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CORRECTIONAL BOUNDARIES: EXAMINING PUNISHMENT IN COMMUNITY; A SPATIAL ANALYSIS OF PROBATION IN CHICAGO, ILLINOIS

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Dedication

"*Thine Own of Thine Own, we offer unto Thee,*
in behalf of all and for all"

- The Holy Anaphora of the Eastern Orthodox Divine Liturgy

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Abstract

Probation is the leading form of correctional control in the United States; however, relatively little is known about the impact of probation on individual behavior, effectiveness in deterring crime, or its impact on communities and public safety. Existing research on probation outcomes narrowly focuses on individual-level characteristics associated with the likelihood of recidivating or evidence-based probation practices associated with lower rates of negative discharge. This study advances scientific research on probation to provide a contextual analysis of probation trends through secondary data analysis examining all closed probation cases (both felony and misdemeanor) in the Adult Probation Department of Cook County, Illinois between 2010 and 2016. The study has three specific aims; first, the study examines the spatial distribution and concentration of adult probationers across Chicago neighborhoods over a six-year period. Second, the study examines neighborhood-level predictors (violent crime rate, concentrated disadvantage, racial/ethnic diversity, and residential stability) of probation rate over time. Third, the study evaluates the relationship between individual probation outcomes and the same neighborhood-level factors over time. The following key set of findings emerged from the study: Adult probationers predictably clustered in poor neighborhoods with high violent-crime rates where most residents are African American. Over time, neighborhood levels of violent crime, concentrated disadvantage, and racial/ethnic diversity predicted a change in the number of adults on probation. Similarly, spatially concentrated probation populations predicted an increase in neighborhood levels of concentrated disadvantage and violent crime. Limited evidence was found to indicate that one’s probation outcome is influenced by the neighborhood context in which one is supervised. The study is unique in that it is the first spatial analysis of probation

drawing from a longitudinal dataset situated within one of the largest probation departments in the country. Second, the study is the first contextual analysis of probation outcomes in its examination of the association between neighborhood-level characteristics and recidivism trends. The research aims in this project, which have received no attention in the literature, merit scientific investigation given the growth of probation populations over the past forty years and emerging concern over the effectiveness of probation in rehabilitating offenders while maintaining public safety.

CHAPTER 1: INTRODUCTION

The leading form of correctional control in the United States is probation. In 2016, there were 4.62 million people involved in the criminal justice system under noninstitutional forms of punishment. This included 3.8 million people on probation (i.e., court-ordered community supervision under a probation agency) and 820,000 people on parole (i.e., individuals conditionally released from prison to serve the remaining portion of their sentence in community) (Kaeble & Bonzcar, 2016; Wagner, 2016). Four decades of correctional expansion in the United States have more than quadrupled the number of individuals in prison or jail, with 2.3 million people behind bars in 2015 (Prison Policy Initiative, 2016). More people are placed on probation than the combined total detained in local jails, state, and federal prisons. The scale of punishment inflicted through incarceration is statistically minor in comparison to the rise of what scholars have termed a *supervised society* (Miller, 2015)—a population that until relatively recently had been overlooked and invisible to public scrutiny due to a narrow focus on prison statistics.

The philosophical goal of probation is to rehabilitate offenders in the community and divert them from further involvement in the criminal justice system. The concept of probation has a long history, going back to the work of protosocial worker John Augustus—the 19th century "Father of Probation" who voluntarily bonded out "drunkards" in Boston courts and assisted in their recovery through mentorship and employment (Cobbs & Tardy, 2012). Probation is defined as a "period of conditional liberty that is protected by due process" (McShane & Krause, 1993, p. 93) during which an individual convicted of a crime remains in the community, while also being legally mandated to comply with specific conditions within a specified period. Probation is generally viewed as an alternative to incarceration and a more cost-effective way to sanction low-risk offenders.

The conditions of probation that can be sanctioned by a court include required reporting to a probation officer, fines, community service hours, and treatment conditions to address issues associated with the criminal behavior that led to conviction (e.g., drug treatment or family counseling) (Petersilia, 1998). Probation is a contract between the individual and the court. If the individual does not want to enter into this contractual agreement or if they violate any part of the contractual agreement, they can be sent to jail, prison, or have their probation sanctions lengthened or amended. The contextual setting where the probationer, the probation officer, and the court navigate this contractual agreement is outside of a penal institution and in the community area in which the individual resides.

The effectiveness of probation is most often measured by the proportion of individuals that successfully complete their probation term. Within Cook County, approximately 40% of felons on probation had their status revoked or were unsatisfactorily discharged over the past two decades (Sentencing Policy Advisory Council, 2013). Upon examining Illinois Department of Corrections admissions between 2009 and 2011, approximately 62% of new admissions were found to have been previously sentenced to probation (Illinois Criminal Justice Information Authority, 2017). Illinois' probation department fares comparatively better than probation departments in other states. In 2016, 73% of probationers in Illinois successfully completed their probation term (37,435/51,106), compared to 47% in Georgia (137,526/294,357), 59% in New York (17,973/30,355), and 44% in Ohio (53,984/123,450) (Kaeble, 2018). High rates of recidivism and unsatisfactory discharge have led some scholars to argue that probation acts more as a "net-widener" than an alternative to incarceration, ushering higher numbers of individuals further into the criminal justice system rather than diverting them from it (Phelps, 2013). These data suggest a need to more rigorously evaluate the role and effectiveness of probation and the challenges facing both probationers and local probation departments in reaching intended goals. Beyond the consequences implied for probationers and their communities, the challenges facing probation should be of national concern if recidivism or unsatisfactory discharge is framed as the "leading statistical indicator of return on correctional investment" (Pew Center on the States, 2011, p. 6).

Research to understand recidivism risk while under community supervision has typically focused on characteristics of the individual or system-level supervision methods. System-level efforts to reduce recidivism include proper training of probation officers, appropriate classification of offenders, and utilization of evidence-based correctional interventions. Andrews and Bonta (2010) identified five core supervision methods associated with effective correctional intervention. These methods, now known as "Core Correctional Practices," include (1) appropriate use of authority, (2) appropriate modeling and reinforcement, (3) skill building and problem solving, (4) effective use of community resources, and (5) relationship factors. The theory behind core correctional practices is to educate correctional officers, including probation officers, about the root causes of criminal behavior (primarily drawing from cognitive, behavioral, and social learning theories). A meta-analysis of studies evaluating programs containing elements of core correctional practices found that use of core correctional practices was associated with higher rates of supervision completion (Dowden & Andres, 2004). Probation departments are incorporating the use of the Risk Needs Responsivity (RNR) model to classify offenders and place them in appropriate programs. This actuarial model assesses offenders based on the level of risk they present, detailing the needs associated with their criminogenic behavior (i.e., highly impulsive behavior associated with stealing), and uses that data to make a recommendation regarding how treatment should be provided (Bonta & Andrews, 2007). Finally, the implementation of client-centered behavioral health interventions within probation departments has been shown to improve the outcomes of individuals under supervision. For example, Taxman and colleagues (2006) found a 38% reduction in the probability of rearrests and warrants filed for technical violations was associated with the use of client-centered behavioral health interventions. Probation practices that specifically aim to address the mental health needs of probationers have been found to improve criminal justice outcomes, resulting in fewer probation violations and fewer days in jail (Wolff et al., 2014).

Characteristics of the individual probationer are also associated with the risk of recidivism (Andrews & Bonta, 2010). Criminological studies examining recidivism cite eight central factors as valid risk indicators (Andrews et al., 2006). These risk factors include history of antisocial behavior, antisocial personality pattern, antisocial cognition, antisocial associates, family-marital circumstances, school-work challenges, leisure-recreation involvement, and history of substance abuse (Andrews & Bonta, 2010). The first four factors listed are the most robust predictors of recidivism. Criminal history is the best predictor of future criminal behavior (Campbell, French, & Gendreau, 2009; Cottle, Lee, & Heilbrun, 2001). The "central eight" factors include both static and dynamic risk factors. Static risk factors are unchangeable and usually refer to criminal history (e.g., age at first offense), whereas dynamic risk factors are changeable and amenable to intervention (e.g., substance abuse patterns or criminal thinking). Probation departments have evaluated both static and dynamic risk factors and have developed tools to evaluate individuals under supervision and assign appropriate services. Examples of these instruments include the Post Conviction Risk Assessment (PCRA) tool and Level of

Service Inventory Revised (LSI-R). An individual who is at high risk for recidivism is assigned more intensive supervision services, such as a higher frequency of contact and monitoring by the probation officer, a longer temporal period of supervision, or mandated behavioral health treatment.

Rarely, however, is community context considered when analyzing probation outcomes. There are only a handful of studies examining the role of neighborhood context in recidivism among parolees. Kubrin and Stewart (2006) found, after controlling for individual-level characteristics, that parolees returning to disadvantaged neighborhoods with high concentrations of individuals living in poverty had higher rates of recidivism when compared to parolees returning to resource rich or affluent neighborhoods. Other scholars have sought to identify specific characteristics of disadvantaged neighborhoods that might be related to parole supervision outcomes (Hipp & Yates, 2009; Wallace, 2015). For example, Hipp and colleagues (2010) found that a one-standard-deviation decrease in the number of social services within a neighborhood increases the likelihood of parole recidivism by approximately 37%. To date, however, no studies have examined the relation of neighborhood context and probation outcomes. Drawing from parole studies, there is reason to believe that neighborhood characteristics might be associated with probation outcomes.

Specific Aims

Probation outcome analysis must move beyond individual-level explanations and system-level practices. The practice of probation in a noninstitutional setting suggests that a context-driven analysis of probation is warranted. Little is known about the spatial distribution of probation or the ways in which neighborhoods are influenced by or influence supervision and probation outcomes across the urban landscape. This study builds upon existing research to explore the spatial logic of probation, the relation between probation density and neighborhood characteristics, and its implications for neighborhoods and probationers. The specific aims of the study are

1. to examine the spatial distribution and concentration of adult probationers in a large metropolitan city;
2. to examine neighborhood level predictors of probation rate and their association over time; and
3. to examine the association between individual probation outcomes and probation rates over time at the neighborhood level.

Background and Significance

Probation is a "period of conditional liberty that is protected by due process" (McShane & Krause, 1993, p. 93) during which an individual convicted of a crime is legally mandated to comply with specific conditions for a specified period of time. Probation is generally viewed as an alternative to incarceration and a more cost-effective way to sanction low-risk offenders. The conditions of probation that can be sanctioned by a court include required reporting to a probation officer, fines, community service, and treatment (e.g., drug treatment, family counseling, etc.) to address issues associated with the criminal behavior that led to conviction (Petersilia, 1998). The standard conditions of probation typically imposed in Cook County, Illinois, include regular meetings with a probation officer, home visitation, abstaining from committing new crimes, abstaining from possessing a weapon, staying within state boundaries, and abstaining from possession and use of illegal substances. Probation is a contract between the individual and the court. If the individual does not want to enter into this contractual agreement or if they violate any part of the contractual agreement, they can be sent to jail, prison, or have their probation sanctions lengthened or amended. The contextual setting where the probationer, the probation officer, and the court navigate this contractual agreement is **outside** of a penal institution and in the community area in which the individual resides.

Probation is the leading form of correctional control, and probation populations have been steadily growing for the past 40 years at both a national level and in the state of Illinois. Only recently have scholars turned their attention to this growth trend and examined policy mechanisms that account for the growth of probation populations (Phelps, 2016). Probation is typically framed as a cost-effective alternative to incarceration, with the cost of incarceration being nearly eight times the cost of supervision in community for the same time period (United States Courts, 2013). In addition to the cost of incarceration, prisons are highly criminogenic environments, with studies finding that between 32% to 66% of inmates experience physical victimization (Copes et al., 2011; Perez et al., 2010) and that inmates are vicariously traumatized through frequently witnessing acts of violence (Daquin et al., 2013). For individuals with mental health or substance abuse issues, there are often limited options for treatment while in prison, with greater access to programs and rehabilitation outside of prisons. Community supervision hypothetically allows for individuals to maintain employment ties and housing, reduce criminogenic exposure, and prevent direct and vicarious victimization. Furthermore, probation eliminates the negative collateral consequences associated with prolonged absence from the family and community due to incarceration, such as negative behavioral consequences for children whose parents are incarcerated (Wakefield & Wildeman, 2013), weakened local economies due to incarceration of a large portion of the potential workforce (Roberts, 2004), debilitated local civic engagement (Lerman & Weaver, 2014), and increased crime rates (Clear, 2009).

Probation departments are typically evaluated based on their ability to matriculate probationers under their supervision with minimal violations and on the number of individuals successfully graduated from caseloads and hypothetically rehabilitated into productive members of their community. Probation outcomes can be defined in many ways. Typically, outcomes are categorized as either positively discharged or negatively discharged (Adams & Olson, 2002). A positive discharge indicates successful completion of supervision requirements during the duration of sentence imposed. A negative discharge can be the result of various outcomes including a new arrest, a technical violation, or absconding. When an individual under supervision is re-arrested for committing a new crime (that may or may not result in a conviction), probation status can be revoked, which may result in a jail or prison sentence.[1]

In addition to the standard conditions of probation previously listed, specialized probation conditions can include victim restitution, community service, supervision costs and fines, drug testing, imposition of curfew, house arrest, mental health treatment, drug treatment, and educational programs. If an individual fails to comply with any of these standard or specialized conditions (for example, missing an appointment with their probation officer or failure to pay fees), they can be charged with a technical violation of their probation sentence. If noncompliance is detected, the probation officer can initiate the revocation process and the probationer can be sent for a judicial hearing to determine consequences for their actions.

[1] Revocation of probation status can mean different things in different jurisdictions. Generally, the revocation process is initiated by the probation officer and results in an individual's community-supervision status being suspended. They are then brought before a judge for a re-evaluation of their case. Judicial review of the revoked probation can lead to the individual serving the remaining part of their sentence in jail or prison, under more intense supervision (increased frequency of contact), a longer probation sentence (increased duration), or mandated treatment for behavioral health issues. Once the revocation process is initiated, the probationer may face pretrial detention in a local jail while waiting for a hearing before a judge.

Finally, absconding refers to active avoidance of supervision by not disclosing one's activities and location to the probation officer. This may or may not entail leaving the state or country. When a probationer absconds, a warrant is issued for their arrest. If found, they are subject to a judicial hearing, their probation status could be revoked, and they will face penalties.

Committing a new crime, nonpayment of a supervision fee, and absconding are all forms of noncompliance. However, they vary in terms of level of severity. Furthermore, the categories are not mutually exclusive. Committing a new crime is both a negative outcome and a technical violation.

Studies evaluating recidivism trends in probation can draw separately from any of the three negative outcome variables or various combinations of them. Among states that publish recidivism rates for probation, recidivism definitions vary considerably, depending not only on what negative outcome variables are used but also the time frame during which recidivism is evaluated. For example, Colorado defines probation recidivism as a "court filing for new offense within 1 year for those discharged successfully from probation" (Wilks & Nash, 2008), while Oregon defines probation recidivism as "a new felony conviction within 3 years after entering probation" (Oregon Criminal Justice Commission, 2017). In 2011, the rate of probation recidivism in Colorado was 5.8%, while in 2008 the probation recidivism rate in Oregon was 20.1%. In a sample of Illinois probationers discharged in November 2000 (n=3400), 45% of Cook County probationers experienced new arrests while on probation, while 32% committed technical violations (Lurigio et al., 2009).

The effectiveness of probation can be understood very differently depending on how the outcomes are defined and measured. Furthermore, the local control and design of probation departments make it difficult to draw comparisons between states and across counties within states, as practices and procedures vary widely. County probation departments can be situated under the jurisdiction of the judicial or executive branches of government (i.e., courts or the Department of Corrections), and in some states, probation is also combined with parole under a separate bureaucracy. In Illinois, where each county probation department operates under the judicial branch and is part of the local criminal justice system, local practitioners can delineate standards for probation (e.g., the judge, State's Attorney, and defense attorney will usually agree on appropriate conditions), recidivist events, and consequences for recidivation.

This study examines the probation outcomes of case revocations and unsatisfactory discharges. These two case outcomes are combined in a variable labeled "negative discharge event," which is explained in greater detail in subsequent chapters.

CHAPTER 2: THEORETICAL FOUNDATION AND LITERATURE REVIEW

Theoretical Foundation

Social Disorganization Theory

The theory of social disorganization states that behavior is influenced by the physical and social environment in which one lives. Social organization refers to the ability of communities to realize common values and regulate social life according to shared values, whereas social disorganization is typified by the absence of such dynamics (Kubrin & Weitzer, 2003). At the core of social disorganization theory is that context and location matters when it comes to predicting illegal behavior (Kubrin & Weitzer, 2003). Context, in this instance, refers primarily to "community"—a defined geographic space and a complex web of familial ties and social networks that influence social processes. The ways in which context shapes individual behaviors (i.e., social norms, rules, laws, societal structures) are referred to as mechanisms of "social control" within this theory. Social control includes both formal and informal mechanisms (Kubrin & Weitzer, 2003). Formal mechanisms include external or institutional mechanisms such as police, criminal justice actors, school teachers and administrators, and other public officials who carry the responsibility of maintaining public order and imposing sanctions for infractions (Sampson, 1986). Informal social control refers to the way in which neighborhood residents activate social ties and networks to regulate public behaviors according to shared values (Sampson, 1986). Neighbors' collective response to a resident who plays loud music late at night rather than calling the police about a noise disturbance is an example of informal social control. When informal mechanisms are weak or ineffective, residents must rely on agents of formal social control to provide public safety. Social disorganization theory highlights the importance of informal social control strategies as essential to realizing public safety, perhaps more so than formal social control (Kubrin & Weitzer, 2003).

Social disorganization theory emerged from early Chicago School sociologists Robert Park and Ernest Burgess (1925) writing *The City*—an examination of how immigration and industrialization impacted Chicago's residential patterns and neighborhood quality of life. Chicago School scholars were particularly interested in the growth of social ills such as disease, crime, disorder, vice, insanity, and suicide in large urban aggregates, all of which were interpreted as indicators of social disorganization. Park and Burgess detected spatial concentrations of these social ills within particular areas. These areas had shared characteristics, including high rates of poverty, high residential mobility, high unemployment rates, and poor housing stock. Park and Burgess hypothesized that these neighborhood characteristics weakened local systems' informal social control, leading to neighborhood social disorganization and the proliferation of crime and vice.

Shaw and McKay's book *Juvenile Delinquency and Urban Areas* (1942) further advanced social disorganization theory, summarizing over two decades of ecological research on juvenile delinquency in Cook County, Illinois. Their analysis revealed that certain neighborhoods experienced high rates of delinquency and that these trends persisted over time. Shaw and McKay explored potential neighborhood factors associated with high rates of delinquency and concluded that four specific characteristics contributed to this delinquency: (1) population heterogeneity, (2) population turnover, (3) physical deterioration, and (4) concentrated poverty. Heterogeneity was associated with low levels of social cohesion and weak social networks. Their interpretation of this finding was that people of different racial and ethnic backgrounds often experience cultural and language barriers to building bonds of trust, presenting a barrier to establishing common values and realizing these values for the common good. This community-level approach for analyzing crime and delinquency inspired decades of scholarly work focused on the relation between neighborhood features and social phenomena.

Bursik and Grasmik (1993) further advanced research on neighborhood-level social processes in their book *Neighborhoods and Crime: The Dimensions of Effective Community Control*. Their research emphasized residential turnover as a driving force behind neighborhood instability, focusing particularly on immigration patterns, although there are many forces related to residential mobility, including land-use changes and real estate policies. Constant residential turnover impedes the formation of social connections that foster informal social control, leading to an excessive reliance on formal social control entities such as police. Bursik and Grasmik highlighted the paucity of available empirical evidence directly testing neighborhood structures, social processes, and the connection to crime due to the cost and effort required to collect data longitudinally at the scale needed to adequately examine these relations.

Sampson and colleagues took up the challenge by launching the Project on Human Development in Chicago Neighborhoods in 1995, developing measures of neighborhood social processes, and surveying nearly 9,000 residents through a rigorous sampling across all neighborhoods in Chicago. Using data from this study, Sampson and colleagues (1997) found collective efficacy—defined as the collective ability of neighborhood residents to realize a common good—as a key mediating factor accounting for neighborhood rates of violence.

Clear and Rose (2003) extended social disorganization theory to the study of mass incarceration, citing *coercive mobility*—i.e., the cycling of residents in and out of prison—as a process that weakens community capacity to exercise informal social control, leading to an increase in neighborhood crime. The coercive mobility thesis challenges the more traditional perspective on the incapacitative benefits of incarceration. Clear and Rose argue that public safety is enhanced when incarceration occurs at low levels within a neighborhood and that public safety is compromised and neighborhood stability diminishes when incarceration is highly concentrated. This “tipping point of effects” was depicted as a curvilinear relationship between prison admissions and neighborhood crime within their study. The tipping point is where the association between the two variables shifts from negative (inversely related) to positive. To test the hypothesized curvilinear relationship, Clear and Rose used negative binomial model estimation techniques. They tested several different models and found that 90% of their estimates of this tipping point fell between 1.65 to 1.73 prison admissions per 1,000 neighborhood residents.

Several other researchers have utilized Clear and Rose’s coercive mobility thesis in studying large urban areas. Renauer and colleagues (2006) tested the coercive mobility hypothesis in Portland neighborhoods, examining the effects of incarceration rates in the year 2000 on crime rates of the following year. Their study addressed methodological critiques of Clear and Rose’s study; negative binomial models log transform the dependent variable and can distort the results in support of a nonlinear relationship between variables (Hannon & Knapp, 2003). Instead, Renauer and colleagues used the Heteroscedasticity Consistent Covariance Matrix (HCCM)—a statistical test with capacity to assess for nonlinear relationships within a small data sample. Their findings supported Clear’s theory of coercive mobility, showing that a tipping point of 3.22 prison admissions per 1,000 neighborhood residents changes the relationship between incarceration and violent crime from negative to positive.

In the current study, social disorganization theory provides the theoretical foundation for examining the effects of probation through a neighborhood-based lens. Probation supervision can be understood as a formal social control mechanism at the neighborhood level, where there is insufficient informal social control to regulate behaviors and advance the collective of residents towards a shared goal. Previous research within the tradition of urban ecology highlights important neighborhood characteristics to consider in predicting the spatial concentration of probation. Concentrated poverty is consistently highlighted as a predictor of a variety of social dislocations. Residential mobility is an important feature to consider as it impacts the ability to form social ties and generate social cohesion—key aspects of informal social control processes. In addition to these variables, crime levels are necessary to consider, not only as an outgrowth of social distress but also as a driver of social distress. Crime impacts social cohesion and sense of community, individual health outcomes over time, and residential stability. In this study, these variables are integrated into analyses examining neighborhood conditions that predict local probation rates (Specific Aim 2). Similar to previous studies in urban ecology, examining local predictors of probation rates contrasts with explanatory frameworks attributing probation growth to individual behaviors. These studies, however, do not examine structural forces (such as social policy) that may shape such local dynamics.

It is assumed that urban centers such as the one in the current study have been historically shaped and are currently reinforced by structural patterns in which racism is embedded. This study aims to both build on and expand this body of work to a population of people who have most likely experienced the long-term effects of these racialized patterns of social disorganization (Petit & Western, 2004; Roberts, 2004; Wakefield & Uggen, 2010). In other words, the unique contribution of race will be isolated in analyses examining local factors that predict the spatial concentration of probationers over time. Racial disparities exist throughout the criminal justice system, ranging from police contact to parole decisions. This study examined the racial composition of a sample of probationers from 2010 to 2016, the residential patterns of Chicago, and the relationship between these two variables. In isolating race as a variable, the intent is not to attribute the concentration of probation to the innate qualities of the predominant racial group in that area but rather to explore potential disparities in probation supervision based on racial identity. It is beyond the scope of the current study to define mechanisms that lead to the over- or under-representation of particular racial groups within the probation population. The intent of the study is to lay the groundwork for future research into how individuals are assigned to probation supervision.

Social Ecological Framework

Bronfenbrenner (1999) describes four levels of influence on human development with varying proximity to the person: the microsystem, mesosystem, exosystem, and macrosystem. This social ecological framework suggests that aspects of each level of influence exert direct influence not only on development but also in interaction with other levels of the system. The *microsystem* represents those aspects of social systems with regular, direct contact with the individual—most typically family members, peers, or caregivers. The *mesosystem* comprises interactions between different components of an individual's microsystem—what Bronfenbrenner refers to as "a system of microsystems" (p. 40)—for example, the interaction between one's parents and one's school environment. The *exosystem* refers to connections between two or more settings, one of which does not directly contain the developing person. Examples of exosystem-level factors include family social networks and neighborhood contexts. Finally, the *macrosystem* is the cultural environment in which a person lives and the factors associated with it (e.g., race, ethnicity, religious beliefs, opportunity structures, and socioeconomic status). Bronfenbrenner later included the *chronosystem* as a fifth layer, defining it as a way in which historical time is factored into the life course development of an individual. According to Bronfenbrenner's ecological systems model, a change or conflict occurring at any one layer ripples throughout all other layers.

Examination of probation within an ecological framework directs attention to the multilayered context within which individuals under correctional supervision exist. Beyond individual characteristics associated with the risk of recidivism (such as the "Central Eight" risk factors), probationers are influenced by proximal social contacts (such as family) and local factors (such as neighborhood characteristics, including poverty rates, availability of educational resources, employment opportunities, law enforcement, etc.). Bronfenbrenner's scholarly work on the developmental ecological model examined youth development in context. For the first time, probation outcomes are examined as an interaction between an individual and their neighborhood context—an interaction between the microsystem and exosystem (Specific Aim 3). Probationers come from different neighborhoods with different circumstances that may play a role in their successful navigation of correctional supervision. One of the neighborhood characteristics included in the analyses is the probation supervision rate. This measure has yet to be examined as an exosystem-level dynamic in association with individual probation outcomes.

Drawing from an ecological framework and based on social disorganization theory, this study examines the relationship between neighborhoods and probation over time in Chicago, Illinois.

Literature Review

Neighborhood Effects and Crime Rates

In continuity with the Chicago-based research that inspired social disorganization theory, modern research continues to confirm that crime is concentrated in particular places, sometimes referred to as "hot spots." These hot spots are characterized by a disproportionate amount of crime within the urban landscape. In an analysis of violence in Boston between 1980 and 2009, over 50% of violent crime within this time period occurred within only 3% of street segments (Braga et al., 2009). Similarly, in an examination of crime trends in Philadelphia between 2006 and 2008, 5% of street corners were locations of nearly 40% of robberies, 42% of aggravated assaults, and 33% of homicides (Ratcliffe et al., 2011). Neighborhood-level predictors of the concentration of violent crime in certain places include concentrated economic disadvantage and high rates of unemployment. For example, reduced access to low-skill jobs was shown to be associated with violent crime rates following the industrial restructuring of urban economics and the shift towards a service-centered workforce between 1970 and 1990 (Shihadeh & Ousey, 1998). Spatial analyses of crime trends have also explored how localized social dynamics contribute to or inhibit public safety threats. For example, high levels of collective efficacy are found to mediate the effects of concentrated disadvantage in neighborhoods that would otherwise experience elevated risk of violence (Sampson et al., 1997).

Neighborhood Effects and Incarceration

More recently, scholars have examined spatial trends in incarceration patterns and similarly found spatial concentrations in certain neighborhoods. In many urban cities, a handful of neighborhoods bear the disproportionate burden of prison admissions. Between 2005 and 2009 in Chicago, 851 city blocks in predominantly African American neighborhoods were identified where at least one-million dollars in public funds was spent on removing individuals from these areas and sending them to prison (Lugalia-Hollon & Cooper, 2018). Many of the same neighborhood features found to predict crime levels were also found to predict the concentration of incarceration. In an analysis of incarceration trends in New York City neighborhoods between 1985 and 1996, the spatial concentration of incarceration “distort[ed] neighborhood social ecology and attenuate[d] the neighborhood’s economic fortunes,” thus predicting continued rates of incarceration independent of crime rates (Fagan et al., 2003, p. 1589). Social factors such as rates of poverty, segregation, and housing structure were all significantly correlated with jail and prison admission rates (Fagan et al., 2003). Similarly, Sampson’s (2010) analysis of incarceration trends in Chicago noted a bidirectional relationship between concentrated disadvantage and concentrated incarceration over time.

In addition to analyses examining spatial features associated with increased levels of incarceration, several studies have examined the impact of incarceration on local social dynamics. At the neighborhood level, concentrated mass incarceration is associated with increased crime rates. This phenomenon is attributed to the impact of incarceration on social dimensions of community life. For example, Fagan and colleagues (2003) examined how concentrated mass incarceration destabilizes crime networks and can create competition, thus increasing crime rates. The high frequency of contact with criminal justice actors (such as police, detectives, and judges) may delegitimize criminal justice sanctions and actors, and thus decrease citizens’ willingness to comply with the law, resulting in more crime and incarceration (Fagan et al., 2003; Fagan & Tyler, 2005; Justice & Meares, 2014).

Neighborhood Effects and Parole Supervision

Scholars have extended research on neighborhood effects to examine the spatial effects of parole supervision (Bensel et al., 2015; Chamberlain & Wallace, 2015; Harding et al., 2013; Hipp & Yates, 2009; Hipp et al., 2010; Kirk, 2015; Morenoff & Harding, 2014; Wallace, 2015). Many states struggle with the successful reintegration of former prisoners upon their release as a consequence of the dramatic increase of prisons and prison populations. Prison reentry occurs at a large scale in a small number of communities—a phenomenon coined as “mass reentry” (Chamberlain & Wallace, 2015)—and is concentrated in discrete urban spaces, most often poor minority communities (Morenoff & Harding, 2014). No studies have specifically examined neighborhood features associated with the spatial concentration of parolees, although spatial concentration is clearly noted (La Vigne, 2004; Peck & Theodore, 2008). Harding and Morenoff (2013) examined residential patterns of parolees using data from the Michigan Department of Corrections. They found that only 41% of prisoners return to their previous neighborhood upon release, and at least 38% lived more than five miles from their preprison neighborhood. Despite the evidence of mobility of former prisoners, Morenoff and Harding note that most parolees move into similar neighborhoods with high concentrations of poverty and social distress (Harding et al., 2013).

Both structural features of a neighborhood and its social dimensions are associated with parole supervision outcomes. Neighborhood disadvantage is a significant predictor of parole recidivism. Parolees residing in neighborhoods that are one standard deviation above the average rate of concentrated disadvantage in California are 12.7% more likely to recidivate (Hipp et al., 2010; Kubrin & Stewart, 2006; Mears et al., 2008). Several studies link scarce or fluctuating levels of neighborhood resources with local recidivism rates, as well (Wallace & Papachristos, 2014). In an analysis of Chicago neighborhood resources and recidivism rates, Wallace (2015) found that the loss of two or more educational resources within a community increased local recidivism rates by 3.6%. The nature of community social networks has also been examined in relation to parole recidivism. Kirk (2009) examined prisoner reentry in New Orleans following Hurricane Katrina in 2005, when many prisoners were unable to return to the neighborhoods where they formerly resided due to the extensive damage. The findings from this natural experiment indicated that reintegrating into a locality different from one's neighborhood of origin substantially lowered a parolee's risk of recidivism. Relocated parolees' probability of reincarceration was 15% lower than those who did not relocate (2009). Significant results were found with both first releases and those with multiple incarceration bids. Kirk's findings suggest that social ties and social networks embedded in community spaces are important to consider when evaluating parole recidivism risk.

Empirical research examining the spatial distribution of crime, incarceration, and parole supervision in an urban landscape confirm nonrandom, predictable patterns. Furthermore, certain neighborhood characteristics are associated with spatial patterns observed. The neighborhood characteristics highlighted in this review have been included as predictors of the spatial concentration of probation. Finally, the parole studies indicate that community context matters for case outcome. The current study examines the significance of community context in association with individual probation outcomes.

In this review, crime, incarceration, and parole are examined in isolation from one another; however, they are often concentrated in the same place. The same communities that experience higher rates of crime also lose a significant number of adult individuals to the prison system and at the same time are disproportionately burdened with receiving the bulk of exiting prisoners. In the Urban Institute's study *Returning Home: Understanding the Challenges of Prisoner Reentry*, researchers followed returning citizens in Maryland, Illinois, Ohio, and Texas to examine challenges faced by individuals reintegrating back into society. The study found that most former prisoners return to highly disadvantaged communities characterized by concentrated poverty and high crime rates. In Illinois, the study's respondents indicated that returning to neighborhoods where they felt unsafe and had few opportunities placed them at greater risk of recidivating (La Vigne et al., 2005). Similarly, Chamberlain and Wallace's (2015) study on "mass reentry" notes that the communities receiving the highest proportion of parolees also have the highest crime rates and the fewest resources. It is highly likely, therefore, that there is a significant spatial overlap of crime, incarceration, and parole supervision, and that each one of these phenomena is interconnected in a self-perpetuating cycle. It is beyond the scope of the current study to examine the unique contribution of probation supervision to neighborhood dynamics such as concentrated disadvantage or violent crime rates. However, it is recommended that future research explore the totality of the "criminal justice imprint" on neighborhood social ecology and its implications for justice involved individuals and neighborhood residents, as well.

Gaps in Research

The current study addresses a gap in empirical research to understand the intersection of community with the criminal justice system in several important ways. First, this is the first empirical study examining the spatial distribution of probationers over time within a large metropolitan area. Second, neighborhood-level predictors of the probation rate over time are examined. Finally, the study examines the association between neighborhood context and probation outcomes, exploring the ecological dynamic of spatially concentrated probation and its implications for individual probationers.

CHAPTER 3: RESEARCH DESIGN AND ANALYTIC STRATEGY

Research Design and Methods

Data Acquisition

The probation data utilized for this study are drawn from the Cook County Adult Probation Department and Social Service Department, which is under the Circuit Court of Cook County's Criminal Court Division. A research collaboration agreement was established with the Research Director of Cook County Adult Probation Department (see Appendix A). Access to the data required a court order issued by the Chief Judge of the Circuit Court of Cook County. Following this court order, the Research Director of Probation compiled the data and transferred it through a password protected file to the Principal Investigator of the study.

Data Set

Probation data.

Probation data is regularly collected during the processing of individuals through the criminal justice system and stored electronically on information systems used by the Adult Probation Department of Cook County. The study sample includes all closed probation cases (primarily felonies) and social service cases (primarily misdemeanors) from all probation subunits (drug, mental health, intensive, etc.) between 2010 and 2016. The list of case-level details that were provided as part of the data-sharing agreement is found in Appendix B.

Neighborhood data.

Census tract was used as the geographic unit representing "neighborhood." This decision was based on previous research of neighborhood effects conducted within Chicago (Henry et al., 2014; Sampson et al., 1997). "Neighborhoods" can be defined via several means, such as establishment of geopolitical boundaries (for example, neighborhoods defined by the City of

Chicago) or social definition (for example, neighborhoods defined by residents who live in a particular area). In Chicago, census tracts generally correspond well with what is commonly meant by the term "neighborhood," both with regards to population and geographic size (Henry et al., 2014). However, census tracts do not always correspond with definitions of neighborhood that are socially agreed upon by Chicago residents. The purpose of this study is not to resolve the issue presented by varying definitions of neighborhood but rather to choose a definition that allows for the most nuanced understanding of neighborhood context given the data available in the study. The most precise neighborhood data available which reference the characteristics highlighted in this study are the census tract level data obtained via the American Community Survey.

The neighborhood data used for the study draw primarily from the American Community Survey 5 Year Estimates. The 5 Year Estimates generate averages for each survey variable based on 60 months of data collection. These estimates are most appropriate to use when analyzing trends among populations within a small area, such as at the census tract level. The following 5 Year Estimates were utilized for estimates: 2007–2011 (2011), 2008–2012 (2012), 2009–2013 (2013), 2010–2014 (2014), 2011–2015 (2015), 2012–2016 (2016). The 5 Year Estimates correspond with census boundaries as defined in 2010. Census tract boundaries are relatively stable over time. However, population fluctuations can lead to the splitting of census tracts or merging of census tracts. In Chicago, between the 2000 Census and 2010 Census, several census tract boundaries shifted. Therefore, the analyses performed for Aims 2 and 3 only use data from 2011 to 2016. Chicago has 801 census tracts, which vary dramatically in size (ranging from 16 to 1,771 acres, excluding three outlying tracts) and population (ranging from 237 to 7,546 residents, excluding seven outlying tracts).

Data Analytic Sample

Because the central aims of this study are to understand the relation of the characteristics of the probationer's neighborhood and probation outcomes, only probation cases that could be geocoded for residence were included in the analyses. Cases that were not able to be geocoded, and therefore excluded from the sample, were typically a result of data input errors (spelling errors, missing data fields, etc.) Appendix C presents a flowchart of how the individual cases within the dataset were managed. Table 3.1 provides a description of sociodemographic features of the data sample.

Table 3.1

Socio-Demographic Features of Closed Probation Cases Between 2011 and 2016

Variable	Measure/Category	Results	Missing Data
Age (Years)	Mean: 31.56	SD: 12.19	34 cases
LSI-R Score	Mean: 16.38	SD: 8.24	11,190 cases
Gender	Male	32,789 (81.00%)	131 cases
	Female	7,545 (18.60%)	
Race	White	4,253 (10.50%)	320 cases
	African American	2,6895 (66.50%)	
	Hispanic	8,642 (21.40%)	
	Other	355 (0.90%)	
Case Outcome	Satisfactory	26,890 (66.50%)	35 cases
	Revoked	4,955 (12.20 %)	
	Unsatisfactory	8,585 (21.21%)	
Total Number of Cases Included in Analysis		40, 591	

Measures

Individual-level variables.

Demographics: Age reported at the time the individual was sentenced to probation; gender was described in binary terms (male, female); racial and ethnic categories were combined and coded using four categories: Non-Hispanic white (white), African American, Hispanic, and Other. If an individual was both Hispanic and African American, they were identified as African American within this study.

Risk Level: Risk level was measured by the Level of Service Inventory-Revised (LSI-R) Score. LSI-R is an actuarial tool used to evaluate both static and dynamic risk factors of individuals under correctional supervision. The tool is scored based on an interview conducted by a probation officer at the initial period of engagement with the client. The LSI-R assessment includes 10 subscales that are differentially weighted: criminal history, education/employment, financial, family/marital, accommodation, leisure/recreation, companions, alcohol/drug problems, emotional/personal, and attitude/orientation. The aggregate score of the probationer determines the level of supervision they receive (see Table 3.2). The possible range of scores for the LSI-R goes from 0 to 56. In the study sample, the aggregate LSI-R score recorded at the time of disposition (initial intake) was recorded and utilized for analytical purposes.

Table 3.2

Risk Categorization Based on LSI-R Score

Score	Risk Assignment	Supervision Level
0-10	Low Risk	Monthly report by mail, in-person every 3 months
11 – 16	Low-Medium Risk	Monthly reporting, alternating between mail and in-person
17-24	Medium Risk	Monthly in-person reporting
25 – 33	High-Medium Risk	Twice monthly in-person reporting
34+	High Risk	Weekly in-person reporting

Probationer Address: Addresses in the dataset were reported at the street-block level with an indicator of whether the address was even or odd. To aggregate each address and case file to the appropriate census tract, each address was assigned a location within the middle of the block. These addresses were uploaded to ArcGIS and geocoded, a process in which X and Y coordinates are assigned to the address. To begin the geocoding process, the appropriate address locator was specified within ArcGIS by downloading a street map of the city of Chicago from the city data portal, and each address was then processed through the geocoding address locator. Cases that were "tied" between two possible locations were reviewed and then matched if there was sufficient evidence to indicate the correct address. Each "unmatched" was also individually reviewed to identify spelling errors, directional clarification (north/south, east/west), and other address specifiers. The corrected unmatched addresses were then reprocessed to ensure the highest percent of viable probation cases for spatial analyses.

Probation Outcome: Two measures of probation outcome are included in the data—probation outcome and court outcome. The probation outcome variable are the data entered by the probation officer. The court-outcome variable refers to the outcome decided by the judge. The Cook County Adult Probation Department uses the court-outcome variable for their analyses. To be consistent with internal analyses, the same outcome variable was used for these analyses. When this variable was missing, the probation outcome was used. The outcomes recorded for both variables include revoked, unsatisfactory discharge, satisfactory discharge, conditions amended, and other (warrant issued, etc.). An unsatisfactory discharge indicates the case was closed without the probationer complying with all the objectives of their supervision period. While the probationer is not penalized for an unsatisfactory discharge at the time the case is closed, an unsatisfactory outcome could be considered for future case and sentencing decisions if rearrested, with the individual more likely to experience a harsher penalty (jail or prison sentence) (Olson & Stalans, 2001).

Illinois Statute does not indicate which manifestations of probation noncompliance warrant an unsatisfactory discharge status. While the probation outcome of unsatisfactory discharge is indicated in other County Probation Departments within the state of Illinois, it is not necessarily an outcome noted outside of Illinois. There are some indications that failure to complete substance abuse treatment, inability to pay fines, or complete community service hours can lead to an unsatisfactory discharge (Stalans et al., 2004). These same circumstances, though, could also lead to a revocation while on probation. While it is generally understood that a revocation is issued when there is a flagrant violation of probation conditions, it appears that the probation officer and their supervisor have discretion regarding response. Given this ambiguity, both revocation and unsatisfactory discharge statutes were combined into a single variable of

"Negative Discharge." Appendix D provides a comparison of the individual-level characteristics for probationers with a case revocation versus an unsatisfactory discharge.

Neighborhood-level variables.

Each neighborhood-level variable was estimated for 2011 to 2016, drawing from the American Community Survey 5 Year Estimates.

Concentrated Disadvantage**:** A measure of neighborhood concentrated disadvantage was calculated using the following variables: percent owner-occupied housing units, percent of families living below the poverty level, percent female-headed households, percent unemployed (Hipp et al., 2010; Hipp, 2010). Principal components analyses (PCA) were conducted using these variables, an appropriate statistic to calculate in order to reduce several variables into a single measure. The results based on 2016 data are listed in Appendix E. Due to the stability of this variable's measurement over time, the PCA results are only listed for one year. These measures of stability are discussed in the analyses for Specific Aim 2.

Residential Stability: A measure for residential stability was calculated combining percent of housing units that moved into their residence within the last five years and percent owner-occupied housing (Hipp et al., 2010). Like Concentrated Disadvantage, principal component analysis was calculated for each year between 2010 and 2016. The results based on 2016 data are listed in Appendix E. Due the stability of this variable's measurement over time, the PCA results are only listed for one year. These measures of stability are discussed in the analyses for Specific Aim 2.

Racial/Ethnic Diversity: Neighborhood-level diversity was measured using the "entropy index" construct (White, 1986). This measure was chosen as it allows for an examination of residential segregation among more than two groups. Most measures of residential segregation, such as the Dissimilarity Index, are an examination of differences in residential patterns of one particular racial/ethnic group in relation to another group within a specified geographic area. As Chicago has a sizeable Hispanic population among other immigrant groups, the Entropy Index measure is a more appropriate estimate of neighborhood racial and ethnic diversity as it describes the spatial distribution of multiple racial/ethnic categories using the following formula:

$$h_i = -\sum_{j=1}^{k} p_{ij} \ln(p_{ij})$$

In this equation k = number of racial/ethnic groups, p_{ij} is the proportion of population j race/ethnicity in tract I (= n_{ij} / n_i), n_{ij} equals the number of population j race/ethnicity in tract I, and n_i is equal to the total population in tract I. Four group categories were included in this calculation: African American, Hispanic, white, and other. African American/Hispanic citizens were counted as African American in this study. The maximum value for the entropy index, therefore, would be equal ln(4), or 1.386. Census tracts with higher values are considered more diverse, and a census tract with a score of 1.386 would have equal proportions of each category. A census tract with an entropy index of 0 contains only one group.

Violent Crime Rate: Violent crime incident data between 2010 and 2016 were drawn from the Chicago Data Portal. Violent crime includes homicide, forcible rape, robbery, battery, and aggravated assault. The violent crime rate was calculated by dividing the total number of violent crimes in each census tract by the total population in that census tract, then multiplying this number by 1,000.

Probation Rate: Probation rate was calculated by taking the total number of closed probation cases within a census tract, then dividing it by the total number of adults between 18 and 65 within that census tract. Probation rate was calculated for every year between 2010 and 2016. Probation rate could then be derived by multiplying this number by 1,000.

Analytic Strategy

Specific Aim 1: Spatial Distribution of Probation

Spatial densities.

The spatial distribution of probationers from 2010 to 2016 was generated using kernel density estimation techniques (Anselin et al., 2000). For each probation case point on a map, a smooth curved surface is generated with a radius of a quarter mile. The surface value is highest at the location of the reference point and diminishes to zero at the end of the radius. The density is calculated by summing the weights for all points within the quarter-mile radius of the reference location. In addition to the spatial distribution of probationers, a kernel density map was generated to illustrate the spatial distribution of negative discharge events.

To test whether probation cases and negative discharge events were randomly distributed or predictably organized, the Average Nearest Neighbor (ANN) statistic was run for both probation cases and negative discharge events. In testing for spatial randomness, there are two orders of randomness to examine (Anselin et al., 2000). The first order indicates that any event has equal probability of being in any location. The second order examines, for each event, whether it is independent from the location of another event. The Average Nearest Neighbor tool examines the first order of spatial randomness by measuring the distance between each probation case and the nearest "neighbor" probationer. If the average distance between probation cases is less than the average for a hypothetical distribution of the same number of cases, then the distribution of probationers included in the analyses is clustered. If the average distances are equal, then the distribution is random. If the average distances are greater, then the distribution is dispersed. The calculation is as follows: ANN = D_O / D_E, where D_O = observed mean distance between each feature and its nearest neighbor, and D_E = expected mean distance for features given a random pattern.

The ANN estimates do not account for the shape of the surface area examined. Data points can appear clustered or dispersed based on the shape of the surface area in which they are contained. Surface shape cannot be defined in ANN analysis; therefore, the tool forms an oval shape that encompasses all data points in the sample in order to construct a spatial surface to test for the randomness of distribution. This was deemed appropriate for the study for two reasons: (a) there are probationers present throughout the entire city; although there are heightened levels of concentration in some areas, every census tract in Chicago has at least one probationer, and (b) the general shape of the city of Chicago is oval.

Population densities.

Spatial densities describe the distribution of probationers across space; however, population densities describe the distribution of probationers among census-tract populations. For 2010–2016, the Probation Rate is estimated for each census tract by aggregating geocoded cases to the census tract and dividing this by the total number of adults age 18–65. Subsequently, the proportion of negative discharge events is estimated among the probation population in each census tract. The total number of negative discharge events recorded in each census tract is divided by the total probation population within that tract. This calculation produces an estimate of the probation rate, and a gradient of the probation rate reflects population densities across the city of Chicago per year.

Specific Aim 2: Neighborhood-Level Predictors of Probation Rate

Following the spatial and population densities examined in Specific Aim 1, analyses conducted for the subsequent specific aim were designed to examine the relation of neighborhood-level characteristics and probation rate over time, including the potential bidirectionality between neighborhood characteristics and probation rate to identify possible reciprocal dynamics in which the variables become mutually reinforcing over time. Drawing from previous studies using a neighborhood-effects framework to examine crime and incarceration, the following neighborhood characteristic constructs were included in the analysis: (1) concentrated disadvantage, (2) neighborhood crime, (3) residential mobility, and (4) racial/ethnic diversity.

Statistical analyses were performed using structural equation modeling in *Mplus 7.3* (Muthén & Muthén, 2015). Full information likelihood (FIML) was used to produce unbiased parameter estimates and standard errors. All available data within the dataset were used to generate a likelihood function for everyone based on available data. Autoregressive cross-lagged models (ACL) were used to evaluate predictors of the probation rate over time. The ACL model is a form of structural equation modeling where the association between two or more variables is measured over time (Selig & Little, 2012), allowing for an examination of the relationship between neighborhood characteristics and the probation rate over time, as well as the direction of relation between them. To build ACL models, two variables, such as concentrated poverty (X) and the probation rate (Y) are measured on two occasions or more (noted by subscripts 1 and 2).

$$X_2 = B_1X_1 + B_2Y_1 + \xi_X$$

$$Y_2 = B_3Y_1 + B_4X_1 + \xi_\psi$$

The coefficient B_1 and B_3 reflect the autoregressive effects of the model or the stability of an individual construct over time (for example, the concentration of probation). If the autoregressive coefficient is small or zero, then there is considerable variation over time for the construct. Stability is reflected in a large coefficient for the variable. Coefficients B_2 and B_4 describe the cross-lagged effect of the variables—the effect of variable X on variable Y measured at a later time. The cross-lagged effects are dependent on the variance of the variables over time (B_2 and B_4). A significant cross-lagged effect indicates that the measurement of X at time 1 is associated with the measurement of Y at time 2. In an ACL model, the significance of the cross-lagged effect between variables X and Y considers previous measurements of Y; in other words, the model reflects the residual variance. The inclusion of prior measurements of variables X and Y reduces the bias in the estimation of cross-lagged effects, a strength of ACL models.

ACL models were used to evaluate stability in probation trends and neighborhood-level characteristics over time, as well as the relationship between neighborhood-level dynamics and the probation rate over time. One-year lags separate each variable for all models while controlling for time-invariant factors. This model allows for an examination of potential reciprocal effects between neighborhoods and concentration of probation. Before running the models, each variable is correlated on itself over time to examine the strength, directionality, and stability of each neighborhood characteristic over time. Subsequently the following models are run:

Model 1: Concentrated Disadvantage – Probation Rate

Model 2: Violent Crime Rate – Probation Rate

Model 3: Residential Mobility – Probation Rate

Model 4: Entropy Index – Probation Rate

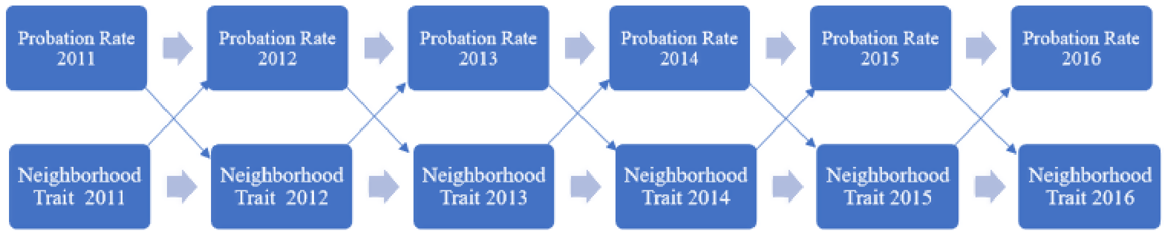


Figure 3.1. An example of auto-regressive cross-lagged panel models (excluding arrows indicating covariance measures to simplify the visualization).

When necessary, model constraints were imposed to provide clarity on aggregate trends over time between variables. The models are first presented using unstandardized coefficients so that results can be interpreted in their own measurement form. Standardized coefficients are presented in order to compare the size of effect of cross-lagged paths if both are statistically significant.

Specific Aim 3: Probation Outcomes and Neighborhood Context

Probationers are nested within larger structures, such as families, neighborhoods, and larger metropolitan contexts. This last question examines the spatial distribution of negative discharge events in Specific Aim 1. If a spatial clustering is observed, an examination of neighborhood-level characteristics and individual outcome variation is warranted. To answer these questions, the following statistical methods were used. First, the spatial distribution of negative discharge events was analyzed using the Average Nearest Neighbor (ANN) estimate. The ANN statistic applied in Specific Aim 3 only addresses the location of negative discharge events and does not distinguish negative discharge events by their attributes (i.e., the probationer attached to the event). Spatial autocorrelation allows for further complexity in examining spatial randomness. The Global Moran's I statistic computed in spatial autocorrelation tests indicates the degree of similarity in value among units of analyses according to their spatial location. In this study, Global Moran's I was used to test against the null hypothesis that the neighborhood rate of negative discharge events among probationers is randomly occurring. If the p-value observed for this test is statistically significant, then one can reject the null hypothesis. Depending on the coefficient of the test statistic (z-score), one can then conclude that the observations are spatially clustered or dispersed. If the z-score is positive, then the spatial distribution is clustered; if the z-score is negative, then the spatial distribution is dispersed.

As the focus of Specific Aim 3 is the role of *neighborhood* context and neighborhood-level probation outcomes, the tests for spatial autocorrelation move beyond singular negative discharge events by examining neighborhood-level rates of negative discharge events among probationers. For each census tract, the total number of negative discharge events observed in a year is divided by the total probation population in that tract. This produces an estimate of the rate of negative discharge events among probationers within that neighborhood. Subsequently, tests of spatial autocorrelation are applied to this statistic, examining whether similar rates of negative discharge events are proximately located or dispersed throughout the city. Only neighborhoods with at least one probationer were included in these analyses. To corroborate these findings, additional maps were generated depicting the proportion of probationers with negative discharge events at the neighborhood level. These maps provide a visual point of comparison to examine whether there are particular neighborhoods where probationers are more or less likely to be satisfactorily discharged from supervision and whether there is stability or change over time.

The residual intra-class correlation coefficients (ICC) were estimated for the closed probation cases from 2011 to 2016. The intra-class correlation coefficient is a measure of how strongly individual observations within the same cluster resemble each other (Maas & Hox, 2005). In this study, the question is whether probationers residing in the same neighborhood (operationalized as census tract) have similar probation outcomes. The ICC describes the proportion of variance observed in negative discharge rates that is not explained by predictors in the model that could be accounted for by clustering at the neighborhood level. Calculating the ICC is useful in determining the type of regression model most appropriate for examining both individual- and community-level factors in association with probation outcomes. If the ICC value is very small, then variance observed in probation outcomes is primarily due to differences between probationers and not the neighborhoods they reside in. If the ICC value is very high, then the variance one observes in probation outcomes across the probationer sample is stemming primarily from grouping (neighborhood) differences. Should this occur, it would be appropriate to build a multilevel model to examine neighborhood context and probation outcomes. There is not a clearly established threshold value for the ICC past which one is recommended to proceed with multilevel modeling; some suggest that at least 10% of the variance must be accounted for by clustering (Hox, 2010; Dyer, Hanges, & Hall, 2005).

The ICC is calculated using the following formula (Snijders & Bosker, 1999):

$$p_i = \frac{\tau_0^2}{\tau_0^2 + \pi^2/3}$$

This statistical approach recognizes that probationers residing in a particular neighborhood may share similar characteristics and a shared risk for a negative discharge event. If probation outcome observations are not independent of one another, then failure to account for the contextual effects of their neighborhood of residence can produce biased risk estimates. A three-level hierarchical binary logistic regression was used because the outcome (negative discharge event) is coded using a binary scheme (Guo & Zhao, 2000).

Multilevel modeling allows for exploration of the interaction between individual- and neighborhood-level factors and negative discharge rates for probationers over time (Raudenbush & Bryk, 2002). In the models here, level one includes individual-level factors to be controlled for in evaluating negative discharge risk. Level two includes neighborhood characteristics examined as predictors of the probation rate in Specific Aim 2. Level three includes time, 2011–2016.

CHAPTER 4: RESULTS

Specific Aim 1 Results: Spatial Distribution of Probationers in Chicago

The Spatial Distribution of Probationers

The spatial distribution of probationers between 2010 and 2016 is presented through a series of maps. Each probationer with a geocoded address is marked by a single dot on the map, and the accumulation of summary of points generates patterns on the map. Kernel density estimation created a smoothed surface to provide a visualization of the distribution pattern. Where there is a clustering of many points (i.e., probationers) within a quarter-mile radius, the kernel density estimation generates a darker-shaded area.

Table 4.1

Organization of Variables for Multilevel Modeling

Independent Variables	**Variable Type**	**Source**	**Measurement**
Individual-Level Variables			
Age	Continuous	Probation Case File	Recorded at time of disposition
Race / Ethnicity	Categorical	Probation Case File	White, African American, Hispanic, Other [African American Hispanics are coded as African American]
Gender	Categorical	Probation Case File	Male, Female
LSI-R Score	Continuous	Probation Case File	Score Ranges: Low Risk (0 – 10), Low-Medium Risk (11 – 16), Medium Risk (17 – 24), High-Medium Risk (25 – 33), High Risk (>34) * The first LSI-R score recorded at the initiation of their probation sentence is utilized in analyses
Neighborhood-Level Variables			
Residential Stability	Continuous	American Community Survey	Principal Component Analysis (percent owner-occupied housing, percent residents living in same unit 5 years or longer)
Concentrated Disadvantage	Continuous	American Community Survey	Principal Component Analysis (percent female-headed household, percent families living below poverty level, percent unemployed, percent owner-occupied housing)
Neighborhood Racial/ Ethnic Diversity	Continuous (0 – 1.386)	American Community Survey	See methods section for calculation and interpretation
Violent Crime Rate	Continuous	Chicago Data Portal	(# of violent crime incidents reported / total population in census tract)
Probation Rate	Continuous	Probation Case Files and American Community Survey	(# of probationers per census tract)/ (adult population 18-65)

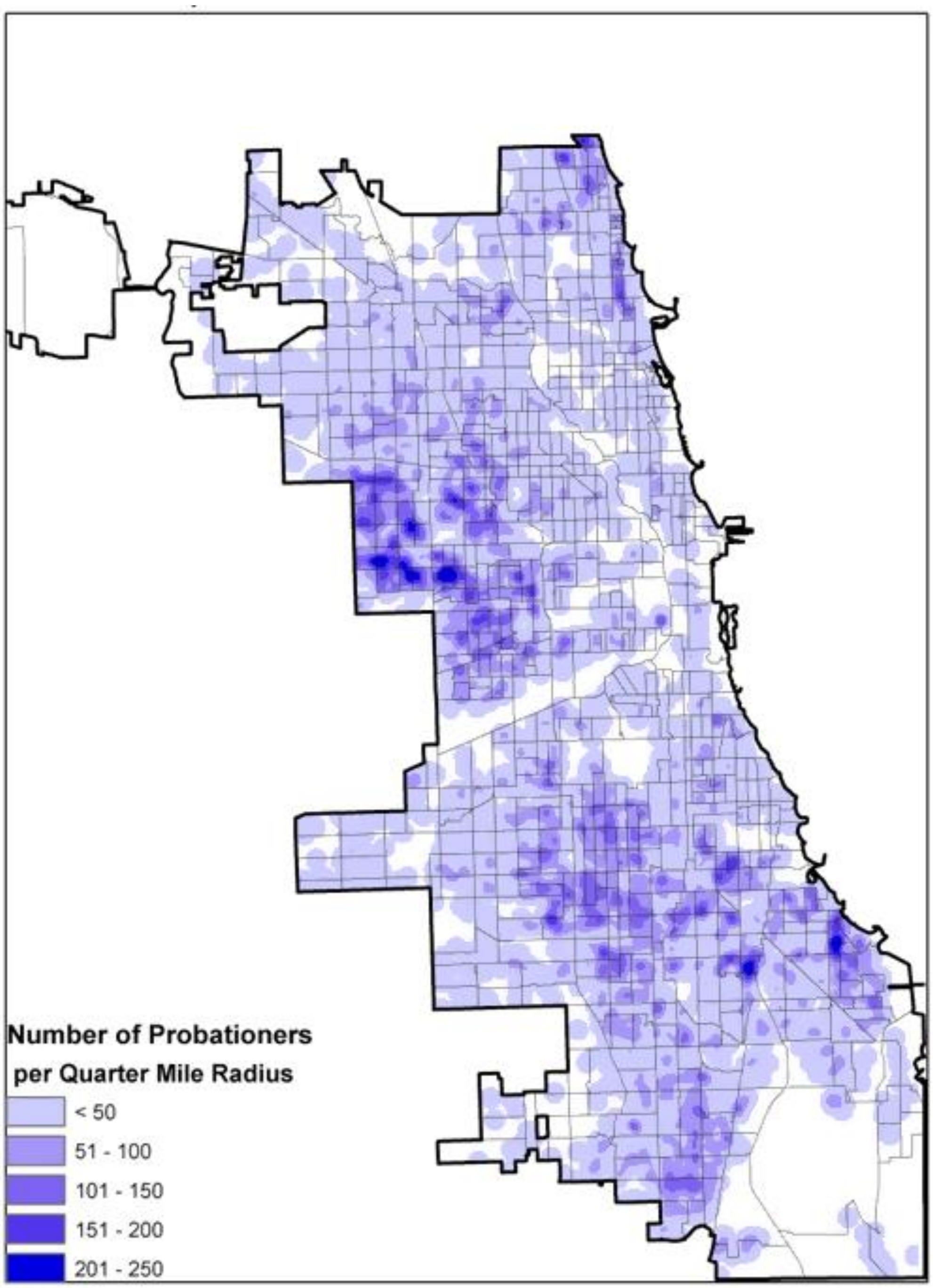


Figure 4.1. The Spatial Distribution of Probationers in 2010.

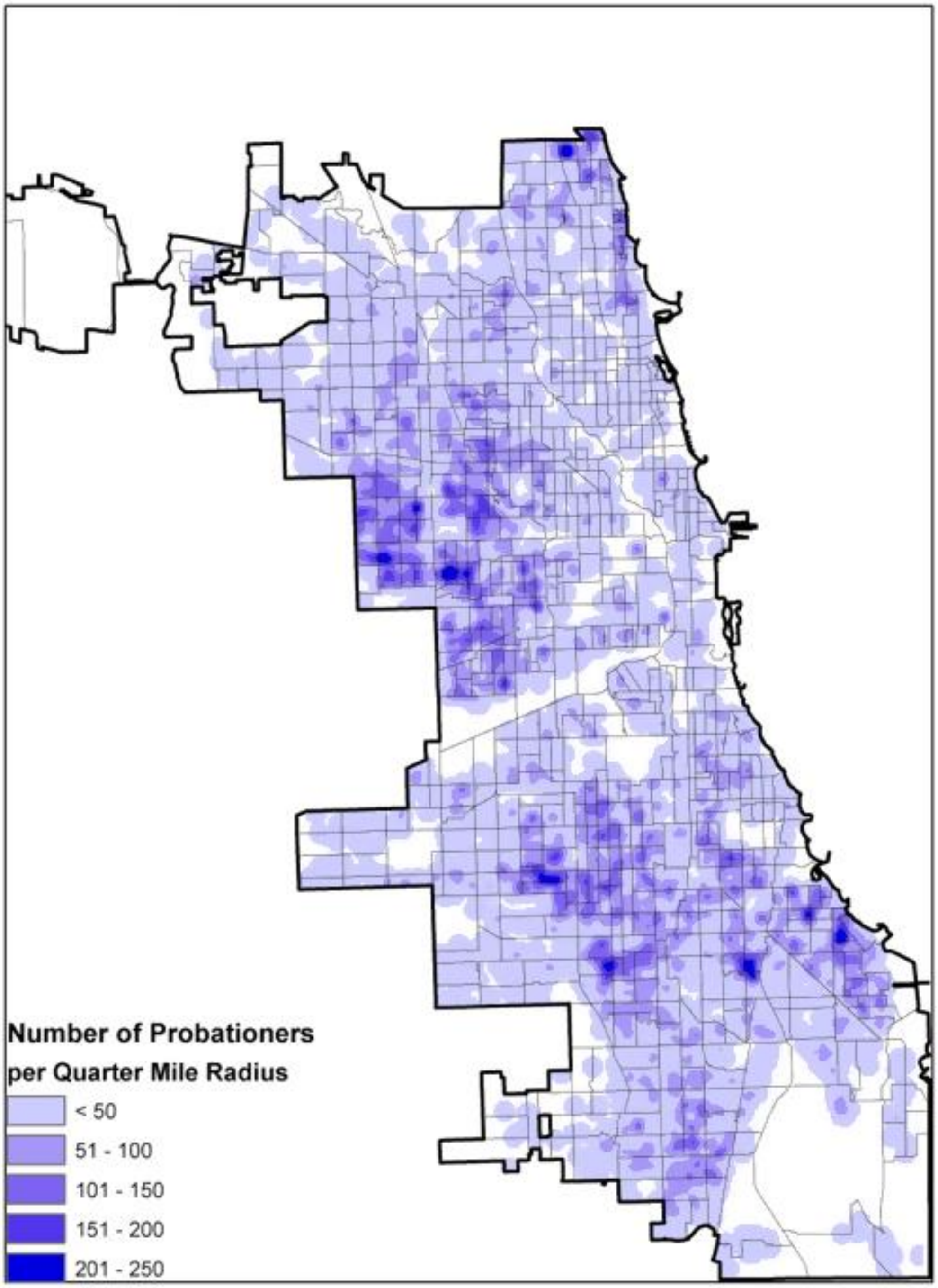


Figure 4.2. The Spatial Distribution of Probationers in 2011.

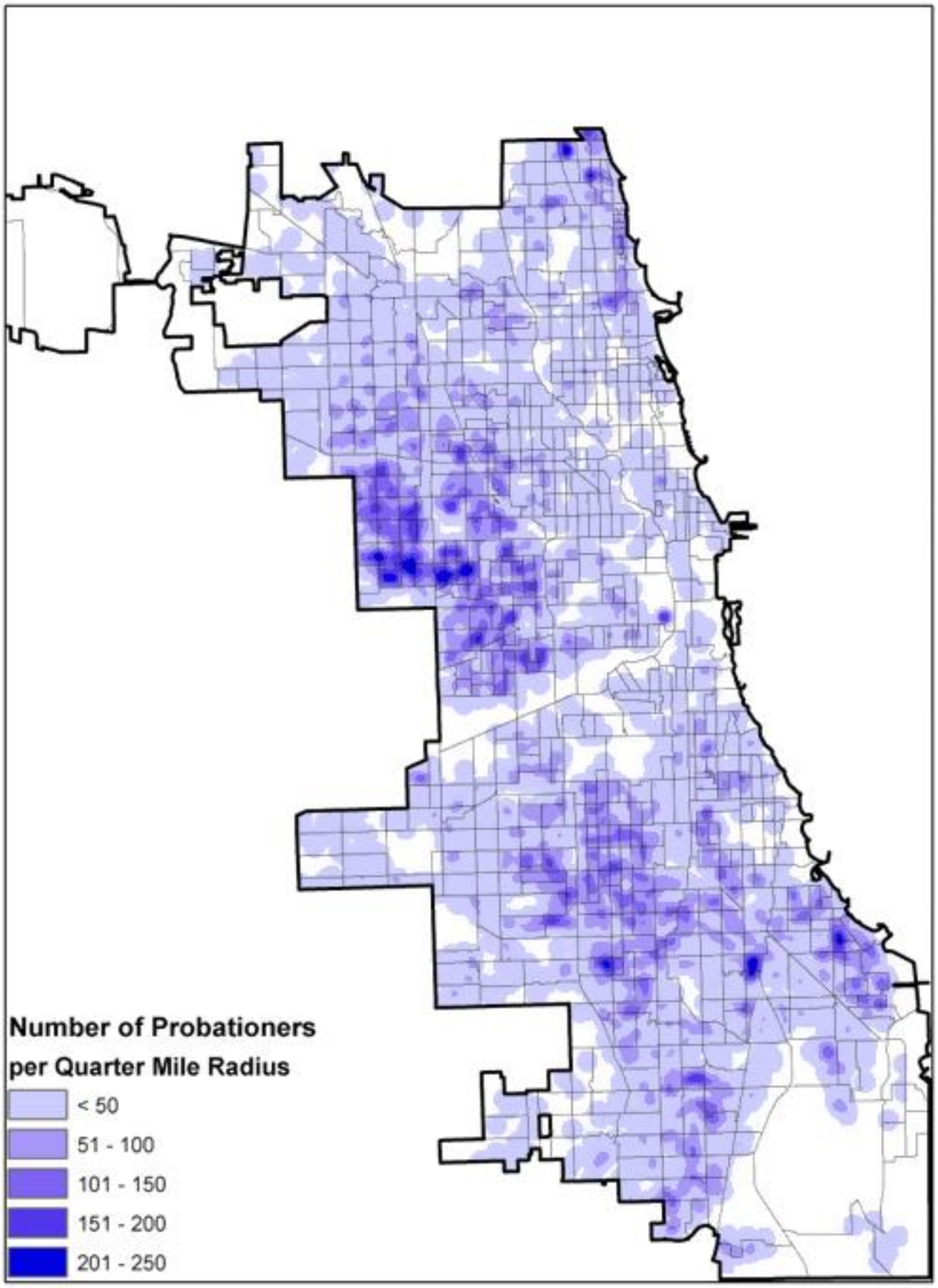


Figure 4.3. The Spatial Distribution of Probationers in 2012.

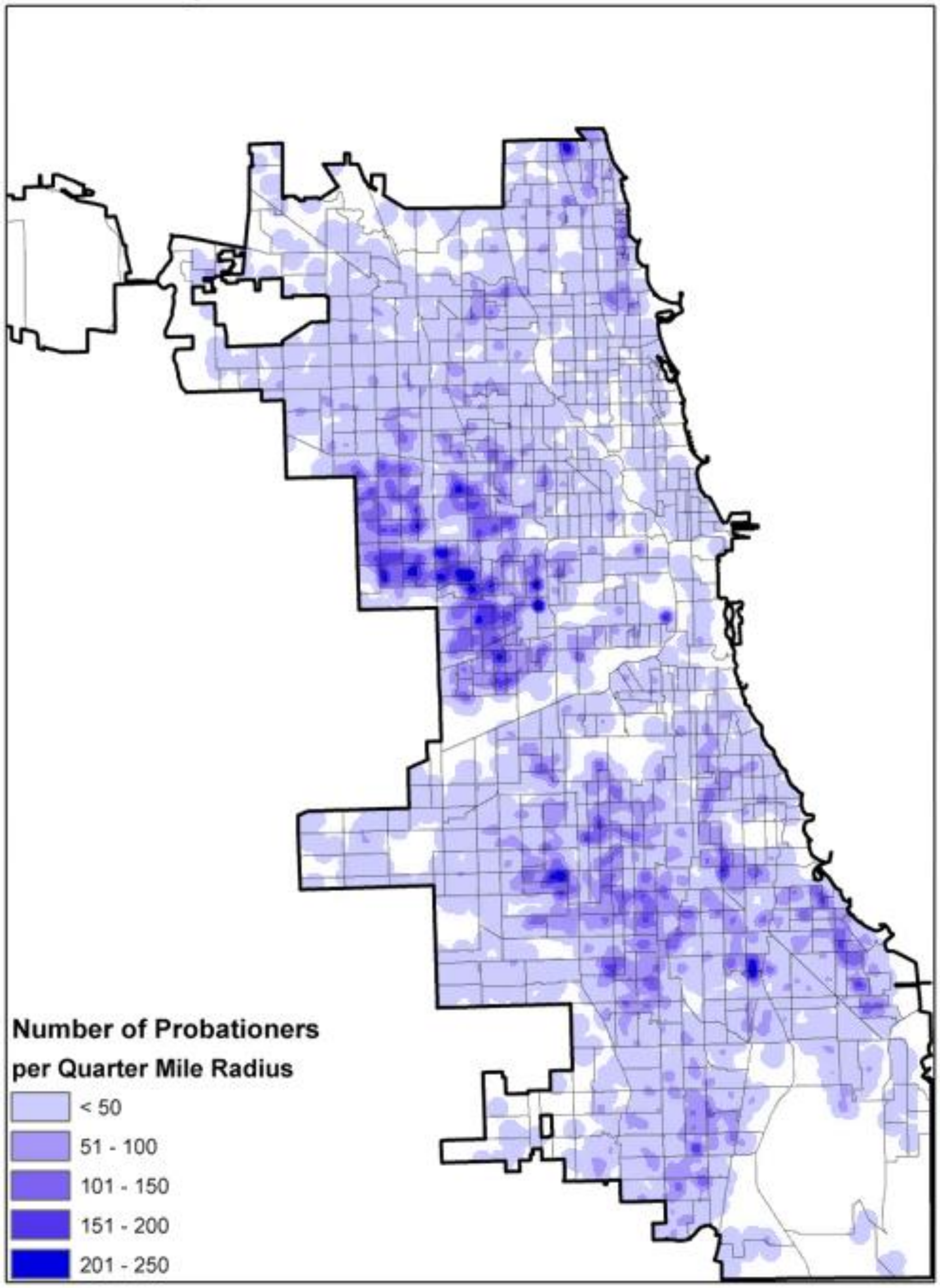


Figure 4.4. The Spatial Distribution of Probationers in 2013.

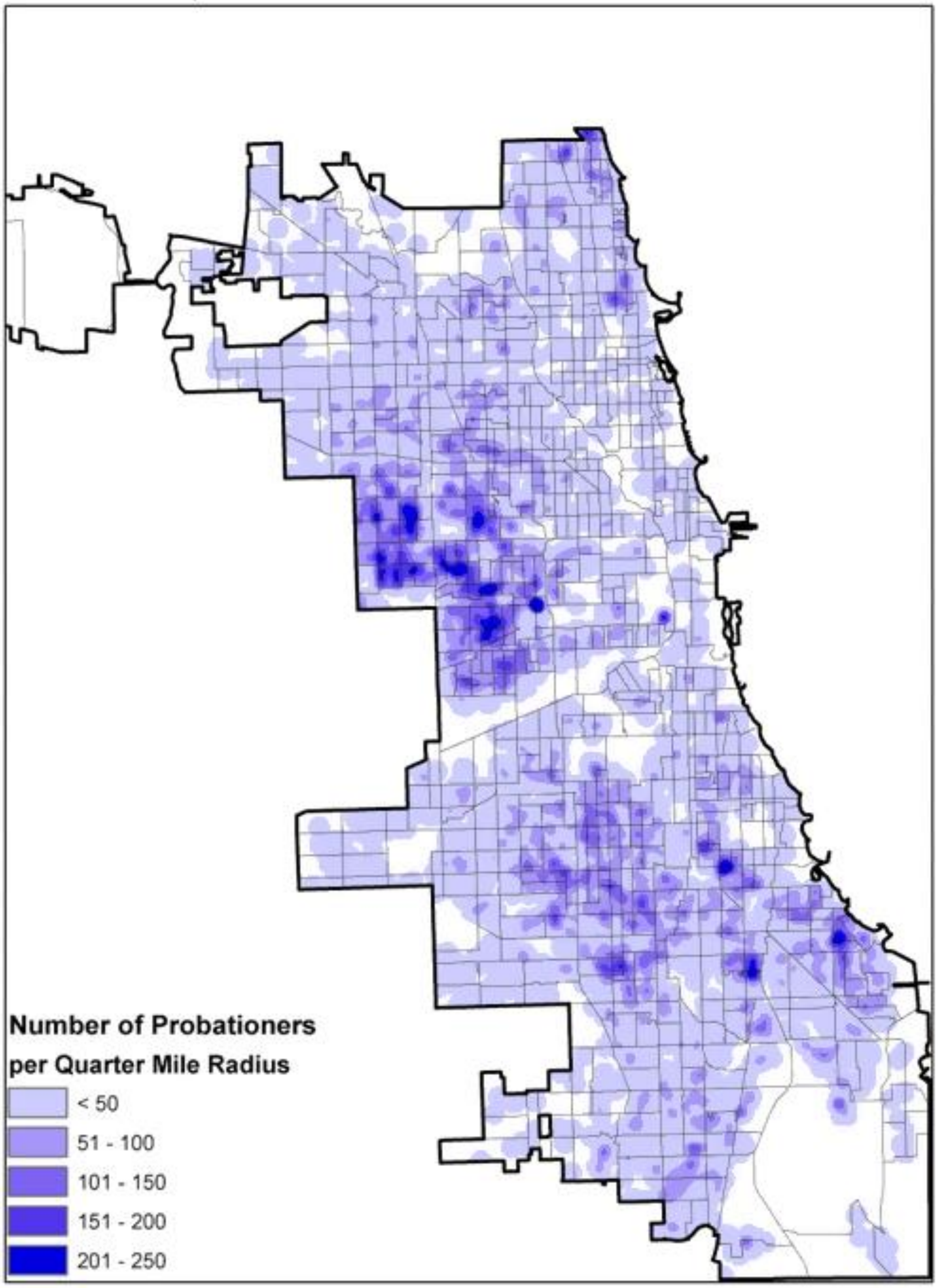


Figure 4.5. The Spatial Distribution of Probationers in 2014.

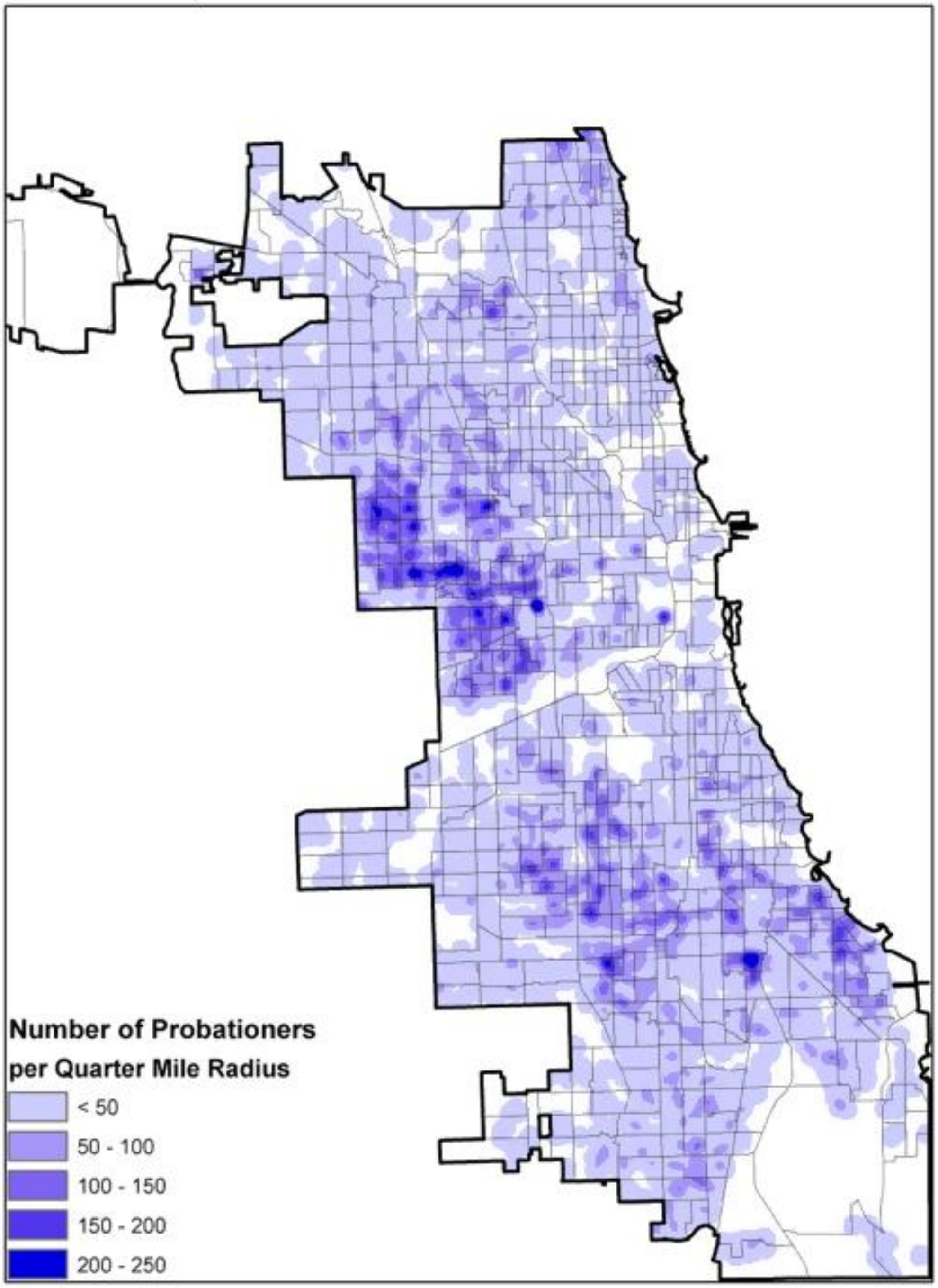


Figure 4.6. The Spatial Distribution of Probationers in 2015.

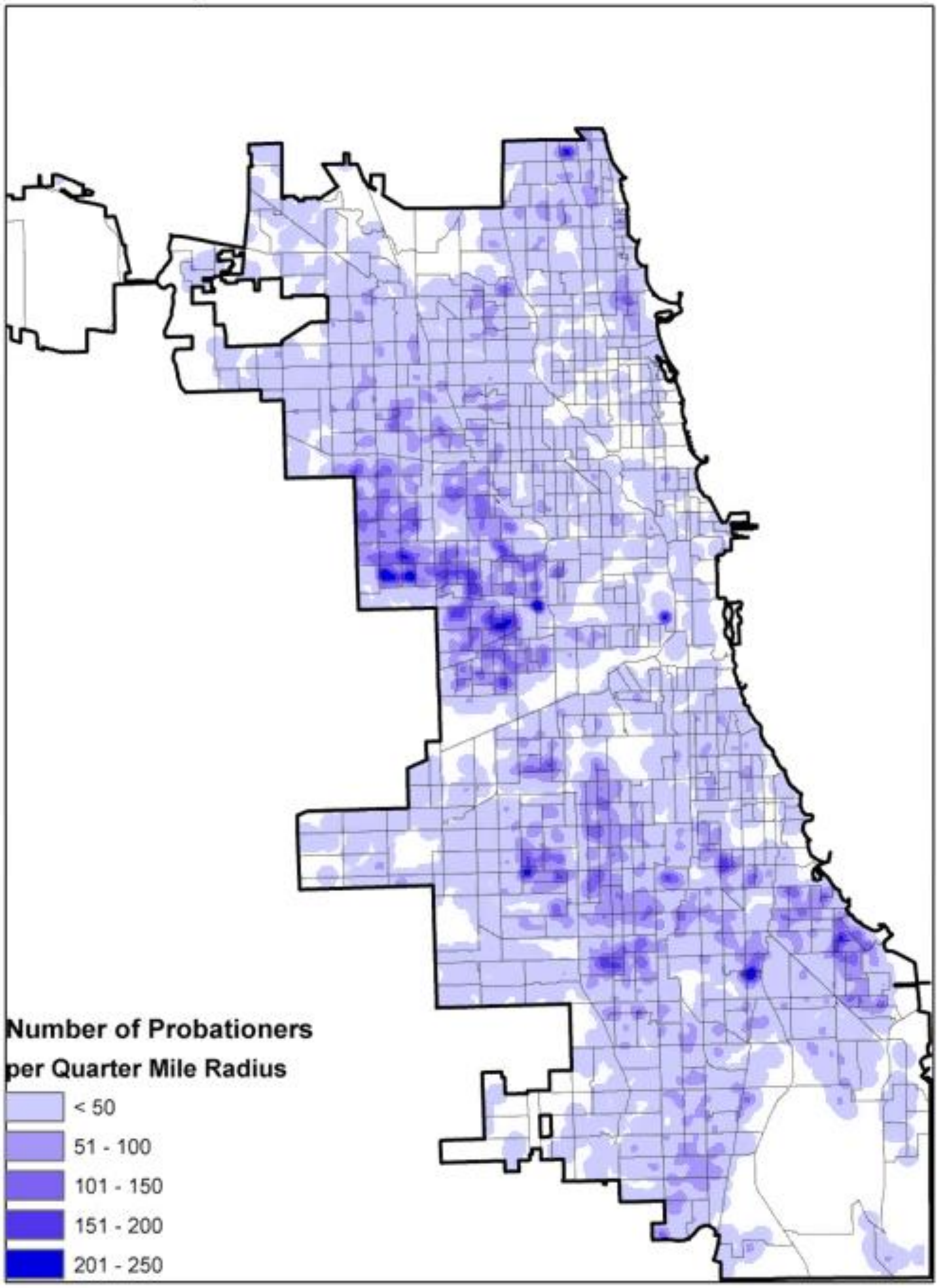


Figure 4.7. The Spatial Distribution of Probationers in 2016.

There are several key observations from these maps. First, probationers can be found in nearly all census tracts within the city of Chicago. On a year basis from 2010 to 2016, closed probation cases were found in 710–740 of the 801 census tracts. The census tracts in which there were few or no probationers were census areas with few residential areas, consisting mostly of large parks (i.e., those right along Chicago's lakefront) or industrial zones (i.e., the corridor along Interstate Highway 55).

Second, the west side of Chicago contains the highest density of closed probation cases. While areas on the south and northeast side of Chicago also show concentrations of probationers, the concentration is over a smaller geographic area and is less concentrated. On the west side, we see spatially contiguous areas with the highest level of density (between 201 and 250 closed probation cases per quarter-mile radius per year), whereas on the south side we see less spatial contiguity and more defined areas of clustering. The census tracts and community areas presenting the highest number of closed probation cases between 2010 and 2016 are presented in Table 4.2. While there is some level of variation in terms of census tracts, there is remarkable stability in terms of the census tracts and community areas that have the highest density of closed probation cases over time. There are no notable shifts of concentration, i.e., spatial densities are not changing to different areas in the city over the six years examined. Areas with a high spatial concentration of probationers remain areas with a high spatial concentration throughout the time frame of the study.

Table 4.2

Census Tracts and Community Areas with the Highest Number of Closed Probation Cases in 2010, 2013, and 2016

2010			2013			2016		
Census Tract	Community Area	Number of Closed Probation Cases	Census Tract	Community Area	Number of Closed Probation Cases	Census Tract	Community Area	Number of Closed Probation Cases
2605	Austin	48	2315	Humboldt Park	48	2521.02	Austin	47
6503.02	West Pullman	46	6606	Hegewisch	45	2909	East Garfield Pa	39
2411	Humboldt Park	37	2521.02	Austin	43	2518	Austin	36
2610	Austin	37	8387	Beverly	42	2312	Humboldt Park	32
6120	Roseland	37	4910	Hyde Park	36	5302	Woodlawn	31
2408	Humboldt Park	36	2519	Austin	35	6606	Hegewisch	31
2608	Austin	36	2522.02	Austin	35	5305.05	South Shore	30
6501	West Pullman	36	5305.01	South Shore	35	2504	West Town	30
2515	Austin	33	2306	Logan Square	35	2315	Humboldt Park	29
2522.01	Austin	33	5302	Woodlawn	34	2519	Austin	29

The Population Distribution of Probationers

The next section of maps shows the population density of probationers in Chicago. In each census tract, the population concentration of probationers is calculated by dividing the total number of closed cases by the number of probation eligible adults (18–65 years of age) in that tract. This set of maps provide a comparison of how probation is distributed across space and people. Evident in these maps is a population concentration of probationers on the west side and south side of Chicago. While the level of population concentration may shift slightly within these census tracts over time (for example, between 1% and 1.5%), there are no changes in population concentration outside of these areas of Chicago. The maps present half-percentage-point increments in population concentration. If one is to infer that that the annual discharge rate of closed probation cases mirrors the current probation caseload status, then one could conclude that a statistically small proportion of residents in these areas is under probation supervision.

Table 4.3

Census Tracts and Community Areas with the Highest Population Concentration of Probationers in 2010, 2013, and 2016

2010			2013			2016		
Census Tract	Community Area	Probation Rate	Census Tract	Community Area	Probation Rate	Census Tract	Community Area	Probation Rate
2912	East Garfield Park	10.90%	2604	Austin	2.89%	8368	Auburn Gresham	1.86%
7004	New City	2.54%	2607	Austin	2.27%	4606	Grand Boulevard	1.85%
4406	Grand Boulevard	2.33%	8374	Auburn Gresham	2.04%	8416	Morgan Park	1.78%
2603	Austin	2.13%	2603	Austin	1.89%	2909	East Garfield Park	1.72%
2718	West Garfield Park	2.01%	6712	Archer Heights	1.88%	2605	Austin	1.68%
2804	West Garfield Park	1.95%	2705	Austin	1.82%	6712	Archer Heights	1.63%
3510	North Lawndale	1.94%	6705	Garfield Ridge	1.82%	6809	Brighton Park	1.57%
3009	Near West Side	1.88%	2912	East Garfield Park	1.75%	2606	Austin	1.54%
2832	East Garfield Park	1.77%	8433	Edgewater	1.72%	2609	Austin	1.53%
2801	West Garfield Park	1.71%	2605	Austin	1.69%	6703	Garfield Ridge	1.52%

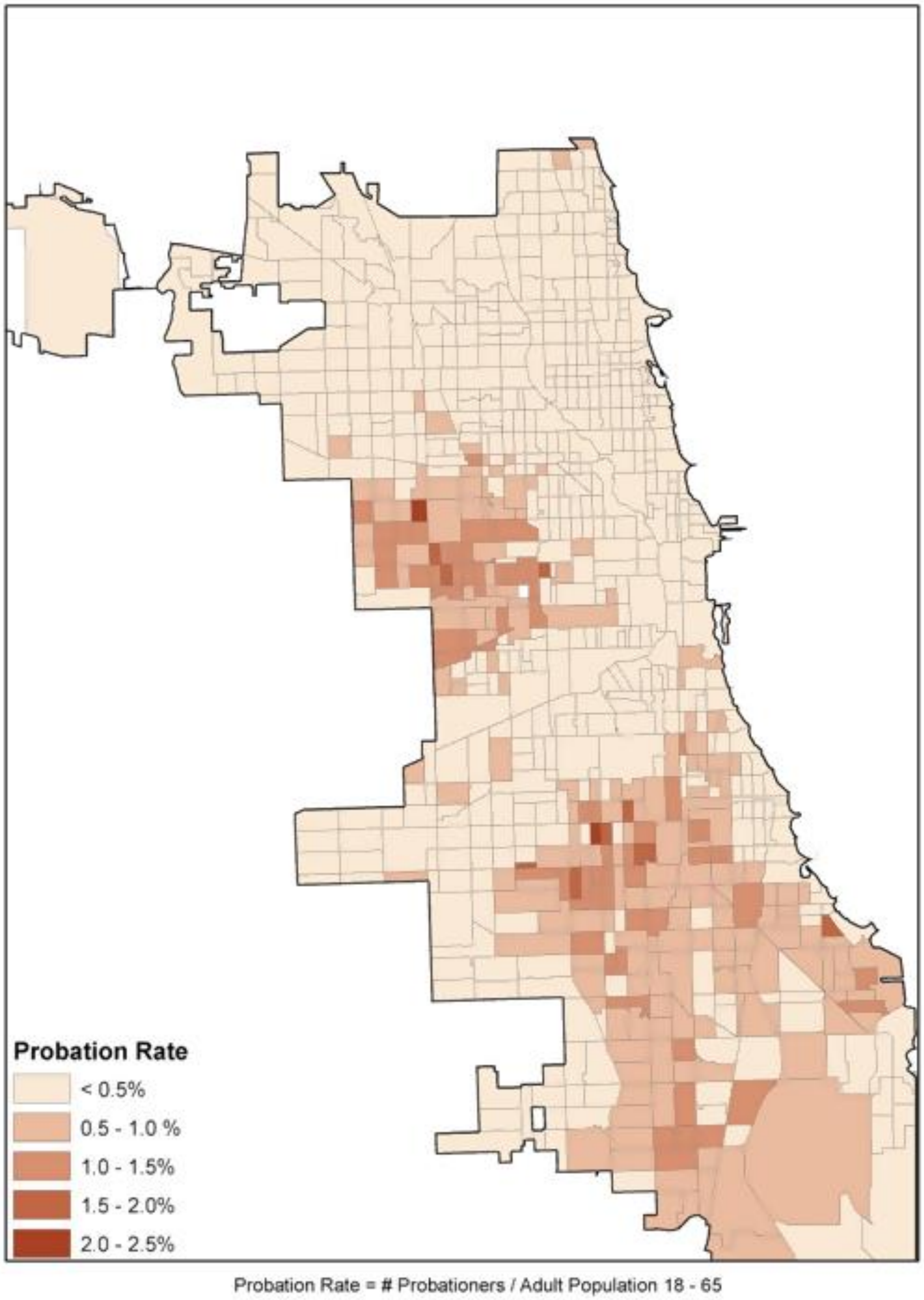


Figure 4.8. Neighborhood Probation Rate in 2011.

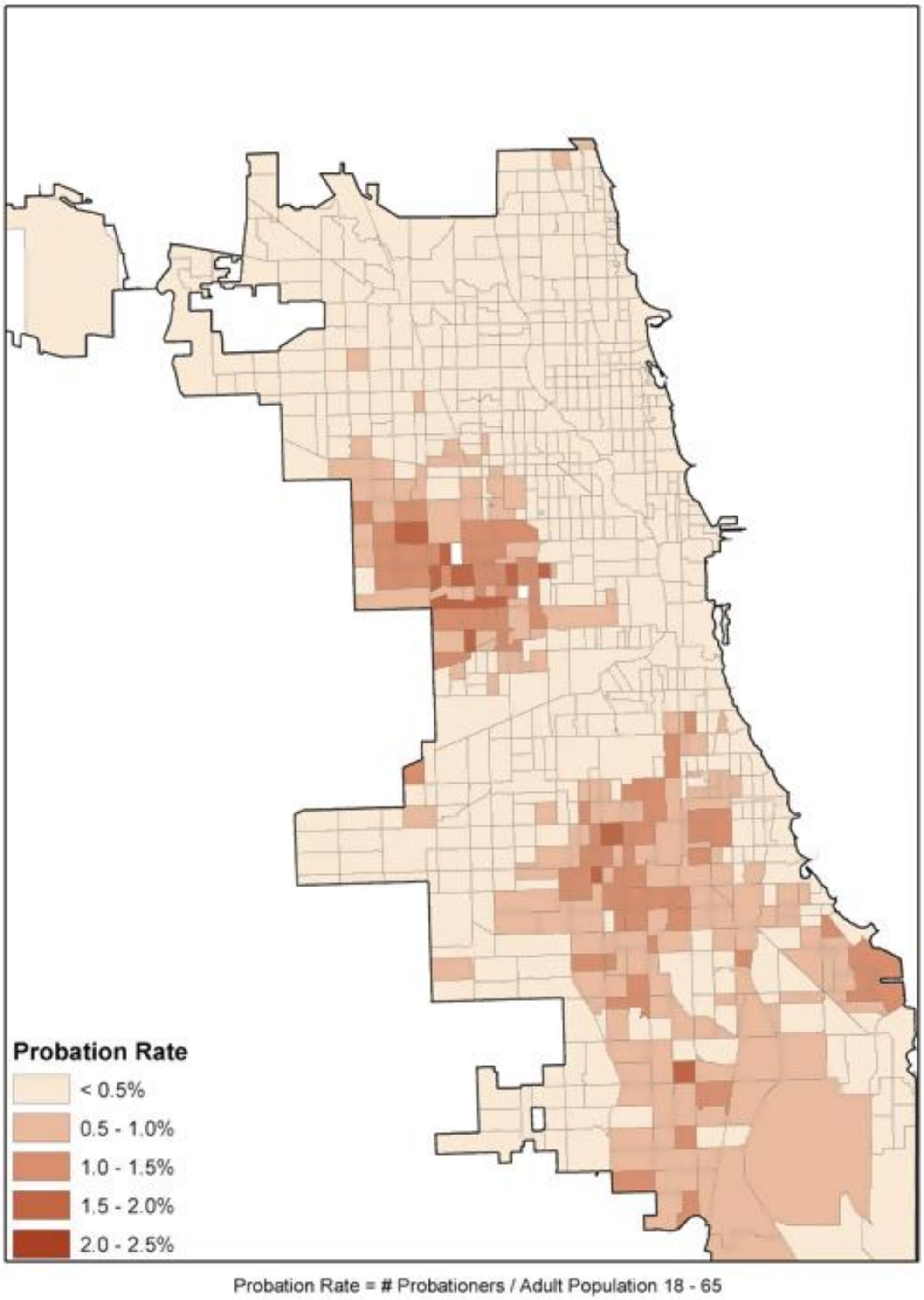


Figure 4.9. Neighborhood Probation Rate in 2012.

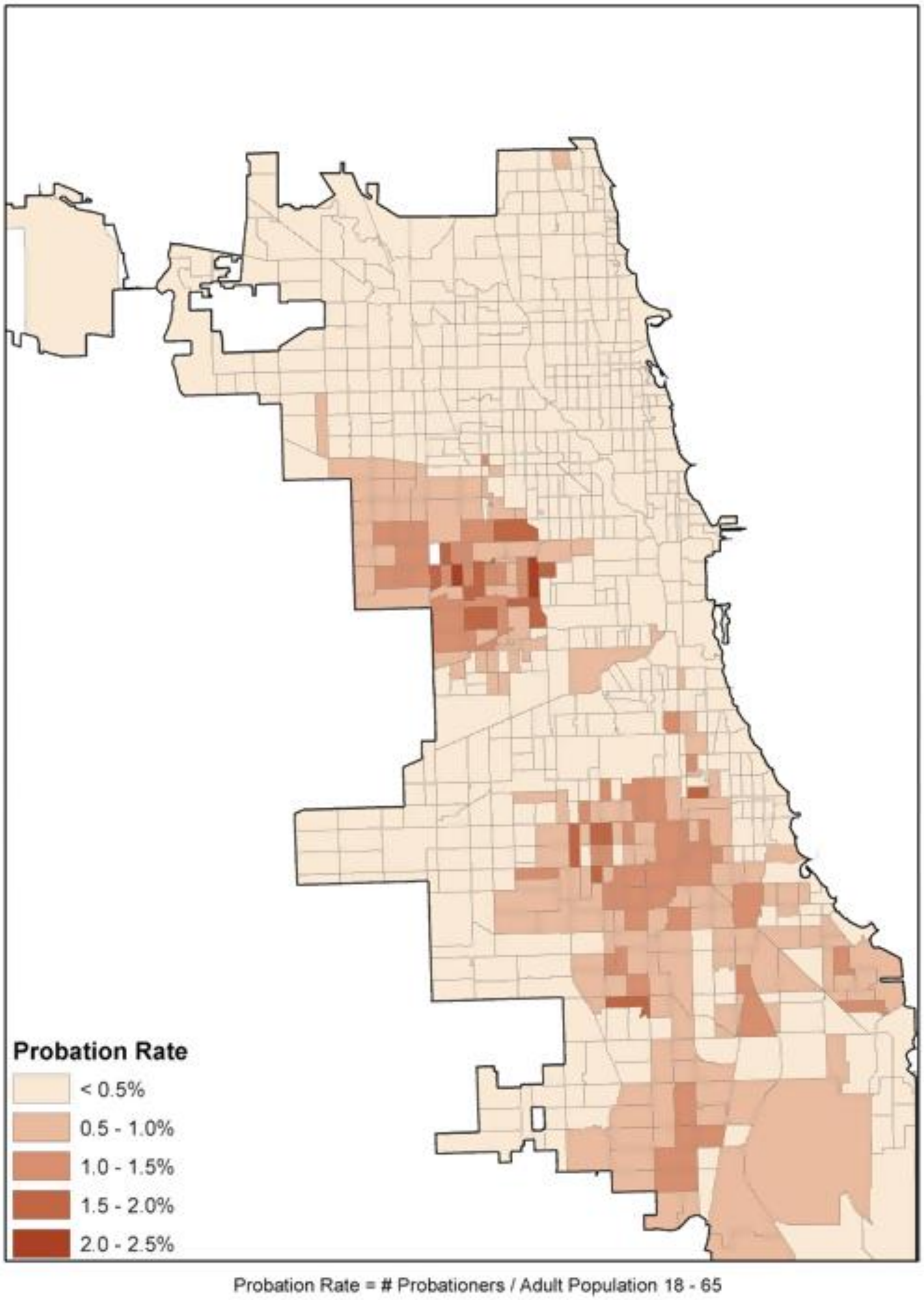


Figure 4.10. Neighborhood Probation Rate in 2013.

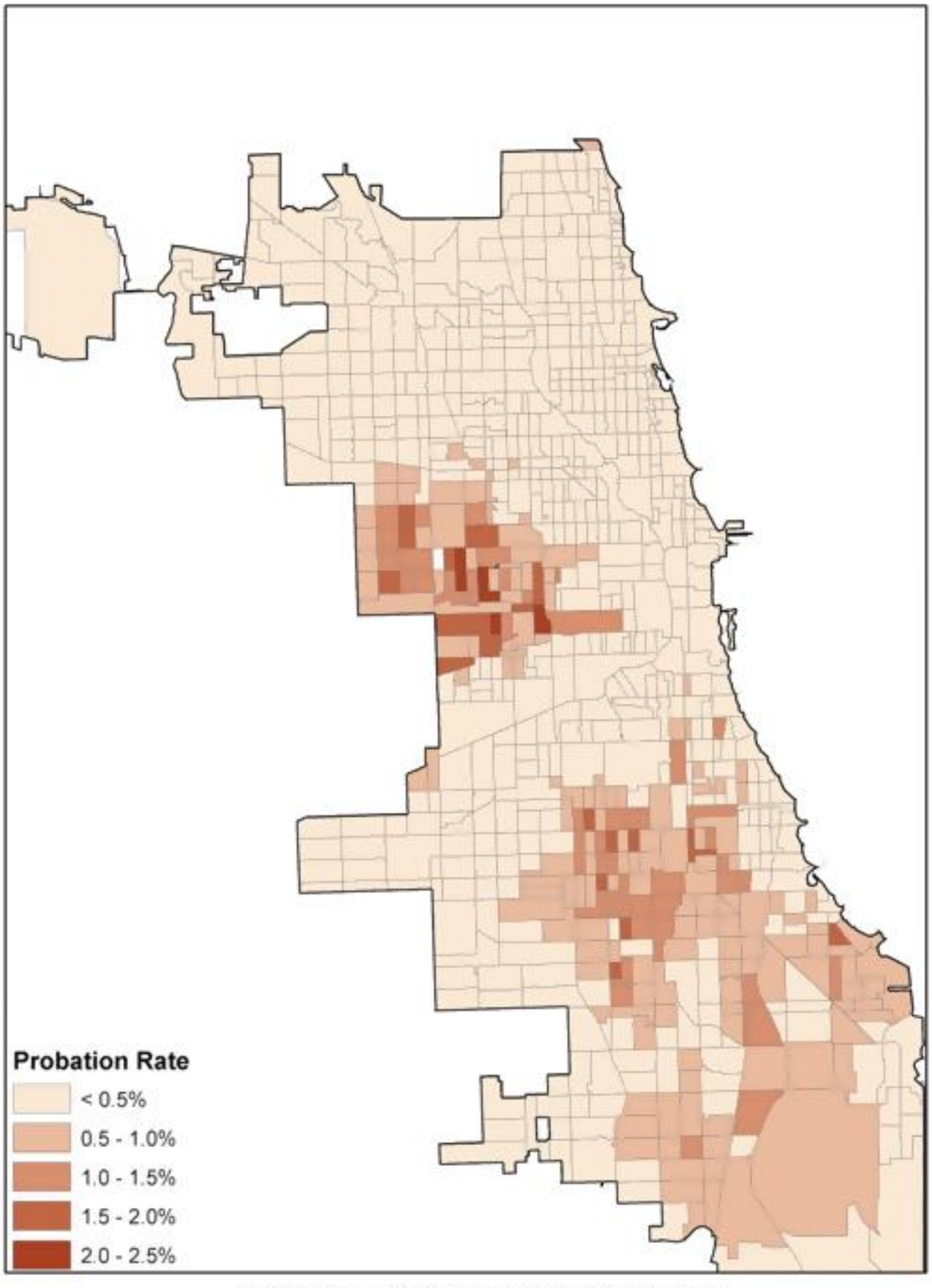


Figure 4.11. Neighborhood Probation Rate in 2014.

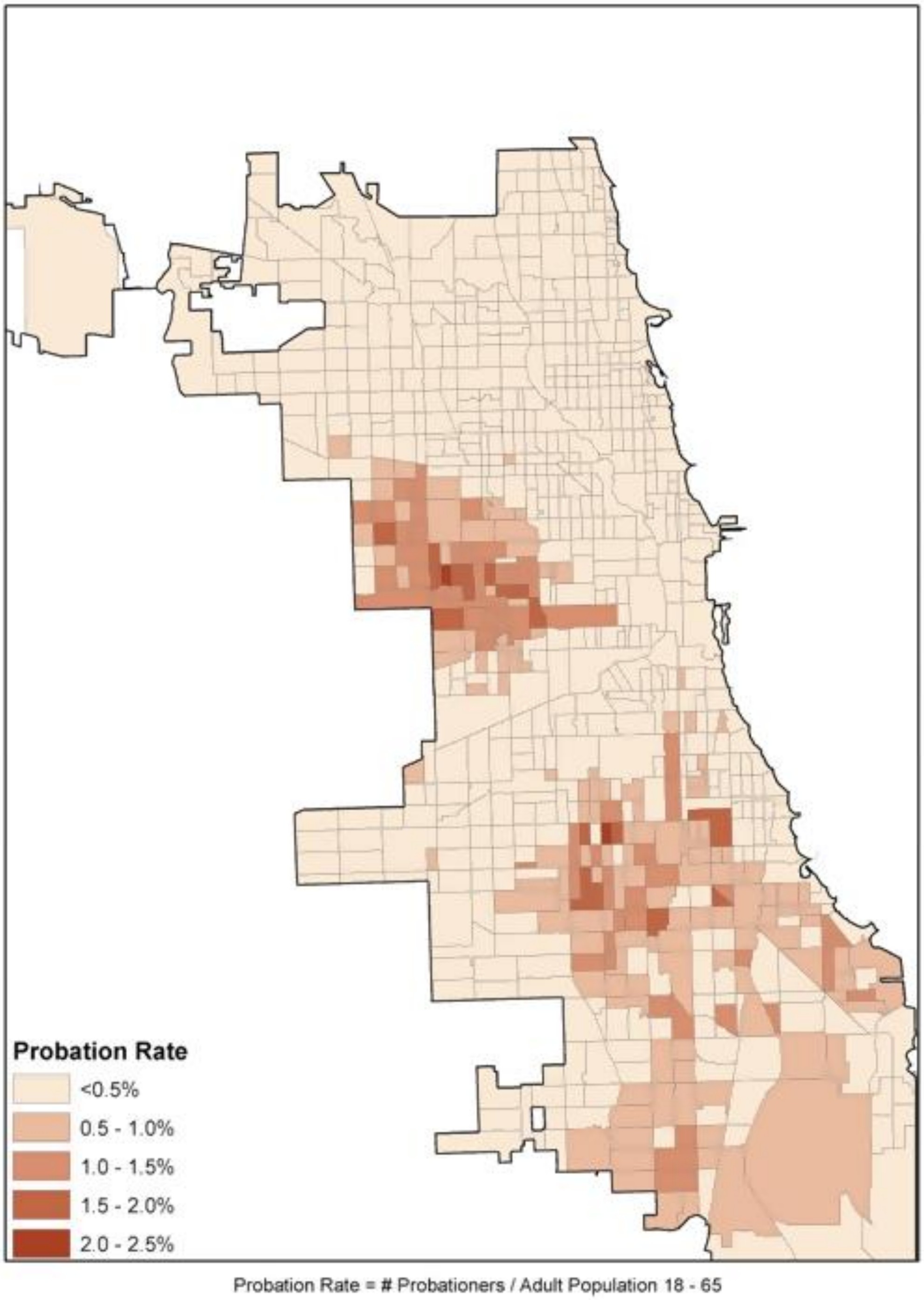


Figure 4.12. Neighborhood Probation Rate in 2015.

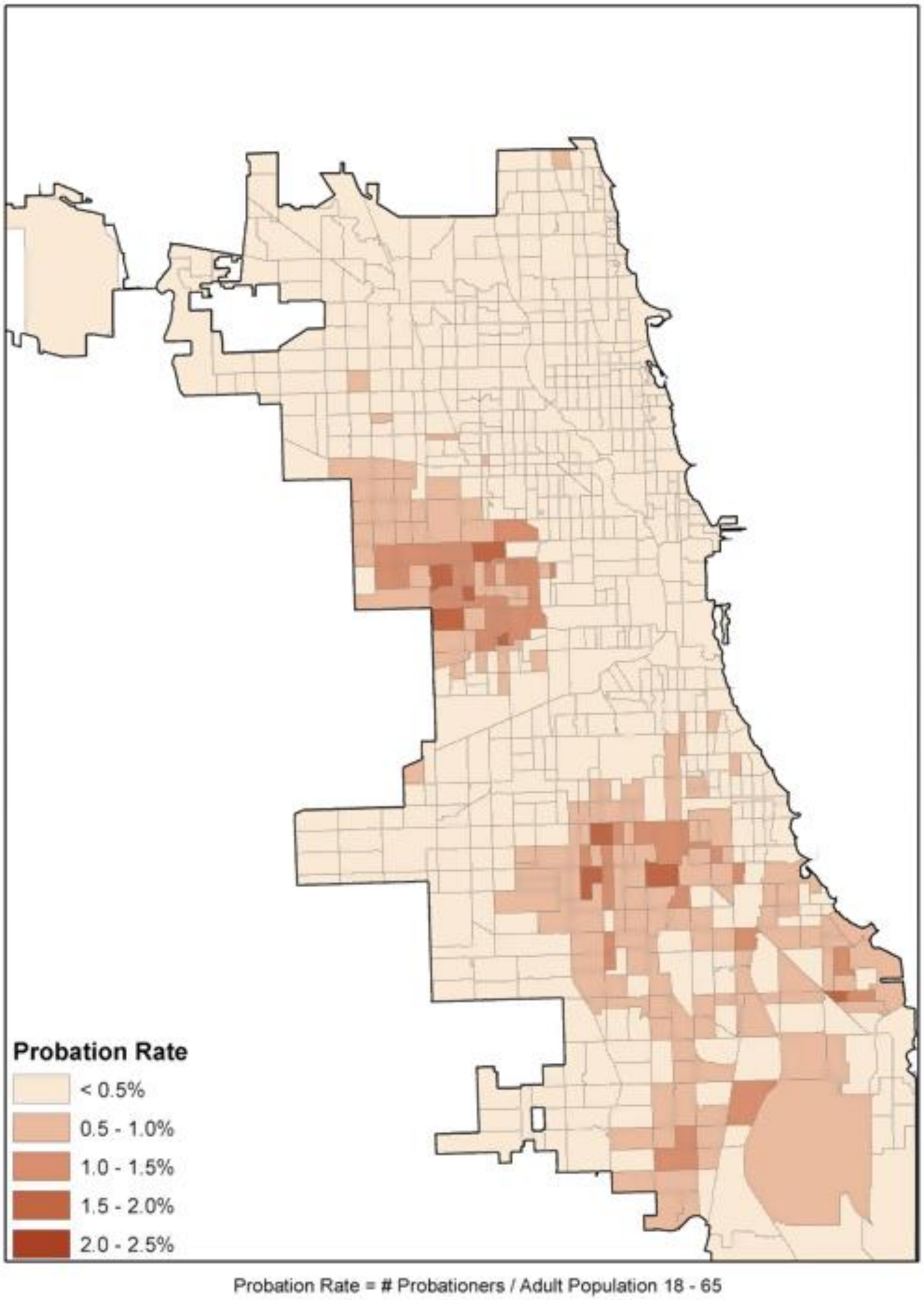


Figure 4.13. Neighborhood Probation Rate in 2016.

Neighborhood Characteristics

The next set of maps shows the level of concentrated disadvantage, violent crime, residential stability, and segregation (entropy index) among census tracts in Chicago. There is remarkable stability in these neighborhood characteristics over time in Chicago. Because these neighborhood characteristics change relatively little over time, one year of data (2016) was used to visualize these characteristics through the maps portrayed in Figures 4.14–4.16. In the map of concentrated disadvantage, the darkest-shaded areas represent the highest level of disadvantage; the most disadvantaged areas in Chicago are located on the west and south sides of Chicago, as well as a small portion of the northeast part of the city. Census tracts with the highest rate of concentrated disadvantage are located in proximity to other census tracts that are similarly distressed, and areas with the lowest rate of concentrated disadvantage are situated near similarly advantaged areas.

The map of residential stability presents less clustering when compared with concentrated disadvantage. The darkest shaded areas in this map present areas with high rates of residential mobility—those with frequent housing changes and fewer homes with occupants living for more than five years. The areas with the most residential stability are located in the central/downtown area of Chicago, and the areas with the highest rate of residential turnover are located at the northern and southern borders of the city.

The Entropy Index map shows level of segregation at the census tract level. The darkest shaded areas in the map have high levels of diversity, i.e., near equal representation of white, African American, and Hispanic residents. The lightest shaded areas represent the highest level of residential segregation, areas with one predominant racial/ethnic group present. The most racially/ethnically segregated areas of Chicago are located on the west and south side of the city.

The most diverse areas in Chicago are scattered generally among the northwest and southwest census tracts. The map following shows the racial composition of the most segregated areas in Chicago. These areas are home to predominantly African American residents. It is clear from this map that across census tracts in Chicago, African Americans are the most highly segregated group. Nearly all census tracts in Chicago fall into one of two categories: 0-10% African American or 78-100% African American.

Finally, the last community map shows the rate of violent crime per 100,000 residents. The areas with the highest concentration of violent crime are located on the west and south sides of Chicago. The north side of Chicago has significantly lower rates of violence comparatively. The spatial distribution of probationer maps presents considerable overlap with the community maps. The poorest neighborhoods in Chicago with the highest rates of violence and disadvantage also have the highest spatial density of probationers. These areas are home to predominantly African American residents.

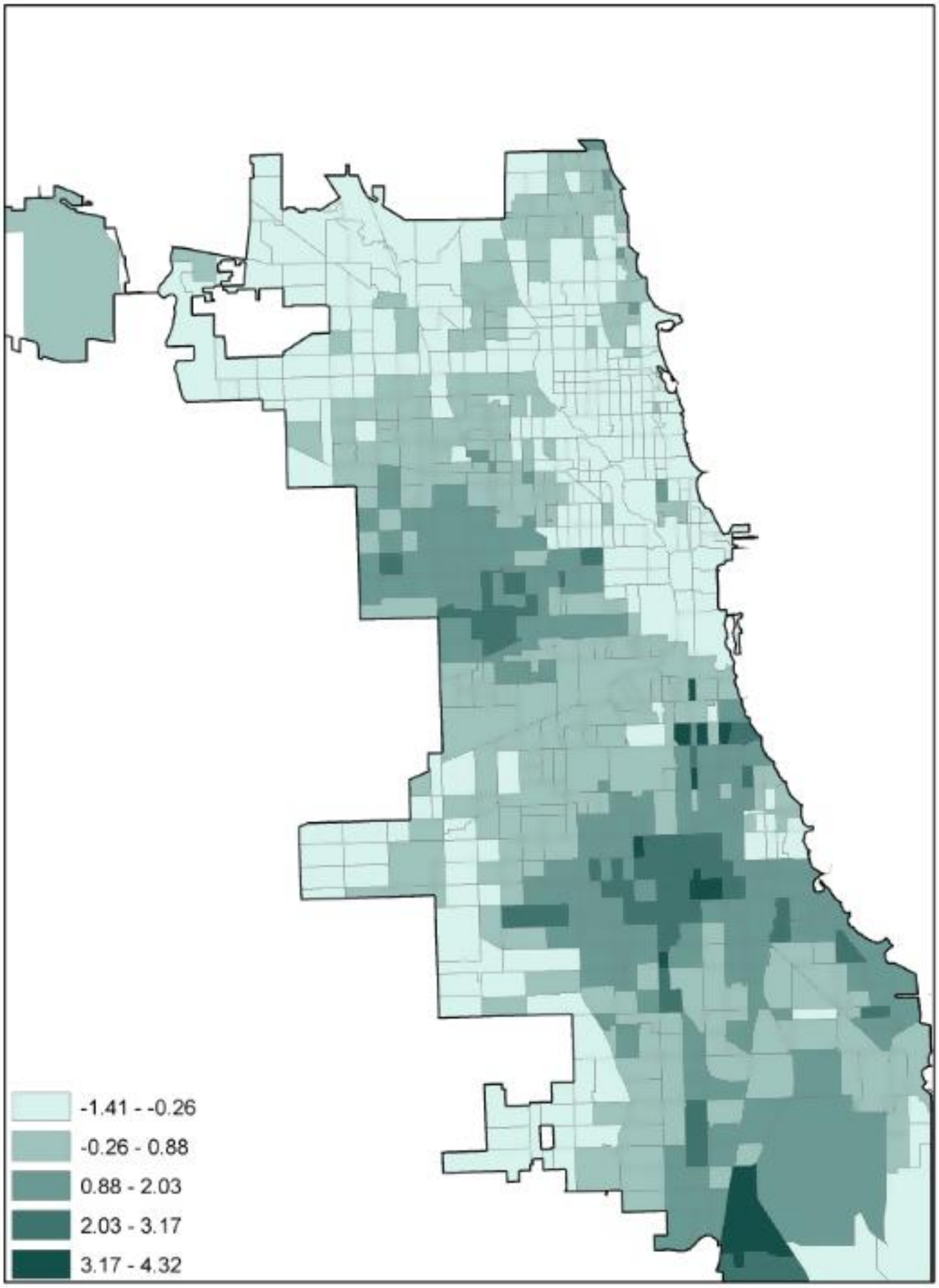


Figure 4.14. Chicago Neighborhood Measure of Concentrated Disadvantage in 2016.

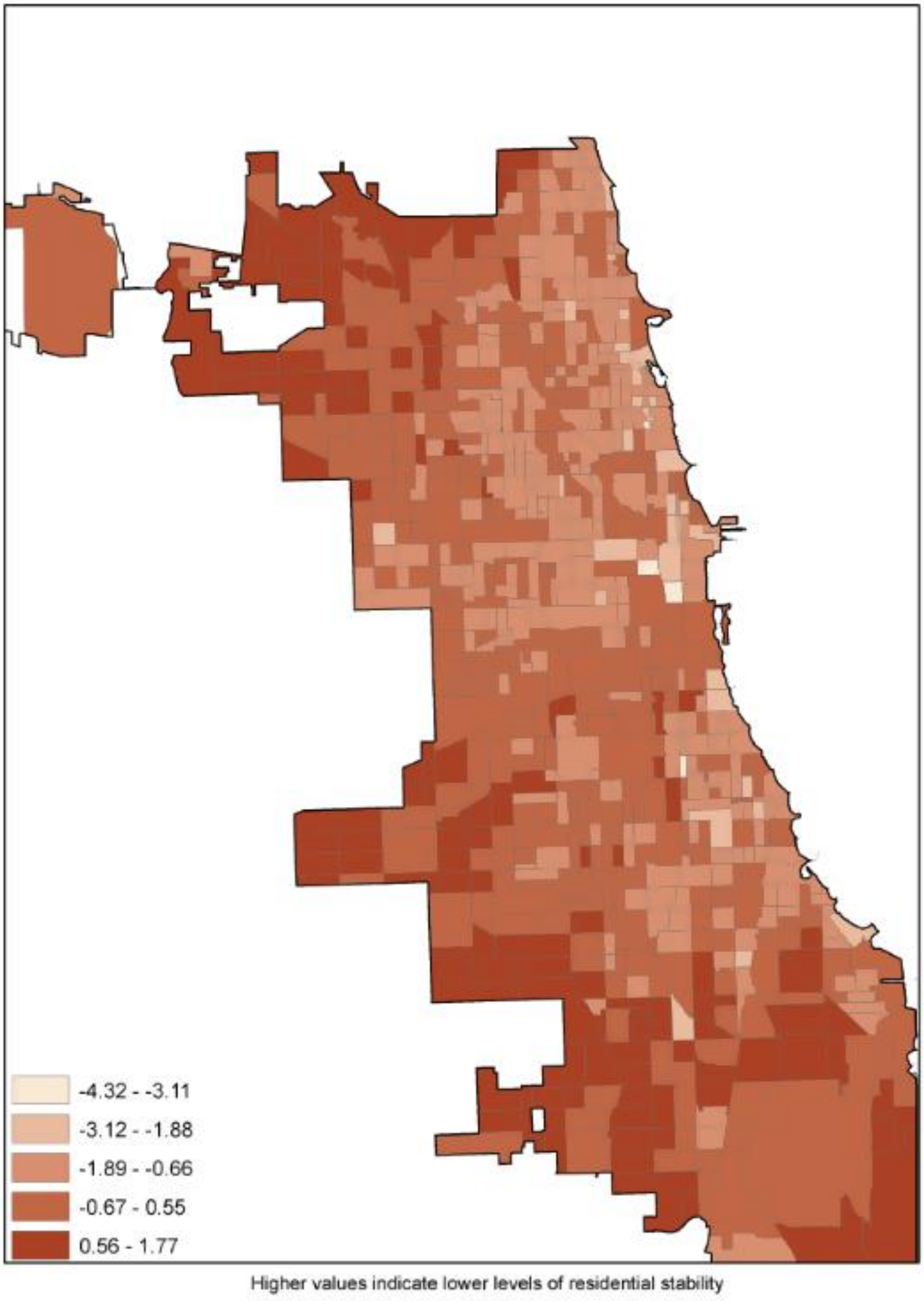


Figure 4.15. Chicago Neighborhood Measure of Residential Stability in 2016.

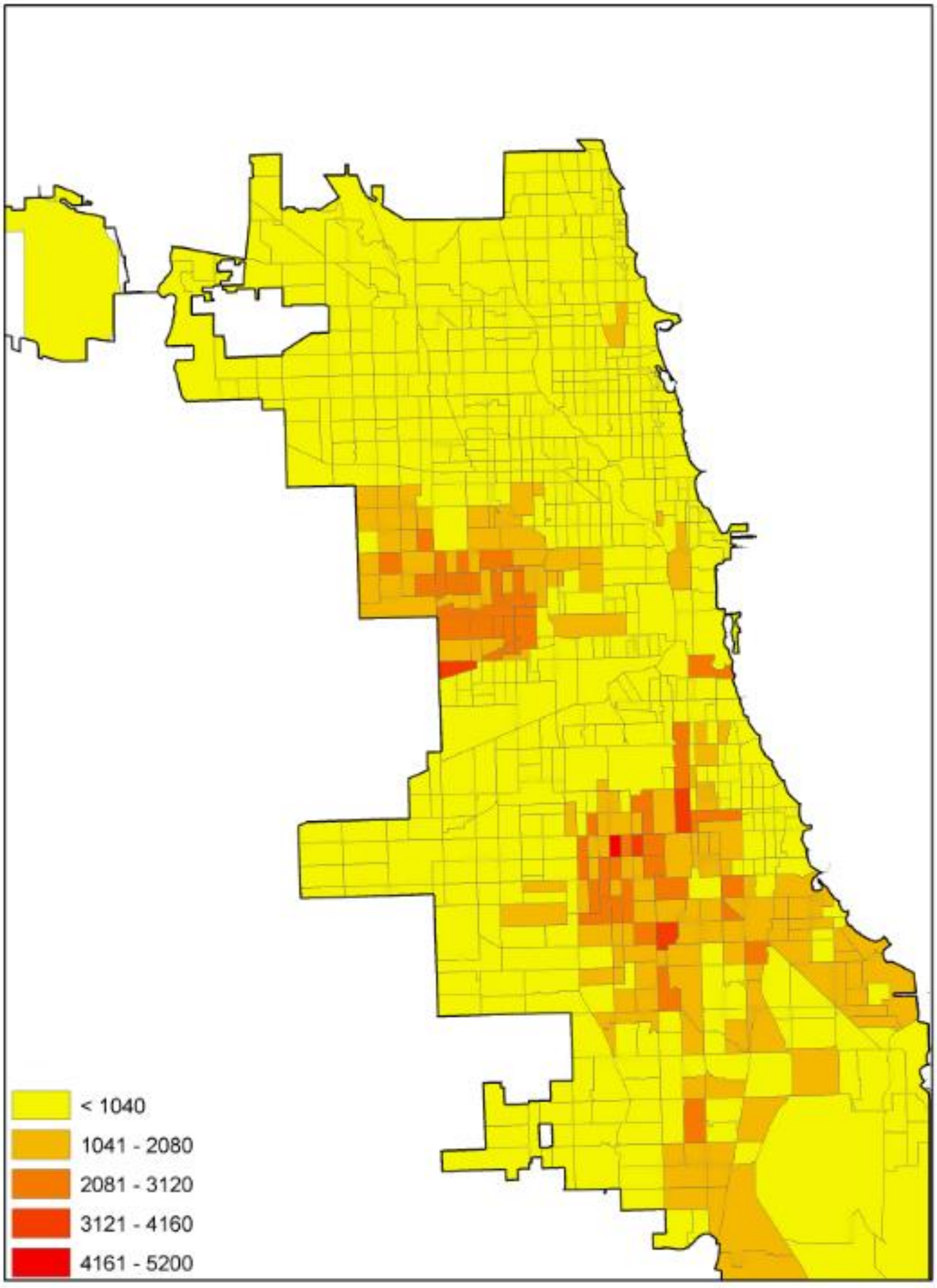


Figure 4.16. Chicago Neighborhood Measure of Violent Crime Rate in 2016.

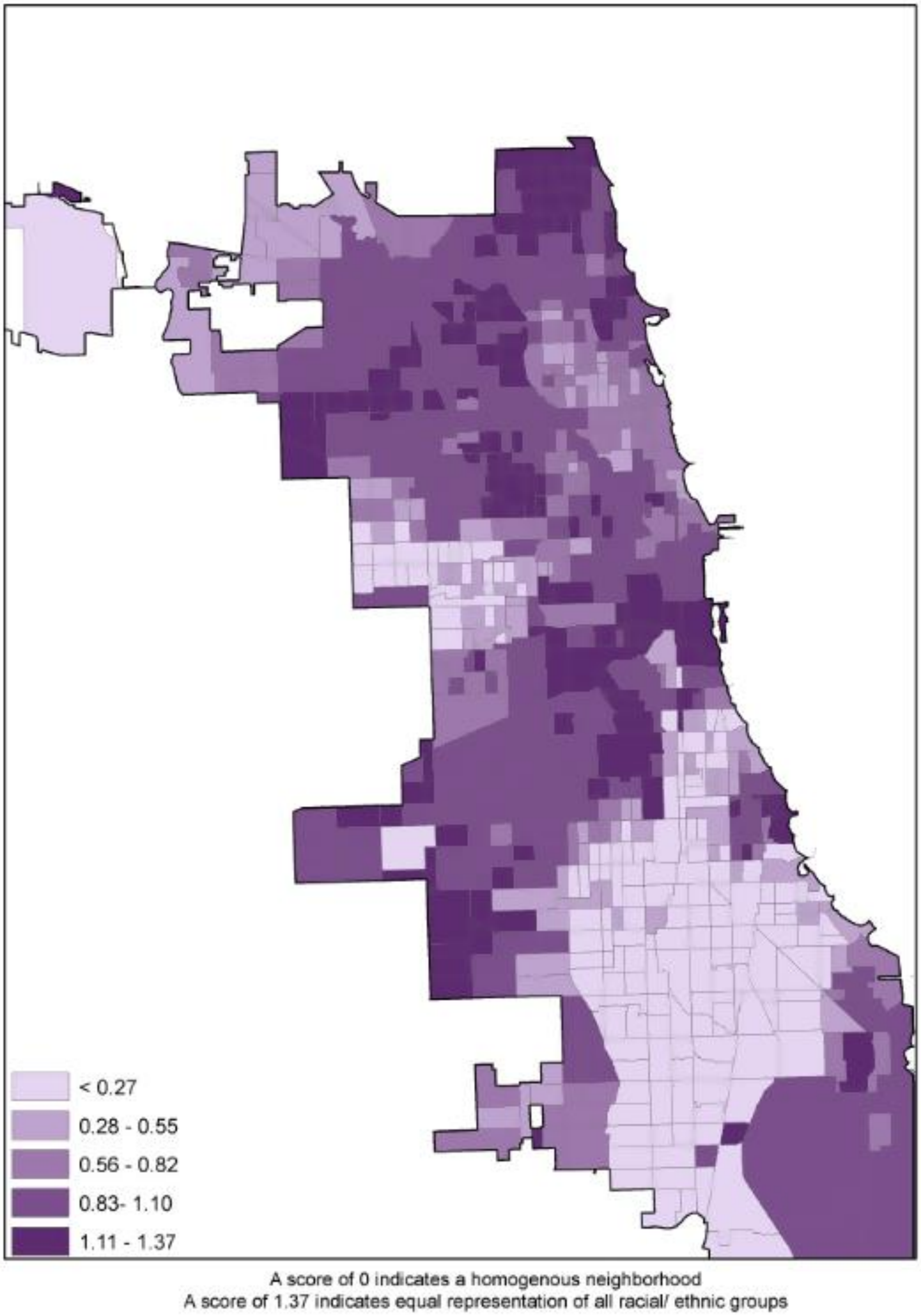


Figure 4.17. Chicago Neighborhood Measure of Racial and Ethnic Diversity in 2016.

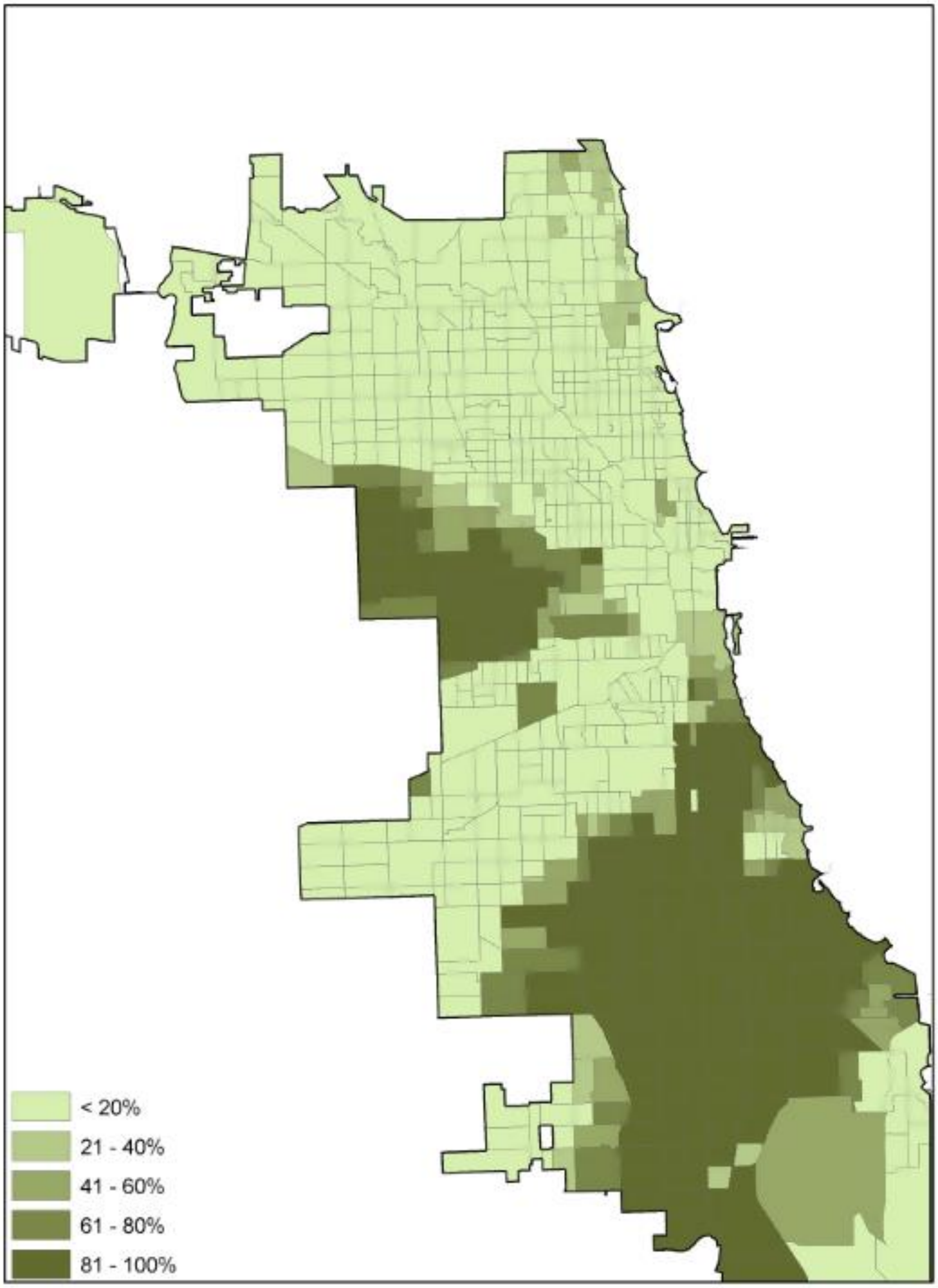


Figure 4.18. Chicago Neighborhoods, Proportion of African American Residents in 2016.

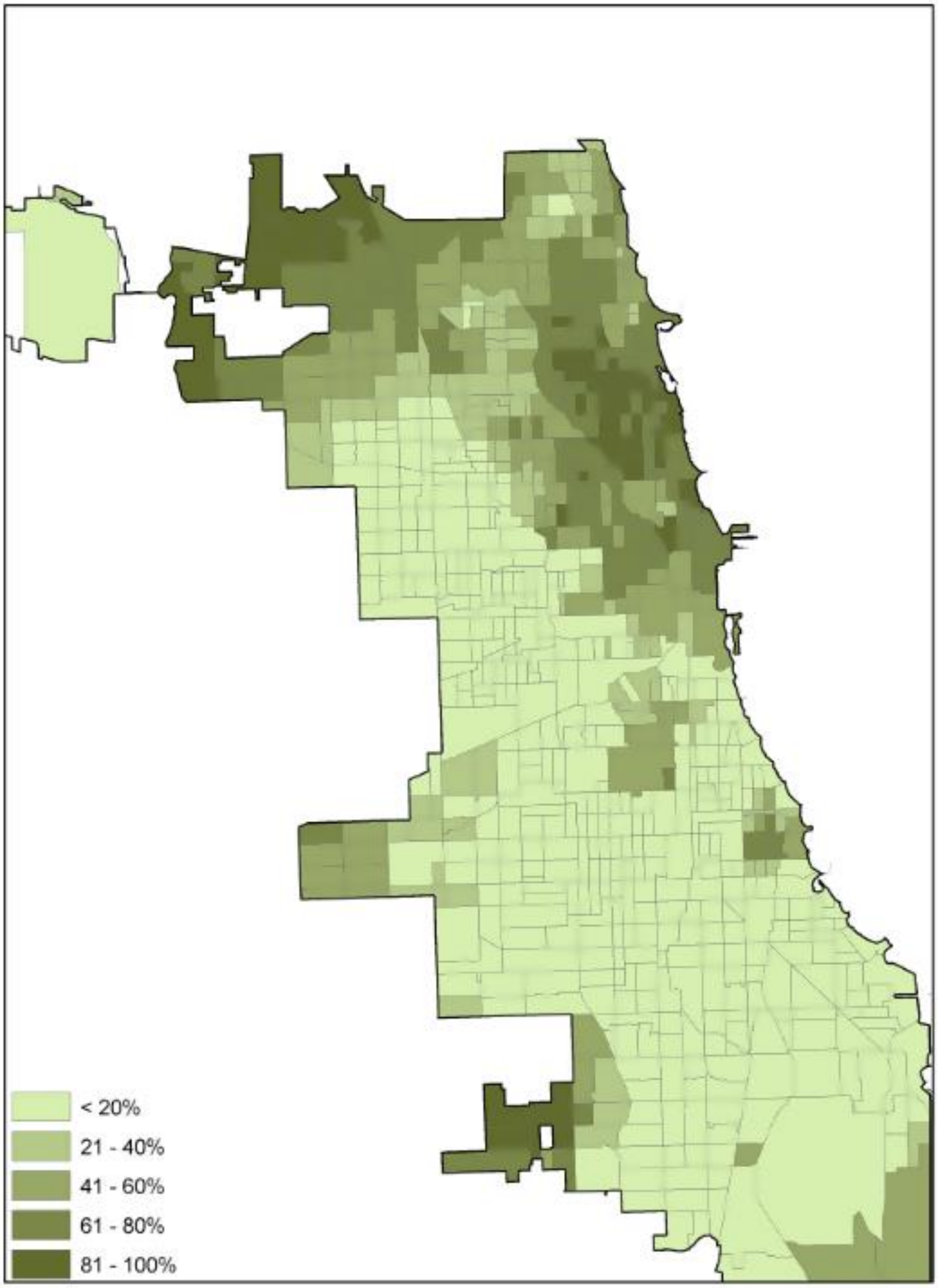


Figure 4.19. Chicago Neighborhoods, Proportion of White Residents in 2016.

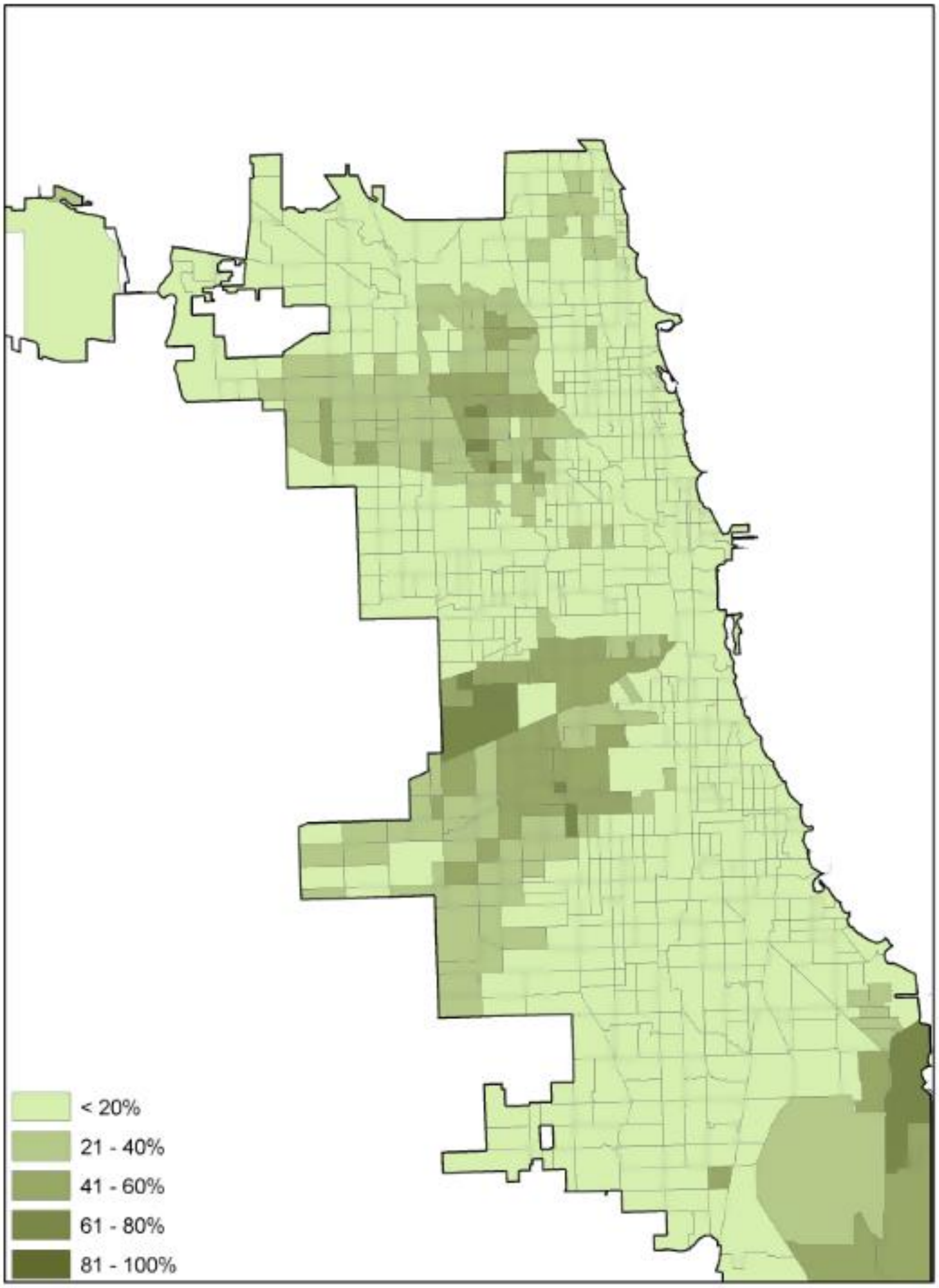


Figure 4.20. Chicago Neighborhoods, Proportion of Hispanic Residents in 2016.

Testing for Spatial Randomness

There are clear visual indications of the spatial and population clustering of probationers in particular areas of the city of Chicago. This is further examined by conducting analyses testing for the spatial randomness of the distribution patterns observed over time. The objective of running spatial analyses is to evaluate whether there are underlying patterns that may not be visually evident in viewing the maps and to test for statistical significance of the patterns observed.

After assessing the spatial and population concentrations of probationers across Chicago, the Average Nearest Neighbor (ANN) estimation was calculated to assess the degree of spatial randomness of probationers' locations. The results for 2011–2016 are listed in Table 4.4. The spatial pattern indicates clustering when the nearest neighbor (NN) ratio is less than one. When the NN ratios are greater than one, the spatial pattern indicates dispersion. The value of 1 indicates perfect random distribution of points across the surface area of analysis.

Table 4.4

Average Nearest Neighbor Estimates
Probation Case Distribution 2011–2016

Year	Nearest Neighbor Ratio	Nearest Neighbor Z Score
2011	0.59	-34.10**
2012	0.49	-74.66**
2013	0.54	-40.50**
2014	0.58	-36.97**
2015	0.52	-69.77**
2016	0.48	-71.95**

*p < 0.05, **p< 0.001

The estimates present clear evidence of the spatial clustering of probationers between 2010 and 2016. The spatial patterns observed between 2010 and 2016 are not random;

probationers are predictably organized in particular areas of the city. It appears based on the maps and the nearest neighbor estimations that there are certain census tracts in the city where probationers are more likely to reside. These analyses do not, however, provide insight into the underlying mechanism accounting for the spatial clustering of probationers. Testing for spatial randomness assumes that the probationers in the sample are free to locate anywhere within the defined spatial context of the study (Chicago). This assumption is most likely not true for most probationers (nor for the general population). One's place of residence is determined by a number of factors including such things as kinship networks, affordability, proximity to employment, and accessibility.

Summary of key findings.

Several key findings emerge from these analyses:

1. While there are areas with higher levels of concentration, probationers are present in nearly all neighborhoods in the city.
2. Probation is spatially concentrated in a small number of west and south side neighborhoods that are spatially contiguous. These patterns are not random, and they persist over time.
3. Within the neighborhoods where probation is spatially concentrated, probationers are approximately 2.5% of the adult population between the ages of 18 and 65.
4. The neighborhoods with both a population concentration and spatial concentration of probationers are highly segregated, predominantly African American, with high rates of violent crime, high levels of concentrated disadvantage, and low residential stability.

These findings suggest an underlying mechanism accounting for the observed spatial patterns. The next set of analyses examines the association between neighborhood-level characteristics and the probation rate over time.

Specific Aim 2 Results: Neighborhood-Level Predictors of Probation Rate

The results of mapping and the previous analyses found probationers clustered within census tracts predominantly on the west side and south side of Chicago. The next set of analyses was performed to examine the relation of neighborhood characteristics and probation concentration, as well as *the effect* of the spatial concentration of probationers across 801 census tracts between 2011 and 2016. More specifically, what is the association between the specified neighborhood characteristics and probation rate over time?

The neighborhood-level characteristics included in analyses were concentrated disadvantage, residential mobility, entropy index, and violent crime rate. Each of these variables was measured at the level of the census tract over the years between 2010 and 2016. Data were drawn from the American Community Survey 5 Year Estimates. The 2010 measure is extrapolated from averaging measures between 2006 and 2010; the 2011 measure is extrapolated from averaging measures between 2007 and 2011, etc. There exists overlap in the estimates derived for each annual measure of the neighborhood characteristics. For each panel model, analyses were conducted using multiple waves of the ACS 5 Year Estimates.

Analyses were performed using autoregressive cross-lagged models, a form of structural equation modeling, using *Mplus 7.3* (Muthen & Muthen, 2015) with full information maximum likelihood estimation (FIML). FIML estimation allows for the estimation of parameters in the presence of missing data. All information is used to estimate parameters' values and standard errors (Little, 2013). There are no missing data in the study variables used to estimate the autoregressive cross-lagged models. Tests of means, kurtosis, variances, covariances, and non-normality for all test variables were performed in SPSS 22.0 using tests of skewness and kurtosis, and results are shown in Appendix F. Additional analyses were run to ensure that skewed variables did not produce biased results. None were indicated from these analyses.

Bivariate correlations of all neighborhood measures and the probation rate are included in Tables 4.3–4.7. Evident in these tables is that the correlation between measures in 2010 and 2011 presents a deviation from measures between 2011 and 2016, most notably among measures of probation rate and violent crime. The change observed in probation rate correlation values between 2010 and 2011 and 2011 to 2016 is attributed to a census tract with an outlying value. In Table 3.5, in 2010, one census tract in the Garfield Park neighborhood situated on the west side of Chicago had a probation rate of 10.9%, whereas the neighborhood with the second highest rate of probation supervision that same year was measured at 2.54%. It is unclear what accounts for the deviation in violent crime trends when comparing these two time periods. A brief review of crime incidents examined the number of assault and battery cases reported to the Chicago Police Department over the years included in the analytic sample. As indicated in Table 4.5, the number of battery cases declines from 2010 to 2015 then increases in 2016. The number of assault cases declines from 2010 to 2014 then begins to increase from 2015. Further investigation would be necessary to determine what accounts for the deviation in violent crime trends.

Table 4.5

Number of Assault and Battery Cases Reported to the Chicago Police Department 2010–2016

Year	Assault	Battery
2010	21,535	65,399
2011	20,409	60,457
2012	19,897	59,130
2013	17,968	53,996
2014	16,885	49,413
2015	17,041	48,894
2016	18,683	50,037

Table 4.6

Correlation Matrix, Probation Rate 2010–2016

	2010	2011	2012	2013	2014	2015	2016
2010	1						
2011	0.20 **	1					
2012	0.20 **	0.82 **	1				
2013	0.23 **	0.76 **	0.82 **	1			
2014	0.26 **	0.76 **	0.81 **	0.86 **	1		
2015	0.19 **	0.76 **	0.80 **	0.81 **	0.82 **	1	
2016	0.21 **	0.73 **	0.79 **	0.81 **	0.82 **	0.82 **	1

Note:
*$p < 0.05$, **$p < 0.001$

Table 4.7

Correlation Matrix, Residential Stability 2010–2016

	2010	2011	2012	2013	2014	2015	2016
2010	1						
2011	0.97 **	1					
2012	0.83 **	0.97 **	1				
2013	0.82 **	0.93 **	0.95 **	1			
2014	0.84 **	0.91 **	0.94 **	0.98 **	1		
2015	0.70 **	0.89 **	0.92 **	0.96 **	0.98 **	1	
2016	0.76 **	0.88 **	0.90 **	0.95 **	0.97 **	0.99 **	1

Note:
*p < 0.05, **p < 0.001

Table 4.8

Correlation Matrix, Concentrated Disadvantage 2010–2016

	2010	2011	2012	2013	2014	2015	2016
2010	1						
2011	0.97 **	1					
2012	0.94 **	0.87 **	1				
2013	0.91 **	0.85 **	0.90 **	1			
2014	0.89 **	0.87 **	0.89 **	0.97 **	1		
2015	0.86 **	0.69 **	0.65 **	0.70 **	0.73 **	1	
2016	0.86 **	0.76 **	0.71 **	0.80 **	0.82 **	0.83 **	1

Note:
*p < 0.05, **p < 0.001

Table 4.9

Correlation Matrix, Violent Crime Rate 2010–2016

	2010	2011	2012	2013	2014	2015	2016
2010	1						
2011	0.16**	1					
2012	0.17 **	0.90 **	1				
2013	0.17 **	0.83 **	0.87 **	1			
2014	0.17 **	0.87 **	0.87 **	0.84 **	1		
2015	0.17 **	0.86 **	0.86 **	0.84 **	0.91 **	1	
2016	0.16 **	0.84 **	0.86 **	0.83 **	0.90 **	0.91 **	1

Note:
*p < 0.05, **p < 0.001

Table 4.10

Correlation Matrix, Racial/ Ethnic Diversity (Entropy Index) 2010–2016

	2010	2011	2012	2013	2014	2015	2016
2010	1						
2011	0.98 **	1					
2012	0.97 **	0.98 **	1				
2013	0.87 **	0.89 **	0.90 **	1			
2014	0.86 **	0.87 **	0.89 **	0.99 **	1		
2015	0.85 **	0.87 **	0.88 **	0.98 **	0.99 **	1	
2016	0.85 **	0.85 **	0.87 **	0.96 **	0.98 **	0.99 **	1

Note:
*p < 0.05, **p < 0.001

One of the assumptions of autoregressive cross-lagged panel models is stability in the measurements of the variable over time. Including 2010 in the panel models challenges this assumption and can generate skewed coefficients that do not accurately describe trends otherwise observed between 2011 and 2016. For this reason, the subsequent analyses presented focus on neighborhood dynamics observed from 2011 to 2016. The same models including 2010 are included in Appendix G. Finally, only census tracts with a population greater than 500 people were included in the study sample. Census tracts with smaller populations are more sensitive to small changes over time and can similarly generate inaccurate estimates. This selection process resulted in 759 of the 801 census tracts in Chicago being included in panel analyses.

Autoregressive cross-lagged models were used to examine the reciprocal relationships and directional influences between the probation rate and neighborhood characteristics over time. Both constrained and unconstrained models were run. In the constrained model, the path coefficients between variables were constrained to be equal to generate a single statistic reflecting trends over the analytical time frame. To test which model fit the data best, the unconstrained and constrained panel models were compared using the Satorra-Bentler Chi-Square test of difference (Kelloway, 2016). The results indicated that the unconstrained model fit the data better. The constrained models and results from the Satorra-Bentler Chi-Square test are included in Appendix H.

The results of each model are presented in the following manner: (1) autoregressive path coefficients, (2) cross-lagged path coefficients, and (3) covariances between neighborhood measures. The autoregressive path coefficients reflect the stability of the neighborhood measure over time. Smaller values indicate more variance in the construct over time—a reflection of less influence from the previous lag in the model. Larger values reflect more stability and influence from the previous lag in the model with little variance in the measure over time. The cross-lagged path coefficients are used to estimate the relationship between the probation rate and neighborhood characteristics over time. Finally, the covariance measures between each pair of variables within each year are reported, estimating the amount of variance in each measure that is not accounted for by measures of these same variables in the previous year in the study.

Probation Rate and Concentrated Disadvantage

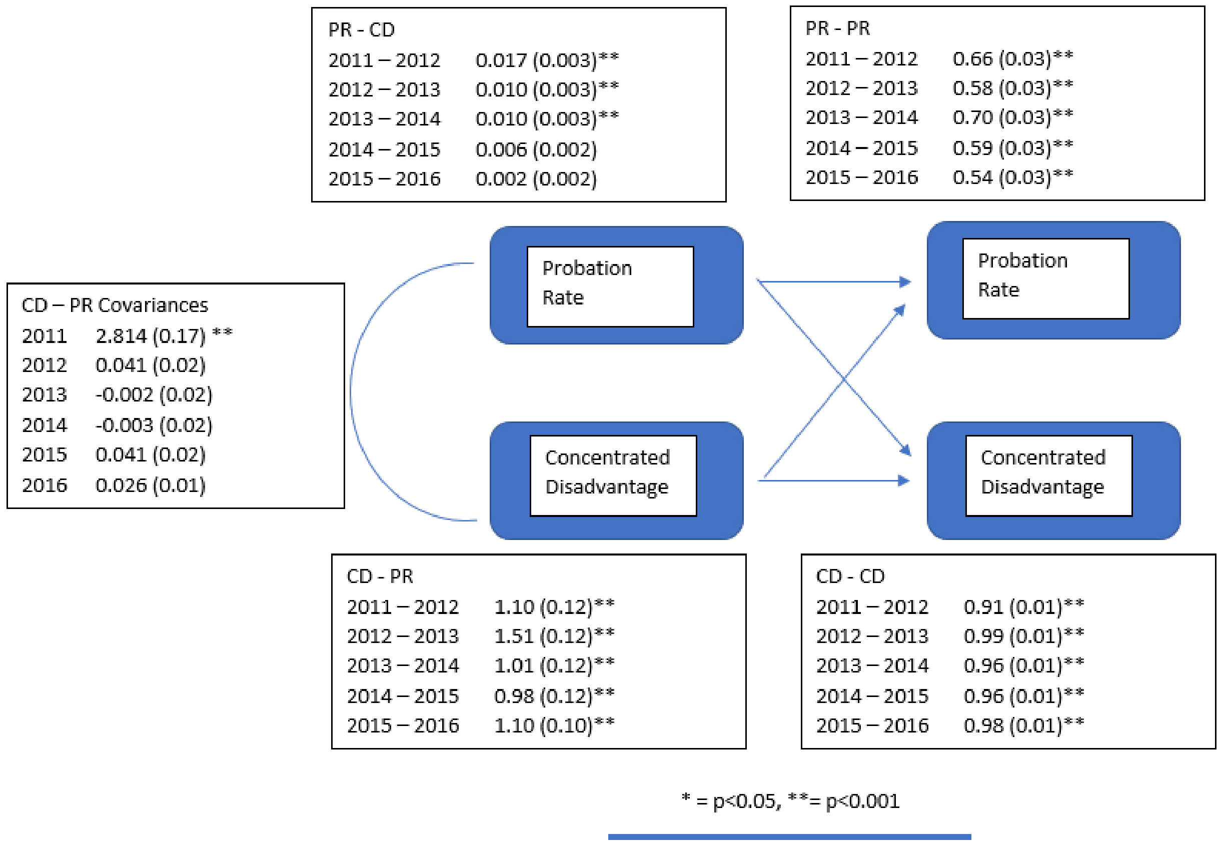


Figure 4.21. Unconstrained Model 2011–2016, Probation Rate and Concentrated Disadvantage.

The unconstrained model examining the probation rate and concentrated disadvantage between 2011 and 2016 included five waves of data with a one-year lag in between. The autoregressive path coefficients for both variables are statistically significant across all years. Measures of concentrated disadvantage across all Chicago neighborhoods reflect little variation over time. Probation rate is similarly stable over time but to a lesser extent than concentrated disadvantage.

The level of concentrated disadvantage in 2011 predicted subsequent increases in probation rate for all following years. The level of neighborhood probation supervision rate observed in 2011 predicted a subsequent increase in concentrated disadvantage from 2012 to

2014; however, this effect did not indicate statistical significance ($p< 0.001$) from 2015 to 2016. The covariance estimates were only statistically significant in 2011, indicating that in all subsequent years the variance observed in each variable is fully accounted for by previous measures of the same variable. Appendix H contains the results of the constrained model estimates using five waves of data. When all path estimates are constrained (except for 2011 covariances), all estimates are statistically significant at $p < 0.001$, and the values can be referenced in the Appendix H. It is important to note that according to the Satorra-Bentler Chi-Square test, the unconstrained model fits the data more parsimoniously than the constrained model.

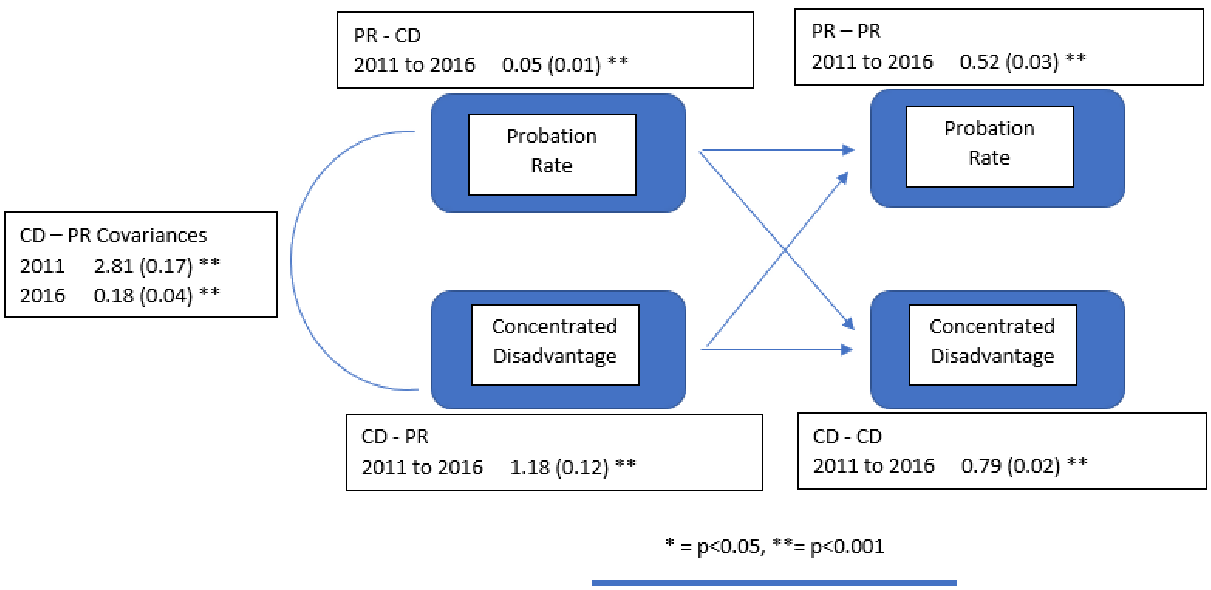


Figure 4.22. Unconstrained Model, 2011 and 2016, Probation Rate and Concentrated Disadvantage.

To further clarify the association between the probation rate on concentrated disadvantage over time, as well as the covariance of these parameters in each year, a subsequent model was estimated using two waves of data: the American Community Survey Estimate of 2011 (which encompasses years 2007–2011) and 2016 (which encompasses years 2012–2016).

There is no overlap in these measures. In this unconstrained model (Figure 4.22), the autoregressive path coefficients for both the probation rate and concentrated disadvantage maintained statistical significance.

The level of concentrated disadvantage in 2011 predicted an increase in the probation rate in 2016 by 1.178 probationers per 1,000 people. Similarly, the probation rate in 2011 predicted an increase in concentrated disadvantage (0.047 units) in 2016. Concentrated disadvantage is a measure composed of several variables with mean of 0 and a standard deviation of 1. For every additional probationer per 1,000 people, there is approximately a 5% standard deviation increase of concentrated disadvantage at the neighborhood level. The covariance measures in 2011 and 2016 are both statistically significant, indicating that the variance observed in each variable is not fully accounted for by previous measures of the variables. Table 4.11 compares the unstandardized and standardized coefficients of the cross-lagged path estimate in the model to examine directionality in the longitudinal relationship. While reciprocal dynamics are observed between concentrated disadvantage and probation supervision rate, there is a stronger effect of concentrated disadvantage on subsequent measures of probation rate at the neighborhood level.

Table 4.11

Comparing Standardized and Unstandardized Coefficients, Probation Rate and Concentrated Disadvantage, 2011 and 2016

	Probation Rate on Concentrated Disadvantage	Concentrated Disadvantage on Probation Rate
Unstandardized	0.05 (0.006) **	1.18 (0.12) **
Standardized	0.18 (0.02) **	0.32 (0.03) **

Note:
*p< 0.05 **p< 0.001

Probation Rate and Violent Crime Rate

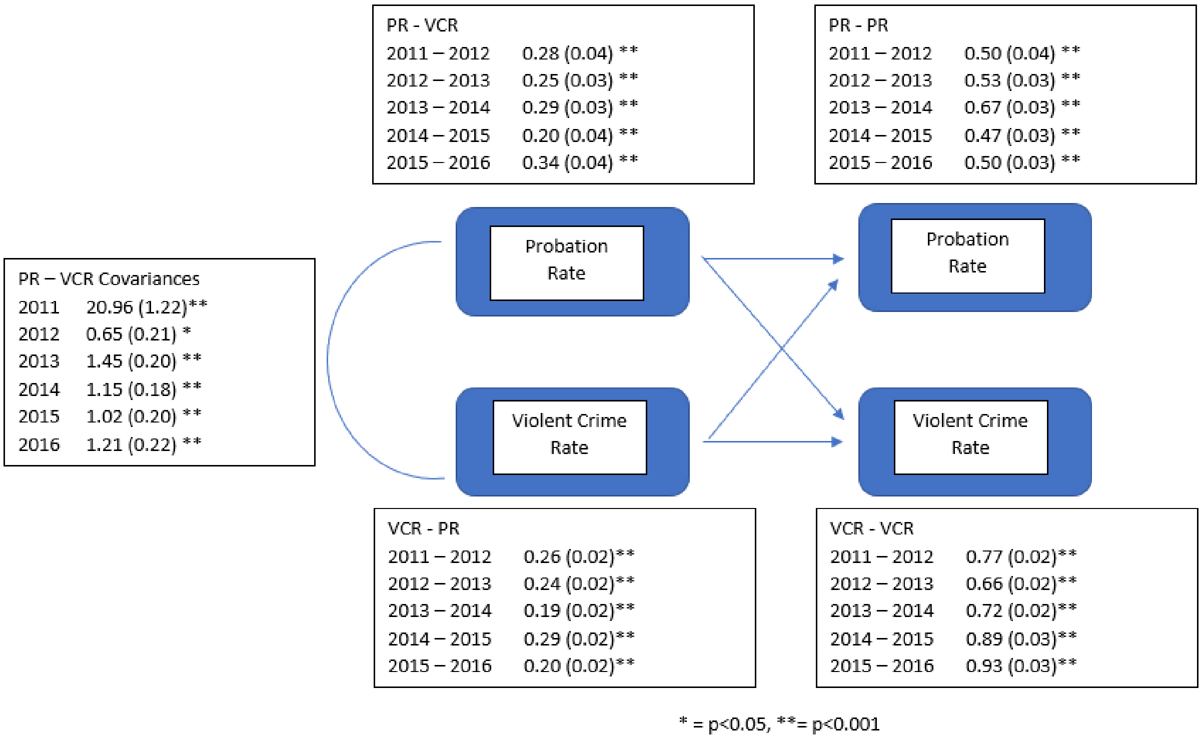


Figure 4.23. Unconstrained Model 2011–2016, Probation Rate and Violent Crime Rate.

The unconstrained model examining the probation rate and violent crime rate between 2011 and 2016 includes five waves of data with a one-year lag. The autoregressive path estimates for both variables are statistically significant across all years. The stability coefficients for the violent crime rate fluctuate between 0.66–0.93, while probation rate ranges between 0.50–0.67. The cross-lagged path estimates between the variables are statistically significant across all years. The 2011 measure of violent crime rate predicts subsequent increases in probation rate across all following years. Measures in a particular year are statistically significant predictors of change in the probation rate levels in subsequent years. Similarly, the probation rate in 2011 led to an increase in violent crime rates for all subsequent years. The covariance estimates between 2011 and 2016 are all statistically significant, indicating there is variance in the measure of each variable that is not accounted for by the measure of the same variable in previous years.

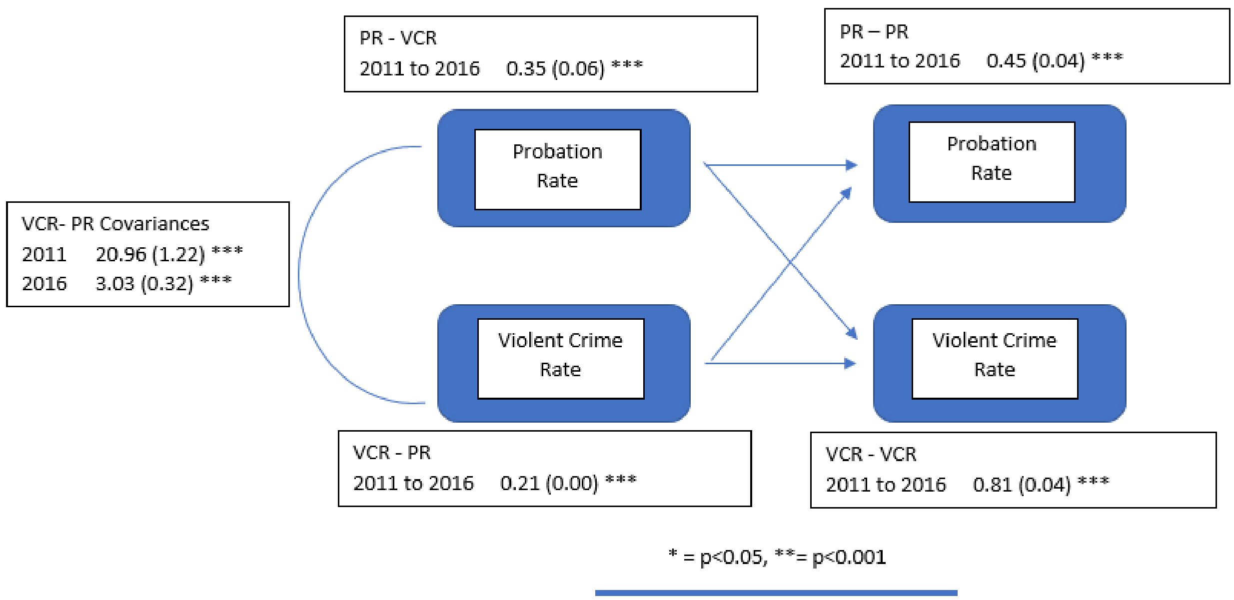


Figure 4.24. Unconstrained Model, 2011 and 2016, Probation Rate and Violent Crime Rate.

To further clarify the association between the probation rate and the violent crime rate, a subsequent model was estimated using two waves of data: the American Community Survey Estimate of 2011 (which encompasses years 2007–2011) and 2016 (which encompasses years 2012–2016). There is no overlap in these measures. In this unconstrained model (Figure 4.24), the autoregressive path coefficient for both variables is statistically significant for both waves. The cross-lagged coefficients were statistically significant; the probation rate in 2011 led to an increase in violent crime rate in 2016 and vice versa. For every additional probationer per 1,000 people in a neighborhood, there is an increase of 0.35 violent crime incidents per 1,000 people. For every additional violent crime reported per 1,000 people in 2011, there is an increase of 0.21 probationers per 1,000 people in 2016; in other words, for every five violent crime incidents in 2011, there was an increase of one probationer in that neighborhood per 1,000 people. The covariance measures in 2011 and 2016 are both statistically significant, indicating that the variance of each variable is not fully accounted for by previous measures of the variables.

In this model, both cross-lagged paths are statistically significant; however, as the coefficient estimates are not standardized, it is difficult to compare the size of the effect of each variable over time. Standardized coefficients for the unconstrained model with two waves of data are reflected in Table 4.12. While reciprocal dynamics are observed between the two variables, the effect of violent crime in 2011 on probation rate in 2016 is twice as large as the reverse relationship.

Table 4.12

Comparing Standardized and Unstandardized Coefficients, Probation Rate and Violent Crime Rate, 2011 and 2016

	Probation Rate on Violent Crime Rate	Violent Crime Rate on Probation Rate
Unstandardized	0.35 (0.06) **	0.21 (0.02) **
Standardized	0.18 (0.03) **	0.38 (0.03) **

Note:
*p< 0.05 **p< 0.001

Probation Rate and Racial/ Ethnic Diversity (Entropy Index)

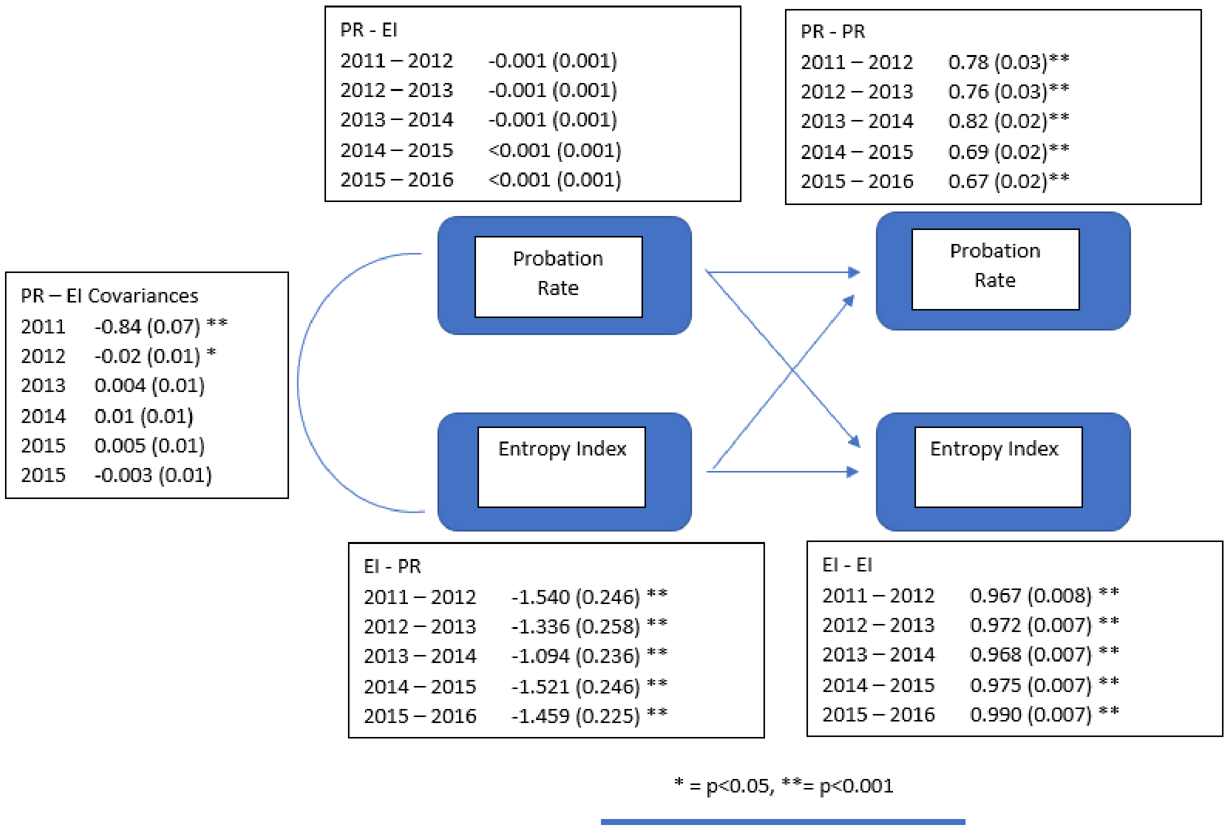


Figure 4.25. Unconstrained Model 2011–2016, Probation Rate and Neighborhood Racial/Ethnic Diversity.

The unconstrained model examining the probation rate and entropy index (neighborhood diversity) between 2011 and 2016 includes five waves of data with a one-year lag in between. The autoregressive path estimates for both variables are statistically significant across all years; the entropy index ranges between 0.97–0.99, while the probation rate ranges in between 0.67–0.82. The level of probation supervision rate in 2011 is not a statistically significant predictor for the measure of neighborhood diversity between 2012 and 2016. However, an increase of neighborhood diversity in 2011 predicts a decrease in probation rate for all subsequent years. The covariance estimates vary in statistical significance between 2011 and 2016.

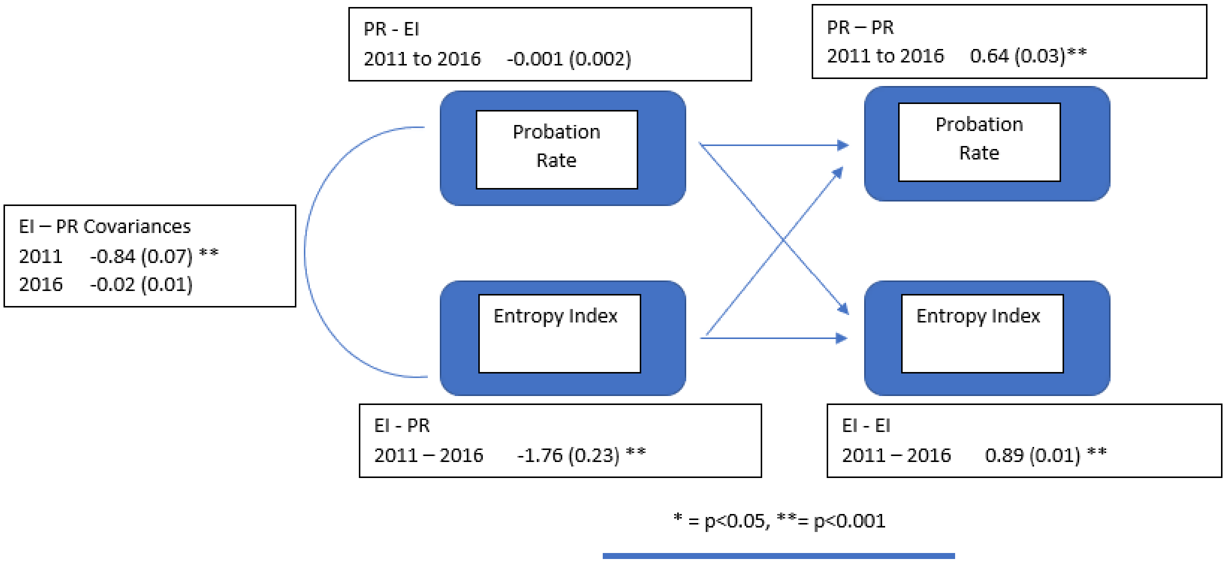


Figure 4.26. Unconstrained Model, 2011 and 2016, Probation Rate and Neighborhood Racial/Ethnic Diversity.

To further clarify the association between the probation rate and neighborhood segregation over time, a subsequent model was estimated using two waves of data: the American Community Survey Estimate of 2011 (which encompasses years 2007–2011) and 2016 (which encompasses years 2012–2016). There is no overlap in these measures. In this unconstrained model (Figure 4.26), the autoregressive path coefficient for both variables is statistically significant for both time waves. The level of neighborhood diversity observed in 2011 predicts a decrease in probation rate in 2016. The entropy index is measured on a scale of 0–1.38, where 1.38 reflects equal representation of all four racial/ethnic groups within a neighborhood. Thus, an increase of the entropy index score from 0 to 1 is associated with a decrease of 1.76 probationers per 1,000 people in a neighborhood. As only one cross-lagged path is statistically significant, one could claim causal predominance of the entropy index on the probation rate over time.

Probation Rate and Residential Stability

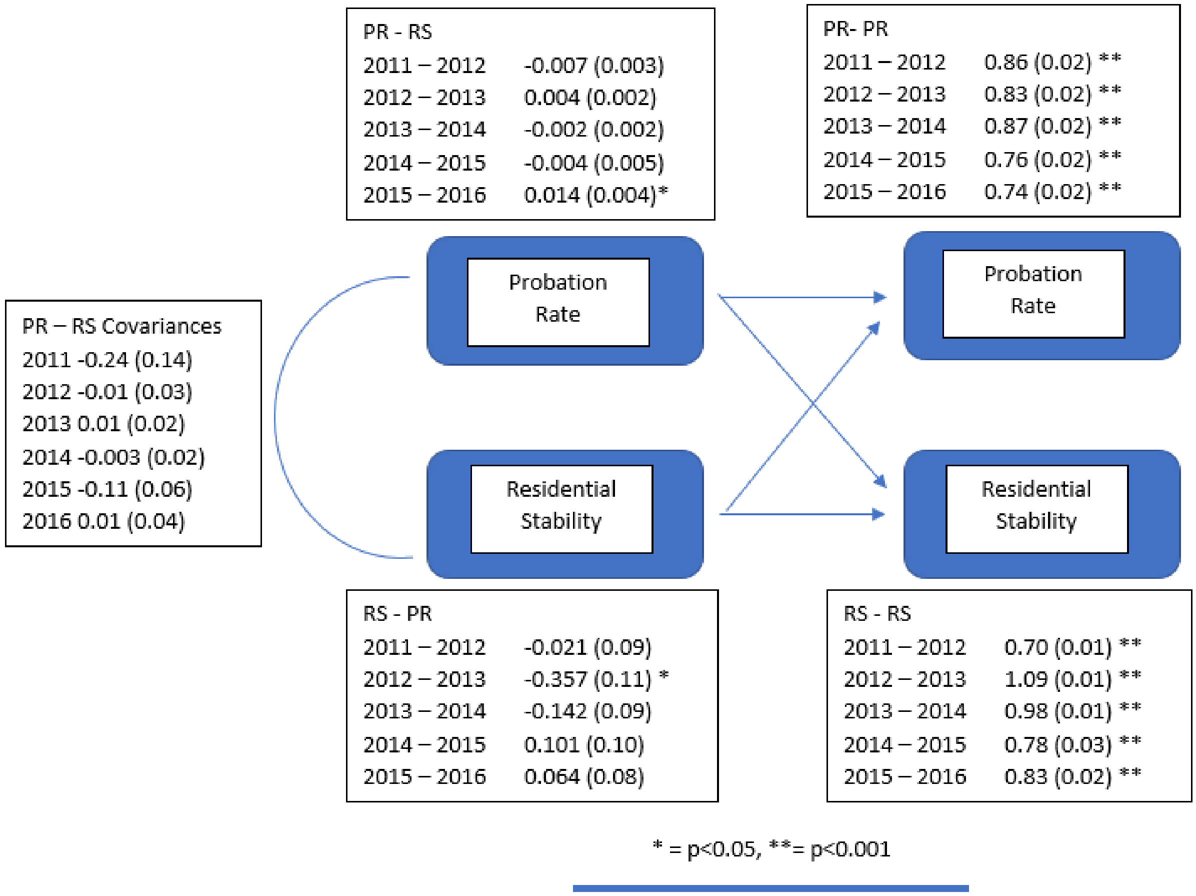


Figure 4.27. Unconstrained Model 2011–2016, Probation Rate and Residential Stability.

The unconstrained model examining the probation rate and residential stability between 2011 includes five waves of data with a one-year lag in between. The autoregressive path estimates for both variables are statistically significant across all years; the estimates for residential stability fluctuate between 0.70 and 1.09, while the probation rate varies between 0.74 to 0.86. In general, the 2011 measure of residential stability does not predict subsequent measures of probation rate or vice versa. Similarly, the annual covariance measures were not statistically significant.

To further clarify the association between the probation rate and residential stability over time, a subsequent model was estimated using two waves of data: the American Community Survey Estimate of 2011 (which encompasses years 2007–2011) and 2016 (which encompasses years 2012–2016). There is no overlap in these measures. In this unconstrained model (Figure 4.28), the autoregressive path coefficient for both variables is statistically significant across all years. The cross-lagged coefficients in both directions are not statistically significant nor were the annual covariance measures between the variables.

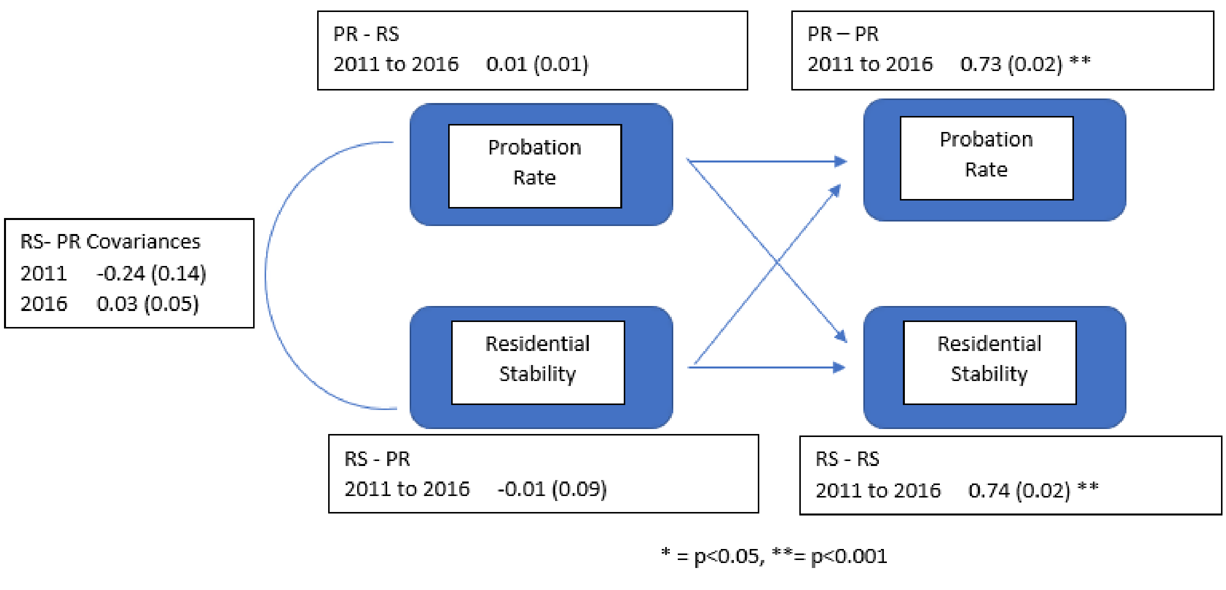


Figure 4.28. Unconstrained Model 2011 and 2016, Probation Rate and Residential Stability.

Comparing Predominantly White and African American Neighborhoods

The entropy index is a measure of neighborhood racial and ethnic diversity. When studying aggregate trends across all neighborhoods, the results indicate that as the entropy index increases, the probation rate decreases. In other words, increased representation of different racial ethnic groups within a specific neighborhood is associated with a decrease in the population concentration of probationers over time. However, aggregate trends do not describe movement patterns among specific racial/ethnic groups. For example, in a predominantly white neighborhood, is a similar pattern observed? If there is an influx of African American and Hispanic residents into a predominantly white neighborhood, would a similar decrease in probation rate be observed over time?

Although the majority of analyses in the study focus on city-wide aggregate-level trends, analyses of more specific subcategories of neighborhood typologies were conducted to provide additional insight into the longitudinal relationship between probation rate and neighborhood racial/ethnic diversity. The following set of analyses are organized in the following manner: First, predominantly white and predominantly African American neighborhoods were identified by selecting census tracts where a minimum of 75% of the population within that tract identified as one of these groups. In the Chicago context, there is only one census tract where at least 75% of the residents are Hispanic-identified populations, and therefore the analyses focused on just two of the four racial/ethnic categories identified. Two waves of neighborhood data were included in the analysis: American Community Survey results from 2011 (summarizing 2007–2011) and 2016 (summarizing 2012–2016).

An additional variable was created in the data set to "group" the neighborhoods according to the predominant racial identity of that tract. Subsequently, multiple group autoregressive cross-lagged panel models examining probation rate and neighborhood traits were run using the "grouping" option in *Mplus 7.3* to generate path coefficients specific to each group. There were 247 predominantly African American neighborhoods identified, and 101 predominantly white neighborhoods were identified in the study sample based on demographics reported in the 2011 American Community Survey. The cross-lagged path coefficients are subsequently compared between the two sets of neighborhoods. There are two analytical tasks associated with this comparison: (a) an examination of the statistical significance of the cross-lagged path coefficients both sets of neighborhoods, and (b) multiple group comparison to see if the strength of relations observed differ by neighborhood racial identity. It is likely that the cross-lagged path coefficients will be different between the two sets of neighborhoods; however, the statistical significance of the path coefficients is not sufficient evidence to indicate that the neighborhood-level dynamics of probation rate operate differentially within this comparison. First, all path coefficients were constrained to be equal across both time waves. Subsequently, a series of tests was run to constrain each cross-lagged path between study variables. The Satorra-Bentler Chi-Square test comparisons then indicate which model fits the data more parsimoniously, and the p-value indicates if there is a statistically significant difference in the cross-lagged path coefficients observed between predominantly white and African American neighborhoods. The unconstrained model is not included in the Satorra-Bentler difference test since it contains no degrees of freedom (since only two waves of data are utilized).

Table 4.13

Comparing Cross-lagged Effects Between Probation Rate and Concentrated Disadvantage in Predominantly White and African American Neighborhoods

Path	**Predominantly White Neighborhoods**		**Predominantly African American Neighborhoods**		**Difference**	
	Estimate (Standard Error)	P Value	Estimate (Standard Error)	P Value	Chi-Square Test (DoF)	P Value
1) Unconstrained Model						
CD > PR	0.01 (0.19)	0.96	1.30 (0.27)	0.00		
PR > CD	0.05 (0.02)	0.02	0.02 (0.01)	0.003		
2) Equality Constraints (All 4 Paths)						
CD > PR	0.43 (0.17)	0.01	0.43 (0.17)	0.01		
PR > CD	0.03 (0.01)	0.00	0.03 (0.01)	0.00		
3) Equality Constraints (CD > PR Relaxed)						
CD > PR	0.015 (0.20)	0.94	1.24 (0.27)	0.00	Comparing 2 and 3	
PR > CD	0.03 (0.01)	0.00	0.03 (0.01)	0.00	13.32 (1)	0.00
4) Equality Constraints (PR > CD Relaxed)						
CD > PR	0.43 (0.17)	0.01	0.43 (0.17)	0.01	Comparing 2 and 4	
PR > CD	0.63 (0.04)	0.00	0.03 (0.01)	0.00	0.77 (1)	0.39

When examining all neighborhoods in Chicago, concentrated disadvantage is a statistically significant predictor of an increase in probation rate over time and vice versa. When comparing predominantly white and African American neighborhoods in the unconstrained model, probation rate is a statistically significant predictor of an increase in concentrated disadvantage over time ($p < 0.05$); however, concentrated disadvantage is a statistically significant predictor of probation rate only in African American neighborhoods. To further examine, the fully constrained model (2) is compared with a semiconstrained model where the association of concentrated disadvantage on probation rate is relaxed. The p-value is less than <0.001, indicating that the association between the two variables is significantly different between the two sets of neighborhoods. Results indicate that the association of concentrated disadvantage on probation rate is driving this difference.

Table 4.14

Comparing Cross-lagged Effects Between Probation Rate and Residential Stability in Predominantly White and African American Neighborhoods

Path	Predominantly White Neighborhoods	Predominantly African American Neighborhoods	Comparison
	Estimate (Standard Error)	Estimate (Standard Error)	Chi Square (DOF)
1) Unconstrained Model			
RS > PR	0.15* (0.06)	-0.52 (0.30)	
PR > RS	0.07 (0.06)	0.001 (0.01)	
2) Equality Constraints (All 4 Paths)			
RS > PR	0.12 (0.06)	0.12 (0.06)	
PR > RS	0.004 (0.01)	0.004 (0.01)	
3) Equality Constraints (RS > PR Relaxed)			Comparing 2 and 3
RS > PR	0.15* (0.06)	-0.58* (0.29)	5.86* (1)
PR > RS	0.004 (0.007)	0.004 (0.007)	
4) Equality Constraints (PR > RS Relaxed)			Comparing 2 and 4
RS > PR	0.11 (0.06)	0.11 (0.06)	2.60 (1)
PR > RS	0.10 (0.06)	0.003 (0.01)	

Note:
*$p < 0.05$, **$p < 0.001$

When examining all neighborhoods in Chicago, residential stability is not a significant predictor of change in probation rate over time and vice versa. The results were largely similar when examining predominantly white and African American neighborhoods with the exception of one cross-lagged path; in predominantly white neighborhoods, residential stability predicts an increase in probation rate over time; however, this effect disappears when the paths are constrained in model 2. The Satorra-Bentler difference test indicates that the path coefficients observed in the two sets of neighborhoods are significantly different, and the association of residential stability on probation rate is the primary driver of this difference. When this cross-lagged path constraint is relaxed in model 3, the effects of residential stability on probation rate have a differential impact when comparing the two sets of neighborhoods. In predominantly white neighborhoods, measures of residential stability in 2011 predict an increase in probation rate in 2016. In predominantly African American neighborhoods, measures of residential stability in 2011 predict a decrease in probation rate 2016. These findings provide two indications: First, the aggregate trends describing the relationship between probation rate and residential stability do not accurately describe the dynamic between these two variables in predominantly white and African American neighborhoods over time. Second, further research is necessary to understand how residential stability has differential effects on probation supervision rates in the two sets of neighborhoods compared.

Table 4.15

Comparing Cross-lagged Effects Between Probation Rate and Violent Crime Rate in Predominantly White and African American Neighborhoods

Path	**Predominantly White Neighborhoods**	**Predominantly African American Neighborhoods**	**Comparison**
	Estimate (Standard Error)	Estimate (Standard Error)	Chi-Square (DOF)
1) Unconstrained Model			
VCR > PR	-0.05 (0.03)	0.17** (0.04)	
PR > VCR	0.13 (0.10)	-0.04 (0.14)	
2) Equality Constraints (All 4 Paths)			
VCR > PR	0.01 (0.02)	0.01 (0.02)	
PR > VCR	0.23* (0.08)	0.23* (0.08)	
3) Equality Constraints (VCR > PR Relaxed)			Comparing 2 and 3
VCR > PR	-0.05 (0.04)	0.11* (0.04)	11.74** (1)
PR > VCR	0.22* (0.08)	0.22 (0.08)	
4) Equality Constraints (PR > VCR Relaxed)			Comparing 2 and 4
VCR > PR	0.01* (0.02)	0.01* (0.02)	5.76* (1)
PR > VCR	0.35 (0.09)	-0.05 (0.14)	

Note:
*p < 0.05, **p < 0.001

When examining all neighborhoods across Chicago, violent crime rate is a statistically significant predictor of an increase in probation rate over time and vice versa. When comparing predominantly white and African American neighborhoods, the unconstrained model indicates that probation rate does not predict changes in violent crime over time. In African American neighborhoods, violent crime rate predicts an increase in probation rate over time ($p < 0.001$); however, this association is not statistically significant in predominantly white neighborhoods. The Satorra-Bentler Chi Square test of difference confirms that the differences observed are statistically significant and that the cross-lagged path that is primarily responsible for these differences is the relationship of probation rate on violent crime. Similar to the observations indicated on residential stability, the analyses suggest that the dynamic between probation rate and violent crime rate is significantly different in the two sets of neighborhoods compared. These analyses are limited in explaining why these differences occur; however, they provide additional support for the conclusion that the spatial patterning of probationers has differential impacts on neighborhoods across the city of Chicago.

Table 4.16

Comparing Cross-lagged Effects Between Probation Rate and Racial/Ethnic Diversity (Entropy Index, EI) in Predominantly White and African American Neighborhoods

Path	**Predominantly White Neighborhoods**	**Predominantly African American Neighborhoods**	**Comparison**
	Estimate (Standard Error)	Estimate (Standard Error)	Chi-Square (DOF)
1) Unconstrained Model			
EI > PR	-0.23 (0.38)	-1.29 (1.21)	
PR > EI	0.05/* (0.02)	0.001 (0.002)	
2) Equality Constraints (All 4 Paths)			
EI > PR	-0.12 (0.39)	-0.12 (0.39)	
PR > EI	0.001 (0.002)	0.001 (0.002)	
3) Equality Constraints (EI > PR Constrained)			Comparing 2 and 3
EI > PR	0.04 (0.42)	-1.39 (1.21)	1.22 (1)
PR > EI	0.001 (0.002)	0.001 (0.002)	
4) Equality Constraints (PR > EI Constrained)			Comparing 2 and 4
EI > PR	-0.32 (0.36)	-0.32 (0.36)	23.4** (1)
PR > EI	0.002 (0.002)	0.002 (0.002)	

Note:
*p < 0.05, **p < 0.001

When examining all neighborhoods across Chicago, an increase in neighborhood racial/ethnic diversity is associated with a decrease in probation rate over time. Probation rate was not a statistically significant predictor of neighborhood racial/ethnic diversity over time. In the unconstrained model, probation rate is a statistically significant predictor of an increase in neighborhood diversity over time in predominantly white neighborhoods (but not vice versa). None of the path coefficients were statistically significant in predominantly African American neighborhoods. In a fully constrained model, none of the path coefficients are statistically significant, and when the cross-lagged paths are relaxed in models 3 and 4, there is no change in the statistical significance of the estimates. The Satorra-Bentler difference test indicates that the estimates observed in the two sets of neighborhoods are significantly different; however, given that none of the path coefficients are significant in models 2–4, the difference test has no practical relevance.

Summary of key findings.

The key findings that emerge from this set of analyses are as follows:

1. Across all neighborhoods in Chicago, neighborhood levels of concentrated disadvantage and violent crime predict an increase in probation supervision rates over time. The racial/ethnic diversity of a neighborhood predicts a decrease in local probation rates over time.
2. Across all neighborhoods in Chicago, neighborhood probation rates predict an increase in neighborhood levels of violent crime and concentrated disadvantage over time. Thus, the association between probation rate and violent crime, as well as probation rate and concentrated disadvantage, is bidirectional and reciprocal.
3. Aggregate-level neighborhood trends do not reflect dynamics observed in predominantly white and African American neighborhoods. Statistically significant differences were observed in the longitudinal associations between probation rate and concentrated disadvantage, violent crime rate, residential stability, and racial/ethnic diversity.

Specific Aim 3 Results

Spatial Dependence and Probation Case Outcomes

Spatial analyses presented in Specific Aim 1 describe how probationers are spatially clustered within a set of spatially contiguous neighborhoods primarily on the west side and south side of Chicago. The analyses presented in Specific Aim 2 explore why probationers may be concentrated in these neighborhoods in addition to the implications of the spatial concentration of probationers on neighborhood dynamics. This last set of analyses explores the influence of community context on individual probation outcomes. More specifically, the probation rate is examined as a neighborhood-level dynamic that may have an impact on outcomes observed in individual probation cases. The neighborhood-level characteristics included in analyses under Specific Aim 2 are incorporated into a multilevel model with individual-level probationer characteristics. Figure 4.29 depicts multiple paths of influence related to an individual's probation outcome.

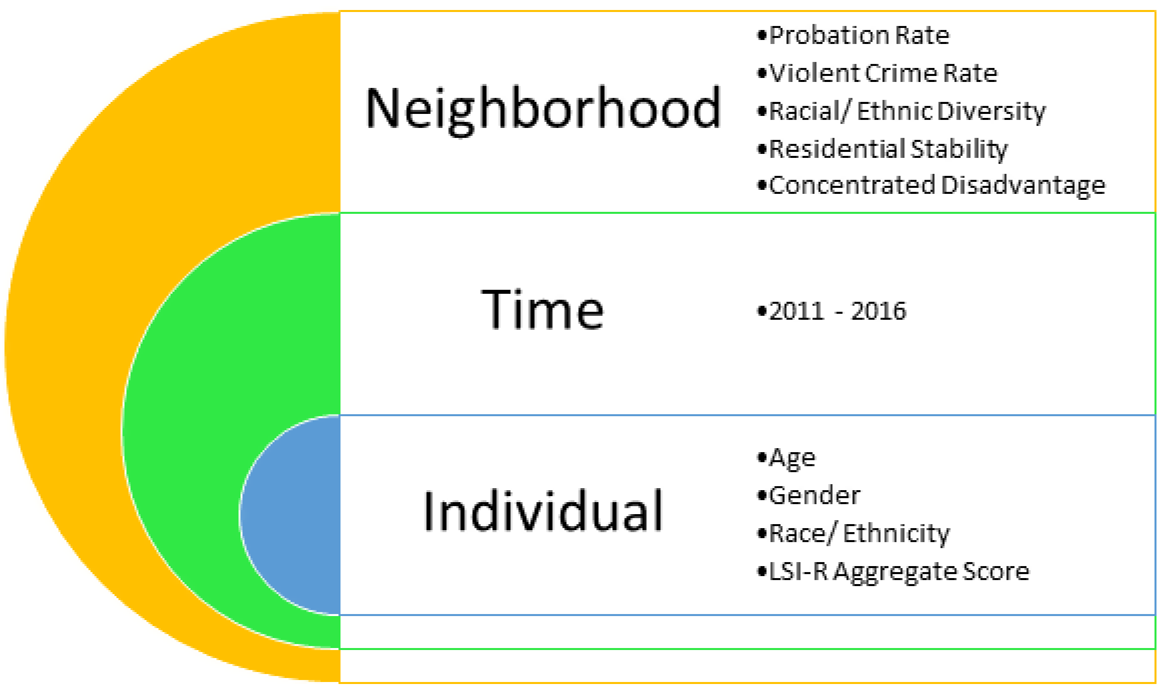


Figure 4.29. Organization of variables in multilevel model.

The analytical strategy of this section is structured to determine how individual and community characteristics contribute to a probationer's risk of a negative discharge event. To begin, the spatial distribution of negative discharge events was analyzed to evaluate if the location of probation cases with these outcomes is randomly distributed or predictably organized. If the spatial patterns observed of negative discharge events is not random, then there is a basis for which one could examine why there are more negative discharge events in certain places over others. The 11,545 cases presenting a negative discharge event were mapped, and the Average Nearest Neighbor statistic was calculated to estimate if the spatial pattern of probationers with negative discharge events was random, dispersed, or clustered in particular areas. The average distance between each probation case with a negative discharge event is calculated and then compared against the average distance expected if the spatial distribution was completely random. The results are indicated in Table 4.17.

Table 4.17

Average Nearest Neighbor Estimates
Negative Discharge Event Distribution

Year	Nearest Neighbor Ratio	Nearest Neighbor Z Score
2011	0.59	-34.10**
2012	0.49	-74.66**
2013	0.54	-40.50**
2014	0.58	-36.97**
2015	0.55	-37.35**
2016	0.60	-30.04**

*p < 0.05, **p< 0.001

The spatial distribution of negative discharge events is not random; they are predictably organized in certain places. These results, however, are point pattern analyses and only analyze patterns among probationers with negative discharge events (approximately one third of the data sample per year). Subsequently, spatial autocorrelation tests examined the spatial randomness of neighborhood rates of negative discharge. These values indicate if the neighborhood rate of negative discharge among probationers is associated with the geographic location of that neighborhood. Please reference the methods section for an explanation of the difference between Average Nearest Neighbor and Spatial Autocorrelation tests.

Table 4.18

Spatial Autocorrelation Results: Neighborhood Rates of Negative Discharge Among Probationers

Year	Index	Z-Score
2011	0.05	4.13 **
2012	0.08	7.98 **
2013	0.07	7.45 **
2014	0.10	8.18 **
2015	0.09	6.37 **
2016	0.09	7.65 **

*p < 0.05, **p< 0.001

Similar to the Average Nearest Neighbor results, the Spatial Autocorrelation tests are statistically significant across all years. These results indicate that there is a significant association between one's case outcome and the neighborhood in which the probationer resides.

Subsequent analyses test if the spatial dependence observed in case outcomes is associated with neighborhood characteristics.

Before proceeding with multilevel modeling, the following maps provide an illustration of how neighborhood rates of negative discharge vary across Chicago's landscape. The neighborhoods that are outlined in red have a probation population of greater than 10. Neighborhoods with small probation populations are more susceptible to dramatic shifts in calculating proportion of negative discharge events. Evident in these maps is that most neighborhoods with the highest proportion of negative discharge events are also neighborhoods with fewer than 10 probationers. There is a considerable amount of fluctuation in the patterns observed in the following maps. The proportion of probationers that negatively discharge in a neighborhood fluctuates between years. To illustrate the point, two census tracts were chosen from the southwest side of Chicago. Census tract 3016 is situated within the South Lawndale community which is predominantly Mexican/Mexican American. Census tract 2909 is situated within the East Garfield Park community, where most residents are African American.

Table 4.19

Number of Probationers and Proportion of Negative Discharge Events in Two Chicago Census Tracts

Year	Census Tract 2909		Census Tract 3016	
	Number of Probationers	Proportion of Negative Discharge Events	Number of Probationers	Proportion of Negative Discharge Events
2012	23	52%	15	20%
2014	35	54%	13	23%
2016	36	41%	12	8%

In census tract 3016, between 2014 and 2016, the proportion of probationers with a negative discharge event decreased 15 percentage points, or by 65.3%. This example illustrates that at the neighborhood level, the proportion of probationers with a negative discharge event can fluctuate dramatically from year to year.

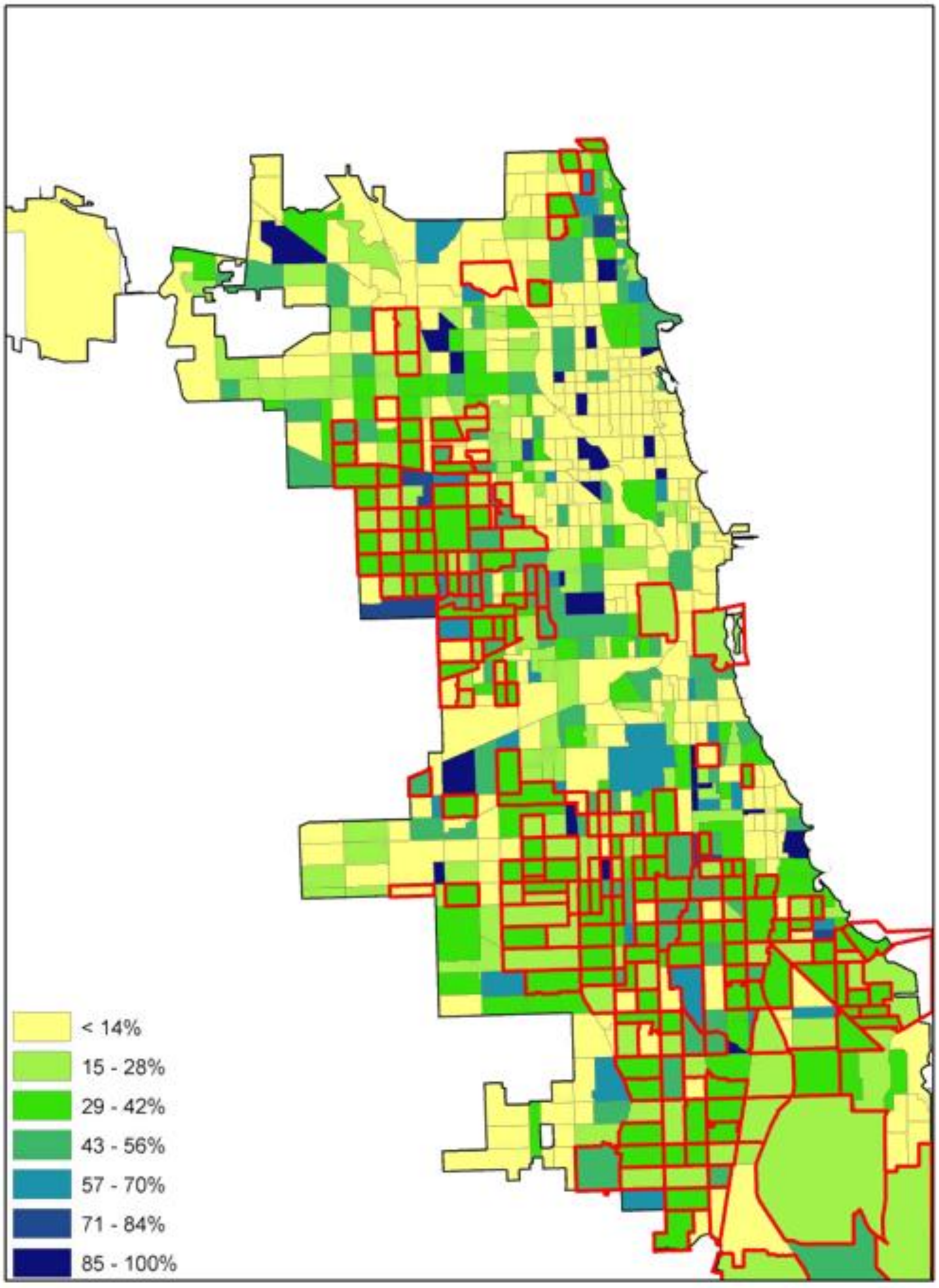
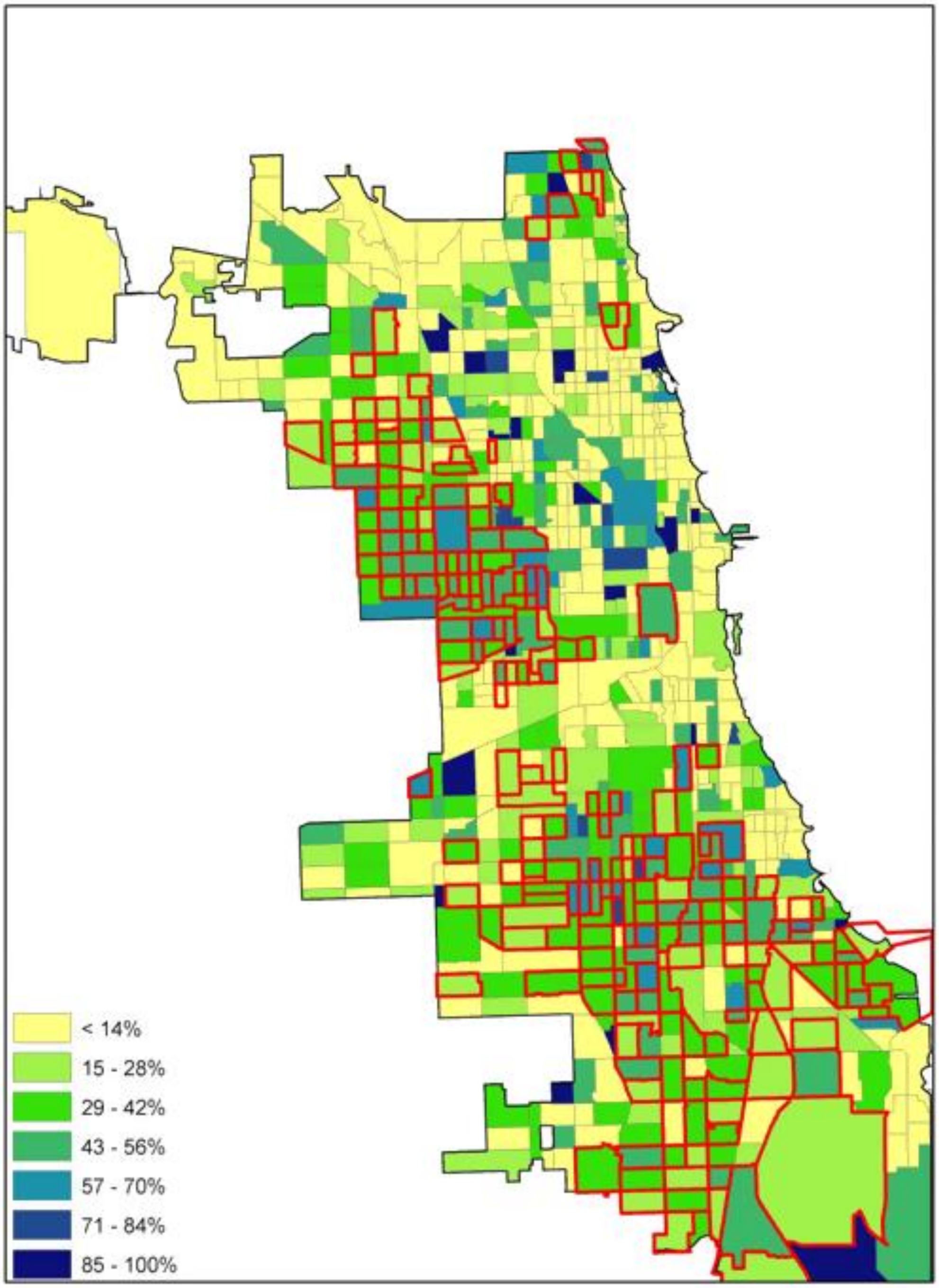
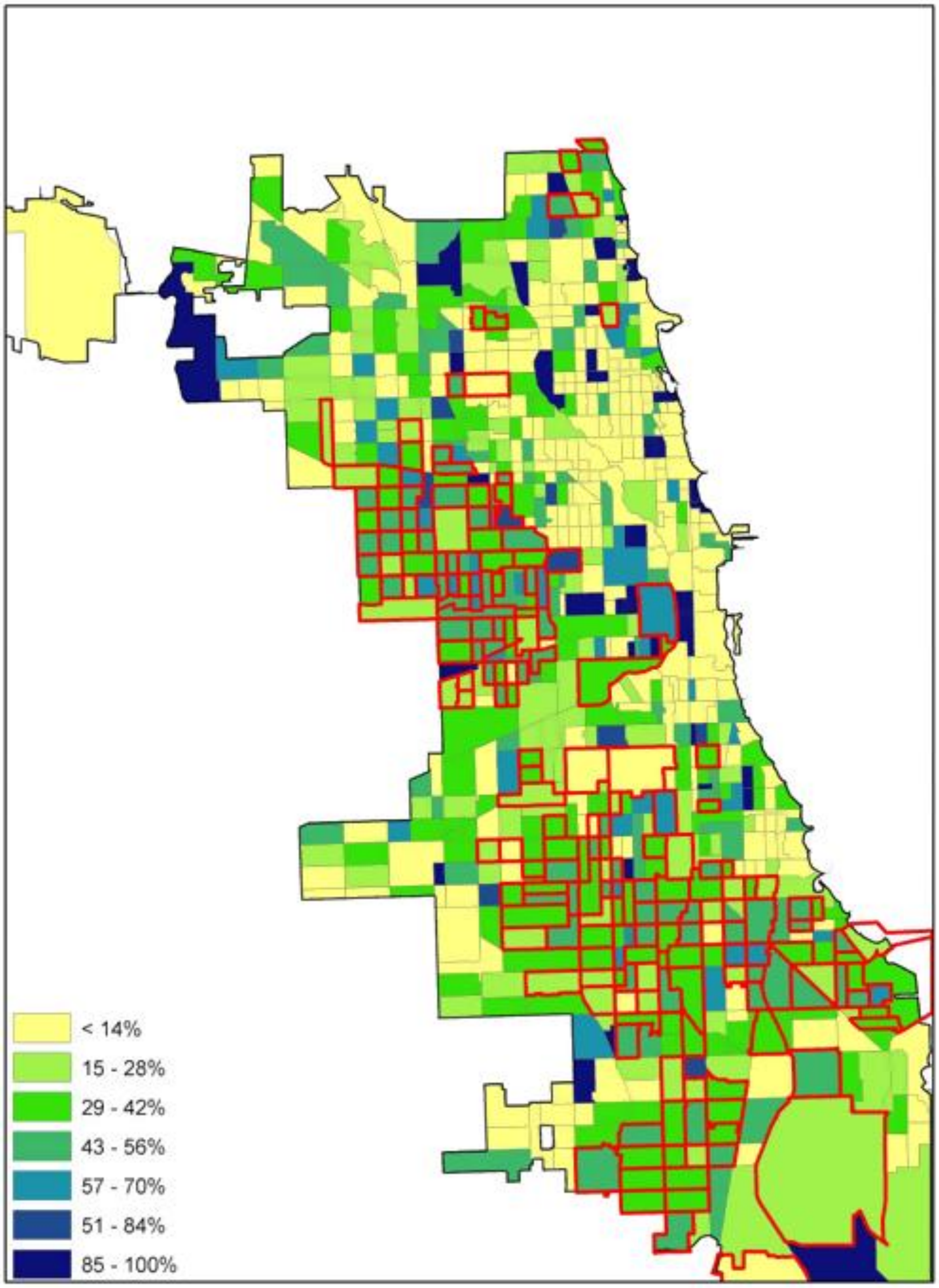


Figure 4.30. Percent of Probation Cases with a Negative Discharge Outcome at the Census Tract Level 2011.



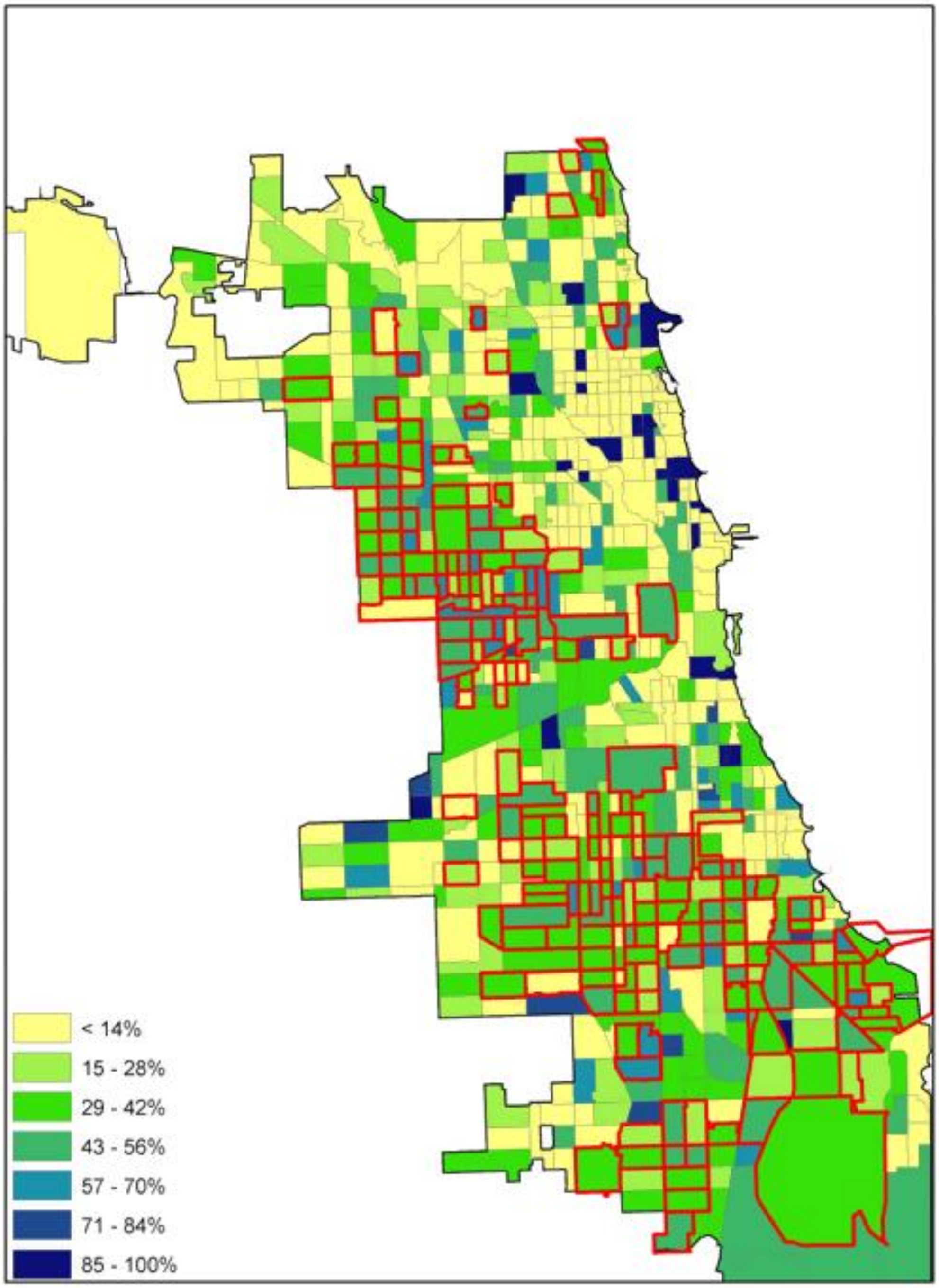
Census tracts circled in red have greater than 10 probationers

Figure 4.31. Percent of Probation Cases with a Negative Discharge Outcome at the Census Tract Level, 2012



Census tracts circled in red have greater than 10 probationers

Figure 4.32. Percent of Probation Cases with a Negative Discharge Outcome at the Census Tract Level, 2013.



Census tracts circled in red have greater than 10 probationers

Figure 4.33. Percent of Probation Cases with a Negative Discharge Outcome at the Census Tract Level, 2014.

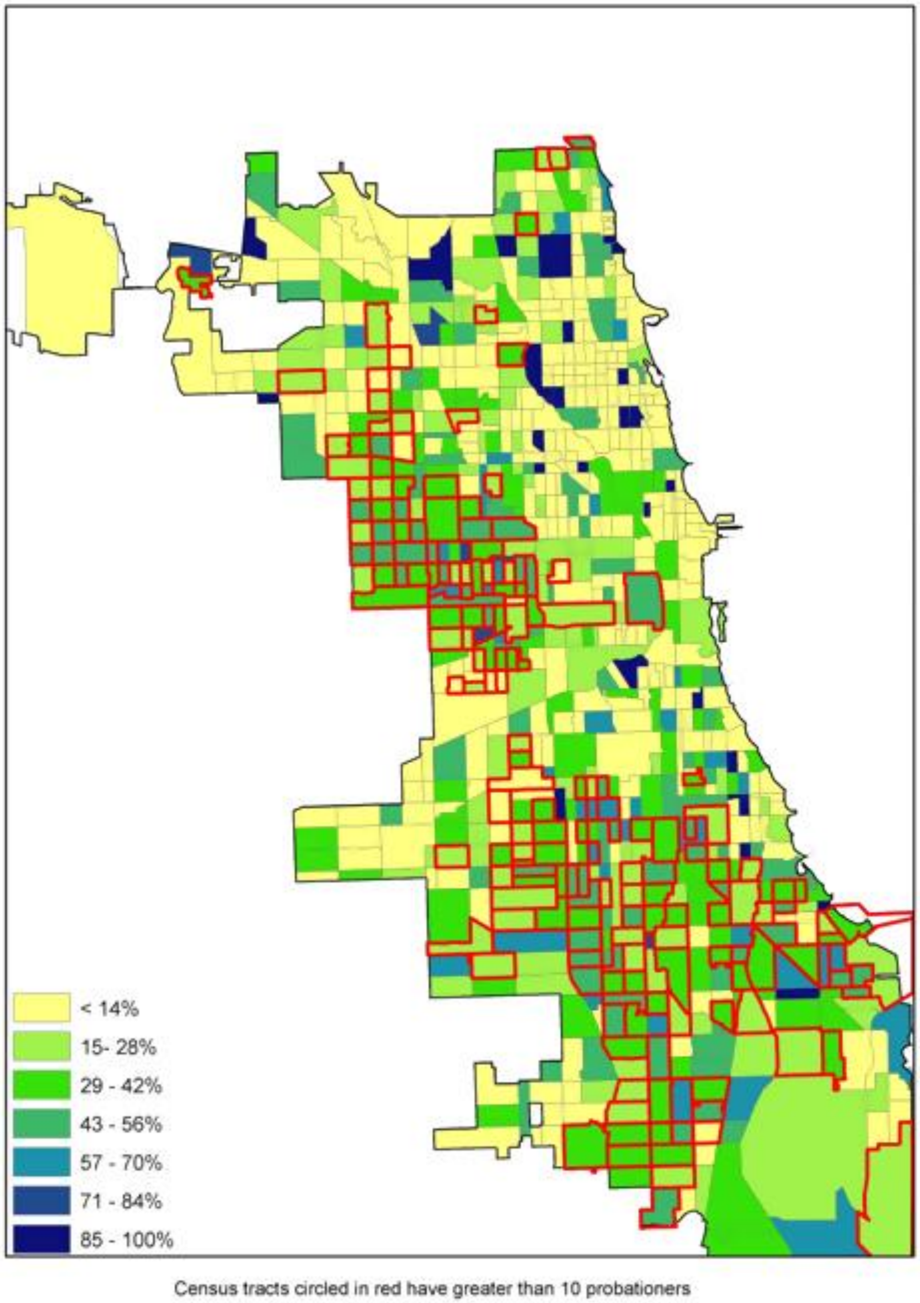
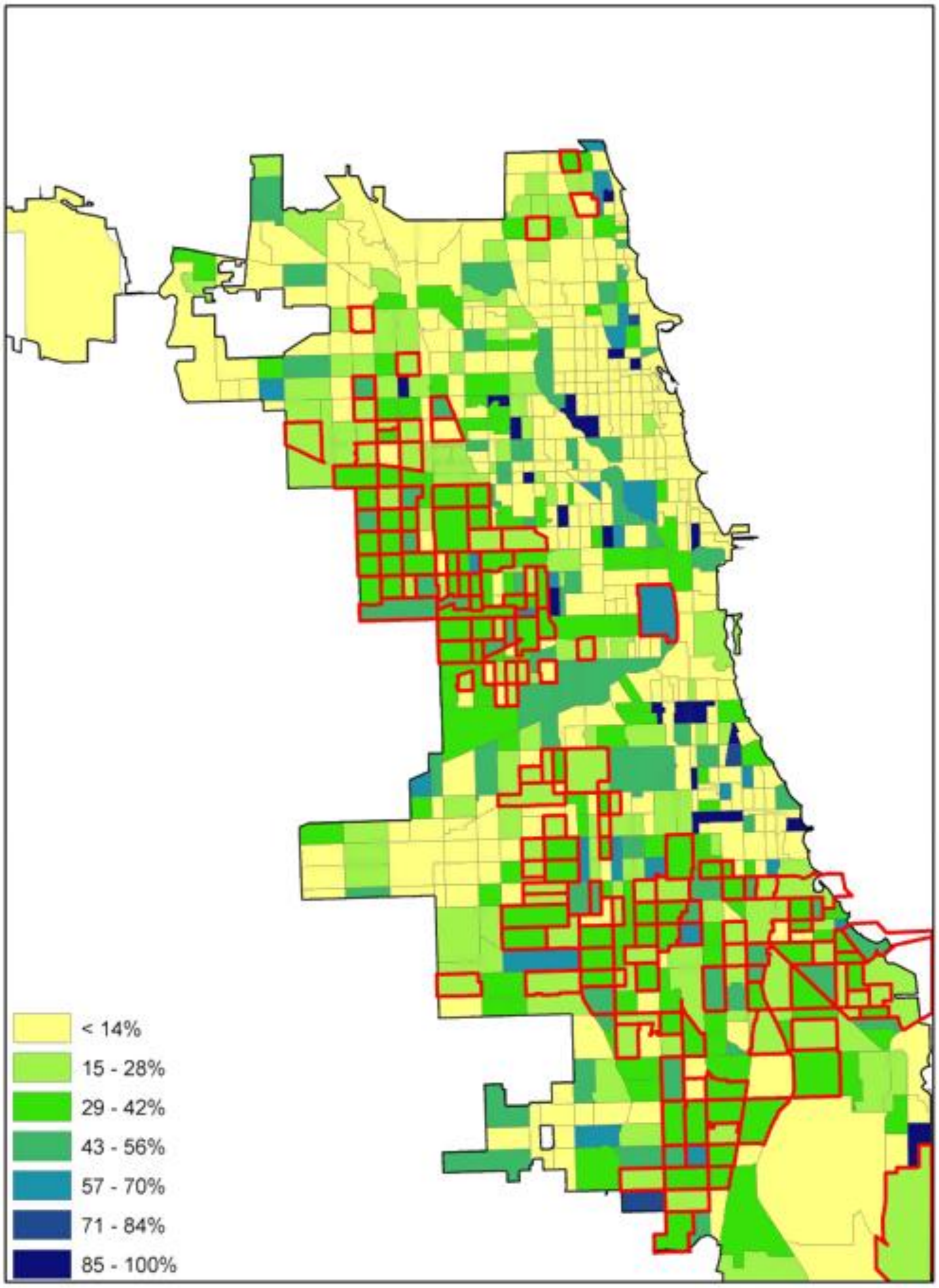


Figure 4.34. Percent of Probation Cases with a Negative Discharge Outcome at the Census Tract Level, 2015.



Census tracts circled in red have greater than 10 probationers

Figure 4.35. Percent of Probation Cases with a Negative Discharge Outcome at the Census Tract Level 2016.

To summarize, while the spatial distribution of negative discharge events is not random, it is unclear the degree to which the neighborhood in which probationers reside is associated with their case outcome. The maps indicate that within a specific neighborhood, the proportion of probationers that present a negative discharge event fluctuates over time. The following set of analyses incorporate individual- and neighborhood-level characteristics to estimate logistic and multilevel models predicting probation case outcomes. In both sets of analyses, the dependent variable is binary: presents negative discharge event or does not present negative discharge event.

Logistic Regression Model Results

Before proceeding with a generalized linear mixed model, each individual- and neighborhood-level variable was examined in a binary logistic regression model. The reference category in each regression model is a white male. When examined in isolation of the other variables, the effect of each variable is associated with predicting a negative discharge event and statistically significant at the p<001 level. For example, for every one-point increase in the LSI-R risk score, the odds of presenting a negative discharge event increase by 22.5%. The relationship between one's probation outcome and residential stability is inversely related; an increase in the residential stability of one's neighborhood of residence is associated with a decrease in odds of presenting a negative discharge event.

Table 4.20

Summary of Binary Logistic Regression Analysis: Individual and Community Predictors of Negative Discharge Events

Predictor	B	SE B	X^2	Odd Ratio
Individual- Level Characteristics				
LSI-R Score	0.20 **	0.01	199.45	1.22
Gender	-0.34 **	0.03	122.69	0.71
Race/ Ethnicity	-0.19 **	0.02	92.81	0.83
Age	-0.02 **	<0.001	593.28	0.98
Neighborhood-Level Characteristics				
Violent Crime Rate	29.58 **	1.64	327.24	<0.001
Residential Stability	-0.012 **	0.01	78.09	0.89
Concentrated Disadvantage	0.24 **	0.01	390.28	1.27
Racial/ Ethnic Diversity	-0.41 **	0.03	242.75	0.66
Probation Rate	0.05 **	0.002	403.83	1.05

*p < 0.05, ** p< 0.001

Evident in this table is that when examined individually, each predictor variable included in the table is statistically significant. However, previous research suggests that these variables are interconnected; one’s race may influence the census tract of residence, which also influences the level of violence to which one is exposed. Following these initial analyses, these variables were then combined into a multivariate binary logistic model to examine the relations between these measures, as well as to estimate the amount of variance that is accounted for by available data on the study sample.

Table 4.21

Summary of Multivariate Binary Logistic Regression Analysis: Individual and Community Predictors of Negative Discharge Events

Predictor	B	SE B	X^2	Odd Ratio
Individual- Level Characteristics				
LSI-R Score	0.02 **	0.002	89.07	1.02
Gender (Male)	-0.40 **	0.04	122.41	0.67
Race/ Ethnicity (White)			36.41	0.85
Other	-0.05	0.17	-0.30	0.68
African American	0.37 **	0.06	6.31	1.44
Hispanic	-0.19 **	0.06	-3.23	0.83
Age	-0.03 **	0.001	450.27	0.98
Neighborhood-Level Characteristics				
Violent Crime Rate	-0.002	0.003	0.39	0.99
Residential Stability	-0.02	0.02	1.21	0.98
Concentrated Disadvantage	0.11 **	0.03	16.07	1.11
Racial/ Ethnic Diversity	-0.06	0.05	1.53	0.95
Probation Rate	0.03**	0.005	33.24	1.03

*$p < 0.05$, **$p < 0.001$

All individual-level characteristics, the probation rate, and concentrated disadvantage were statistically significant predictors ($p < 0.001$) of an individual probationer's risk for negative discharge. Subsequently, a multilevel model was estimated, simultaneously incorporating all individual- and neighborhood-level predictors while accounting for clustering at the neighborhood-level. Collinearity diagnostics were run for all community-level variables, and the Variance Inflation Factor statistic for each variable is indicated in Table 4.22. The results do not provide any strong indicators of collinearity among community-level variables.

Table 4.22

Summary of Diagnostic Tests
for Multicollinearity
Neighborhood-Level Variables

Variable	Variance Inflation Factor
Racial/ Ethnic Diversity	2.07
Residential Stability	1.65
Concentrated Disadvantage	3.58
Probation Rate	2.47
Violent Crime Rate	3.14

Multilevel Model Results

The first step in multilevel modeling is to estimate the intraclass correlation coefficient (ICC), which describes the extent of nonindependence of probation outcome observations within neighborhood clusters. A small ICC indicates that within-neighborhood variance is much greater than between-neighborhood variance of probation outcomes. In other words, there is a considerable amount of variability of probation outcomes among probationers residing in the same tract. Such a finding suggests that individual-level characteristics account for varying trends in probation outcomes. A large ICC indicates that within a neighborhood there is little variation in probation outcomes (i.e., probationers within a census tract have similar outcomes), and that variance among probation outcomes among the pool of probationers between 2011 and 2016 is better accounted for by examining neighborhood differences. Such a finding suggests that neighborhood-level characteristics account for varying trends in probation outcomes.

The intraclass correlation coefficient for all closed probation cases between 2011 and 2016 is 0.0624; 6.24% of variance in probation outcomes among the study sample is accounted for by clustering at the neighborhood level. The random effect covariance is statistically significant; while the effect of clustering is small, there is sufficient justification for proceeding with a multilevel model.

Multilevel models were computed using generalized linear mixed model functions in SPSS version 22.0. Individual- and community-level variables were entered in as fixed effects into the generalized linear mixed model. The census tract of residence was specified as a random effect within the model. Each individual- and neighborhood-level variable was incorporated into a multilevel model including interaction effects for each year. For both models, 71.8% (24,743) of the probation cases between 2011 and 2016 were included in analyses. Excluded cases had missing data, primarily from the LSI-R field (see Table 3.1). While required to administer this risk assessment at the initiation of one's probation sentence, these data were not always entered into the probation data system (PROMIS).

The purpose of including the interaction effects was to generate a singular model incorporating each year of closed probation cases between 2011 and 2016, while at the same time permitting for indicators if one of the independent variables varied significantly over time. If none of the interaction effects within the model are statistically significant, then the interaction effects can be removed. Appendix J includes a table describing the outputs of a model including interaction effects between each independent variable and time. Results indicate that only LSI-R scores vary significantly over time in their association with probation outcomes. All other interaction effects were removed and a multilevel model incorporating all individual- and community-level variables over time was run. Results are presented in Table 4.22.

LSI-R score was the only predictor variable that varied significantly during the time frame of study. For this reason, in the final model the only interaction effect maintained was LSI-

R score and time. The final model incorporated the following variables: age, gender, race/ethnicity, LSI-R score, LSI-R score and its interaction effects with time (year case was closed), Concentrated Disadvantage, Violent Crime Rate, Probation Rate, Entropy Index, and Residential Stability. The results of this model are indicated in Table 4.23.

Table 4.23

Summary of Multilevel Modeling Results: Generalized Linear Mixed Models

Predictor	B	SE B	T	Odd Ratio
Individual- Level Characteristics				
LSI-R Score	0.02 **	0.002	89.07	1.02
Gender (Male)	-0.40 **	0.04	122.41	0.67
Race/ Ethnicity (White)				
Other	-0.05	0.17	-0.30	0.68
African American	0.37 **	0.06	6.31	1.44
Hispanic	-0.19 **	0.06	-3.23	0.83
Age	-0.03 **	0.001	450.27	0.98
Neighborhood-Level Characteristics				
Violent Crime Rate	-0.002	0.003	0.39	0.99
Residential Stability	-0.02	0.02	1.21	0.98
Concentrated Disadvantage	0.11	0.03	16.07	1.11
Racial/ Ethnic Diversity	-0.06 *	0.05	1.53	0.95
Probation Rate	0.03**	0.005	33.24	1.03

*p < 0.05, **p < 0.001

To summarize the results indicated in the table, all individual-level characteristics, the probation rate, and entropy index are statistically significant predictors of one's probation outcome. When combined in a multi-level model, all neighborhood-level predictors lose statistical significance with the exception of the probation rate and neighborhood racial/ethnic diversity.

The probationer's age at time of disposition is a statistically significant predictor of their probation outcome. The odds of presenting a negative discharge event decrease 2% with each year that the probationer ages. Female probationers have 33% lower odds of presenting a negative discharge event when compared to men. When compared to white probationers, African American probationers are more likely to present a negative discharge event. Their risk of presenting a negative discharge event is 43% greater than white probationers, holding all other individual- and community-level characteristics constant. Hispanic probationers, however, are less likely to present a negative discharge event when compared to white probationers. Their comparative risk of presenting a negative discharge event is 17% less than white probationers. Probationers with higher LSI-R scores have an increased risk of presenting a negative discharge event. For each one-point increase in LSI-R score, the probationer's odds of presenting a negative discharge event increase by 4%.

The only neighborhood-level variables that are statistically significant predictors of a negative discharge event are the probation rate and neighborhood racial/ethnic diversity. A one-unit increase in the entropy index (an increase in neighborhood racial/ethnic diversity) decreases the odds of a negative discharge event by 5%. Similarly, an increase in the level of the probation rate (number of probationers per 1,000 adults) at the neighborhood level is associated with an increase in the odds of a negative discharge event for the individual probationer. In other words, probationers who live in areas where they are surrounded by many other probationers are at increased risk of a negative case outcome. Every additional probationer per 1,000 neighborhood residents is associated with a 3% increase in odds of a negative discharge event.

An alternative way to interpret these models is to compare the amount of variance observed in clustering effects that is explained by examining only individual-level characteristics versus individual- and community-level characteristics. Appendix I contains a table comparing individual versus individual- and community-level characteristics in a multilevel model. Comparing the random effects covariance estimates in the model shows that 7.5% of the variance in observed case outcomes among probationers in the sample is accounted for by community characteristics. It is important to note that this comparison accounts for a small proportion of variance in probation outcomes in the analytic sample; it is an examination of what proportion of 6.24% (ICC value) is accounted for by individual-level predictors versus community-level predictors. To corroborate this finding, the predicted case outcome for each probationer using this final model was compared to the observed case outcome of the study sample. The model improved the predictions of individual case outcomes by just 0.9%.

In order to estimate the proportion of variance that is explained in this final model, a measure of R^2 appropriate for multilevel modeling with a binary outcome was estimated. This estimate is represented by the following equation (Snijders & Bosker, 1999).

$$R^2_{\text{binary}} = \frac{\sigma_F^2}{\sigma_F^2 + \tau^2 + \pi^2/3}$$

In this equation, σ^2_F is the sample variance indicated by the linear predictors, τ^2 is the variance of the random intercept in multilevel model, and $\pi^2/3$ is assumed as the level one residual variance measure. R^2 estimates were calculated for a multilevel model with individual-level predictors. The R^2 estimate for a multilevel model with individual-level predictors only is 5.89%. When community-level predictors are added, the R^2 estimate only increases by half a percentage point to 6.43%. The vast majority of variance in probation outcomes for the study sample is accounted for by predictors that are not included in the model, and therefore, the interpretation of the results indicated in the final model should be evaluated with this limitation in mind.

Summary of key findings.

The key findings from this set of analyses are as follows:

1. Neighborhood clustering accounts for 6.24% of variance observed in probation outcomes among probationers between 2011 and 2016.
2. In a multilevel model accounting for this small amount of clustering, individual-level characteristics of the probationer account for the majority of the variability explained in the outcome measure.
3. The only neighborhood-level characteristic that is a statistically significant predictor ($p < 0.001$) of a probationer's case outcome is the level of the probation rate experienced within their neighborhood
4. The individual- and neighborhood-level variables included in the final model account for only 6.43% of variance observed in case outcomes among probationers in the data sample.

CHAPTER 5: DISCUSSION SECTION

The Spatial Logic of Probation in Chicago

Findings of the current study reveal that probation rates are unequally distributed across neighborhoods in Chicago. While probationers can be found in nearly every neighborhood in the city, certain neighborhoods are disproportionately burdened with probation supervision. There are areas of the city, concentrated on the west and south side of Chicago, where as many as 250 probationers in a single year reside within a quarter-mile or two-block radius.

The spatial patterns observed are stable over time and are not random. Probationers predictably reside in certain geographic areas of the city, and the areas of high concentration do not change over time. As indicated in Appendix C, the number of closed cases per year from 2011 to 2016 gradually decreased from 6,031 to 5,210. Thus, the areas of high concentration remain so even while the total number of closed cases per year is declining. One could therefore conclude that there is a certain spatial logic of probation in Chicago; probation supervision is a durable local institution in particular neighborhoods.

The patterns of spatial concentration of probation observed parallel spatial observations made of crime, incarceration, and parole. Neighborhoods that are disproportionately burdened with violent crime, incarceration, and parole supervision are also impacted by high levels of probation supervision (Lugalia-Hollon & Cooper, 2018; Sampson & Loeffler, 2010; La Vigne, 2004). Probation supervision, however, covers a broader geographic area in Chicago. Whereas incarceration and prisoner reentry are relatively nonexistent within middle- to upper-class neighborhoods with low concentrations of minority residents, probation supervision also occurs in these neighborhoods. However, probation is considerably more diluted in such neighborhoods when compared with poor, minority neighborhoods in Chicago. The spatial overlap of crime, probation, incarceration, and parole supervision indicates a redundancy of criminal justice contact within specific neighborhoods in Chicago.

The communities with the highest concentration of probation supervision have the highest rates of neighborhood segregation and highest rates of violent crime. Probationers are typically from African American communities with high rates of concentrated disadvantage—a trend that is similarly observed when dissecting the demographics of victims of violent crime, incarcerated subjects, and parolee populations. This finding deviates from both state and national trends observed in terms of probation demographics. In Illinois, 53% of the probation population is non-Hispanic white, 31% is African American, and 13% is Hispanic. Nationally, 43% of the probation population is non-Hispanic white, 38% is African American, and 17% is Hispanic.

The racial and ethnic disparities observed at various points in the criminal justice system are similarly observed among probation populations in Chicago. This finding bears potentially grave consequences keeping in mind that probationers are the largest criminal justice population, and a negative discharge on probation can increase the risk of jail or prison time. Thus, probation could be a mechanism, among many others, that accounts for the disproportionate burden of incarceration experienced within African American communities. For example, one multisite study indicates that black probationers have higher revocation rates than white and Hispanic probationers, and these observations were made after controlling for nonracial and nonethnic characteristics (such as age, gender, risk score, criminal history, etc.) (Janetta, 2014).

Correctional Boundaries: The Impact of Spatially Concentrated Probation on Chicago Neighborhoods

The spatial clustering of probationers observed between 2010 and 2016 in Chicago is not trivial. The impact of probation supervision extends beyond the individual probationer; the “boundaries” of the sanction imposed encompass entire neighborhoods. This claim may seem exaggerated considering that in the most highly impacted neighborhoods, no more than 2 to 3% of the adult population is under probation supervision during a given year. The numbers seem low, but the results of these analyses suggest that high-concentration neighborhoods remain so over time. Therefore, 2 to 3% of the population in one year becomes 12 to 18% within a six-year time frame in the same community. However, the areas with the highest rates of probation supervision exhibit varying rates of residential stability (see Figure 4.16). The cumulative estimation of 12–18% assumes high rates of residential stability. Operating under this assumption, as the proportion of neighborhood residents who have experienced probation supervision over time grows, it becomes clearer how spatially concentrated probation can affect neighborhood rates of concentrated disadvantage and violent crime over time.

Neighborhood probation supervision rates were found to be related to an increase in concentrated disadvantage and violent crime over time. Future studies should be conducted to understand the potential mechanisms related to these trends. Several possible factors may be at play. For example, probation often is associated with financial burdens, including supervision fines and/or victim restitution, and, in some cases, fees associated with behavioral health treatment, such as substance abuse counseling or domestic violence counseling. These costs may be difficult to pay, depending on the employment status of the probationer. Family members and friends might also be burdened with these costs if the probationer is marginally employed or unemployed. In addition, probation status and criminal histories may impede one’s ability to sustain gainful employment, thus contributing to disadvantage. Compliance with probation sanctions, such as drug treatment and community service hours, could also limit access to job opportunities. The probationer is required to explain at some point in the hiring process that they are under supervision and are, therefore, mandated to participate in various activities that could impact their work availability. There exists an extensive body of research which shows that criminal justice contact negatively impacts one's economic opportunities (Sampson & Laub, 1993; Western, 2002; Pager, 2003; Pager, 2008).

The longitudinal relationship between neighborhood probation rates and violent crime may seem contradictory given the purpose of probation supervision, which is to maintain public safety. The association of probation rates with an increased level of violent crime, however, parallels findings from studies examining neighborhood incarceration rates and crime (Fagan, West, & Holland, 2003; Renauer et al., 2006; Clear, 2009). Clear's coercive mobility hypothesis posits that spatially concentrated incarceration may be a disorganizing factor within neighborhoods, reduce social cohesion and increase social isolation, and decrease informal social control mechanisms. The findings from this study suggest that spatially concentrated probation may similarly contribute to neighborhood disorganization, resulting in more crime, not less. Additional analyses are needed to further examine the longitudinal relationship between neighborhood probation rates and violent crime.

Findings also provide an account of how the ecological characteristics of a neighborhood (e.g., concentrated disadvantage, violent crime, and diversity measures) influence the rate of probation supervision observed. The predictive power of concentrated disadvantage and violent crime aligns with previous scholarship examining the social ecological dynamics of urban ghettos. The social experience of concentrated disadvantage is associated with weak informal social control mechanisms (such as collective efficacy) and increased reliance on formal social control agents (such as a law enforcement) to provide public safety to neighborhood residents. Therefore, it makes sense that violent crime and poverty are predictors of the imposition of a formal social control mechanism such as probation supervision. This study provides evidence, however, that probation as a crime control strategy may be ineffective and, in fact, exacerbates the social conditions correlated with crime. Neighborhood diversity as a predictor of reduced probation rates contradicts findings of previous studies based on social disorganization theory, which posits that homogeneity is associated with lower levels of social disorganization.

Reciprocal dynamics were observed between violent crime rates and concentrated disadvantage. This may indicate that probation supervision is not only a response to crime but also an endogenous component of a neighborhood's ecology that elevates crime levels. The bidirectionality between concentrated disadvantage and violent crime suggests that their relationship with neighborhood probation rates is self-sustaining and reinforcing. Concentrated disadvantage predicts an increase in probation rates within a neighborhood, and increased probation rates predict an increase in concentrated disadvantage over time. The stability of neighborhood levels of concentrated disadvantage and violent crime observed within this study suggests that this self-reinforcing cycle is sustained over time. Fagan and colleagues (2003) conducted one of the few studies examining reciprocal dynamics between criminal justice interventions and neighborhood ecologies over time. Their study examined five waves of data between 1985 and 1997 and found that each prison admission increased the likelihood of a felony crime complaint within the same police precinct by a factor of nearly two, with reciprocal effects. The current study examines reciprocal effects over a more recent time frame, examining consecutive years at the more granular level of census tract, laying a foundation for further research into how criminal justice interventions may become endogenous to neighborhood ecologies over time and contribute to self-reinforcing cycles that perpetuate disadvantage and marginalization.

The final set of analyses examined neighborhood-level predictors of probation supervision rates over time in predominantly African American and white neighborhoods. Results indicated that there are significant differences between African American and white neighborhoods with regard to the longitudinal relationships between concentrated disadvantage and probation rate and between violent crime rate and probation rate. In predominantly white neighborhoods, probation rate predicts an increase in concentrated disadvantage over time. However, neighborhood rates of concentrated disadvantage are not predictive of any changes in probation rate over time. In predominantly African American neighborhoods, reciprocal effects are observed, with concentrated disadvantage predicting an increase in probation rate over time, and vice versa. The relationship that is responsible for the significant difference between African American and white neighborhoods is the measure of concentrated disadvantage in 2011 and its influence on probation rate in 2016. These findings indicate that poverty is differentially associated with probation between the two neighborhood groupings.

When examining violent crime, neither cross-lagged path was statistically significant in predominantly white neighborhoods. In predominantly African American neighborhoods, violent crime in 2011 was a significant predictor of an increase in probation rates in 2016. However, the probation rate in 2011 did not predict a change in concentrated disadvantage in 2016. These observations are especially interesting considering that reciprocal dynamics were observed when examining all neighborhoods in an aggregate fashion. Satorra-Bentler Chi-Square difference tests indicated that both cross-lagged paths contributed to the significant differences observed between the two sets of neighborhoods. An interpretation of this finding is that violent crime rate predicts an increase in the criminal justice response of probation within African American neighborhoods, but this does not hold true in predominantly white neighborhoods. Furthermore, probation rate is not predictive of changes in violent crime in either set of neighborhoods. The implications of spatially concentrated probation, as they pertain to public safety, do not appear to describe the longitudinal relationship between these variables in predominantly African American and white neighborhoods. The theoretical implications later discussed, then, do not apply to these neighborhood groupings but rather reference the aggregate trends observed.

Punishment in Community: Understanding Probation Outcomes in Context

Results indicate there is a very small, statistically significant nonzero association between individual probation outcomes and neighborhood probation rates (while holding constant all individual-level predictors). The following discussion centers on the evidence of probation rate as a community-level predictor associated with a negative case outcome. Proximity to other probationers could have a cascading effect; i.e., the more probationers within a neighborhood, the greater the risk of a negative discharge event.

There are several hypothesized mechanisms underlying the association between the probation rate and individual case outcomes. The spatial concentration of probationers within a neighborhood may be indicative of heightened levels of surveillance by both probation officers and police officers. More law enforcement resources are deployed in areas with elevated levels of violent crime or high concentrations of justice-involved individuals. Heightened levels of surveillance can lead to an increased likelihood of being arrested for misconduct, which may lead to a negative discharge from probation. Alternatively, the spatial concentration of probationers may exhaust local support services necessary for complying to court-ordered sanctions. For example, long waiting lists to receive substance abuse treatment may mean that addictions go untreated and place the individual probationer at greater risk of having a negative urinalysis test, providing grounds for an unsatisfactory discharge or revocation. The spatial concentration of probationers may also be indicative of a clustering of criminal networks. Probationers in these areas have more opportunities to interact with potentially antisocial peers, thus elevating their risk for misconduct or noncompliance while under supervision.

Implications and Future Research

Implications for Theory

Social disorganization theory provides the foundation for the analyses of the current study's findings. This theory has been criticized as race-neutral and dismissive of the oppressive structural dynamics of institutionalized racism that lead to the concentration of disadvantage in predominantly African American neighborhoods. In this study, probation trends were analyzed in an aggregate manner, examining entire cohorts and the entire city. The analyses associated with neighborhood-level predictors of probation rate, however, suggested that the racial composition of neighborhoods matters when accounting for the clustering of probationers within specific places. Furthermore, the aggregate level trends do not adequately describe the ecological dynamics of probation supervision within predominantly white and predominantly African American neighborhoods.

The differential experience of minority communities and their contact with the criminal justice system is apparent from the analyses examining race-specific variations. Given that two thirds of the analytic sample identified as African American, the findings from this study suggest that a theoretical orientation that explicitly accounts for race when examining crime and place is necessary. For example, in a critique of more than a century of gang research based on social disorganization theory, Hagedorn (2006) stated, "Chicago gangs have been influenced by deep seated racism, racial politics, real estate speculation, segregation, police brutality, and white supremacist terrorism" (p. 194). This "racial blind spot" in place-based theories (such as social disorganization theory) has been criticized for incorrectly diagnosing why certain social ills are concentrated in particular places. Both historical research and recent analyses indicate the centrality of race and racial discrimination, along with large economic shifts in the economy, as factors that have shaped the structure of communities in large Rust Belt cities such as Chicago, Milwaukee, Detroit, and Cleveland, and the life chances and outcomes of low-income minorities, especially the African American poor in “African American ghettos” (Drake & Cayton, 1945; Massey & Denton, 1993; Wilson, 2012). In a post-mass-incarceration era where probation populations may continue to grow, it is necessary to explicitly acknowledge racial disparities and how criminal justice interventions entrench existing disadvantage in already marginalized communities.

Two neighborhood variables frequently used in studies referencing a social disorganization theoretical framework do not coincide with the trends observed in studies conducted by Chicago School sociologists. In this study, residential stability was not a statistically significant predictor of the probation rate over time. Furthermore, neighborhood racial and ethnic heterogeneity were predictive of lower levels of probation rate, not higher as might be presumed from previous research drawing from social disorganization theory. Originally Chicago School sociologists hypothesized that increased diversity within neighborhoods would weaken social ties, prevent social cohesion, and inhibit informal social control. Lower levels of diversity are associated with high rates of probation in this study, suggesting that there are race-specific dynamics associated with the concentration of probationers in predominantly African American neighborhoods.

This study provides one additional insight into future directions for testing social disorganization theory. In Clear and Rose’s (2003) initial test of the coercive mobility hypothesis, they stated that their experiment was the first time that a criminal justice intervention was conceptualized as an antecedent of crime, not just a response to it. Probation supervision rates were found to predict an increase in concentrated disadvantage and violent crime in the Chicago context between 2011 and 2016. These findings build on Clear and Rose's work by suggesting that spatially concentrated probation supervision should also be considered as an ecological dynamic that contributes to social disorganization, rather than acting as a resolution to the issue. When considering that probationers are most heavily concentrated in neighborhoods with high rates of incarceration and parole supervision in Chicago—and that these neighborhoods have persistently high rates of violent crime—these findings indicate that expanding formal social control responses to crime as a means of supplementing weakened informal social control systems does not work.

Implications for Practice

Implications for probation practice.

Based on trends over the past four decades, probation populations are expected to continue to grow in Cook County and the state of Illinois. This growth is occurring at a time when the State is experiencing a budget crisis, and there are multiple competing demands for public safety funds among local governments. The findings from this study highlight locations of need for probation-related services and can be used to inform probation departments about how to most efficiently utilize resources to manage caseloads and allocate service contracts for maximal impact. Currently, probation caseloads are organized primarily according to risk level assigned by validated risk assessment tools. Service contracts are disbursed to applicant organizations without consideration of their geographic location within the city. Although a place-oriented approach to probation has previously been suggested, few such models exist, and few technical evaluations of such practice have been conducted. One model that is in place and has been evaluated is the Proactive Community Supervision (PCS) Model, developed by the Maryland Department of Probation and Parole. This community-centered approach to probation practice was found to reduce probation noncompliance, and probationers participating in the PCS model were 38.3% less likely to be rearrested for a new crime (Taxman et al., 2006). Two elements of PCS make it unique: its emphasis on “behavioral management” focusing on changing antisocial attitudes and its place-based approach to supervision. Probation officers are trained to work actively with supervisees in community-based settings and to coordinate referrals and linkages among social service agencies in particular neighborhoods.

Some have argued that these types of programs have not gained more traction because of a lack of available data to inform local practice. A place-oriented approach necessitates using available data to determine where probationers are clustered. These findings from this study clearly describe where probationers are and have been clustered. The analyses conducted here can and should be replicated throughout Illinois’ circuit-court-based system of probation, given the potential to improve outcomes among a substantial amount of the state’s criminal justice population. A place-oriented approach to probation, however, may not resolve the issues facing departments across the country. It is possible that concentrated probation services in a specific area may increase the likelihood of noncompliance detection and therefore increase the rates of negative discharge. If a place-oriented approach to probation is implemented, it must include training that reorients officers to the community justice mission of community corrections. Such training assumes a more expansive role of the officer that involves a holistic concern for the quality of life of all neighborhood residents (Clear, 2005). A probation officer operating under such a professional framework would, hypothetically, consider it a responsibility to participate in various community-building activities, such as local coalitions around public safety, neighborhood clean-ups, and block parties.

Implications for social work practice.

Smart decarceration is one of the “grand challenges” identified by the American Academy for Social Work and Social Welfare (Uehara et al., 2013). The goal of smart decarceration is to conduct and use research to transform the criminal justice system and reduce jail and prison populations. One of the primary strategies listed under this initiative is to “identify a continuum of viable exit strategies from the criminal justice system,” a strategy that implicates probation (Pettus-Davis & Epperson, 2015, p.6). Many states, including Illinois, are attempting to reduce prison populations by expanding the number of offenses eligible for probation supervision. The findings from this study, however, suggest that expanding probation, without careful examination of how, where, and with what services, may further disadvantage neighborhoods that already have high concentrations of probationers and negative discharge rates that hover around 50%.

Second, many social workers are likely situated in agencies that are in areas with high concentrations of probationers. These agencies may offer services that could benefit the probation population, yet no existing linkage agreements or referral mechanisms exist. As previously stated, probation is an “invisible” institution: Most officers wear plain clothes, do not have community-based offices, and have caseloads spanning wide geographic areas, making it difficult to engage local community stakeholders. The findings from this study can inform potential collaborations between existing community social service agencies and the Adult Probation Department of Cook County with the ultimate goal of improving outcomes for individuals under probation supervision. The potential benefits of such collaboration should not be overlooked given the chronic challenges most probation departments face in adequately supervising a large number of individuals with very limited resources.

Limitations of the Study

The current study has several limitations. The data used to measure neighborhood-level characteristics were drawn from census and other administrative data that only allow for measurement of structural characteristics of the neighborhood. No measures of neighborhood social organization (e.g., informal social control, collective efficacy) are available that coincide with the dates of the data used in this study.

Furthermore, these analyses did not consider law enforcement activities. Data from previous studies (i.e., Peterson & Krivo, 2010; The Sentencing Project, 2000) highlight the variation of policing activities that occur in different neighborhoods within the city. These same studies highlight disproportionate rates of arrest, particularly for African American men (Justice & Meares, 2014). As noted earlier, it is possible that probation outcomes are impacted by greater surveillance and increased likelihood of arrest. For example, race was a significant predictor of a negative discharge event among probationers in this study's sample; African American probationers have a 43% greater likelihood of a negative discharge event when compared to white probationers with similar characteristics. This estimate, however, may reflect differences in policing within predominantly African American neighborhoods or racial bias in arrest patterns. Future studies should be conducted to address these questions.

Finally, there are several variables that may be associated with the spatial concentration of probation in addition to an individual's probation outcomes. The Circuit Court of Cook County has approximately 400 judges across ten court divisions and six geographic districts. A presiding judge is assigned to each division and district. Each judge has discretionary power in how they apply existing law to the processing of a particular dispute. Appendix K lists nonprobationable offenses according to Illinois Statute 730CS 5/5-5-3(c). All offenses not listed are eligible for a probation sentence. In court, each judge has discretionary power with regard to how to sanction individuals who have committed crimes eligible for probation. Two different judges may make different decisions for the same case: One might sanction probation; another might sanction a jail sentence. It is beyond the scope of the current study to examine the role of judicial discretion in the frequency of probation sentencing and how this might be related to the spatial distribution of probation within Cook County. To measure judicial discretion and probation sentencing in Cook County would require an analysis of court documents, federal sentencing guidelines, and state sentencing guidelines.

Apart from the role of judicial discretion, there are various other features of local probation departments that may be associated with probation trends. Cook County has several different probation districts and specialized programs spanning districts. Previous research confirms that the structure of local probation departments, the degree to which they implement evidence-based practices, and their caseload size all are associated with the outcomes of individuals under supervision (Clear & Karp, 2002; Garland, 2001; Taxman, 2002, 2008). This study does not control for various probation variables (for example, caseload size) due to data limitations.

Future Research

This study provides a first set of findings regarding the distribution of the probation population over time within a large metropolitan area. These findings make clear that probationers are not randomly distributed across the city. Rather, probationers are clustered in poor African American neighborhoods that are also characterized by high rates of violent crime.

These findings suggest that neighborhood-level dynamics account for the spatial patterns observed. The analyses in this study also focused on the probation population in the aggregate. Future research should be conducted to understand potential differences in findings for different populations of probationers. Disaggregating the probation population by age, gender, race/ethnicity, offense category, or supervision level may provide for interesting subsequent analyses.

Most probation departments across the country use risk assessments such as the LSI-R to determine supervision levels and make case assignments. These risk assessments include scales that assess for criminal propensity based on antisocial thinking and association with antisocial peers, among other variables. However, these individual-level characteristics may be heavily conditioned based on one's environment. Research suggests that living in a neighborhood with high levels of exposure to community violence is associated with greater risk of antisocial thinking and associating with antisocial peers. Future research should examine the relation of LSI-R scores and neighborhood of residence. Such research is of great importance to probation departments within the state of Illinois, as their mission is to promote public safety while effectively reducing the risk of the offender population. Understanding behaviors within context and how they are evaluated using risk assessments would lend additional insight into the role of neighborhood context and one's probation experience.

Given that the findings in this study were limited in their ability to evaluate the extent to which community context is predictive of individual probation outcomes, it is recommended that additional research be conducted to examine the association between neighborhood context and probation experience. The current study reveals that among all individuals within the criminal justice system, probationers are the most likely to be influenced by neighborhood structure.

Future research should be conducted to examine the range and variation of outcomes, such as the number of arrests that occur during probation supervision or postsupervision period.

Conclusion

This study examines the effect of probationers on neighborhoods in addition to the effects neighborhoods may have on probationers. The study sample is drawn from one of the largest probation departments in the country, with data spanning a six-year time frame. These results contribute to empirical knowledge by constructing and examining a unique set of data over time from one of the largest probation departments in the United States. The results may not generalize to smaller departments in nonurban settings.

The evidence that spatially concentrated probation can affect neighborhoods is important and suggests that nuanced and innovative approaches to probation practice are necessary. Beyond probation practice, however, neighborhood residents, community development corporations, local activists, and neighborhood business sectors must consider the implications of spatially concentrated criminal justice interventions as they consider holistic neighborhood development. The study provides a foundation for further exploration into community investment as a decarceration strategy. It is possible that community development work could lead to a reduction in probation populations while simultaneously improving the outcomes of those on active caseloads. At the very minimum, this study provides a beginning point for understanding the invisible institution of probation’s tangible effect on neighborhoods.

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Appendix A

Research Collaborative Benefits Agreement

MEMORANDUM

TO: CHIEF JUDGE TIMOTHY EVANS
FROM: KATHRYN BOCANEGRA
SUBJECT: DATA REQUEST AND DATA PROTECTION
DATE: JULY 31, 2017
CC: PETER COOLSEN, JORDAN BOULGER, EILEEN HEISLER, STEPHEN BRANDT

Per our meeting on Thursday July 27th, 2017 the following research collaboration was discussed and approved of.

Research Goals:

1. Measure the degree of geographic/spatial concentration among adults supervised by the Cook County Adult Probation and Social Service Departments.
2. Evaluate the influence of community characteristics (e.g., poverty, resource availability, crime) on supervision outcomes
3. Evaluate the concentration/spatial concentration of supervised adults receiving supervision services relative to available community-based services

Data Request:
All individuals under the supervision of the Cook County Adult Probation Department (including Case Management) whose cases were closed between 2006–2016 will be examined. The case-specific information will include:

- Basic Demographic Information: name, date of birth, race, ethnicity, gender
- Illinois State Police-issued State Identification Number (SID)
- Probation case number
- All residential addresses reported while under supervision
- Date sentenced to probation
- Date discharged from probation
- Reason for discharge from probation
- Conditions of probation (including court-ordered fees, fines, community service, treatment, etc.)
- Compliance with court-ordered conditions.
- LSI-R risk level

In addition to the case-level information, information regarding the name and location of community-based service providers that work in collaboration with the Probation and Social Service Departments.

Data Protection:
The following data protection measures will be implemented to ensure utmost respect and confidentiality for the research subjects. The protocol outlined below has been previously approved by the Criminal Court Division for research conducted by Dr. David Olson and Dr. Matthew Epperson.

- No direct contact with subjects will be made.
- All data collected for this project will be extracted from existing information systems (PROMIS) that contain data on the research subjects already collected during the normal processing of individuals through probation and the justice system.
- Institutional Review Board approval and protection from the University of Chicago
- Data file will be stored on a password protected, encrypted disk on a password protected computer at the University of Chicago on a secure, encrypted server
- Only individuals on the research team (listed below) will have access to the data and will be held to ethical standards according to the Institutional Review Board
- The research will in no way affect the rights or welfare of the participants as they will not be contacted for purposes of research

Research Team:
Kathryn Bocanegra, third year doctoral student at the University of Chicago's School of Social Service Administration, will lead data analysis. Her research team includes:

- Dr. Deborah Gorman Smith: Dean, University of Chicago School of Social Service Administration, Dr. David Olson, Criminology, Loyola University, Dr. Matthew Epperson, School of Social Service Administration, University of Chicago, Jordan Boulger, Research Director, Adult Probation Department

If there are any questions regarding the proposed data request my contact information is:

Kathryn Bocanegra
Kathryn.Bocanegra@gmail.com
847-347-3828

Appendix B

Data Sharing Court Order

State of Illinois
Circuit Court of Cook County

Timothy C. Evans
Chief Judge

50 West Washington Street
Suite 2600
Richard J. Daley Center
Chicago, Illinois 60602
(312) 603-6000
Fax (312) 603-5366
TTY (312) 603-6673

November 7, 2017

RE: Spatial Analysis of Probation in Cook County (Protocol #17-003)

Dear Mr. Lyons:

Please be advised that on Thursday, July 27, 2017, I approved the release of case-level, identified probation data to Kathryn Bocanegra for her doctoral dissertation following a meeting attended by Peter Coolsen, Jordan Boulger, Dr. Matthew Epperson, and Dr. David Olson. Unfortunately, you were not able to attend.

The proposal was reviewed and approved by the University of Chicago Individual Review Board (IRB), but I understand that the Court's IRB requested changes to which Mrs. Bocanegra and her advisors have agreed.

Pursuant to that meeting and your requirements, please consider this letter confirmation of my approval of her proposal. This letter should be deemed an order of the court, as required by 730 ILCS 110/12, for the release of the case-specific probation data requested in the following form:

1. data for all closed probation cases from 2006 to 2016 in de-identified format (no name or date of birth):
2. Address aggregated to block level
3. age in years relative to December 31, 2016
4. race, gender, ethnicity
5. conviction status
6. date sentenced to probation
7. date discharged from probation
8. reason for discharge from probation
9. conditions of probation

10.compliance with court-ordered conditions

11. LSI-R aggregate score

In addition to the case-specific data, the names and addresses of providers for social service contracts will be shared.

Please inform me immediately if the IRB has any further issues, so they can be resolved prior to your next meeting.

Sincerely,

Timothy C. Evans
Chief Judge

TCE:sb

Appendix C

Flowchart of Analytic Sample

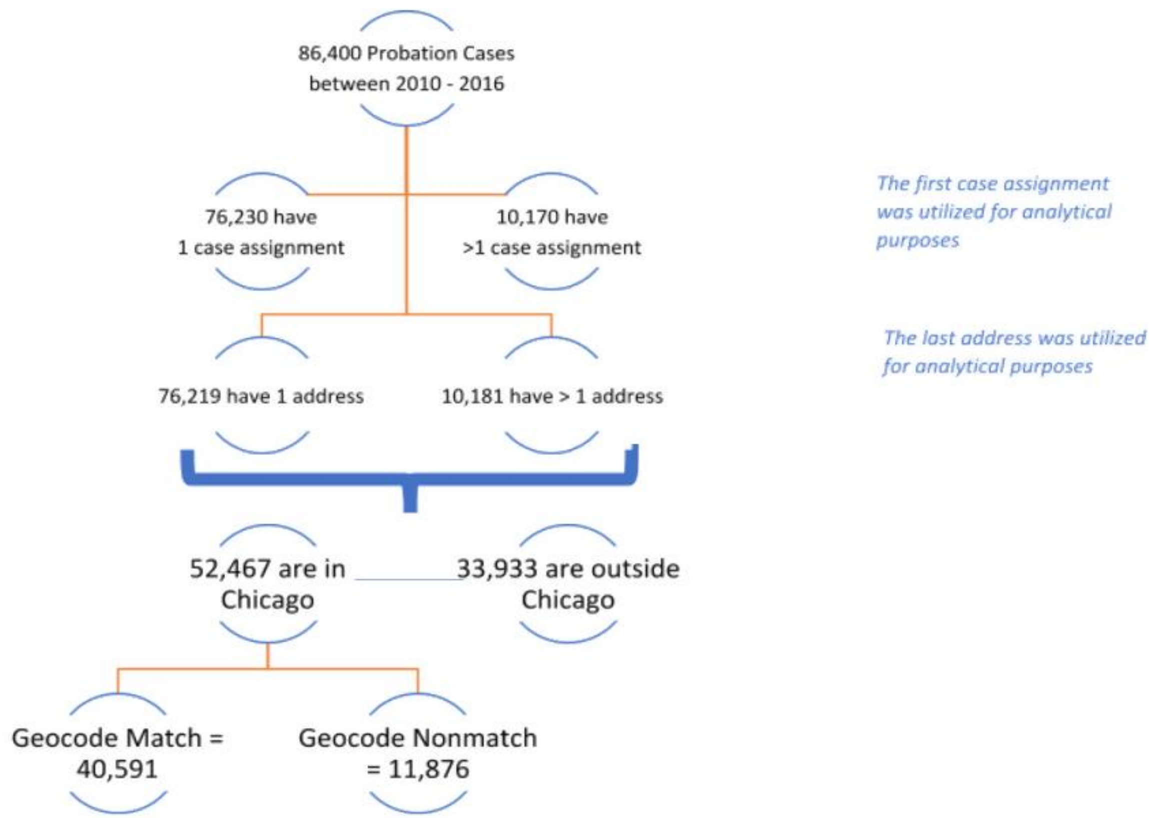

Figure C1. *Flowchart of analytic sample.*

Table C1

Number of Closed Cases Per Year in Analytic Sample

Year	Number of Closed Cases
2010	6,031
2011	6,084
2012	5,924
2013	5,832
2014	5,851
2015	5,659
2016	5,210
Total	40,591

Appendix D

Comparison Of Populations With Unsatisfactory Discharges Versus Revocations

Table D1

Comparisons of Populations With Unsatisfactory Discharges Versus Revocations

Probation Case Outcome	**First LSIR-Score (Mean, SD)**	**Age in Years at Disposition (Mean, SD)**	**Sex**	**Race / Ethnicity**
Revoked	18.13 (8.91)	29.25 (12.11)	3911 (86.6%) Male 582 (12.9%) Female	359 (8.0%) Other 3506 (77.7%) African American 587 (13.0%) Hispanic 27 (0.60%) White
Unsatisfactory	17.00 (8.65)	29.44 (11.82)	5832 (82.9%) Male 1181 (16.8%) Female	609 (8.7%) Other 5123 (72.9%) African American 1203 (17.1%) Hispanic 48 (0.70%) White

This comparison involves probationers in the analytic sample who had their case revoked and an unsatisfactory discharge. Based on this comparison, probationers who have a revocation versus an unsatisfactory discharge are the same risk categorization (low-medium) and approximately the same average age. The sample of probationers with a revocation includes a slightly larger African American population (6.5 percentage-point difference) and a slightly smaller Hispanic population (31.5 percentage points).

Appendix E

Principle Component Analysis Results
Concentrated Disadvantage and Residential Stability

Table E1

Principle Component Analysis, Residential Stability

	Communalities: Extraction			Total Variance Explained Initial Eigen Values		
Factors	2011	2013	2016	2011	2013	2016
Percent Living in Same Unit 5 Years or Longer	0.83	.80	.70	82.65	80.37	70.23
Percent Owner Occupied Housing Units	0.83	.80	.70	17.35	19.63	29.77

Table E2

Principle Component Analysis, Concentrated Disadvantage

	Communalities: Extraction			Total Variance Explained Initial Eigen Values		
Factors	2011	2013	2016	2011	2013	2016
Percent Owner Occupied Housing Units	.42	.37	.35	65.81	67.77	68.65
Percent Families Below the Poverty level	.79	.84	.86	20.19	19.92	20.69
Percent Female Headed Household	.79	.78	.83	7.37	7.05	5.63
Percent Unemployed	.64	.72	.71	6.63	5.27	5.03

Appendix F

Tests for Skewness and Kurtosis of Neighborhood Variables

Table F1

Tests for Skewness and Kurtosis of Neighborhood Variables

VARIABLE	Minimum Statistic	Maximum Statistic	Mean Statistic	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
ENTROPY INDEX 2010	0	1.38	0.68	-0.29	0.09	-1.3	0.18
ENTROPY INDEX 2011	0	1.38	0.69	-0.33	0.09	-1.3	0.18
ENTROPY INDEX 2012	0	1.38	0.69	-0.33	0.09	-1.3	0.18
ENTROPY INDEX 2013	0	1.36	0.70	-0.36	0.09	-1.25	0.18
ENTROPY INDEX 2014	0	1.37	0.71	-0.38	0.09	-1.22	0.18
ENTROPY INDEX 2015	0	1.37	0.72	-0.39	0.09	-1.21	0.18
ENTROPY INDEX 2016	0	1.37	0.73	-0.42	0.09	-1.17	0.18
PROBATION RATE 2010	0	0.11	0.004	9.09	0.09	158.19	0.18
PROBATION RATE 2011	0	0.023	0.004	1.26	0.09	1.37	0.18
PROBATION RATE 2012	0	0.028	0.004	1.49	0.09	1.99	0.18
PROBATION RATE 2013	0	0.029	0.004	1.57	0.09	2.73	0.18
PROBATION RATE 2014	0	0.027	0.004	1.70	0.09	3.24	0.18
PROBATION RATE 2015	0	0.021	0.004	1.46	0.09	1.82	0.18
PROBATION RATE 2016	0	0.0186	0.004	1.46	0.09	1.88	0.18
RESIDENTIAL STABILITY 2010	-2.37	2.66	0.01	0.39	0.09	-0.40	0.18

(continued)

Table F1 (Continued)

	Minimum Statistic	Maximum Statistic	Mean Statistic	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
RESIDENTIAL STABILITY 2011	-2.28	2.80	0.01	0.47	0.09	-0.35	0.18
RESIDENTIAL STABILITY 2012	-5.48	1.39	-0.49	-0.11	0.09	1.49	0.18
RESIDENTIAL STABILITY 2013	-4.45	1.83	-0.39	0.19	0.09	0.01	0.18
RESIDENTIAL STABILITY 2014	-3.62	1.93	-0.39	0.35	0.09	-0.30	0.18
RESIDENTIAL STABILITY 2015	-4.34	1.66	-0.34	-0.37	0.09	0.31	0.18
RESIDENTIAL STABILITY 2016	-3.86	1.77	-0.36	-0.04	0.09	-0.08	0.18
CONCENTRATED DISADVANTAGE 2010	-1.76	3.75	-0.004	0.74	0.09	0.04	0.18
CONCENTRATED DISADVANTAGE 2011	-1.80	3.25	-0.004	0.64	0.09	-0.20	0.18
CONCENTRATED DISADVANTAGE 2012	-1.17	3.64	0.50	0.66	0.09	-0.22	0.18
CONCENTRATED DISADVANTAGE 2013	-1.42	3.95	0.37	0.69	0.09	-0.15	0.18
CONCENTRATED DISADVANTAGE 2014	-1.37	3.79	0.37	0.68	0.09	-0.16	0.18
CONCENTRATED DISADVANTAGE 2015	-1.47	3.74	0.36	0.67	0.09	-0.19	0.18
CONCENTRATED DISADVANTAGE 2016	-1.40	3.80	0.35	0.71	0.09	-0.09	0.18
CONCENTRATION VIOLENTCRIME 2010	0	0.06	0.007	1.98	0.09	6.38	0.18

(continued)

Table F1 (Continued)

	Minimum Statistic	Maximum Statistic	Mean Statistic	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
CONCENTRATION VIOLENT CRIME 2011	0	0.04	0.007	1.39	0.09	1.59	0.18
CONCENTRATION VIOLENT CRIME 2012	0	0.03	0.006	1.38	0.09	1.43	0.18
CONCENTRATION VIOLENT CRIME 2013	0	0.03	0.005	1.31	0.09	1.0	0.18
CONCENTRATION VIOLENT CRIME 2014	0	0.03	0.005	1.28	0.09	0.86	0.18
CONCENTRATION VIOLENT CRIME 2015	0	0.03	0.006	1.49	0.09	1.80	0.18
CONCENTRATION VIOLENT CRIME 2016	0	0.05	0.007	1.65	0.09	2.84	0.18

Appendix G

Panel Models Including 2010

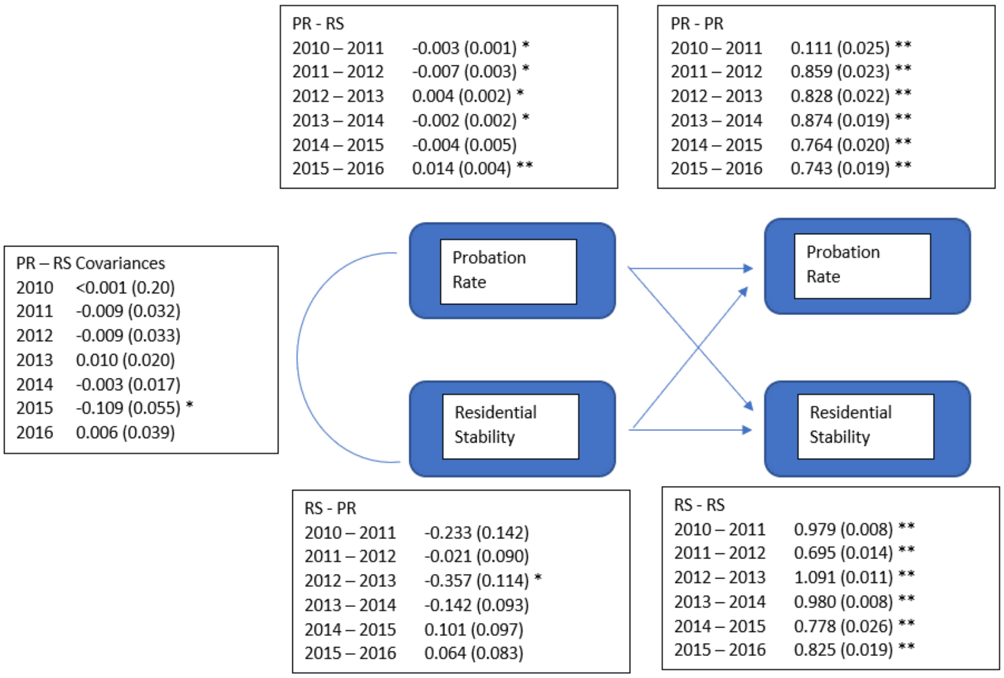

Figure G1. *Unconstrained Model, 2010–2016, Probation Rate and Residential Stability.*

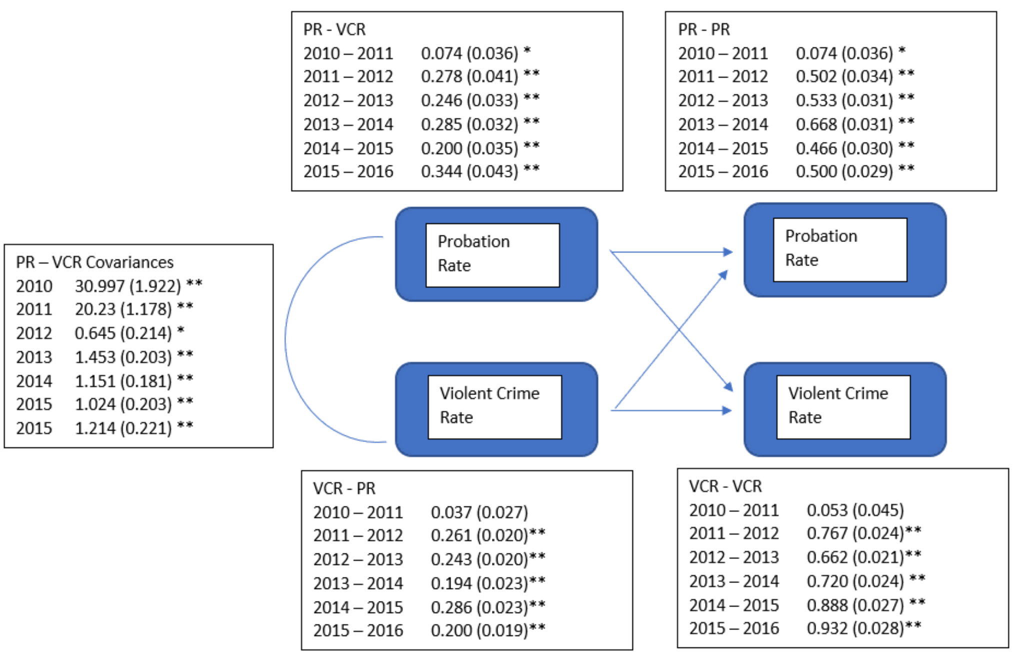

Figure G2. *Unconstrained Model, 2010 – 2016, Probation Rate and Violent Crime Rate.*

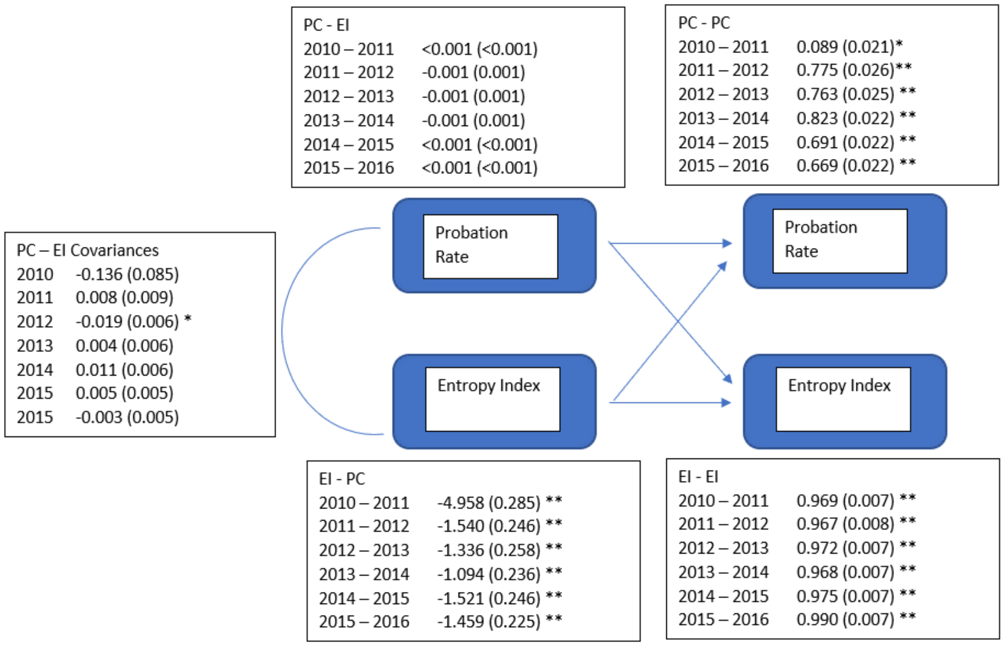

Figure G3. *Unconstrained Model, 2010 – 2016, Probation Rate and Entropy Index*

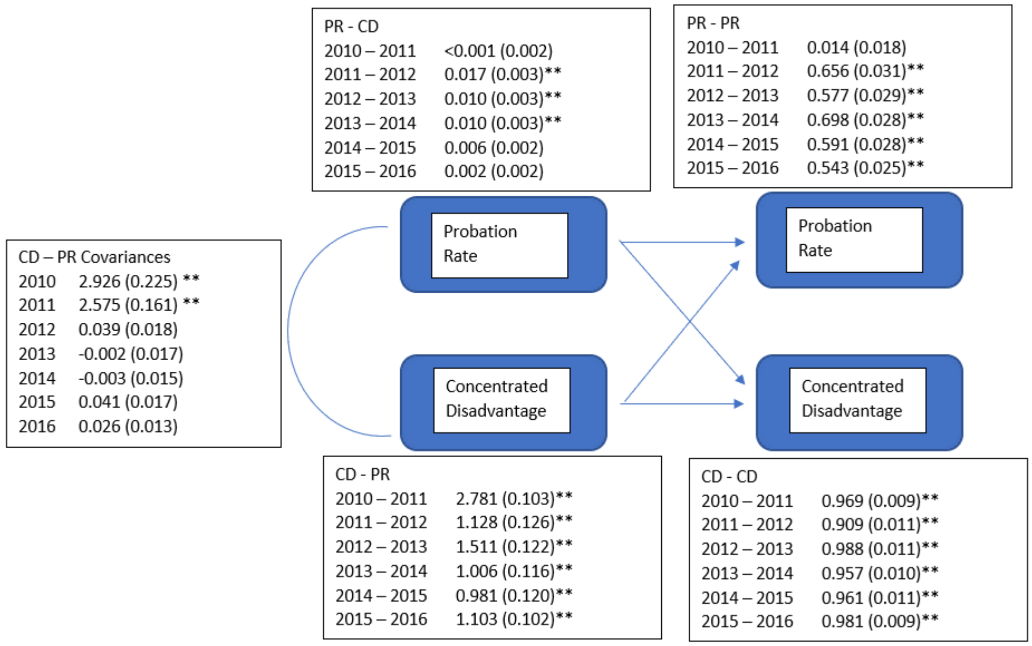

Figure G4. *Unconstrained Model, 2010 – 2016, Probation Rate and Concentrated Disadvantage.*

Appendix H

Constrained Models and Fit Comparison

For all constrained models the 2011 covariances were left unconstrained to account for variance in years preceding 2011.

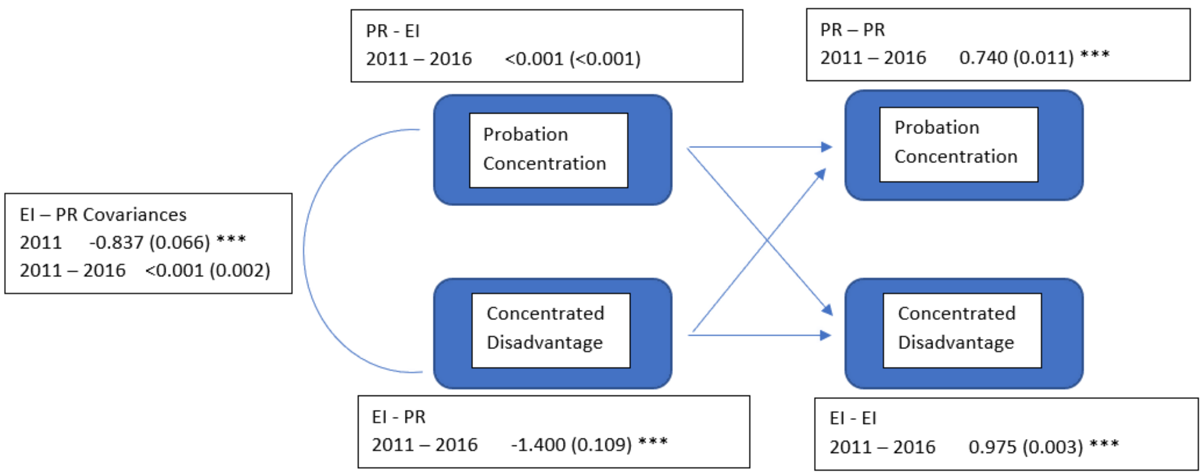

Figure H1. *Constrained model, 2011–2016, entropy index and probation rate.*

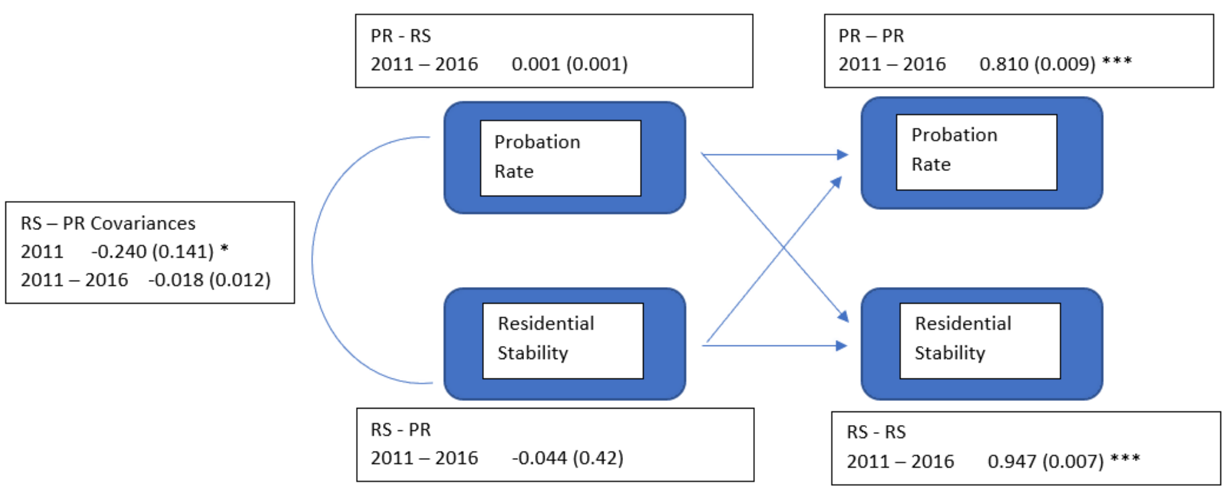

Figure H2. *Constrained model, 2011–2016, residential stability and probation rate.*

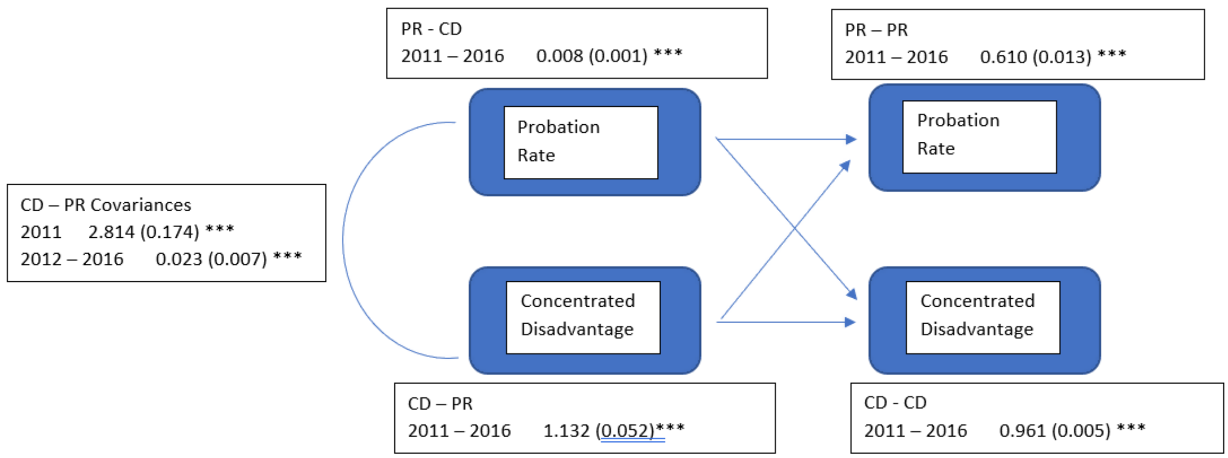

Figure H3. *Constrained model, 2011–-2016, concentrated disadvantage and probation rate.*

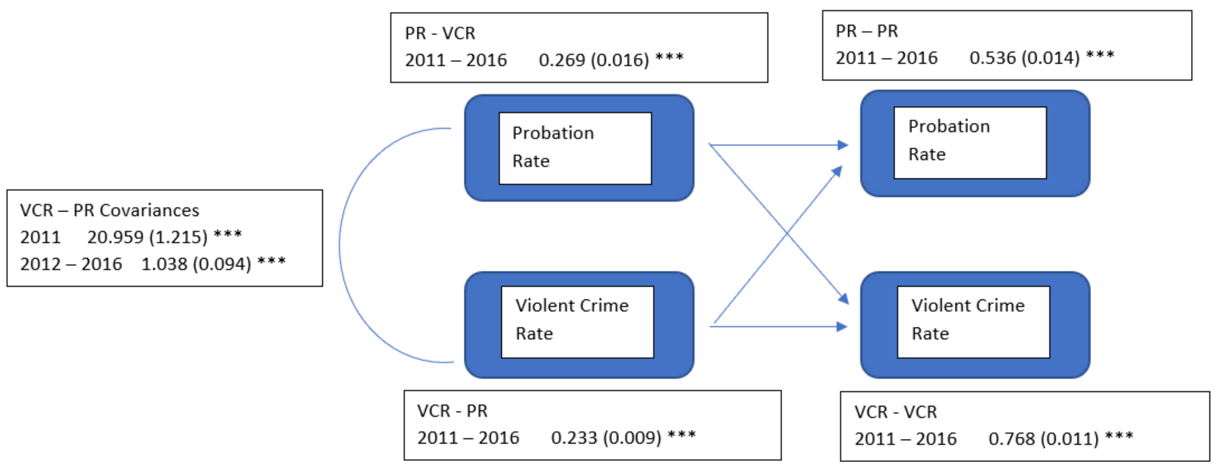

Figure H4. *Constrained model, 2011–2016, violent crime rate and probation rate.*

Table H1

Comparing Model Fit: Concentrated Disadvantage

Measures	Values
With Equality Constraints	
H_o Value	-10556.84
H_1 Value	-10233.17
Number of Free Parameters	30
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	60
Without Equality Constraints	
H_o Value	-10504.48
H_1 Value	-10233.17
Number of Free Parameters	50
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	40
Satorra- Bentler Chi Square Test	
-2LogLikelihood Unconstrained Model (Degrees of Freedom)	21008.96 (40)
-2LogLikelihood Constrained Model (Degrees of Freedom)	21113.68 (60)
Difference	104.72 (20) **

* $p < 0.05$, ** $p < 0.001$

Table H2

Comparing Model Fit: Violent Crime Rate

Measures	Values
With Equality Constraints	
H_o Value	-21558.72
H_1 Value	-20911.81
Number of Free Parameters	30
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	60
Without Equality Constraints	
H_o Value	-21392.77
H_1 Value	-20911.82
Number of Free Parameters	50
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	40
Satorra- Bentler Chi Square Test	
-2LogLikelihood Unconstrained Model (Degrees of Freedom)	42785.54 (40)
-2LogLikelihood Constrained Model (Degrees of Freedom)	43117.43 (60)
Difference	331.89 (20) **

* $p< 0.05$, ** $p < 0.001$

Table H3

Comparing Model Fit: Entropy Index

Measures	Values
With Equality Constraints	
H_o Value	-6073.66
H_1 Value	-5682.72
Number of Free Parameters	30
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	60
Without Equality Constraints	
H_o Value	-6044.05
H_1 Value	-5682.72
Number of Free Parameters	50
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	40
Satorra- Bentler Chi Square Test	
-2LogLikelihood Unconstrained Model (Degrees of Freedom)	12088.10 (40)
-2LogLikelihood Constrained Model (Degrees of Freedom)	12147.31 (60)
Difference	59.21 (20) **

* $p< 0.05$, ** $p < 0.001$

Table H4

Comparing Model Fit: Residential Stability

Measures	Values
With Equality Constraints	
H_o Value	-13501.88
H_1 Value	-12570.44
Number of Free Parameters	30
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	60
Without Equality Constraints	
H_o Value	-13196.58
H_1 Value	-12570.44
Number of Free Parameters	50
Degrees of Freedom (Baseline Model)	65
Degrees of Freedom (Model Fit)	40
Satorra- Bentler Chi Square Test	
-2LogLikelihood Unconstrained Model (Degrees of Freedom)	26391.17 (40)
-2LogLikelihood Constrained Model (Degrees of Freedom)	27003.76 (60)
Difference	612.59 (20) **

* $p< 0.05$, ** $p < 0.001$

Appendix I

Multilevel Model Results

Table I1

Multilevel Model Results:
Comparison of the Amount of Variance in Clustering Accounted for by Individual and Neighborhood-Level Predictors

	Unconditional			Individual			Community		
Variable	B	SE	Exp (B)	B	SE	Exp (B)	B	SE	Exp (B)
Intercept	-0.76 **	0.02	0.47	-1.10 **	0.14	0.29	-1.41 **	0.15	0.25
Individual- Level Factors									
Female				-0.40 **	0.04	0.68	-0.40 **	0.04	0.67
Age				-0.03 **	0.001	0.98	-0.03 **	0.001	0.98
African American				0.46 **	0.05	1.58	0.36 **	0.06	1.43
Hispanic				-0.16 *	0.06	0.86	-0.19 **	0.06	0.83
Other				-0.06	0.17	0.94	-0.04	0.17	0.96
LSI-R Score				0.04**	0.04	1.04	0.33 **	0.04	1.4
Community- Level Factors									
Concentrated Disadvantage							0.03	0.03	1.03
Violent Crime Rate							0.003	0.004	1.003
Residential							-0.02	0.02	0.98
Probation Concentration							0.02 **	0.005	1.02
Entropy Index							0.12 *	0.05	1.13
Random Effects Covariance									
Estimate	0.08			0.02			0.12		
Z-Score	7.98 **			2.79 *			1.92		

Calculations:

- Amount of variance in clustering that is accounted for by individual-level characteristics =

  0.080 – 0.019 / 0.080 = 0.7625 = 76.25% of variance in probation outcomes is accounted for by individual-level characteristics

- Amount of variance that in clustering that is accounted for by individual + community-level characteristics =

  1. 0.080 – 0.013 / 0.080 = 83.75%
  2. Difference = 7.5%

Appendix J

Multilevel Models and Time Interaction Effects

Table J1

Summary of Fixed Effects

Source	F Statistic	Significance
Sex	108.16	< 0.001
Race	43.34	< 0.001
Age	441.80	< 0.001
LSI-R Score	149.21	< 0.001
Year Case Closed	1.48	0.19
Sex * Year	0.38	0.86
Race * Year	0.93	0.53
Age * Year	1.24	0.29
LSI-R Score * Year	7.65	< 0.001
Entropy Index	3.6	0.06
Residential Stability	1.37	0.24
Concentrated Disadvantage	0.46	0.50
Probation Rate	12.63	< 0.001
Violent Crime Rate	0.38	0.54
Entropy Index * Year	1.20	0.31
Residential Stability * Year	1.05	0.39
Concentrated Disadvantage * Year	0.73	0.60
Violent Crime Rate * Year	0.76	0.58
Probation Rate * Year	1.09	0.36

Appendix K

Offenses Not Eligible for Probation in Cook County, Il

According to Illinois Statute 730CS 5/5-5-3(c), these are

- first degree murder,
- attempt first degree murder,
- all class x offenses,
- a class 2 or greater offense if the offender has been convicted of a class 2 or greater offense within 10 years of the date on which the offender committed the offense for which they are being sentenced,
- residential burglary,
- criminal sexual assault,
- aggravated battery of a senior citizen,
- vehicular hijacking,
- a second or subsequent conviction for a hate crime when the underlying offense for which the hate crime is based is felony aggravated assault or felony mob action,
- a second or subsequent conviction for institutional vandalism when the damage is more than $300,
- cannabis trafficking,
- calculated criminal cannabis conspiracy,
- controlled substance trafficking,
- delivery of controlled, counterfeit, or look-alike substance to a person who is under the age of 18, or if the delivery occurs within 1,000 feet of a school, place of religious worship, roadside safety rest area, or truck stop,
- possession with intent to deliver, or delivery of, 5 grams or more of a controlled substance containing heroin, cocaine, fentanyl, or analog thereof,
- unlawful use of weapons when the weapon is a machine gun, or when the possession is within 1,000 feet of a school, place of religious worship, public housing, or public park and the weapon is a device used to silence a firearm, a rifle with a barrel shorter than 16 inches, a shotgun with a barrel shorter than 18 inches (and the total length is less than 26 inches),
- unlawful use of weapons, aggravated unlawful use of a weapon, and unlawful use of a weapon by a convicted felon or by a person within a correctional facility if some of the statutory mandatory prison requirements are present such as: it is a second or subsequent felony offense for unlawful use of weapons or a felony violation of the firearm owners identification card act, or if the offender has been previously convicted of a forcible felony, stalking or aggravated stalking, or has a prior class 2 or greater conviction under the controlled substance act, methamphetamine control act, or cannabis control act,
- aggravated unlawful use of weapons when the offender has a previous felony conviction,
- a forcible felony if the activities are related to an organized gang,
- a violation of the compelling organization membership of persons statute,
- all child pornography charges except simple possession without any aggravating statutory factors,
- residential arson and arson of a place of worship,
- gunrunning,

- a second or subsequent conviction for a violation of the methamphetamine control act,
- a second or subsequent violation for driving on a suspended or revoked license when the reason for the revocation is a previous reckless homicide or similar provision of law in another state; and
- unlawful purchase of a firearm.