given level and specify how variables at one level influence relations occurring at another" (p.6-7). Further, multilevel modeling provides the ability to make statistical conclusions across different levels of analysis and incorporate individual and group level causal processes (Johnson, 2011). This approach has multiple advantages in that, it allows for the assumed highly skewed nature of homicide (i.e., fatal shootings) and non-fatal shooting data, it allows for random effects across neighborhoods, and incorporates the spatial distribution of fatal and non-fatal shootings (Morenoff, Sampson & Raudenbush, 2001). Both Morenoff et al., (2001) and Braga et al. (2010) constructed negative binominal and Poisson distributions for their outcome measures (i.e., aggravated battery with a firearm and homicides), and this study will operationalize the outcome measure (i.e., fatal and non-fatal shootings) as a count variable.

For the analyses, two study data sets will be created: one for the individual street segment-level and one for the census tract-neighborhood level. Street segment data will be fitted to a regression equation at level-1, which will produce model estimates at the individual street segment level. Census level data will be fitted to a regression equation at level-2 and will display whether the street segments differ by neighborhood context.

Chapter Summary

This chapter provides a description of the dependent measure(s) and independent measures that will be included in the statistical models to answer the proposed research questions. Additionally, the unit of analysis was described at both the macro and micro level, and which measures will be operationalized at each level of analysis. The analytic strategies that will be used to conduct this research study were also described. This study will analyze how fatal and non-fatal shootings cluster within and across census tracts and street segments. Additionally, this study will examine how social disorganization, community disorder and collective efficacy are associated with levels of fatal and non-fatal shootings between and within census tracts and micro street segments using spatial regression analyses and HGLM. The following chapter will present the results of these analyses.

Chapter 6: Results

The purpose of this dissertation is to assess the relationship between fatal and non-fatal shootings and community contextual measures of neighborhoods across Indianapolis. This chapter presents the results of the descriptive, bivariate, and multivariate statistical models used to examine the research questions in this study; (1) What are the characteristics of neighborhoods associated with high levels of fatal and non-fatal shootings? (2) Is there a relationship between social disorganization, collective efficacy, disorder, and geographic patterns of fatal and non-fatal shootings? And (3) What are the micro-place geographic patterns of fatal and non-fatal shootings at the street segment level? The results will be presented using the cone of resolution (Taylor, 1997) and begin at the census tract level, and move down to the street segment level.

The initial set of analyses will examine the similarities and differences between patterns of fatal and non-fatal shootings across Indianapolis. Research has traditionally only examined spatial patterns of homicides (Cohen & Tita, 1999; Morenoff et al., 2001; Zeoli et al., 2014, 2015) but recent work demonstrates that non-fatal shootings occur at a higher rate than fatal shootings (Hipple et al., 2016; Hipple & Magee, 2017). Therefore, it is important to understand if fatal and non-fatal shootings are spatially correlated and if they are, where they are spatially clustered to better understand the geographic patterns of firearm violence.

Firearm Violence

The first step in the analyses was to examine the spatial distribution of fatal and non-fatal shootings across Indianapolis and was conducted in multiple stages. The first stage was to examine the spatial concentration of both fatal and non-fatal shooting rates by census tract, the second stage was to explore the rate ratio of fatal versus non-fatal shootings, and the last step was to explore the spatial correlation between fatal and non-fatal shootings.

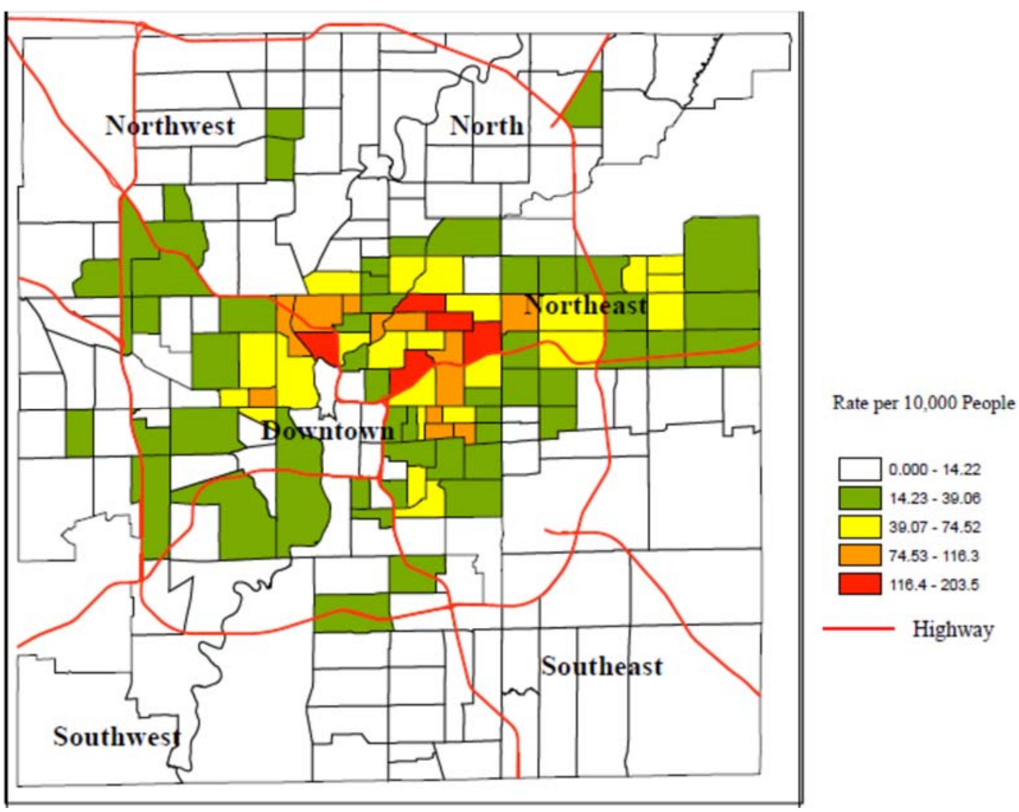
There are 212[7] census tracts (i.e., neighborhoods) within Indianapolis and 179 experienced at least one shooting incident during the three-year study time frame. That is, 84 percent of neighborhoods within Indianapolis experienced at least one act of firearm violence within three years. Figure 2 displays the fatal and non-fatal shooting rate per 10,000 for each census tract in Indianapolis[8] , although the spatial concentrations were explored independently (i.e., only fatal shootings or only non-fatal shootings) initially, the combination of both fatal and non-fatal shootings better displays the concentration of shootings. When the shooting incidents were examined individually as fatal and non-fatal shootings, the rates of firearm violence were drastically different. For example, the highest rate in a neighborhood for fatal shootings was 55.6 per 10,000 people, whereas the highest rate in a neighborhood for non-fatal shootings was 203.5 per 10,000 people. Further, areas of the city that appeared to not have high levels of fatal shootings, emerged as areas with high levels of firearm violence when non-fatal shootings were included in the total number of firearm shooting incidents.

When fatal and non-fatal shootings were combined into one variable of firearm violence a more complete picture was displayed of where firearm violence is occurring and the prevalence in certain neighborhoods. For example, there are eleven census tracts that display fatal and non-fatal shooting rates of over 100 per 10,000 people. Nine of these census tracts are considered stable rates, where the total of fatal and non-fatal shooting incidents exceeds 20 incidents and the population of each census tract is over 500 individuals. Base rates for each neighborhood were calculated to determine areas with low numbers of fatal and non-fatal shootings and identify areas with unstable rates. The majority of neighborhoods (n=89) had base rates with less than

[7] The census tracts that primarily fell in the cities of Beech Grove, Lawrence, Speedway, and Airport Authority were excluded because they are out of IMPD's jurisdiction.
[8] The rate was calculated using the equation (total number of fatal and non-fatal shooting incidents/total population of census tract*10,000).

five fatal and non-fatal shootings suggesting these are unstable rates, could vary over time, and could be influenced by unusual events in any given year. Although these areas were considered to have unstable rates, they are still experiencing firearm violence and could be considered emerging areas and should be monitored over time. The majority of firearm violence is centered around the immediate downtown area, with rates as high as 116 per 10,000 individuals and 203 per 10,000 individuals in five census tracts. The rate of firearm violence decreases as you move further outside the downtown area, to rates as low as 3.09 per 10,000 individuals. This spatial pattern of fatal and non-fatal shootings follows Park and Burgess' concentric zone pattern from the 1920s. Although these rates seem to drop the further from the city center, these outer areas of the city still have incidents of firearm violence where a person suffers a violent injury from being struck by a bullet.

Figure 2: Firearm Shooting Incidents in Indianapolis, 2014 - 2016



The second step was to examine the rate ratio of fatal and non-fatal shootings and display the spatial differences by neighborhood, which is displayed in Figure 4. The rate ratio was calculated by taking the fatal shooting rate divided by the non-fatal shooting rate (fatal shooting rate/ non-fatal shooting rate). The rate ratio displays the disparities across neighborhoods based on lethality of the shooting incident. Neighborhoods highlighted in pink have a higher risk for fatal shootings (n=9), whereas the neighborhoods highlighted in blue have a lower risk for fatal shootings, and therefore a higher risk of non-fatal shootings (n=89). The neighborhoods highlighted in gray display no difference between the risk of fatal versus non-fatal shootings (n=9). Table 9 displays the average number of fatal and non-fatal shootings per neighborhood type. For instance, the blue neighborhoods that display a higher risk for non-fatal shootings averaged 10.5 non-fatal shootings, compared to 3.4 fatal shootings over the three-year time period. Whereas the neighborhoods with a higher risk for fatal shootings averaged 3 fatal shootings and only 1.9 non-fatal shootings over the study time period. The gray neighborhoods that displayed no difference in lethality had an average of 2.4 incidents for both fatal and non-fatal shootings. Figure 3 displays the distribution of the fatal versus non-fatal shooting across the three neighborhood categories. These findings suggest there are spatial disparities between fatal and non-fatal shootings in regards to risk of lethality but that adding non-fatal shootings to the examination of firearm violence increases the understanding of where and how often shootings are occurring.

Table 9: Average Rate Ratio, Fatal and Non-fatal Shooting per neighborhood

Neighborhood Category	NFS Rate (mean)	Fatal Rate (mean)	Firearm Violence Rate (mean)	Rate Ratio (mean)
NFS Neighborhood (n=89)	10.5	3.4	13.9	0.36
Fatal Neighborhood (n=9)	1.9	3	4.9	1.74
No Difference (n=9)	2.4	2.4	2.1	1

Figure 3: Distribution of rate ratio of fatal and non-fatal shootings

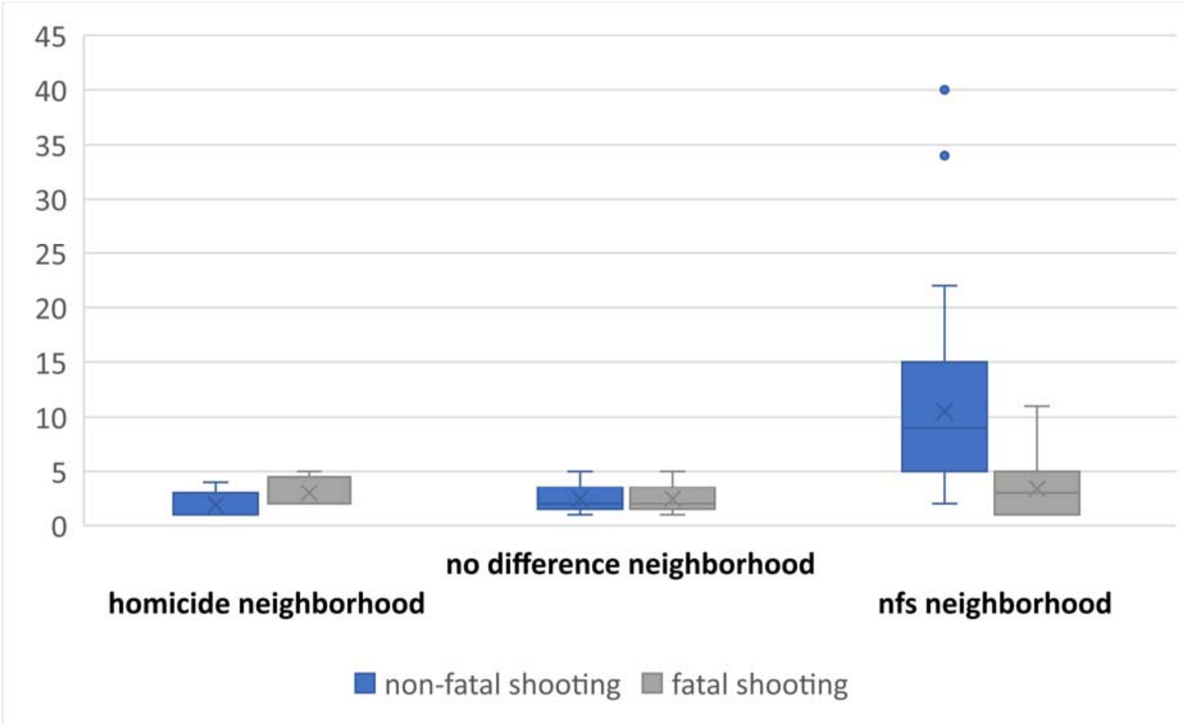
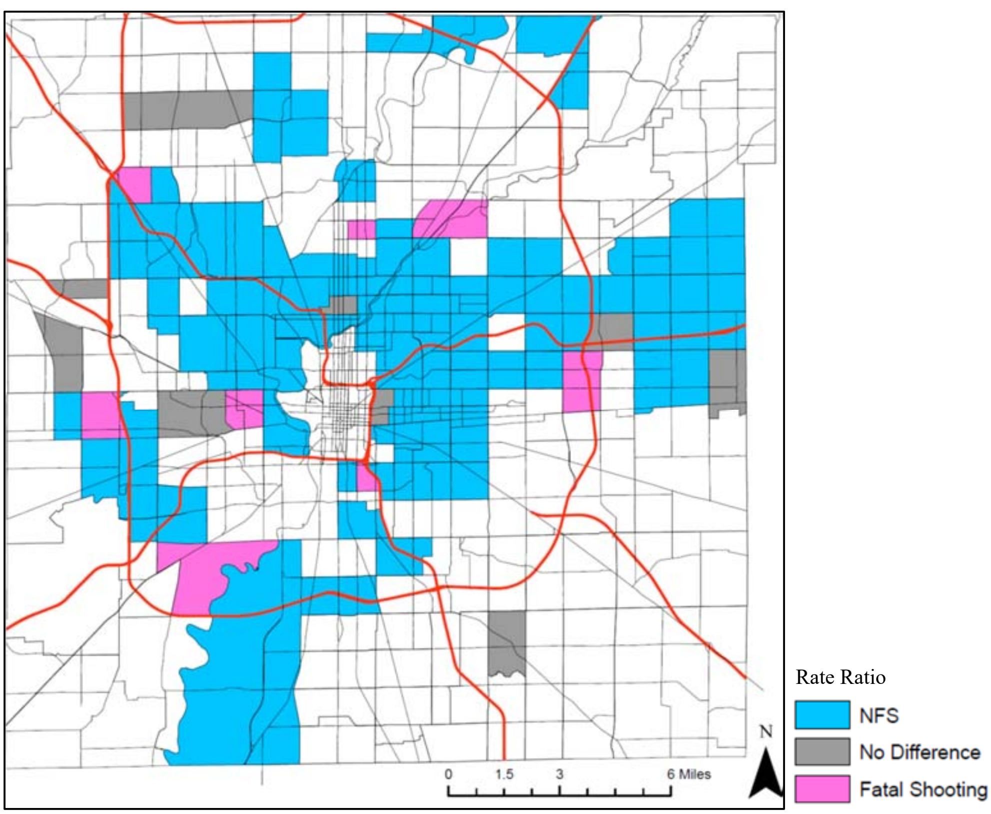


Figure 4: Rate Ratio of Fatal and Non-fatal Shootings in Indianapolis, 2014 – 2016.



The next step to examine the spatial similarities and differences between fatal and non-fatal shootings was to conduct a Local Moran's I to test the spatial autocorrelation. Spatial autocorrelation examines if geographic units are influenced by similar events (e.g., firearm shooting incident) because of spatial proximity. It examines how the observed value at one location depends on values observed at neighboring locations (Anselin, 2003). The results suggest there is spatial autocorrelation between the rate of non-fatal and fatal shootings in certain areas of the city, with statistically significant p-values (p=.001), positive Moran's I (I=0.56) and z-score (14.3), when 999 permutations were run. The z-score demonstrates the level of concentration and the higher the number the more spatially concentrated the measure is, a z-score of 14.3 suggests high levels of spatial autocorrelation between fatal and non-fatal shootings.

Figure 5: Bivariate Local Moran's I between rate of non-fatal and fatal shootings

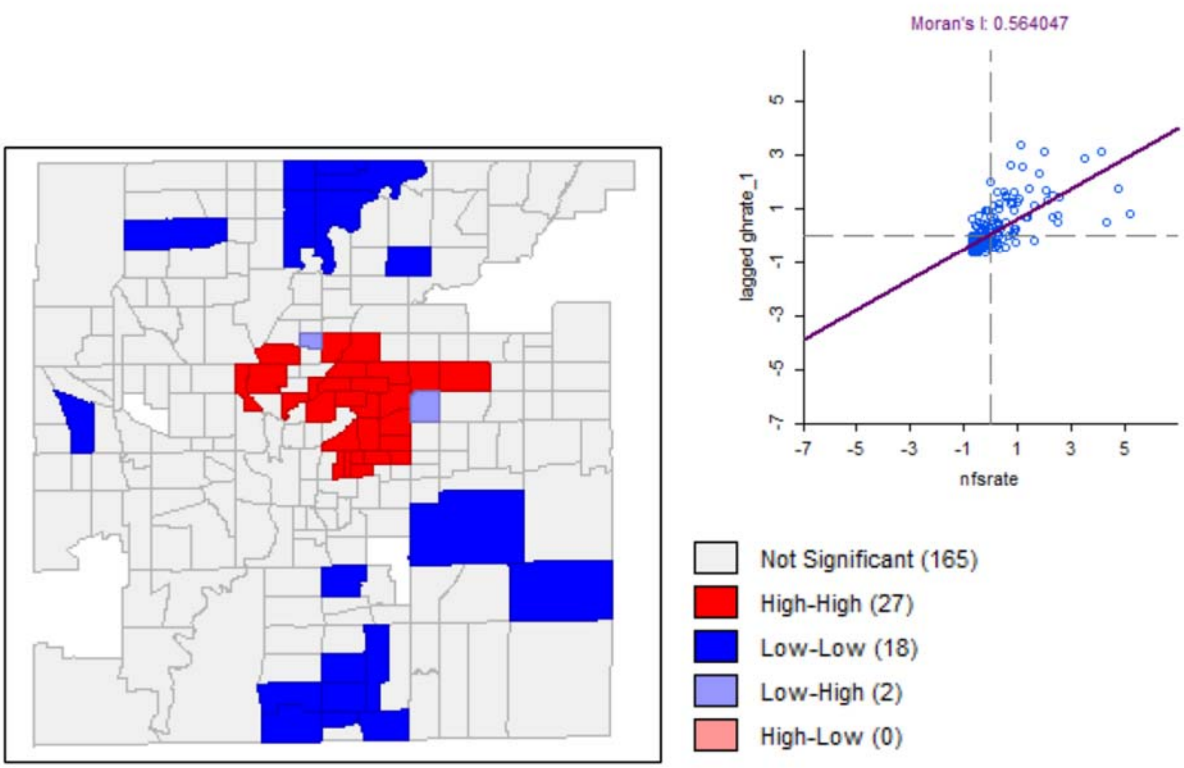


Figure 5 displays the bivariate Local Moran's I cluster map which shows the spatial clustering of the relationship between non-fatal and fatal shootings. The areas highlighted in red are areas that have both high levels of non-fatal and fatal shootings and are spatially related to other areas with high rates of non-fatal and fatal shootings. These areas in red are also the areas with the highest levels of firearm violence (mean = 25.8), whereas the areas in blue are areas with low-low values of both non-fatal and fatal shootings (firearm violence mean = 1.8). The areas in purple display areas of the city that have low rates of non-fatal shootings and high rates of fatal shootings but display a spatial relationship with areas that have high rates of firearm violence. These purple areas are considered spatial outliers. The two neighborhoods highlighted in purple border the areas of the city with the highest levels of firearm violence and suggest there may be other community or social processes occurring in those areas that may lower the occurrence of shootings (firearm violence mean = 5).

The prior three analyses examine the spatial patterns of fatal and non-fatal shootings across Indianapolis. Overall the results suggest that including non-fatal shooting incidents into the study of firearm violence gives a more complete understanding of where individuals are being victimized by shooting incidents and the prevalence of firearm violence in Indianapolis. Secondly, these results display that the risk of being a fatal shooting victim is higher in some areas of the city compared to other areas where the risk of being a non-fatal shooting victim is higher, again suggesting that including non-fatal shootings into the study of firearm violence gives a more complete picture of where shootings are occurring and the individual risk of victimization. Lastly, these results suggest that fatal and non-fatal shootings are spatially correlated, that is incidents are similar to one another and there is a spatial pattern to them. Due to the spatial relationship between fatal and non-fatal shootings, they will be combined into one variable depicting firearm violence for the remainder of the analyses.

The next step in these analyses is to include all the independent community measures into the descriptive and multivariate models to better understand the spatial relationship between social disorganization, disorder, collective efficacy and firearm violence. The univariate and bivariate descriptive statistics will be discussed next, followed by a series of multivariate analyses, and lastly each of the community measures and firearm violence at the street segment level of analysis.

Univariate Results

Table 10 displays the measures of central tendency and dispersion for the outcome measure of firearm shooting incidents, as well as other covariate measures at the neighborhood level.

Table 10: Descriptive Statistics for Dependent and Independent Measures

Variable	N	Mean	Std. Dev.	Min	Max
Firearm Violence	212	7.17	8.15	0	46
Poverty	212	3	1	.65	5.4
Residential Mobility	212	3	1	.45	4.9
Ethnic Heterogeneity	212	3	1	1.8	8.0
Social Disorder	212	1036.7	697.2	0	3981
Physical Disorder	212	38.97	32.83	3	196
CE – Public	212	278.1	234.4	0	939
CE – Trash	212	156.5	169.2	0	1323
CE – General	212	430.2	331.8	0	1993

The measures of poverty, residential mobility and ethnic heterogeneity are factor scores based on census measures described in the prior chapter. A constant of 3.0 was added to the factor measures of poverty, residential mobility, and ethic heterogeneity in order to eliminate the negative values because independent variables are not permitted to have negative values in regression models (Morenoff et al., 2001). The outcome measure of firearm violence is a continuous variable, representing the count of fatal and non-fatal shootings per neighborhood. The other independent variables representing contextual community level measures are also all measured as continuous variables. The measures of collective efficacy-public, trash and general were reverse coded.

Table 11: **Correlation Matrix of Independent Variables**

	Poverty	Residential Mobility	Ethnic Heterogeneity	Social Disorder	Physical Disorder	CE – Public	CE – Trash	CE – General
Poverty	1.00							
Residential Mobility	-0.482*	1.00						
Ethnic Heterogeneity	0.213*	-0.317*	1.00					
Social Disorder	0.617*	-0.299*	0.232*	1.00				
Physical Disorder	0.612*	-0.206*	-0.043	0.704*	1.00			
CE – Public	-0.551*	0.105	0.078	-0.584*	-0.707*	1.00		
CE – Trash	-0.409*	0.069	0.000	-0.444*	-0.5012*	0.741*	1.00	
CE – General	-0.266*	0.126	-0.026	-0.479*	-0.399*	0.684*	0.701*	1.00

*p = .05

Table 11 displays the correlation matrix of the interrelationships between the independent variables. The variables of physical and social disorder are highly correlated together, which is expected given that neighborhoods with more disorganization have higher levels of disorder and each measure is an indicator that a community needs police assistance. Additionally, these results display the interrelationships of the three measures of collective efficacy. The variables of collective efficacy – public, collective efficacy trash, and collective efficacy general are all highly intercorrelated with each other at the .7 level, suggesting they are measuring similar dimensions of collective efficacy[9].

[9] A principal components analysis was also conducted, and all three collective efficacy measures loaded on the same factor with scores greater than .5, indicating they are measuring the same concept.

Spatial Concentration of Neighborhood Measures and Firearm Violence

The next step in the analyses was to explore the spatial variation of each community measure across neighborhoods within Indianapolis. Figure 6 displays maps for each independent variable and indicates the spatial concentration across the city of Indianapolis. The categories were determined using natural breaks, which allows ArcGIS to identify natural cut points within the distribution of each independent measure.

Figure 6: Spatial Concentration of Independent Variable Measures

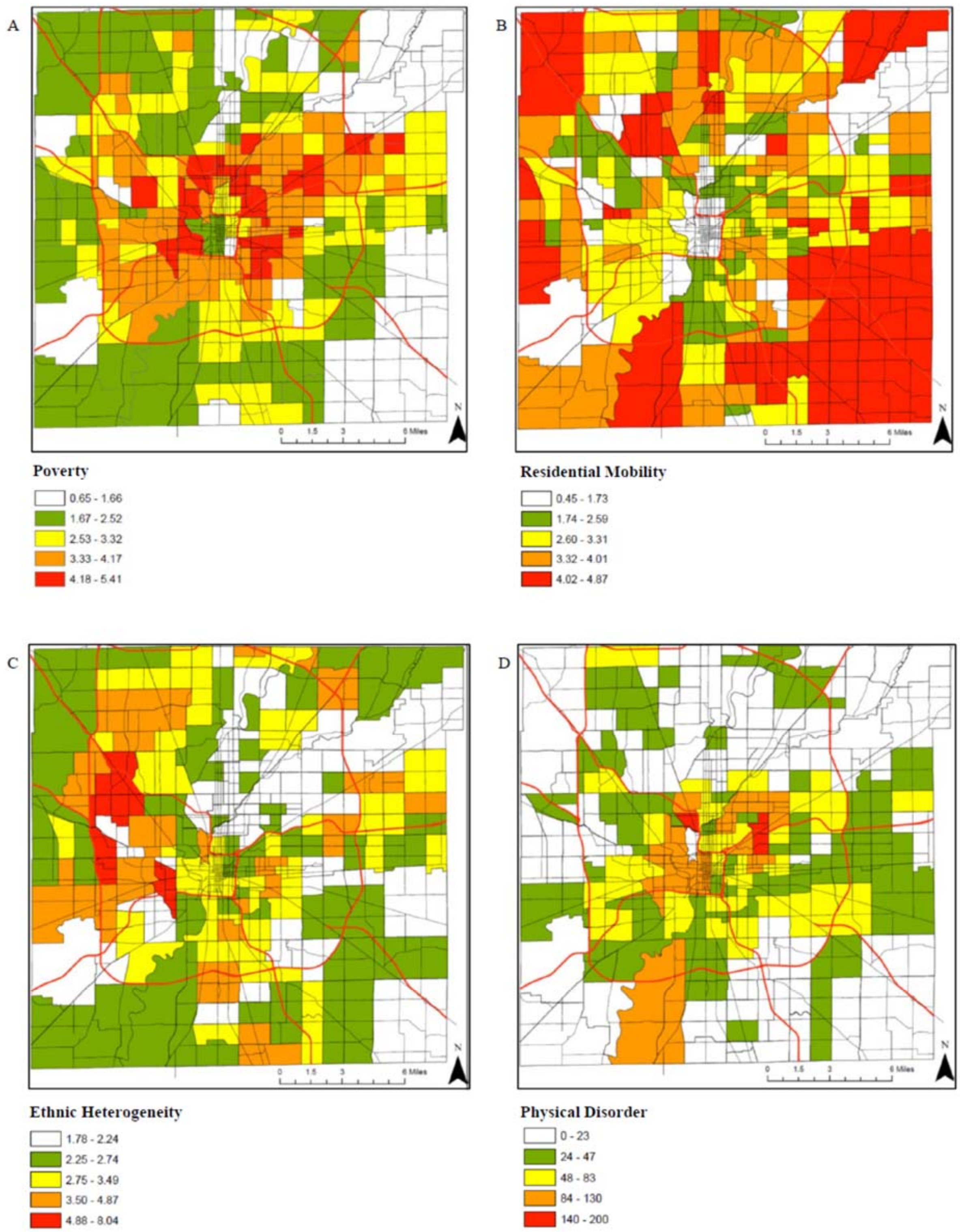


Figure 6 (cont'd)

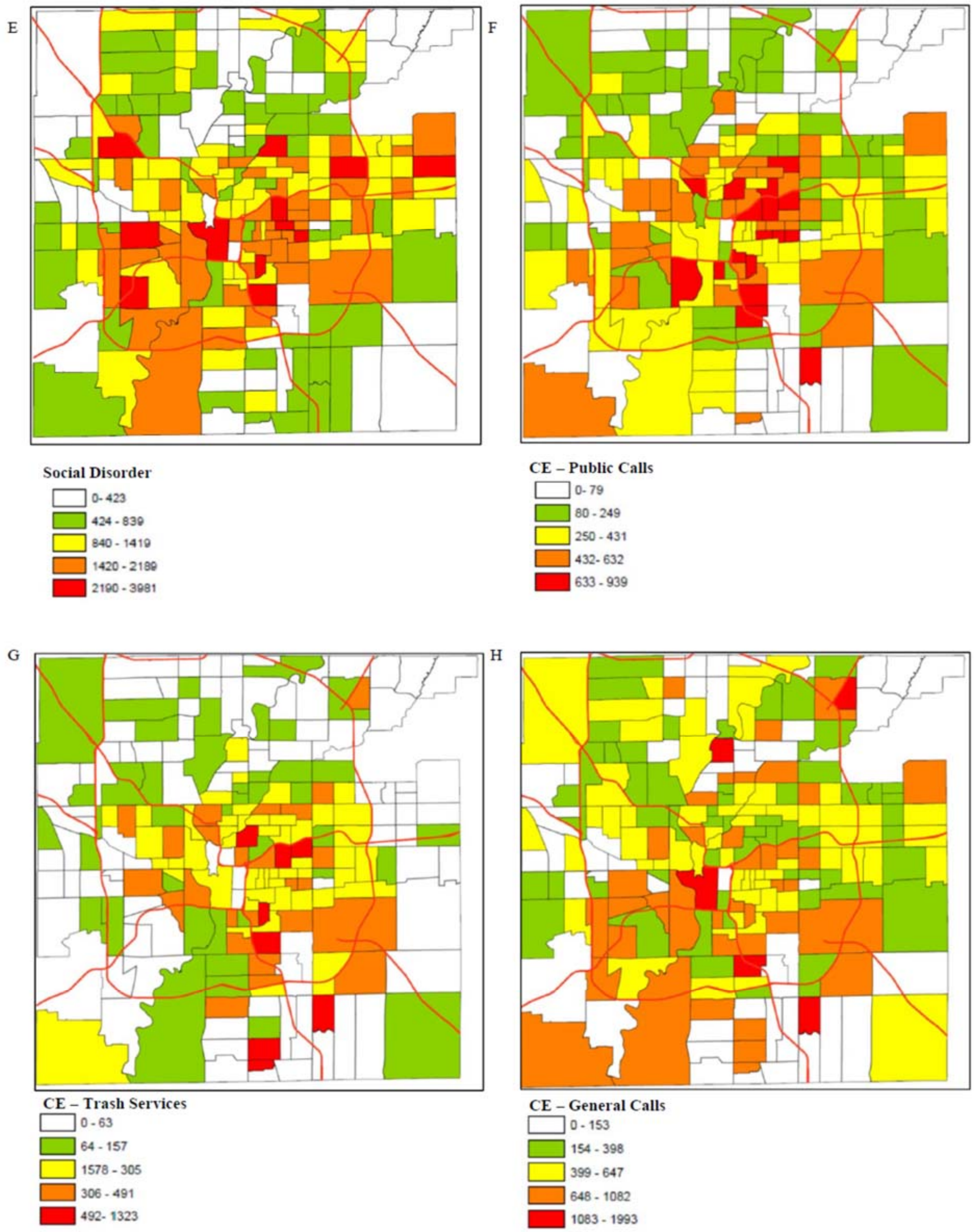


Figure 6A displays where levels of poverty are highest across the city. The neighborhoods with the highest levels of poverty are centered around the immediate downtown area and spread across most of Indianapolis. The lowest levels of poverty are in the outer most neighborhoods, which border affluent suburbs, and the north center of the city, which is a unique area of the city with older affluent homes. Figure 6B displays residential mobility and indicates that there are pockets of the city where residential mobility is higher than others but is generally concentrated on the four corners of the city. The far Southeast side, far Northeast and far Northwest side are areas where new development has occurred in the past ten years and directly boarders the more affluent suburban communities. Figure 6C displays where the levels of ethnic heterogeneity are highest, which are concentrated mainly on the West side of town, with random pockets dispersed around the city. The areas highlighted in red are communities that are known to have high Hispanic populations and these neighborhoods follow pockets of the city that are known to have high ethnic populations.

Figure 6D displays the spatial classification for physical disorder. There are neighborhoods dispersed around the city that display high levels of physical disorder, but the highest levels are concentrated around the Downtown area with a few pockets on the South side. Figure 6E displays the spatial classification for social disorder. There are neighborhoods with high levels of social disorder randomly dispersed across the city but the majority of communities with high levels of social disorder are concentrated in the area surrounding Downtown. Figures 6F, 6G and 6I show where the Mayor's Action Center calls are generated across the city. The three maps display the calls for public issues (e.g., calls for high weeds, trash, graffiti, etc.), calls for a more personally motivated reason (i.e., issues with their trash services), and general calls (e.g., potholes, street lights, etc.). These maps display that the Mayor's Action Center is utilized by the entire city, but that there is spatial variation in the type of calls. For example, the calls for public space have higher levels in the areas immediately surrounding Downtown compared to the outer neighborhoods on the county boarder.

Bivariate Analysis

Table 12: Pearson Correlations between Firearm Violence and Independent Measures

Variable	Firearm Shooting Incident	p-value
Poverty	0.77*	p < .001
Residential Mobility	-0.37*	p < .001
Ethnic Heterogeneity	0.06	p <.05
Social Disorder	0.59*	p < .001
Physical Disorder	0.66*	p < .001
CE – Public	- 0.64*	p < .001
CE – Trash	- 0.45*	p < .001
CE – General	- 0.38*	p < .001

Table 12 displays the Pearson correlations between the eight independent variables and the outcome measure of fatal and non-fatal shootings. Four of the variables have a positive, statistically significant relationship with firearm shooting incidents, and four have a negative relationship with firearm violence. The strongest relationship was observed between poverty (r = .77), physical disorder (r = .66), and collective efficacy measure of public calls (r = -.64). The variable of residential mobility produced a negative, statistically significant (r = -.37) relationship with firearm shootings, and the measure of ethnic heterogeneity did not reach the level of statistical significance. Residential mobility is in the opposite direction as is expected from classic social disorganization theory, whereas the measures of collective efficacy are all negatively associated with firearm violence, which is expected from social disorganization theory.

Bivariate Spatial Correlation

Next, to examine the spatial relationship of each measure a bivariate local Moran's I was conducted between each independent community measure and firearm violence. This tests the spatial correlation between each independent variable and firearm violence. The prior Pearson correlation assessed the correlation between each variable and firearm violence but did not account for the spatial relationship, as these analyses do. The results are displayed in Table 13.

Table 13: Bivariate Local Moran's I between Firearm Shooting Incident & Independent Measures

Variable	Moran's I	z-value	Sd	E[I]	Mean
Poverty	0.59*	14.00	0.0425	-0.0047	-0.0046
Residential Mobility	-0.23*	-6.62	0.0351	-0.0047	0.0011
Ethnic Heterogeneity	0.0097	0.29	0.0342	-0.0047	-0.0005
Social disorder	0.430*	11.36	0.0383	-0.0047	-0.0051
Physical disorder	0.509*	13.39	0.0383	-0.0047	-0.0031
CE – public	- 0.438*	- 11.44	0.0386	-0.0047	0.0032
CE – trash	- 0.239*	- 6.53	0.0371	-0.0047	0.0026
CE – general	- 0.119	- 3.45	0.0357	-0.0047	0.0037

* p-value = .001 /999 permutations

The results suggest there is statistically significant spatial autocorrelation with each of the community measures and firearm violence, besides general calls into MAC. The measures of poverty, collective efficacy, social and physical disorder, and collective efficacy trash are all spatially clustered based on high or low expected values in relation to firearm shooting incidents. Figure 7 displays the cluster map and scatterplot for each bivariate relationship. The scatterplot and cluster maps display how each neighborhood is classified above (high) or below the mean (low), and how such neighborhoods spatially cluster across the city.

Residential mobility produced a negative local Moran's I score suggesting values are more dispersed than is expected and there are neighborhoods where high and low values are presenting a competing process. Figure 7B displays that the areas on the South side of the city have high levels of residential mobility and low levels of firearm violence, whereas the neighborhoods in the center of the city highlighted in red have high levels of residential mobility and high levels of firearm violence. The areas in purple display areas with low levels of residential mobility but high levels of firearm violence, suggesting there is not a lot of people moving in and out of neighborhoods with high levels of firearm violence. When examining the cluster map for ethnic heterogeneity, there are pockets of the city that have low levels of ethnic populations, in close proximity to areas with high levels of firearm violence (in purple), and areas with high ethnic populations and firearm violence (in red), but these spatial patterns were not statistically significant.

Maps 7D and 7E display the results for physical and social disorder and are nearly identical. The majority of areas surrounding the immediate downtown area have both high physical disorder and firearm violence, and high social disorder and firearm violence, which is highlighted in red on both maps. There are differences in neighborhoods with low levels of physical disorder and social disorder and firearm violence, which is highlighted in purple on each map. These results suggest there may be different social processes occurring within each individual neighborhood that effects the level of firearm violence.

The remaining maps display the spatial relationship between each of the three measures of collective efficacy – public, trash services, and general calls. Each measure has a negative relationship with firearm violence and negative Moran's I score, suggesting dissimilar patterns cluster together. Figures 7F, 7G, and 7H display nearly identical spatial patterns between each measure of collective efficacy and firearm violence, with some variation in the type of call across neighborhoods. For example, there are a higher number of general calls on the immediate northeast side of downtown associated with high levels of firearm violence, which is highlighted in red in Figure 7H. These bivariate results, along with the basic descriptive statistics and high intercorrelations of the three collective efficacy measures suggests two things; (1) that the entire city uses the Mayor’s Action line, and (2) each collective efficacy measure of public, trash services and general calls are measuring a similar concept of community engagement and action to improve the city of Indianapolis. Although as O’Brien et al. (2015) suggests, the only difference is the motivation behind the call type. This study is interested in measuring the concept of residents being engaged within their neighborhood and taking some sort of ownership, therefore the main measure of collective efficacy will be calls into the Mayor’s Action line for calls relating to public space (i.e., collective efficacy – public space). Although the calls for trash services and general calls appear to also be measuring community engagement, a call about trash services can be more privately motivated (O’Brien et al., 2015), and general calls into the Mayor’s Action line for issues related to pot holes and street lights may have been done by citizens from outside each neighborhood as they drive to work or conduct other activities where they are just driving through the neighborhood.

Figure 7: Bivariate Local Moran's I Cluster maps and scatterplots

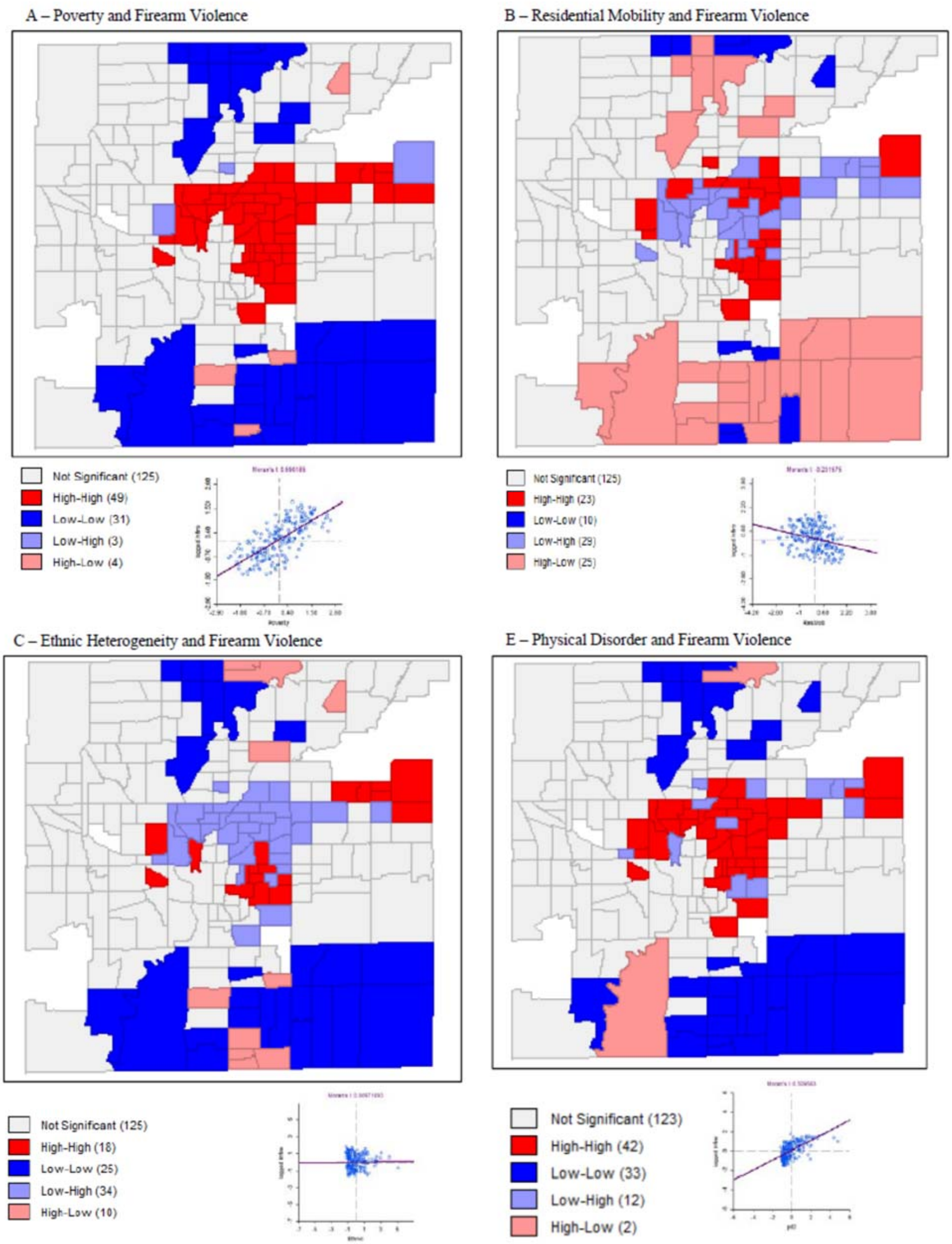
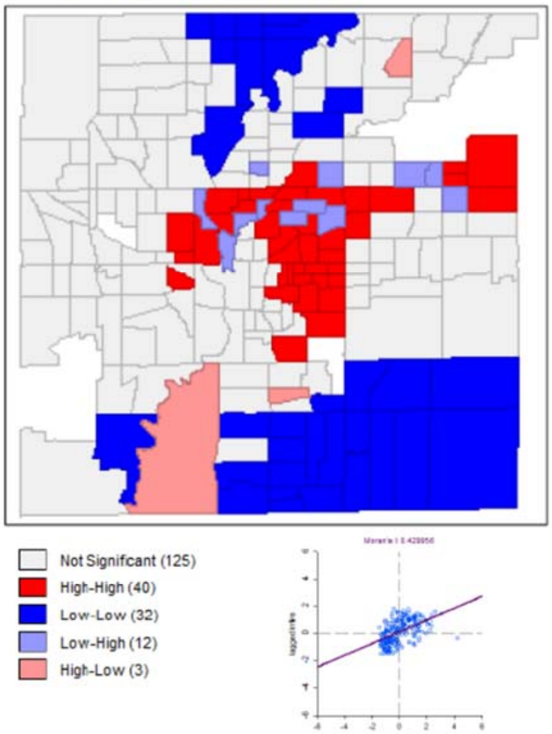
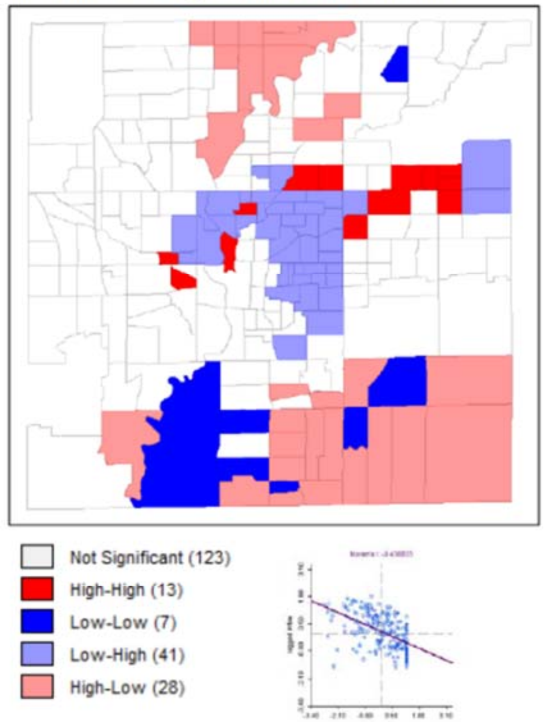


Figure 7 (cont'd)

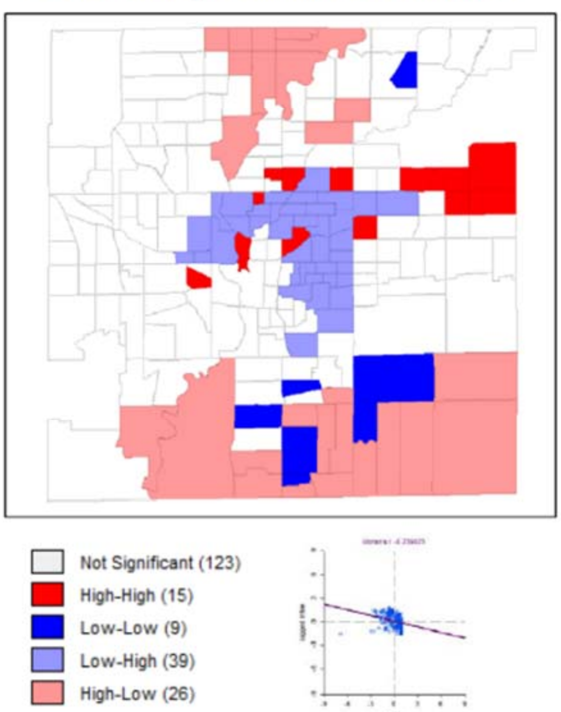
E – Social Disorder and Firearm Violence



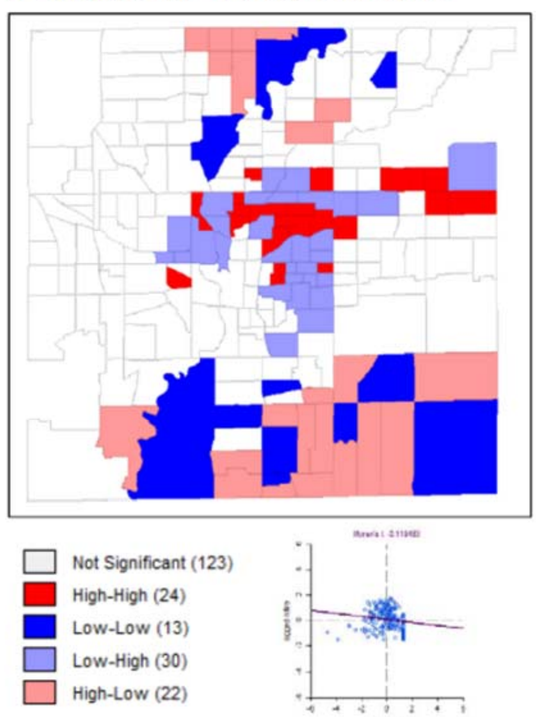
F – Collective Efficacy – Public and Firearm Violence



G– Collective Efficacy – Trash Services and Firearm Violence



H – Collective Efficacy –General and Firearm Violence



Multivariate Results

Next, all the independent variables were entered into the ordinary least squares (OLS) regression models[10], to test the relationship between each independent measure and fatal and non-fatal shootings, which is displayed in Table 14. Even though the prevalence of firearm shooting incidents being higher when non-fatal shootings are added to the equation, the incidents are still considered rare events and are highly skewed to the right. For that reason, following prior research (Corsaro & McGarrell, 2010; Schell et al., 2017; Cahill & Mulligan, 2007) the count of firearm shooting incidents was transformed into the expected firearm shooting rate through a natural logarithmic function per 10,000 (ln(firearm shooting incident/population*10,000) . The log of fatal shooting incidents is used as the dependent variable in both the ordinary least square regression and geographically weighted regression, as it is normally distributed and at the continuous level. Even though ethnic heterogeneity was not statistically significant in the bivariate analysis, it was included in these models due to it being a key measure in social disorganization theory. Additionally, a series of diagnostic tests were conducted to test for multicollinearity and all values of the variance inflation factor (VIF) were less than four, suggesting that multicollinearity is not a problem.

[10] All assumptions of OLS were met prior to running the multivariate regression models.

Table 14: Results of ordinary least squares regression on firearm violence and community measures

Variable	Model 1		Model 2		Model 3	
	Beta (S.E.)	t	Beta (S.E.)	t	Beta (S.E.)	t
Poverty	.795*** (.072)	16.32	.595*** (.082)	10.71	.540*** (.088)	9.11
Residential Mobility	-.023 (.076)	-0.45	-.072 (.071)	-1.52	-.068 (.071)	-1.46
Ethnic Heterogeneity	-.105* (.069)	-2.31	-.058 (.063)	-1.38	-.055 (.066)	-1.23
CE – Public			-.299*** (.0003)	-6.09	-.219** (.0004)	-3.75
Physical Disorder					.129 (.003)	1.92
Social Disorder					.036 (.0001)	0.58
Constant unstan. coeff.	-.688 (.45)	-1.52	-.332 (.422)	-0.79	-.281 (.418)	-0.68
Adj R^2	0.62		0.67		0.68	

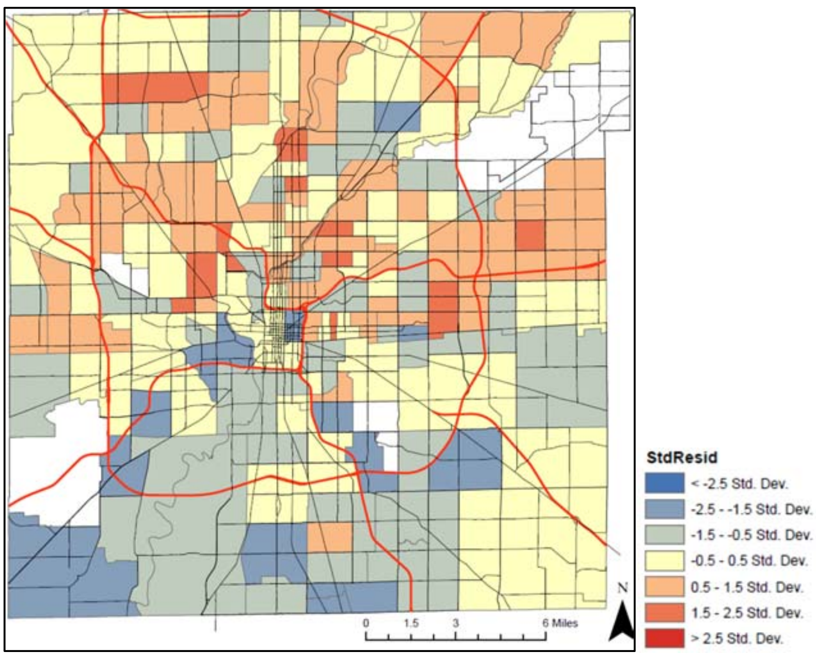
Model 1 tests the social disorganization theoretically driven variables of poverty, residential mobility, and ethnic heterogeneity. The overall model explains 62 percent (R^2=.62) of the variance. Poverty is positively related to shootings and for every standard deviation increase in neighborhood poverty, neighborhood shooting rates increase by .795 standard units. Ethnic heterogeneity (β= -.105) is negatively related to shootings and suggests that neighborhoods with high ethnic populations may act as a protective factor against shootings. Residential mobility did not reach the level of statistical significance. The negative association of ethnic heterogeneity and non-significance of residential mobility are both in the unexpected direction from classic social disorganization theory. The unexpected findings of ethnic heterogeneity and residential mobility may reflect broader changes in urban environments (e.g., gentrification) since the development of social disorganization and will be discussed in greater detail in the concluding chapter.

Model 2 added the measures of collective efficacy into the model to test if collective efficacy mediates social disorganization and firearm violence. The overall model explains 67 percent (R^2=.67) of the variance and is an improved model fit from model 1, which suggests that collective efficacy does help explain levels of firearm violence. The results suggest that for every standard deviation increase in neighborhood collective efficacy there is a .299 unit decreases in the rate of neighborhood firearm violence. Further, the beta coefficient value of poverty decreased in significance from .795 to .595 when collective efficacy was added to the model suggesting that collective efficacy mediates the relationship between neighborhood poverty and firearm violence, consistent with Sampson et al.'s foundational findings (1997). The measures of residential mobility and ethnic heterogeneity did not reach the level of statistical significance.

Model 3 added the measures of social and physical disorder to the model and the model continued to control for all theoretically relevant measures. The overall model explained 68 percent (R^2=.68) of the variance, again displaying an improved model fit, although minor. The measure of poverty (β= .540) remains statistically significant and suggests for every standard deviation increase in poverty levels, a neighborhood's rate of shootings increases by .540 standard units, respectively. The measure of collective efficacy for public type calls reached the level of statistical significance and suggests for every standard increase in collective efficacy, the rate of neighborhood firearm violence will decrease by .219 (β= -.219). The measures of physical disorder and social disorder did not reach the level of statistical significance, which is an unexpected finding using social disorganization theory. Similarly, from model 2, residential mobility and ethnic heterogeneity did not reach the level of statistical significance. Additionally, the strength of the relationship between poverty and firearm violence decreased from β= .595 to β= .540, and similarly with the relationship between collective efficacy β= -.299 to β= -.219 and firearm violence when the model controlled for physical and social disorder. These results suggest that disorder has a moderating effect on social disorganization.

The next step in the analyses was to map the residuals and test for spatial autocorrelation. Spatial autocorrelation examines if geographic units are influenced by similar events (e.g., firearm shooting incident) because of spatial proximity. It examines how the observed value at one location depends on values observed at neighboring locations (Anselin, 2003). The results suggest there is spatial autocorrelation among residuals from model 3 of the OLS (Moran's I =0.205*, z=8.36), and reached statistical significance when running 999 permutations ($p <.000$). These findings are important to understand for subsequent analyses because prior research has shown that spatial autocorrelation can be a problem when trying to model the relationship between crime and place (Morenoff and Sampson, 1997; Morenoff et al., 2001), as it violates the assumption in many regression models of independence, therefore leading to biased estimates (Baller, Anselin, Messner, Deane, and Hawkins, 2001). Secondly, these results highlight the importance of examining the spatial locations of firearm shooting incidents. Figure 8 displays a map of the residuals from model 3. The areas in dark red are the neighborhoods that the current model is not explaining very well. Interestingly, there are four specific neighborhoods where the model is not explaining the patterns well and are some of the areas with the highest rates of shooting incidents. Whereas other neighborhoods with high levels of shooting incidents are highlighted in blue, indicating the model has predicted well. These results suggest there is spatial variation in neighborhood factors associated with rates of firearm violence. Overall, the theoretical model provided a good fit to the data, but there were a relatively small number of neighborhoods for which the model did not provide a good fit. That is, not all neighborhoods with high levels of firearm shooting incidents are caused by the same contextual factors, or there are other underlying factors at play that are creating high levels of spatial autocorrelation. To further explore these underlying spatial relationships that are violating the OLS assumption of independence, a geographically weighted regression was conducted.

Figure 8: OLS Residuals across Indianapolis neighborhoods



Geographically Weighted Regression

To better understand the spatial variation between the community factors and fatal and non-fatal shootings across neighborhoods, a geographically weighted regression (GWR) was conducted. In the traditional OLS regression, or global model, only one parameter is estimated for each variable included in the model and is assumed to be constant across the study area. Whereas, GWR extends the traditional regression approach and allows each parameter to vary at the local level, which is each regression point and by location (locations were defined by the spatial coordinate at the centroid of each census tract) (Cahill & Mulligan, 2007; Graif &

Sampson, 2009). GWR is important as each neighborhood may have certain community factors that contribute to the level of neighborhood firearm violence that differs from another neighborhood. That is, instead of one global regression model (OLS) explaining what factors contribute to firearm violence in all of Indianapolis, GWR allows us to conduct 212 regression models within each of the neighborhoods (i.e., census tracts) to understand which community factors influence the levels of firearm violence within each individual neighborhood.

Geographic weights were assigned using the Gaussian kernel function since the outcome variable is continuous and the kernel is defined by the bandwidth. The larger the bandwidth, the wider the kernels and smoother the parameter surfaces, the optimal bandwidth can be suggested by the data by minimizing the Akaike Information Criterion (AIC). Therefore, GWR provides the opportunity to increase the explanatory power of the regression model by incorporating the important spatial relationships. Additionally, spatial regression models allow for spatial autocorrelation and relaxes the assumption of spatial independence by including local relationships in the error covariance structure (Anselin, 1988).

Table 15: Gaussian geographically weighted regression analyses estimating firearm shooting incidents at the neighborhood level

Model	Bandwidth	K	Adj. R^2	AICc	Diff AICc
Global GR	na	1		773.6	
GWR	42	1	0.57	600.9	172.7
GWR (Pov)	44	2	0.66	547.5	53.4
GWR (Pov, CE - Public)	46	3	0.73	499.7	47.8
GWR (Pov, CE – Public, Phy Dis, Soc Dis)*	48	4	0.74	494.9	4.8

The results from the GWR are presented in Table 15. The results display there is a sharp reduction in the (AIC) from the global model to the GWR models, demonstrating the need to model the spatial variation of firearm shooting incidents across neighborhoods. The reduction in

AIC indicates an improved model fit with each additional measure that was added. All measures varied at the local level within the model (i.e., within each individual neighborhood). Poverty was included as a global measure (i.e., across all neighborhoods) but did not change the results, suggesting these measures vary locally within Indianapolis neighborhoods. Additionally, the high adjusted R^2 values suggest there is high spatial variation within the data. The individual coefficients from the final model are displayed in the maps in Figures 9A through 9G. These maps display this spatial variation of each independent measure and fatal and non-fatal shootings, and how each measure varies across the city while controlling for the other measures.

Figure 9: Geographically weighted regression

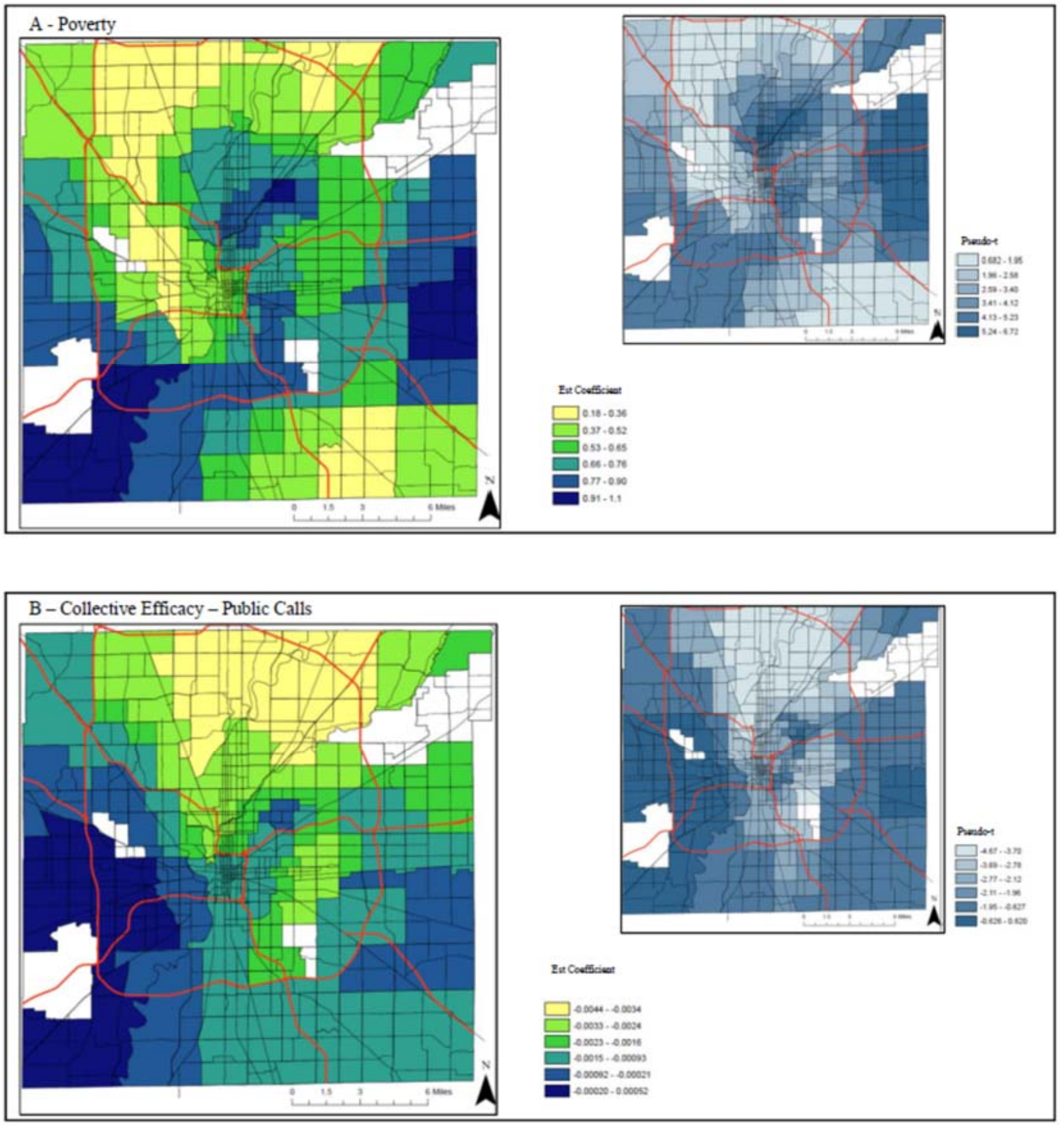


Figure 9 (cont'd)

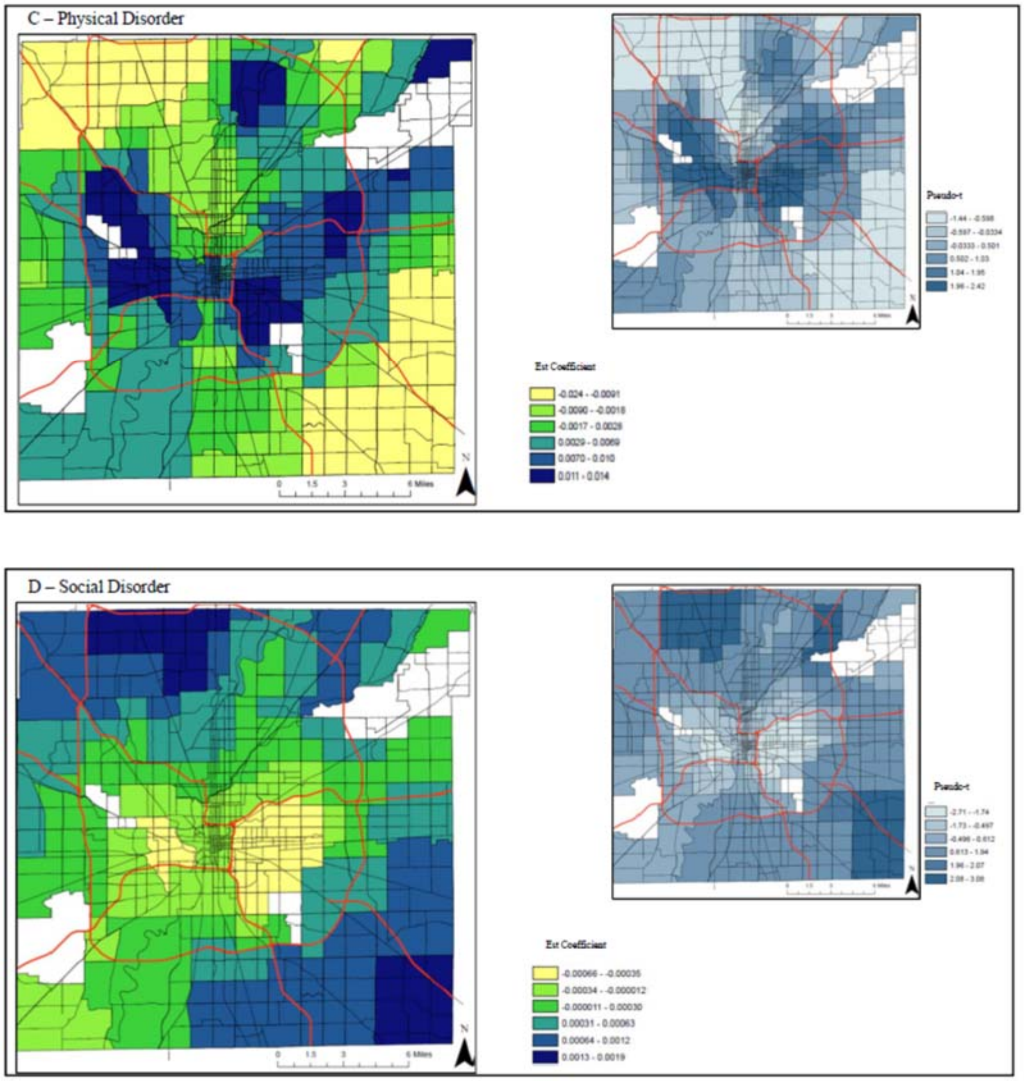
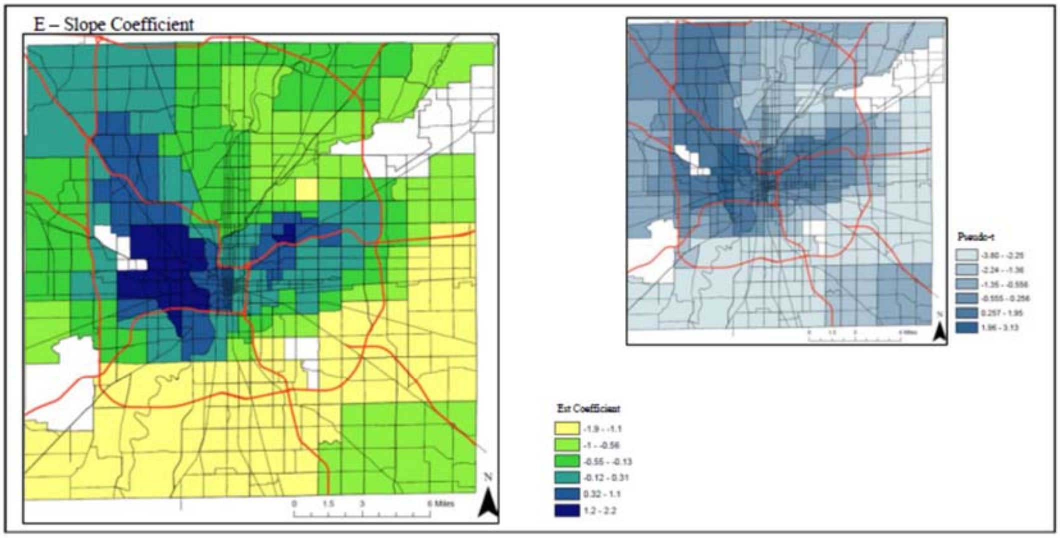
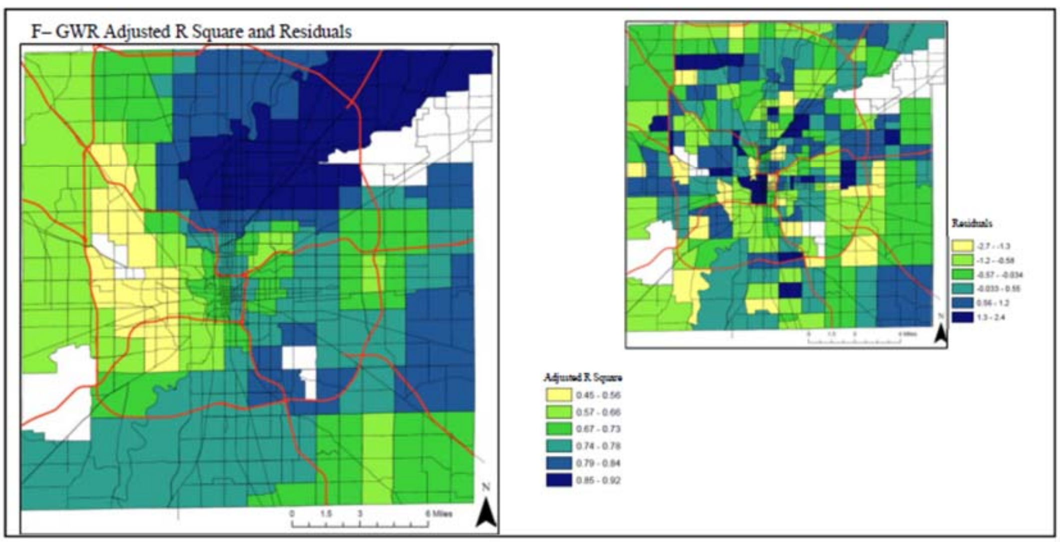


Figure 9 (cont'd)





The spatial variation in the poverty parameter is shown in Figure 9A and depicts the differing effects of poverty on fatal and non-fatal shooting incidents across Indianapolis. All of the parameters are significantly positive but are smaller in magnitude on the North and Northwest side of the city. The area in the center of the city just North and East of downtown, has coefficient values between 0.66 and 1.1, which suggest for every 0.66 – 1.1 increase in poverty rates there is an increase in firearm violence. The area in yellow west of the downtown center of the city has the weakest association between poverty and firearm violence. As seen in prior spatial analyses this is the area of the city with higher levels of ethnic heterogeneity, suggesting there may be other processes occurring in these neighborhoods and poverty is not driving levels of firearm violence. The pseudo-t values indicate that areas of the city with values over two have significantly interesting relationships (Fotheringham, Brunsdon, Charlton, 2000). These values of greater than two are seen across the majority of the city, but the highest levels in darker blue are concentrated just north of the center of the city, which consequently are also the neighborhoods with the highest levels of fatal and non-fatal shootings, and on the far east side.

Figure 9B displays the spatial variation in collective efficacy across Indianapolis neighborhoods. The parameters show all negative values but are very small, suggesting there are differences across neighborhoods but very slight. On the far North side for every unit increase in collective efficacy there is a -.0044 - -.0034 decrease in rate of fatal and non-fatal shootings. Whereas, there is less of a relationship between collective efficacy and rates of neighborhood shootings on the far West, South, and Southeast side of the city. There is an area immediately north of the Downtown area that is highlighted in dark blue, consequently this is one of the neighborhoods with the highest rate of firearm violence. Indicating that levels of collective efficacy may not be as high in certain neighborhoods with high levels of firearm violence, as other neighborhoods that are experiencing firearm violence. Overall, these results suggest that in the global OLS model collective efficacy is negatively associated with neighborhood firearm violence, but GWR indicates there is variation across neighborhoods. That is, not all levels of neighborhood collective efficacy influences levels of firearm violence the same.

Figure 9C displays the spatial variation of physical disorder across Indianapolis neighborhoods. Parameters are both negative and positive, and significantly vary across neighborhoods. Although the estimated parameters are small the areas on light yellow and green are neighborhoods where physical disorder has a negative relationship with rates of firearm violence. The areas immediately North of the Downtown area highlighted in lime green have a negative relationship suggesting that physical disorder is not driving the rates of firearm violence in these communities. Interestingly, these are some of the neighborhoods with the highest levels of firearm violence. The areas displayed in blue and dark blue have the strongest relationship between levels of physical disorder and rates of firearm violence, with estimate parameters between .0070 and 0.014, respectively.

Figure 9D displays the spatial variation of social disorder and the differing effects of social disorder on fatal and non-fatal shootings across Indianapolis. Although the parameters are extremely small, the results display both positive and negative values. Interestingly, the urban core of the immediate downtown area displays a negative relationship with firearm violence, whereas the outer areas of the city display a positive relationship. These results suggest a negative relationship between social disorder and firearm violence in the neighborhoods with the highest levels of firearm violence. This finding could explain why social disorder was not statistically significant in the global OLS regression model, as there is variation across neighborhoods regarding the relationship between social disorder and firearm violence and the neighborhoods surrounding downtown with the highest levels of firearm violence are negatively associated with social disorder. Social disorder negatively being associated with communities with high levels of firearm violence is opposite of what was expected from prior research and social disorganization theory. When assessing the pseudo T values, the maps suggest there are areas of the city that are significantly interesting.

Figure 9E displays the estimated slope coefficient obtained from the GWR model. The parameter estimates display the degree of fatal and non-fatal shooting rates after the spatial variations in the community measures have been taken into account. The high values that occur primarily in the areas surrounding the Downtown area, predominantly to the west indicated in dark blue, suggest a higher rate of firearm violence even when high levels of poverty, collective efficacy, physical disorder and social disorder are taken into account. The neighborhoods displayed in green indicates poverty, collective efficacy, physical and social disorder better explain community levels of firearm violence but there is observed variation across neighborhoods. These results suggest that the model still does not adequately account for the high levels of firearm violence in the areas immediately surrounding the downtown area, which are the areas with the highest levels of firearm violence rates, and therefore, there may still be community processes that are missing from the current models.

Figure 9F displays the adjusted R square map and residual map from the geographically weighted regression. The overall adjusted R^2 in the overall model was high at .74 but the map displays the distribution across Indianapolis, and where the model is being explained better than other areas. The model explains the most variation in firearm violence on the North side of the city (R^2 = 0.85 – 0.92), indicated in dark blue, and the model explains the least variation on the West side of the city (R^2=0.45 – 0.56), indicated in yellow. When examining the residual map, there are still neighborhoods with high levels of firearm violence that have high residual values, suggesting there are still relevant measures missing from the current models. Similar, to the global regression model residual map (see Figure 8), there is variation across neighborhoods with high firearm violence rates. For example, two of the neighborhoods with the highest levels of firearm violence on the North side of the city are not being explained well by this model, whereas similar areas with comparable firearm violence rates are being better explained, as indicated in yellow and green. These results suggest there is variation in neighborhood factors and community processes that lead to high rates of firearm violence across the same city.

Overall, the results from the GWR suggest there is spatial variation across neighborhoods regarding the relationship between the poverty, collective efficacy, physical disorder, social disorder and neighborhood levels of firearm violence. That is, each community measure does not influence rates of firearm violence across neighborhoods equally. Whereas the global OLS model indicated that poverty increases the level of neighborhood firearm violence and collective efficacy decreases the level of neighborhood firearm violence within Indianapolis neighborhoods, when controlling for all theoretically relevant variables. The GWR models indicate that the relationship between poverty, collective efficacy, and physical and social disorder and firearm violence differs between neighborhoods. That is, collective efficacy influences rates of firearm violence differently depending on the neighborhood. These prior sets of analyses examined the spatial relationship of fatal and non-fatal shootings, and the association between a variety of community measures and firearm violence at the neighborhood level. The next step of the analyses will be to examine the spatial relationships at the micro level of analysis, which is operationalized at the street segment.

Micro Level of Spatial Concentrations of Firearm Violence

To further examine the spatial concentration and variation in fatal and non-fatal shootings across neighborhoods in Indianapolis, I explored the spatial distribution of each community measure and firearm violence at the micro level (i.e., street segment). Table 16 displays the measures of central tendency and dispersion for each independent measure and fatal and non-fatal shootings at the street segment level.

Table 16: Descriptive Statistics for each Independent Variable and Firearm Violence at the Street segment

Variable	N	Mean	Std Dev	Min	Max
Firearm Incident	53,922	0.02	0.17	0	6
Social Disorder	53,922	2.96	10.56	0	586
Physical Disorder	53,922	0.100	1.29	0	109
CE – Public	53,922	0.86	3.98	0	112

For the outcome variable of firearm violence there was a maximum number of six fatal and non-fatal shootings on an individual street segment during the three-year study time frame. The highest number of calls for one individual street segment was 586 calls for issues relating to social disorder, the other community measures had similar high calls per street segments at around 100 for the three-year time period. Additionally, one street segment had a maximum number of nine abandoned homes, which is included in the physical disorder measure.

Micro Places of Firearm Violence

Another goal of this study is to examine the spatial concentration of firearm shooting incidents at the street segment level. There are 929 street segments that experienced at least one fatal or non-fatal shooting. Table 17 displays the distribution of firearm violence across street segments. The majority of street segments never experienced an incident of firearm violence (98%), and another 775 (1.44%) only experienced one incident of firearm violence over the three-year time period. There were 109 street segments that experienced two incidents of firearm violence (0.20%), 31 that experienced three shooting incidents, and 14 street segments that experienced four or more firearm shooting incidents during the study time frame. These results display that firearm violence is occurring on less than three percent of street segments in Indianapolis and is extremely spatially concentrated, as found in prior studies (Braga et al., 2010; Koper et al., 2015).

Table 17: Number of firearm violence incidents per street segment

# of Firearm Violence Incidents (n=1,142)	# of street segments	Total % of Street segments
>4	14	0.03
3	31	0.06
2	109	0.20
1	775	1.44
0	52,993	98.28
Total	53,922	100

Figure 10 displays the spatial distribution of street segments with the total of fatal and non-fatal shootings at each micro place and Figure 11 displays a zoomed in version of the street segments to the center of Indianapolis. The results are dispersed around the city but are primarily concentrated in the immediate areas surrounding downtown. The neighborhoods with rates of fatal and non-fatal shootings over 100 per 10,000 are outlined in dark blue and have the greatest concentration of street segments with shooting incidents. Interestingly, these neighborhoods do not include all the street segments with more than one fatal and non-fatal shooting incident, nor do they include the street segments with the highest number of incidents per street segment.

Table 18 displays the categorization of the number of street segments that experienced a specific number of fatal and non-fatal shooting incidents within the neighborhoods based on rates of firearm violence. In the neighborhoods with a firearm violence rate over 100, there were 124 street segments that experienced one shooting incident, 37 that had two shooting incidents, 14 that had three shooting incidents, and only four street segments that experienced four fatal and non-fatal shootings. Within the neighborhoods with the highest levels of firearm violence, none of the street segments experienced five or six shootings as in other areas of the city. For example, on the far east side there are eight street segments with more than three shooting incidents, which is not one of the neighborhoods with a firearm violence rate over 100 per 10,000. As displayed in Table 18 the number of street segments with four or more shootings is fairly evenly distributed across neighborhoods regardless of the rate of neighborhood firearm violence, with the highest concentrated of shootings per street segment occurring in neighborhoods with firearm violence rates over 100 and between 20 and 39 per 10,000 residents.

Table 18: Number of Fatal and Non-fatal shootings per street segment in the neighborhoods

Neighborhood Firearm Violence rate per 10,000	# of street segments with 1 shooting (n=775)	# of street segments with 2 shootings (n=109)	# of street segments with 3 shootings (n=31)	# of street segments with > than 4 shootings (n=14)
> 100	124	37	14	4
> 80 and < 99	61	7	1	1
> 60 and < 79	82	14	2	1
> 40 and < 59	111	13	3	2
> 20 and < 39	169	26	6	4
< 20	228	12	5	2

Figure 10: Fatal and Non-fatal Shootings at the street segment level within census tracts

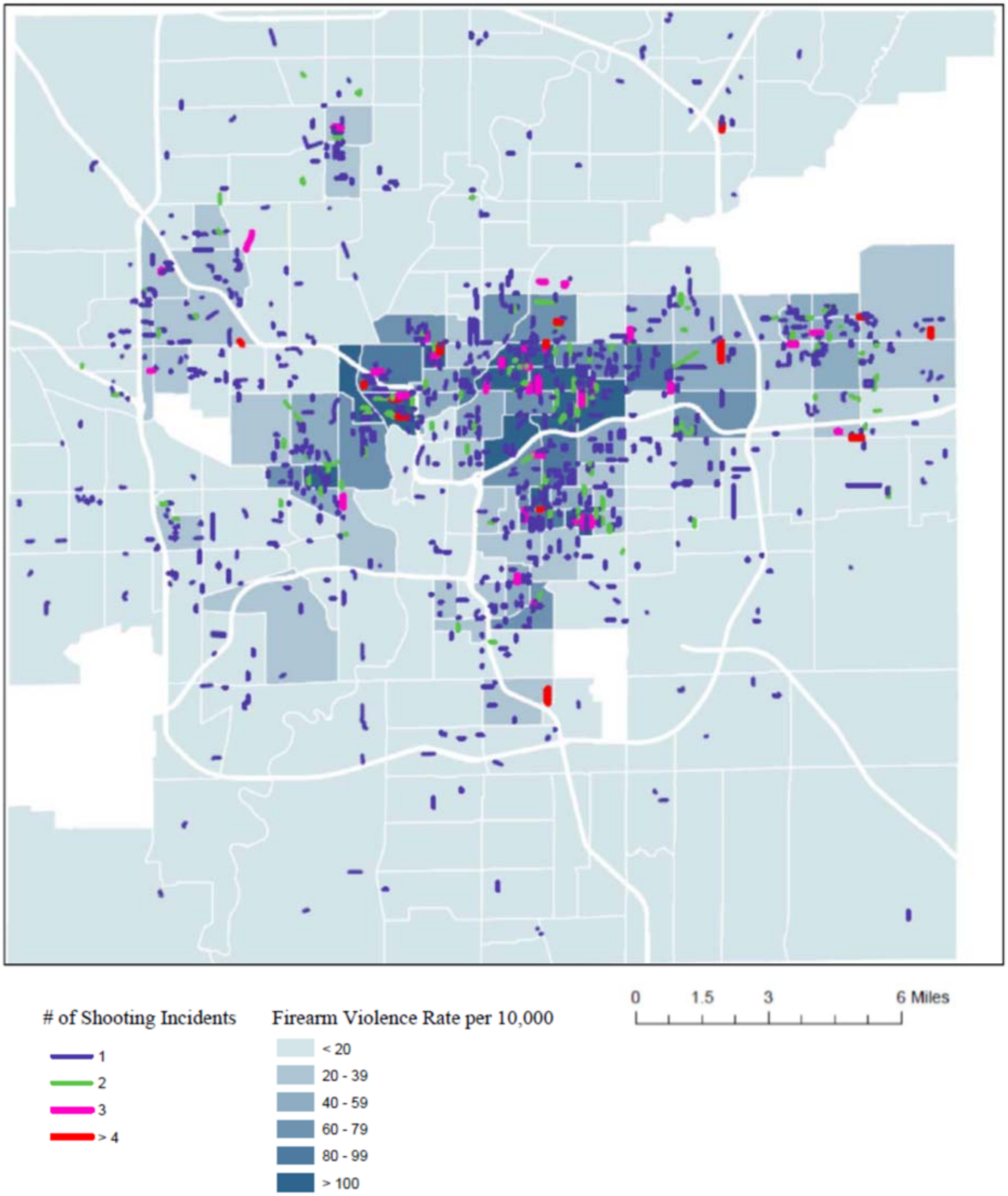
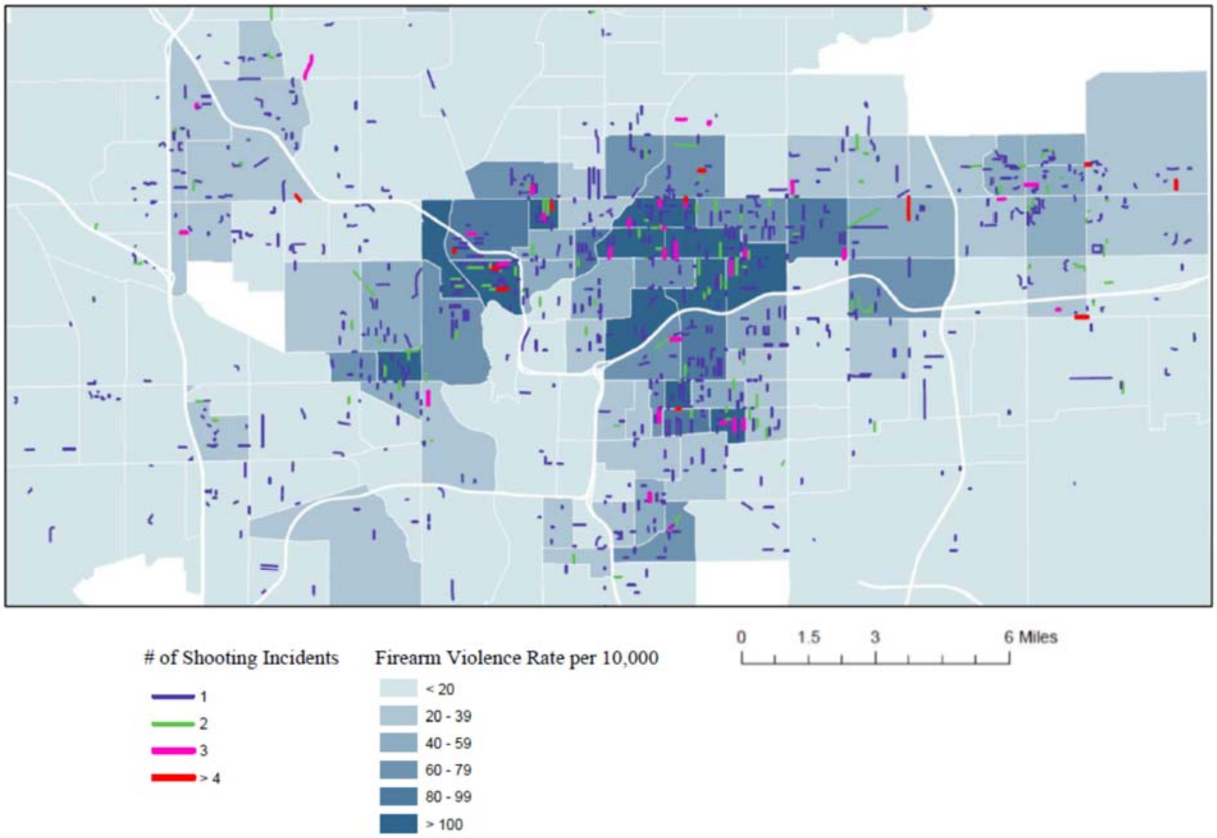


Figure 11: Fatal and Non-fatal Shooting incidents zoomed into Center of Indianapolis



Community Measures

Next, I examined the spatial concentration of community measures at each street segment. Table 19 displays the spatial concentration of each community measure by street segment[11]. The results suggest the majority of street segments never experienced incidents of social or physical disorder, although more street segments experienced acts of social disorder throughout the city than physical disorder. For example, 1,153 street segments experienced over 30 incidents of social disorder, whereas only 19 street segments have documented cases of more than 30 incidents of physical disorder. The measure of collective efficacy is also spatially

[11] Outliers were examined to identify potential bias. Only one street segment for social disorder (Marion County Jail address) appeared and was removed from the sample.

concentrated, with over 229 street segments calling the Mayor's Action Center more than 30 times over the three-year study time period.

Table 19:Number of community measures per street segment

N of calls per street segment	Social Disorder	%	Physical Disorder	%	CE - Public	%
0	35,657	66.13	52,114	96.65	47,786	88.62
1 – 9	13,642	25.30	1,711	3.17	4,603	8.54
10 – 19	2,531	4.69	55	0.10	966	1.79
20 – 29	939	1.74	23	0.04	338	0.63
30 or more	1,153	2.14	19	0.03	229	0.42
Total	53,922	100	53,922	100	53,922	100

Micro Place Spatial Relationship

The next step in the analysis was to explore the relationship between the community factors and fatal and non-fatal shootings at the street segment level. These analyses presented a challenge due to the high levels of skewness at the micro level (i.e., street segment). Even when the street segments with one or more community factor and fatal and non-fatal shooting incident was examined, as done in prior research (Braga et al., 2010), the data were still extremely skewed to the right. Therefore, a number of steps were taken to examine the relationship of the community factors and fatal and non-fatal shooting incidents. First, a descriptive table was created with the average number of community factors per street segment for the given number of fatal and non-fatal shootings. Secondly, the independent variables of physical disorder and social disorder and dependent variable of firearm violence were binary coded into yes, no. That is, *0 = no* measure on that street segment, and *1 = yes* that street segment experienced at least one incident or call for that specific measure[12]. Although, these analyses will not take into account the number of incidents of physical disorder, social disorder and fatal and non-fatal

[12] The natural log of collective efficacy – public was able to transform the variable into a normal distribution. The variable was then reserve coded.

shooting incident per street segment, it can identify if there is a relationship between the community factors and fatal and non-fatal shootings at the street segment level. Prior research suggests that examining the presence or absence of disorder on a street block in a dichotomous fashion can be more important than the actual number of disorder issues (Sampson & Raudenbush, 1999). Therefore, a binary logistic regression model was conducted to test the relationship, and lastly a hierarchal linear model was conducted to test the variation of community level factors at the street segment level within neighborhoods.

Micro Level Descriptive Statistics

Table 20: Mean of the community factors per street segment with fatal and non-fatal shootings

N of Firearm Shooting Incidents per street segment	Social Disorder (mean)	Physical Disorder (mean)	CE – Public (mean)
1	21.2	0.665	4.43
2	38.7	0.963	6.73
3	37.4	0.968	12.8
> than 4	137.1	0.357	5.5

Table 20 displays the mean of each community level variable per street segment that has experienced at least one fatal and non-fatal shooting and classifies the street segments by the number of fatal and non-fatal shootings. Street segments with one firearm shooting incident averaged 21.2 calls for social disorder, 0.665 calls for physical disorder, and 4.43 calls into the MAC for public spaces indicting collective efficacy. The average number of calls for social disorder increased as expected with the number of fatal and non-fatal shootings per street segment. For instance, on the street segments that experienced four or more shooting incidents there was an average of 137.1 calls for social disorder, whereas there was only an average of 21.2 for street segments that experienced only one shooting incident. The measure of physical disorder had an average of .963 for street segments with two fatal and non-fatal shootings, and

0.968 for streets with three or more shootings than decreased with each additional shooting incident. Calls into the MAC for public spaces averaged 4.43 calls for street segments with one shooting incident, 6.73 calls for street segments with two shooting incidents, 12.8 calls for street segments with three shooting incidents, and 5.5 calls for street segments with four or more shooting incidents. The two highest levels of collective efficacy are on street segments that experienced two and three fatal and non-fatal shootings over the three -year study time period, indicting high levels collective efficacy on those street segments. The average number of calls for collective efficacy did not decrease significantly on the street segments with more shooting incidents, as would be expected. Additionally, street segments that experienced at least one shooting incident had high numbers of abandoned homes, for example, street segments with one shooting incident averaged 0.17 abandoned homes on that street block and the highest average of abandoned homes was 0.97 per street block that experienced three shooting incidents. Abandoned homes are included in the measure of physical disorder but speaks the number of residents actually living on the street block and able to call issues into the Mayor's Action Center.

Micro Level Bivariate Analyses

The next step in the analyses was to explore the bivariate relationship between each community level measure and fatal and non-fatal shooting incidents. As noted previously, the measures of physical disorder, social disorder and firearm violence variable was binary coded into yes/no due to the high level of skewness. The results from each of the bivariate binary logistic regression models are displayed in Table 21.

Table 21: Binary Logistic Regression for firearm violence and community measures

Variable	Firearm Shooting Incident (Odds Ratio)	p-value
Social Disorder	9.40*	$p < .001$
Physical Disorder	8.16*	$P < .001$
CE – Public	.423*	$p < .001$

Indicators of physical disorder on each street segment increased the odds of a shooting incident occurring by approximately 8 percent (OR=8.16, $p <.001$). Calls for social disorder increased the odds of a fatal or non-fatal shooting occurring on that street segment by almost 10 percent (OR = 9.40, $p <.001$). Calls into the MAC for public spaces decreased the odds of a shooting incident occurring by nearly 60 percent (OR= .423, $p<.001$). These results suggest that community level factors are associated with firearm violence at the street segment level.

Hierarchical Generalized Linear Models

The last step in the analyses was to conduct a hierarchical general linear model (HGLM) model to assess the relationship of all the community level variables on firearm violence at the street segment level to see if they vary across neighborhoods[13]. The results are displayed in Table 22.

[13] All variables were grand-mean centered before entered into the HGLM models (Johnson, 2011).

Table 22: HGLM mixed model of firearm violence and community level variables

Variable	Model 1		Model 2	
	Beta (S.E.)	Odds Ratio (OR)	Beta (S.E.)	Odds Ratio (OR)
Intercept	-4.48 (.106)	.011*	-4.97 (.096)	.007*
CE – Public			-.347 (.059)	.707*
Physical Disorder			1.07 (.105)	2.91*
Social Disorder			1.98 (.090)	7.21*
Neighborhood Level Measure				
Poverty	.799 (.321)	2.22*	.484 (.201)	1.86*
Deviance Statistic[14]			483.65	
AIC	8702.3		7740.7	

*p<.01

Since the outcome measure of firearm violence is binary variable[15] (yes/no) a multilevel logistic regression was conducted. A mixed effects logistic regression estimates the odds that a shooting incident will occur as a function of both the community level measures at the street segment level and levels of neighborhood poverty. A null model was first constructed to assess the necessity of conducting a multilevel model across street segments and neighborhoods. The intraclass correlation coefficient (ICC) displays the proportion of the total variance that is due to the between-group differences (Sommet & Morselli, 2017). The ICC was .324 for the null model, suggesting there is variation between street segments and neighborhoods. Model 1

[14] The deviance statistic was calculated as D1-D2, where D1 is the -loglikelihood for Model 1 and D2 is the -loglikelihood for Model 2.
[15] The variable was first modeled as a count variable with a Poisson distribution but the model would not converge after running for 48 hours.

displays the average log-likelihood that a shooting incident will occur across neighborhoods based on the variation in levels of poverty. Prior research has demonstrated that poverty and concentrated disadvantage explain levels of violence (Cohen & Tita, 1999; Rosenfeld et al., 1999; Morenoff et al., 2001). Therefore, this relationship will serve as a baseline to better understand the association of the other community measures at the street segment level. The average likelihood that a shooting incident occurred significantly increased across neighborhoods as the level of neighborhood poverty increased by nearly two times (OR = 2.22).

Model 2 displays the variation in shooting incidents at both the street segment and neighborhood level, simultaneously. The neighborhood level measure of poverty is still statistically significant when controlling for community level factors at the street segment level but the odds are less than two (OR=1.86, $p<.01$), compared to Model 1. Model 2 displays the fixed effects community level factors at the street segment level and suggests that higher levels of collective efficacy decreases the odds of a shooting incident occurring by 30 percent (OR=.707, $p<.01$), and the presence of both physical disorder (OR=2.91, $p<.01$) and social disorder (OR=7.21, $p<.01$) increases the odds of a shooting incident occurring by nearly 3 times and 7 times, while accounting for levels of poverty[16] across neighborhoods. The AIC also decreases from Model 1 to Model 2, suggesting an improved model fit when adding in the community factors at the street segment level.

[16] The neighborhood level factors of residential mobility and ethnic heterogeneity were also entered into Model 3 but the model did not converge after running for 24 hours. I ran two additional HGLM models with only residential mobility and ethnic heterogeneity but these did not converge either. This is common when the variance is near zero and indicates that they do not vary much (Hamilton, 2013), which is plausible given neither measure has been statistically significant in prior analyses.

Chapter Summary

This chapter examined the spatial relationship between firearm violence and community contextual features of both neighborhoods and street segments across Indianapolis. The relationship was explored using bivariate and multivariate regression models, at both the neighborhood and street segment level of analysis. The findings at both the neighborhood and street segment levels are largely consistent with social disorganization theory, although the multivariate models suggest that some of the variables suggested in classic social disorganization theory were not predictive in this contemporary urban environment. The results also suggest there is a spatial relationship between community contextual factors and firearm violence, but these factors vary across neighborhoods. Additionally, the results demonstrate that firearm violence is concentrated on a small number of street segments, but the street segments with the highest number of shootings do not necessarily fall into the boundaries of the neighborhoods with the highest rates of firearm violence. Lastly, the HGLM suggests that community level factors vary at the street segment level, even when controlling for levels of neighborhood poverty. The following chapter will further discuss these results and the implications they have on theory and the criminal justice field. The next chapter will also discuss the limitations of this research and directions for future research.

Chapter 7: Discussion

This ecological study examined the relationship between community contextual factors and fatal and non-fatal shootings over a 3-year time period in Indianapolis. This chapter will focus on the overall results from the previous analyses, the theoretical implications, limitations, and directions for future research. First, this chapter will summarize the findings from this study and discuss the important theoretical implications for the criminal justice field. Lastly, a number of limitations from the current study will be discussed and conclude with providing directions for future research in the area of communities and crime and firearm violence. Policy implications will also be discussed throughout the chapter.

Summary of Results

Overall this study examined the spatial distribution of fatal and non-fatal shootings and assessed the spatial relationship of key community measures and firearm violence. The analyses were conducted in multiple stages and conducted at both the macro (i.e., neighborhoods) and micro (i.e., street segments) levels of analyses. The first set of analyses examined the similarities and differences between spatial patterns of fatal and non-fatal shootings by census tracts (i.e., neighborhoods) and found there is a spatial correlation between fatal and non-fatal shootings across specific neighborhoods. Although when examining the rate ratio of fatal versus non-fatal shootings, there are disparities across neighborhoods based on the lethality of the shooting incident. The differences in lethality across neighborhoods could be explained by the adversary effects model, which contends that victim and incident characteristics determine if an offender chooses to use lethal force during an assault (Felson & Messner, 1996; Felson & Pare, 2010). This is especially plausible given the differences observed in social disorder at both the neighborhood and street segment levels. The lethality of the shooting incident may be determined by the motive of the incident (e.g., robbery, retaliation, drugs) and vary by neighborhood based on neighborhood culture, such as code of the streets (Anderson, 1999).

Furthermore, when examining both fatal and non-fatal shootings across neighborhoods there are specific neighborhoods with high continuous stable rates of firearm violence, suggesting that it is important to include non-fatal shootings into the study of firearm violence, as it describes a more accurate prevalence rate of firearm violence than just relying on homicides. Overall, the results suggest that fatal and non-fatal shootings spatially cluster and are not randomly distributed across the city, which aligns with prior studies that found homicides spatially cluster across cities (Cohen & Tita, 1999; Rosenfeld et al., 1999; Morenoff et al., 2001; Zeoli et al., 2014), and the one prior study that found non-fatal shootings followed similar patterns of homicides over a 29-year period (Braga et al., 2010).

This study also examined key community measures of social disorganization, collective efficacy and physical and social disorder in relationship to firearm violence at the neighborhood level (i.e., macro level). The results suggest that across neighborhoods, poverty, collective efficacy, and physical disorder have the strongest relationship with firearm violence at the bivariate level of analysis and there is a two-way spatial correlation between each of these community measures and firearm violence. When all the theoretically relevant measures were entered into a global multivariate OLS regression model the community measures explained approximately 70 percent of the variance, suggesting a fairly good model fit. Poverty had the strongest relationship with neighborhood shooting rates with collective efficacy mediating this relationship and controlling for physical and social disorder. The results suggest that neighborhoods with high levels of poverty also experience higher levels of firearm violence, which is expected from prior research on the spatial patterns of homicide (Cohen & Tita, 1999; Rosenfeld et al., 1999; Morenoff et al., 2001; Zeoli et al., 2014).

Interestingly, the measures of residential mobility and ethnic heterogeneity were not associated with firearm violence at the neighborhood level. The measure of ethnic heterogeneity reached the level of statistical significance in the first model that tested social disorganization theory, but the relationship was negative, suggesting that neighborhoods with high levels of ethnic heterogeneity have lower levels of firearm violence. This finding is not what is expected from classic social disorganization theory and suggests that neighborhoods with high rates of firearm violence may be much more homogenous today than prior research suggests (Shaw & McKay, 1942; Sampson et al., 1997). Although recent research examining the concentration of immigrants and rates of violent crime in Los Angeles found a reduction in violent crime as the immigrate population increased within neighborhoods (MacDonald, Hipp and Gill, 2009) and similar research by Chavez and Griffiths (2009) suggest Chicago neighborhoods with low homicide rates were the neighborhoods immigrants were most likely to move into.

Residential mobility never reached the level of statistical significance in any of the four models. These results may suggest that residents are moving within the study area or that people are not moving into the neighborhoods with high levels of firearm violence, which is plausible given the relationship between abandoned homes and firearm violence. Furthermore, Figure 5B displays the distribution of residential mobility across Indianapolis and the areas with the highest levels of residential mobility are the surrounding neighborhoods that border the affluent suburbs. These are also the areas that have built new homes and neighborhoods in the past ten years and have the better school districts, therefore, people are moving into these communities and out of the immediate downtown area. Another factor that may help explain the reverse theoretical finding of high residential mobility and higher levels of violence is the notion of gentrification or neighborhood change. Gentrification refers to changes in neighborhoods due to demographic shifts and private investment, which often displaces current residents, but has been associated with declining homicide rates (Smith, 2014; Papachristos, Smith, Scherer & Fugiero, 2011). There are a number of historically violent neighborhoods in Indianapolis that have experienced neighborhood change or gentrification within the last five years and could be impacting firearm violence. Further assessing this relationship is a clear direction for future research.

The negative association of collective efficacy – public calls into the MAC and firearm violence aligns with prior studies, that concluded neighborhoods with higher levels of collective efficacy have lower levels of crime, no matter the crime outcome used (Sampson et al., 1997; Sampson & Raudenbush, 1999; Morenoff et al., 2001; Browning 2002, 2004, 2009; Kirk, 2008; Rhineberger-Dunn et al., 2009). These findings indicate that residents within communities with lower levels of firearm violence are calling the city to help address their nuisance issues within their neighborhood, therefore indicating levels of collective efficacy, as residents are taking responsibility for public space (O'Brien et al., 2015). This finding is similar to prior studies that suggest lower levels of collective efficacy predict higher rates of neighborhood homicide (Morenoff et al., 2001).

Physical and social disorder produced interesting findings as prior research suggests that increased levels of physical and social disorder within a neighborhood represents a lack of care by the residents and that physical decay and abandoned buildings can lead to opportunities for crime to occur (Skogan, 1990; Wilson & Kelling, 1982). The measures of physical and social disorder never reached the level of statistical significance in the global OLS model at the neighborhood level[17]. Social disorder not being a predictor in neighborhood firearm violence rates could merely be an artifact of the measure being comprised of 911 calls, and neighborhoods with high rates of firearm violence not calling the police due to legal cynicism (Kirk & Papachristos, 2011) or code of the streets (Anderson, 1998). Therefore, when there are fights, people drunk in public, and loud disturbances, the neighborhood may address it themselves and not call the police, suggesting a level of neighborhood cohesion as found by Pattillo-McCoy (1998) and Venkatesh (1999). Whereas, other neighborhoods may be more likely to call the police as soon as a disturbance occurs, therefore indicating a stronger relationship with shooting incidents. Although these findings are contrary to prior research (Wilson & Kelling, 1982) on broken windows theory, others have found that disorder shares similar features with violence and are explained by the same constructs of concentrated disadvantage and low collective efficacy, especially at the neighborhood level (Sampson, 2012). Even though disorder may not have a causal link with firearm violence, perceptions of disorder may discourage efforts to invest in these communities and therefore lead to greater levels of concentrated disadvantage and segregation.

Overall the global OLS model strongly supported the theoretical model of social disorganization theory but indicates that poverty has a stronger association with rates of neighborhood firearm violence than residential mobility and ethnic heterogeneity. Additionally, poverty is only weakly related to ethnic heterogeneity and negatively related to residential mobility which are different patterns than found in classic social disorganization theory and could be due to a contemporary urban environment, therefore the study findings demonstrate a

[17] In a post-hoc analysis physical disorder was statistically significant when controlling for trash service and general calls into the MAC. This suggests that the measures of collective efficacy and physical disorder are distinct.

different relationship between these characteristics and poverty. Furthermore, the contrary findings of residential mobility and ethnic heterogeneity could be due to a cultural change in the urban neighborhoods since Shaw and McKay did their work in the 1920s, and perhaps neighborhoods have become more homogenous and segregated with higher levels of poverty and concentrated disadvantage (Morenoff & Sampson, 1997; Massey & Denton, 1993). Prior research by Zeoli et al. (2014) found the homicide epidemic was mostly in areas of Newark with racial isolation and similarly, Rosenfeld et al., (1999) found a higher percentage of homicides were concentrated in areas with high African American populations. Recent work displayed racial segregation may increase the disparity in firearm homicide at the state level (Knopov et al., 2018), and is a clear direction for future research. Additionally, the measure of collective efficacy – public calls mediates poverty and demonstrates that neighborhoods with lower levels of firearm violence are taking action to address issues within their communities, which is therefore a good indicator of neighborhood collective efficacy. Lastly, the spatial distribution of the residuals displays there are a small number of neighborhoods where the overall model did not provide a good fit and suggests that other contextual or social factors may be missing from these models. It may also be that these confounding factors are causing the spatial autocorrelation within these neighborhoods with high rates of fatal and non-fatal shootings. Future research should examine the social processes occurring within these outlier neighborhoods through interviews, surveys or systematic social observations to better understand the underlying factors (e.g., gang issues, drugs, robberies, etc.) that may be causing high rates of firearm violence within these communities.

Spatial Patterns of Firearm Violence and Micro Place Findings

These analyses also demonstrate the importance of the spatial relationships between contextual community factors and fatal and non-fatal shootings. All measures had high spatial correlation at the univariate and bivariate levels, suggesting there is a spatial relationship between the community contextual factors and firearm violence at the neighborhood level of analysis. Further, exploration of the spatial variation across neighborhoods was examined using geographic weighted regression (GWR). Similar to the OLS global model, the GWR model displayed strong overall support for the theoretical model but results revealed that the spatial relationships between poverty, collective efficacy and disorder vary across neighborhoods. These results suggest examining contextual factors at the global level may miss important community features that are associated with firearm violence. Furthermore, these findings suggest there may be pockets of firearm violence or micro places within the neighborhoods where there are higher concentrations of firearm violence and that community contextual factors impact firearm violence differently (St. Jean, 2007; Weisburd et al., 2004; 2012).

The last step of this study examined the distribution of fatal and non-fatal firearm violence and community contextual factors at the micro – street segment level. As prior research suggests that crime concentrations at the block face or street segment and remains fairly stable over time (Weisburd et al., 2004; 2012). This study concludes that both fatal and non-fatal shootings are highly concentrated at the street segment and only three percent of all street segments in Indianapolis experienced at least one shooting incident over the three-year study period. The distribution of shootings at the street segment level ranged from 0 to 6 incidents, with the majority of street segments that experienced a shooting incident, only experiencing one fatal or non-fatal shooting. An interesting finding suggests that the street segments with multiple shooting incidents (3 or more) did not always fall into the expected neighborhoods with high firearm violence rates. That is the two street segments with 6 shooting incidents were not within the neighborhoods with firearm violence rates over 100 per 10,000. Therefore, when examining the spatial distribution of fatal and non-fatal shootings both neighborhoods and street segments are important, as they both give different pictures of firearm violence. For example, if one only examined neighborhood rates of firearm violence one would miss the problem street segments on the far East side of the city that are independently contributing to a large number of fatal and non-fatal shootings. Whereas, if one only examined the street segments that collectively produce high volumes of fatal and non-fatal shootings, one would miss the neighborhoods that collectively produce the highest rates of neighborhood firearm violence. From this, one can conclude that the correct operationalization of neighborhood may depend on the research question or goal of the police intervention. For instance, a police intervention focused on directed patrols or pulling levers (i.e., Operation Ceasefire) may be better operationalized at the neighborhood level and identifying neighborhoods with high rates of firearm violence across the majority of street segments within the neighborhood. Whereas, an intervention like Crime Prevention through Environmental Design (CPTED) may benefit from identifying the street segments with the highest number of shootings and targeting those specific street segments, as more resources may be focused on a small area such as a street segment, compared to an entire neighborhood. Neighborhoods with high rates of fatal and non-fatal shootings appear to be driven mostly by poverty, which incorporates larger social issues that require action from a number of social organizations. However, consistent with Sampson et al. (1997), the finding that collective efficacy mediates poverty effects on firearms violence, suggest the importance of community building efforts.

Another goal of this study was to identify if community contextual factors varied and concentrated at the micro-street segment level of analysis, as prior research out of Seattle suggests (Weisburd et al., 2012). The results conclude that community contextual factors are highly concentrated at the street segment level and are highly correlated with firearm violence. The measure of collective efficacy varied at the street segment level in both the bivariate and HGLM models and suggest that lower levels of collective efficacy increase the odds of a shooting incident occurring. Further, these results suggest that collective efficacy does vary at the street segment level and across neighborhoods when accounting for levels of poverty. Therefore, interventions or community engagement efforts should focus on individual street segments within larger neighborhoods. Unlike the global regression model where the measures of physical and social disorder did not predict levels of neighborhood firearm violence, at the street segment level, both physical and social disorder presents the highest odds ratios of a fatal or non-fatal shooting occurring on that street segment in both the bivariate and HGLM models. Even when controlling for levels of collective efficacy, the presence of perceived physical or social disorder increases the likelihood of a street segment experiencing a shooting by roughly three and seven percent. These results are similar to those found in Seattle (Weisburd et al., 2012; Yang, 2010) but extend the findings to firearm violence at the street segment level.

Methodological Implications

The findings from this study contribute to a number of methodological and theoretical domains; communities and crime, social disorganization, and firearm violence. Communities and crime scholars have consistently debated what the best conceptualization of a neighborhood should be, especially in relationship to social disorganization theory. Some have argued census tracts and census blocks are appropriate units of analysis (Klinger et al., 2016; Rosenfeld et al., 1999; Taylor), while others suggest micro places or street segments best conceptualize a neighborhood (Sherman & Weisburd, 1995; Braga et al., 2010; Weisburd et al., 2009). This study concludes that both the neighborhood level and street segment are important to the understanding of the spatial distribution of firearm violence. Additionally, differences were found between community contextual factors of social and physical disorder, at both the neighborhood and street segment level, when controlling for levels of collective efficacy.

This study also offered an alternative measure of collective efficacy. Traditionally, collective efficacy is measured using community surveys (Sampson et al., 1997; Morenoff et al., 2001; Browning, 2002, 2009; Mazerolle et al., 2010) but recent research by Weisburd et al., (2012) extended the conceptualization of collective efficacy to utilize publicly available data and operationalization of the measure using the number of active voters on each street segment in Seattle. This study sought to extend Weisburd and colleagues work and operationalize the measure of collective efficacy using a unique data source to Indianapolis, called the Mayor's Action Center. Other cities, such as Boston and Washington, DC, have similar call centers for citizens to record issues with the city government in order to improve or fix issues within their community, and other scholars have used such data as measures of physical disorder within the community (O'Brien et al., 2015, Wheeler 2017). This study built off the work of O'Brien et al., (2015), who suggest that citizens calling into the 311 (i.e., MAC) displays levels of civic engagement, since citizens have to (1) know about the system and be willing to use it, and (2) decide to take action and responsibility for a public space. This study examined three groups of call types into the MAC as a measure of collective efficacy; calls for public space, calls for trash services, and general calls. Intercorrelations suggest that each of the three calls types are highly correlated with each other and are likely measuring the similar concept of collective efficacy. The calls for public space was the best operationalization of collective efficacy in this study because it represents citizens taking action to obtain resources from outside their neighborhood to improve their community, and as Sampson (2012) argues, collective efficacy needs to focus on actions that are generated "on the ground" and not outside the neighborhood (p.156). The categories of calls for trash services and general calls were good measures to better understand how citizens utilized the MAC system and do suggest levels of collective efficacy but calls for trash services is a more personally motivated call and may not represent a resident caring about their neighborhood. Although, a citizen calling about their trash services does suggest they care about their personal property and are not willing to let trash and other physical disorder build up on their property. Similarly, general calls into the MAC represent citizens calling to improve the conditions of the community but this category represents calls for street repaving, potholes, street lights, and animals and therefore may be made by citizens from outside those communities. For instance, a citizen may call about a large pothole while driving to work and does not reflect their personal tie to that community and that they care about that specific neighborhood, just about their drive to work.

Overall, using secondary data to better understand the concept of collective efficacy and the relationship with neighborhood firearm violence seems to be a good alternative to traditionally used surveys. First, it is beneficial to the researcher, as using secondary, publicly available data is both more time and cost effective. Secondly, the MAC data allowed the concept of collective efficacy to be measured at multiple levels of analysis (e.g., neighborhood and street segment) due to the individual address location of each citizen's reported issue. Lastly, utilizing the MAC data to measure collective efficacy gave a better overview of where citizens are willing to take action for their community and for which specific reasons (e.g., trash, weeds, animals, etc.). Therefore, giving researchers a better understanding of which communities and street segments could benefit from specific interventions, community building efforts, or city services that may help improve their neighborhood and consequently lower levels of firearm violence.

Additionally, this study adds to the theoretical implications of social disorganization and collective efficacy in relation to firearm violence. This study contends that levels of collective efficacy can vary at both the neighborhood and street segment levels, and higher levels of collective efficacy is associated with lower levels of firearm violence across neighborhoods and street segments. These findings contribute to the prior research which debated whether collective efficacy can be impacted at the street segment level (Braga & Clarke, 2017; Weisburd et al., 2012), as these findings suggest levels of collective efficacy at the street segment impacts the level of firearm violence. Additionally, the negative and non-significant findings for both residential mobility and ethnic heterogeneity are important to the overall theoretical findings of social disorganization theory. Perhaps residents are able to form informal friendship networks through social media platforms and modern-day technologies, such as cell phones, and it is not as important to know your next door neighbor. As Sampson (2012) argues informal social control can also be requesting governmental resources for their community and that residents can perceive trust and have the same expectations for their neighborhood without having to know their neighbors. This study found a stronger association between measures of poverty and firearm violence than other measures of classic social disorganization theory and perhaps it is time to modify social disorganization theory, as Sampson (2012) suggests, and therefore better understand the underlying factors of poverty, segregation, and neighborhood change. At the very least, these should be directions for future research.

Lastly, this study contributed to the overall theoretical understanding of firearm violence. Clearly, including non-fatal shootings in the measure of firearm violence helps explain the overall prevalence of firearm violence and better explains the spatial variation of firearm violence across neighborhoods and street segments. This study also concludes that both fatal and non-fatal shootings spatially cluster across the study site and cluster on individual street segments, but there are differences in lethality across neighborhoods. Although this study was not able to examine the differences based on victim demographics or incident motive, as this study was concerned with the ecological and contextual community measures associated with fatal and non-fatal shooting incidents, this is a clear direction for future research.

Limitations

These results should be interpreted with caution as there are a number of limitations. First, this study was conducted in one metropolitan city within an urban environment and therefore may not be generalizable to other cities. Secondly, the outcome variable of fatal and non-fatal shootings was only operationalized at the incident location and did not account for differences in victim demographics or incident circumstances. There may be differences between fatal and non-fatal shooting victims, as seen in prior studies (Hipple and Magee, 2017), that merits examining each incident type separately. These factors would be important in considering neighborhood and street segments levels of lethality (fatal to non-fatal shootings) and testing the hypothesized adversary effects model across multiple cities.

Additionally, each contextual community measure and the measurement of fatal and non-fatal shootings have their own limitation. The measures of physical and social disorder are operationalized using police data which are known to be problematic (Black, 1970) from a reporting standpoint and biased from a community standpoint, as not all communities call the police at similar rates (Black, 1970; Kirk & Papachristos, 2011). Furthermore, the relatively small numbers of shootings and community level factors at the street segment level of analysis only allowed for binary analyses and perhaps more sophisticated methods can be conducted in future studies with a longer time frame and therefore larger sample. The measure of collective efficacy measures the number of calls residents make into the MAC but not all neighborhoods experience the same levels of issues and therefore do not need to utilize the system at the same rate. Therefore, the association between collective efficacy and firearm violence should be interpreted with caution.

Additionally, not all contextual community measures and fatal and non-fatal shootings could be accurately geo-coded to a census tract or street segment and are therefore missing from these analyses. Lastly, this study was conducted cross-sectionally and only included data for a three-year time frame. The spatial patterns and community contextual factors associated with firearm violence may change and move overtime and is a clear direction for future research.

Future Research Directions

There are a number of directions future research should explore to better understand firearm violence, the spatial concentration of firearm violence, and the relationship between contextual community factors and firearm violence. Future studies should extend this work from a solely ecological study to a socioecological study and examine the individual demographics of the victims and motivation behind each incident. Additionally, future work should examine the difference between fatal and non-fatal shootings, as there may be differences based on victim characteristics (Hipple & Magee, 2017). Also, a better understanding of the individual factors contributing to each shooting incident will also help determine if non-fatal shootings are just failed fatal shootings or if there are other underlying causes that define a fatal shooting versus a non-fatal shooting, as is suggested by the adversary effects model (Felson and Messner, 1996).

Another clear direction for future studies is exploring the difference of fatal and non-fatal shootings across neighborhoods. As the rate ratio map displayed in this study there are neighborhoods that an individual has a higher risk of being a fatal shooting victim compared to a non-fatal shooting victim and surviving the gunshot wound. Differences across neighborhoods may be due to a quicker 911 response, proximity to hospitals or higher levels of collective efficacy. Perhaps there are specific neighborhoods that have such high legal cynicism that residents are not even willing to call 911 when a person is shot, and therefore the lack of immediate medical attention contributes to the higher lethality rate.

This study displays the importance of examining community contextual characteristics across and within neighborhoods and future studies should continue this work by exploring the relationship between firearm violence and gentrification and neighborhood change. Private investment and change in neighborhood demographics may impact the levels of collective efficacy and decrease the likelihood of homicides (Smith, 2014; Papachristos et al., 2011) but this also displaces prior neighborhood residents and may contribute to higher levels of segregation and concentrated disadvantage (Knopov et al., 2018). Future research should also explore the relationship between different types of segregation using the dissimilarity index (Massey & Denton, 1998) and firearm violence. As well as how neighborhood change contributes to residential segregation and rates of neighborhood firearm violence.

Lastly, further works needs to be conducted at both the neighborhood and street segment level in the relationship with firearm violence. This study noted the high concentration of firearm violence on a small number of street segments but did not explore the differences or why firearm violence is not occurring on all neighborhood street segments at the same rate. There is a clear difference between neighborhoods with high rates of firearm violence and the concentration of street segments with high numbers of shootings that needs to be further explored. Future studies should specifically examine the "outlier" street segments that have the highest number of shooting incidents through qualitative interviews with residents and systematic social observations (Sampson et al., 1997) to better understand the community factors that are contributing to such high rates of shooting incidents. Additionally, future studies should explore the relationship between neighborhoods and firearm violence using the "pockets of peace" notion, an approach to better understand what protective factors are occurring within high violence neighborhoods (Leech, 2011; Sow, Leech & Irby-Shasanmi, 2016). As perhaps it is time to better understand why firearm violence is not occurring on the majority of street segments across Indianapolis and try to deconstruct the community level factors, such as collective efficacy that are protecting neighborhoods and street segments from firearm violence and try to apply them to the areas with high firearm violence.

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