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Neighborhood Ecology and Recidivism: A Case Study in NYC

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NEIGHBORHOOD ECOLOGY AND RECIDIVISM: A CASE STUDY IN NYC

by

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ABSTRACT

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The last decade has witnessed unprecedented efforts to reform the criminal justice system and stem the tide of mass incarceration in the United States. Persistently high rates of recidivism among justice-system involved individuals, however, present a significant obstacle to the success of these efforts. Thirty years of research in the fields of social psychology and criminology has produced a shared understanding of the individual characteristics that drive recidivism, but less is known regarding the influence of social environment. This research makes several unique contributions to a growing body of scholarship examining recidivism in the context of neighborhood, including being one of the first studies to isolate the effect of neighborhood-based police enforcement tactics. Using hierarchical linear modeling, the present study separately examines the effects of neighborhood policing and concentrated disadvantage on individual recidivism, while controlling for a robust model of individual risk. Findings confirm the importance of individual risk factors for predicting recidivism, but also suggest that neighborhood factors play a role in shaping individual risk. Policy implications are discussed.

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This work is dedicated, with love, to Lucille and Leslie, for teaching me to believe in myself.

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Chapter 1

Introduction

Following thirty years of "get tough" crime policy and a more than 300 percent increase in prison and jail populations nationally (Glaze & Kaeble, 2014), criminal justice reform has emerged as a leading social change priority for scholars and policymakers in the United States. It is widely acknowledged that persistently high rates of criminal recidivism are a key obstacle to stemming the tide of mass incarceration, with recent national statistics estimating that more than 65% of individuals released from state prisons are re-arrested within three years of release (DuRose, Cooper & Snyder, 2014), and data from select cities suggesting that similarly high rates of offender "cycling" is occurring in local jails (Subramanian, Delaney, Roberts, Fishman & McGarry, 2015). Although the individual clinical and socioeconomic factors fueling recidivism have been the subject of study for over 30 years, the field still lacks a comprehensive understanding of how these factors may interact with environmental characteristics to shape individual risk.

The present study contributes to a recent, but growing, body of literature that examines recidivism through an ecological lens. Wikstrom (2004) aptly describes this theoretical perspective as one which views criminal behavior as a matter of "kinds of individuals in kinds of settings," rather than separately a matter of individual *or* setting (p. 19). To date, research examining the effects of environmental factors on recidivism has focused primarily on the influence of neighborhood-level socioeconomic characteristics on individual outcomes such as re-arrest, re-conviction, or re-incarceration. This work has yielded mixed findings, with some studies finding that neighborhood concentrated disadvantage and economic inequality increase recidivism (e.g., Kubrin & Stewart, 2006; Hipp, Peterselia & Turner, 2010), and others suggesting that recidivism is primarily a function of individual factors alone (e.g., Tillyer & Vose, 2011).

While these recent studies have advanced our understanding of recidivism as an ecological phenomenon, there are several notable gaps in the existing literature. First, most existing research has relied on individual criminal history as a proxy for individual risk, despite the documented importance of criminogenic needs and other dynamic factors for predicting criminal activity (e.g., see Andrews et al.,1997; Brennan & Dietrich, 2009). Additionally, contextual research on recidivism has yet to extend beyond the examination of neighborhood-level socioeconomic factors (e.g., unemployment rates, income inequality) as predictors, though other neighborhood features may be theoretically relevant. Indeed, recent scholarship in this area has called both for more robust models of individual risk (Kubrin & Weitzer, 2006), and research on the direct effect of the geographically concentrated policing on recidivism (Onifaade, Peterson, Bynum & Davidson, 2011).

Finally, the lion's share of research on recidivism prediction has focused on "deeper end" offenders, such as recently released prisoners, individuals serving probation terms, or those housed in community corrections environments (e.g., halfway houses). In particular, there has been little to no empirical study of the interaction between individual and contextual risk factors specifically among individuals charged with misdemeanor offenses. This gap is notable, in light of the 10 million misdemeanor defendants that cycle in and out of local jails across the country each year, as well as the high rates of substance abuse, mental illness, and recidivism that have been documented in local jail populations (Freudenberg, Daniels, Crum, Perkins & Richie, 2008; Olson & Huddle, 2013). In short, it remains largely unknown whether prevailing models for understanding--and, in turn, reducing-- recidivism among individuals charged with more serious offenses are truly transferable to the majority of criminal defendants.

Individual Risk

At the individual level, established causes of recidivism include untreated clinical and social service needs (Andrews & Bonta, 1990, 2007; Skeem, Manchak & Peterson, 2011; Monahan & Skeem, 2014) and the collateral consequences of prior justice system involvement (Howell, 2009; Natapoff, 2012; Kohler-Hausmann, 2014). A rich body of literature, drawing primarily from the field of social psychology, provides a theoretical basis for understanding individual risk for recidivism. With respect to clinical and social service needs, this body of research has culminated in Risk-Need-Responsivity (RNR) theory, which argues for the use of therapeutic and human service interventions, rather than incarceration, to address those specific needs that can be statistically tied to criminal behavior (Andrews & Bonta, 1990). RNR theory explicates a small number of consistent predictors of recidivism and is supported by over three decades of meta-analytic research (e.g., see Andrews et al., 1997; Lipsey, Landenberger & Wilson, 2007). At the same time, research from the criminology literature suggests that the strain and social dislocation produced by incarceration may exacerbate individual risk (Dejong, 1996; Listwan, Sullivan, Agnew, Cullen & Colvin, 2013; Lowenkamp, Van Nostrand & Holsinger, 2013).

Neighborhood Effects

Despite significant advances in individual-level crime theory and risk assessment over the past 30 years, a distinct literature on "neighborhood effects" suggests that the focus of past research on individuals may prove inadequate to understanding criminal behavior. Evidence supporting the independent effects of social environment on crime is over a century old (Cahill, 2005; Sampson, 2012). Neighborhood effects literature dates back to the early work of the

Chicago school, beginning with Shaw and McKay (1942) who documented consistently high delinquency rates in certain areas of Chicago despite significant shifts in the demographic profiles of residents over time. Shaw and Mckay's work gave rise to social disorganization theory, which posits that neighborhood-level characteristics such as poverty, residential instability, ethnic heterogeneity, and weak social networks increase the likelihood of crime among residents (Kubrin & Weitzer, 2003).

Over the last 20 years, a considerable body of literature has amassed underscoring importance of neighborhood context on an array of individual and group outcomes. Specifically, research has linked neighborhood-level economic disadvantage to delayed adolescent cognitive development (Sharkey & Elwert, 2011); higher likelihood of crime victimization (Rountree, Kenneth & Miethe, 1994); higher violent and property crime rates (Bellair, 1997; Sampson, Raudenbush & Earls, 1997); and increased likelihood of recidivism (Kubrin & Stewart, 2006; Mears, Wang, Hay & Bales, 2008; Hipp et al., 2010). These findings also have meta-analytic support, in the form of a 2005 analysis of over 200 empirical studies, which concluded that neighborhood-level social disorganization--and in particular high levels of concentrated disadvantage--is a comparatively stable predictor of crime (Pratt & Cullen, 2005).

While the theoretical relevance of ecological factors for understanding criminal behavior is thus well established, there are crucial gaps with respect to testing this theory in the field of criminology. First, neighborhood effects studies have only recently begun to isolate recidivism as an outcome distinct from neighborhood crime rates or individual victimization and perpetration, and so our understanding of the mechanisms linking neighborhood characteristics with recidivism is still nascent. Additionally, the empirical literature on neighborhood effects has largely overlooked neighborhood-focused policing practices as a factor relevant to individual outcomes (for an exception, see Geller, Fagan, Tyler & Link, 2014). This oversight is particularly relevant to recidivism studies, given the intuitive importance of exposure to policing to individual arrest patterns. Finally, the small group of existing studies that examine individual recidivism as a function of neighborhood context have relied primarily on samples of returning prisoners, potentially overlooking the unique influence of neighborhood factors on recidivism among misdemeanor defendants, who account for the vast majority of arrests and prosecutions in cities across the country (Natapoff, 2012; 2015).

Misdemeanors & Recidivism

In an effort to correct popular imagination of the "typical" crime, legal scholar Alexandra Natapoff has recently described misdemeanor offenses as "…the paradigmatic American crime and the paradigmatic product of the American criminal system." (Natapoff, 2015, p. 296). An estimated 80 percent of state-level criminal court cases nationwide are misdemeanors (LaFountain et al., 2010) and admissions to local jails—primarily composed of misdemeanor defendants-- exceed ten million annually (Subramanian et al., 2015). The term misdemeanor may encompass a wide variety of offenses, but typical crimes falling under the misdemeanor umbrella include theft, minor assault, drug possession, and quality-of-life crimes such as trespassing or public disturbance. The petty nature of many misdemeanor crimes should not necessarily be associated with system leniency, however, as a conviction and short-term incarceration remains the default response to misdemeanor charges in many jurisdictions.

While nationally aggregated data on misdemeanor crime is not available, recent national research examining jail populations suggests high rates of unaddressed criminogenic needs and recidivism among individuals charged with misdemeanor crimes (James & Glazer, 2006). Local studies support this contention. For example, a 2013 study of the Chicago's jail population revealed that 21% of people admitted to the Cook County jail between 2007 and 2011 accounted for 50% of all admissions (Olson & Huddle, 2013). In New York City, a study of risk and need among nearly 1,000 misdemeanor defendants mandated to community-based ATI programs found that 40% of the sample were re-arrested within six months of the interview (Rempel, Lambson, Picard-Fritsche, Adler & Reich, 2018). The "chronic" nature of misdemeanor arrest and incarceration is frequently attributed to the inability of criminal justice systems to adequately address the significant underlying behavioral health and social service needs of this population. Mental illness, unemployment, homelessness, and drug addiction are prevalent among individuals recently released from jail (Freudenberg et al., 2008; Lim et al., 2012. and research has repeatedly shown that that the majority do not receive adequate treatment while incarcerated (e.g., National Center on Substance Abuse & Addiction, 1998; 2010).

To complicate matters further, a marked upward shift in misdemeanor caseloads and jail populations began in the 1980s and has affected jurisdictions across the country (Subramanian et al., 2015; LaFountain et al., 2010), while patterns in factors traditionally associated with low-level criminal behavior, such as drug abuse and unemployment, have held comparatively steady.[1] This trend implies that an individual behavioral framework may be insufficient to understanding recidivism in the contemporary U.S. context. Particularly poignant support for attending to the neighborhood and policy context of misdemeanor crime can be drawn from the case of New York City, where misdemeanor caseloads jumped 40% in a single year following the 1994 implementation of Order Maintenance Policing (OMP)—a neighborhood policing strategy focused on the aggressive enforcement of misdemeanor criminal codes in particular geographic areas (Greene, 1999). Also in New York City, misdemeanor caseloads rose again with the

[1] National drug use trends are available at: http://www.drugabuse.gov/publications/drugfacts/nationwide-trends; National unemployment trends data are available at: http://data.bls.gov.

increase in Stop-Question-Frisk (SQF) tactics associated with the implementation of Operation Impact in 2003 (Golden & Almo, 2004). While SQF was explicitly intended to reduce the prevalence of illegal guns, one of its practical effects has been to increase arrests more generally, particularly for lower-level crimes (New York State Office of the Attorney General, 2013) and in economically disadvantaged areas (MacDonald, Fagan & Geller, 2016). Although OMP and SQF have been subject to criticism in recent years (Fagan, Geller, Davies & West, 2009; Harcourt & Ludwig, 2006), they remain integral to the distribution of police resources in many cities, including Baltimore, Boston, Chicago, New York, and Los Angeles (Roberts, 1999; Harcourt, 2009). Despite these trends, the influence of environmental factors on arrest patterns among individuals charged with misdemeanor offenses has yet to be explicitly studied.

Study Purpose & Research Questions

The present study appeals to Risk-Need-Responsivity theory, as well as prior empirical and theoretical literature on "neighborhood effects," as a foundation to begin addressing some of the identified gaps in recent recidivism literature. Specifically, it seeks to assess the impact of neighborhood-level policing tactics and concentrated disadvantage on individual recidivism, after controlling for a robust model of individual risk that includes criminal history, criminogenic need, and demographic factors. The study draws on a diverse sample of felony and misdemeanor defendants arrested in Brooklyn, New York, and makes a final contribution by examining whether neighborhood factors have a unique influence on individuals charged with misdemeanor offenses.

Specific research questions to be addressed include:

1. Does a set of individual risk factors-- including criminal history, demographic and criminogenic need factors rooted in RNR theory-- predict recidivism in a diverse sample of criminal defendants?

2. After controlling for individual risk, what is the net effect of neighborhood-level concentrated disadvantage on the likelihood of recidivism?

3. After controlling for individual risk, what is the net effect of neighborhood-focused police enforcement tactics on the likelihood of recidivism?

4. Do neighborhood factors (concentrated disadvantage, policing tactics) influence the relationship between individual risk factors and likelihood of recidivism?

5. Compared with defendants charged with felony offenses, are defendants charged with misdemeanor offenses more vulnerable to the influence of neighborhood factors on recidivism?

Chapter 2

Literature Review

The present research contributes to a growing body of scholarship examining criminal recidivism as a function of both individual and environmental risk factors. It draws on two major theoretical fields in the criminal justice: (1) individual criminal risk rooted in risk-need-responsivity theory; and (2) neighborhood effects on criminal behavior, as explained both by social disorganization theory and neighborhood-focused policing strategies. Additionally, this work makes two unique contributions to the literature on recidivism. First, it is one of the first studies to-date that explicitly considers the influence of neighborhood-focused policing on individual re-arrest patterns. Second, the research separately considers the hypothesized relationships between neighborhood factors and recidivism on a subsample of misdemeanor defendants, based on the theory that when compared to felony defendants, they may be particularly vulnerable to the effects of neighborhood factors on re-arrest.

Chapter 2 begins by summarizing the renewed scholarly interest in recidivism as an ecological phenomenon. This is followed by an in-depth survey of relevant theoretical literature, with a focus on Risk-Need-Responsivity theory, Social Disorganization theory, and the literature on enforcement-focused and other proactive policing strategies. The chapter concludes by discussing the potential relevance of the current research to addressing high rates of recidivism among individuals charged with misdemeanor offenses, and situating the present study within an ecological framework.

Recidivism as an Ecological Phenomenon

Despite rapid growth in the study of neighborhood context on crime beginning in the 1980s, almost no scholarship specifically examining the effects of neighborhood factors on individual recidivism was published prior to the early 2000s. In one exception, Gottfredson and Taylor (1986) studied the effect of neighborhood "physical incivilities" (loitering, appearance of disorder) on re-arrest among 500 released inmates in 90 Baltimore neighborhoods. The researchers found that while neighborhood did not exercise an independent influence on recidivism, the interaction of neighborhood-level incivilities and individual risk factors increased the probability of recidivism among these releasees. Despite the intuitive importance of neighborhood environment to the successful reintegration of former prisoners, no new empirical studies of the effect of neighborhood on recidivism emerged for nearly 20 years.

Driven in part by methodological advances in multi-level modeling, as well as a renewed focus on recidivism risk by criminal justice policymakers, at least a half-dozen studies examining individual recidivism as an ecological phenomenon have been conducted in the last decade. Several of these studies strongly suggest that neighborhood context *does* matter for understanding recidivism. First, in a multi-level analysis of over 4,600 parolees and probationers residing in 156 census tracts in Multnomah County, Oregon, Kubrin and Stewart (2006) found that a neighborhood concentrated disadvantage index increased the odds of re-arrest by 12% when controlling for individual risk factors such as demographic traits and criminal background. Similarly, a 2007 study of over 40,000 ex-inmates returning to 62 Florida counties suggested that neighborhood-level racial inequality significantly increases the probability of reconviction among African-American parolees (Reisig, Bales, Hay & Wang, 2007), and a 2010 study of over 100,000 parolees in California found that neighborhood concentrated disadvantage significantly increased the odds of re-incarceration (Hipp, Peterselia & Turner, 2010).

Despite these findings, the empirical literature regarding neighborhood context and recidivism is best described as nuanced. Indeed, mixed and null findings have emerged from other recent work. This includes a study of nearly 4,000 parolees in Michigan, which showed that concentrated disadvantage at the census-tract level influenced re-arrest among nonwhite parolees and those released without supportive housing, while white parolees and those with supportive housing were unaffected by neighborhood characteristics (McNeeley, 2017). Similarly, Huebner and Pleggenkuhle (2015) examined returns-to-prison among paroled men and women in Missouri, and found that concentrated disadvantage only increased re-incarceration among men. Finally, Stahler and colleagues studied more than 3,000 individuals released to Philadelphia from the Pennsylvania Department of Corrections and found no significant variation in recidivism across 381 census tracts (Stahler et al., 2013).

Particularly germane to the current research, a recent study of nearly 6,000 individuals released from Iowa Department of Corrections custody utilized a multi-level model and found that county-level ecological factors such as concentrated disadvantage, residential instability, and immigrant concentration had little to no effect on recidivism after controlling for a robust model of individual risk that includes both static and dynamic risk factors (Tillyer & Vose, 2011).[2] This study represents an important step in the examination of neighborhood effects on recidivism, as similar research to-date has been limited to controlling for static factors (i.e., criminal history, demographic factors) at the individual level, despite the well-documented importance of criminogenic needs such as substance abuse and unemployment for predicting new arrest. While Tillyer and Vose also found little difference in the strength of the relationship between individual risk factors and re-arrest across counties, other recent research contradicts this finding. Specifically, Onifaade and colleagues (2011) studied a similar risk instrument (the

[2] Specifically, the study examined the effect of county socioeconomic characteristics on recidivism after controlling for individual score on the Level of Services Inventory-Revised (LSI-R), a well-validated risk-need assessment instrument (Andrews and Bonta, 1990).

LS-CMI) among youth in a Midwestern county, and discovered that individual risk scores had a stronger influence on recidivism among youth in economically disadvantaged areas. Other recent research suggests that the influence of both neighborhood-level and individual-level risk factors vary by group characteristics such as race and gender (e.g., see Chuahan, Reppucci & Turkheimer, 2009; Holtfreter, Resig & Morash, 2004).

Taken as a whole, empirical study over the last decade suggests that individual risk models may be insufficient to understanding recidivism patterns, which are frequently found to vary based on the structural characteristics of neighborhoods. There are several notable limitations to this body of work, however. First, the bulk of existing research in this area focuses on neighborhood socioeconomic characteristics such as racial heterogeneity, concentrated disadvantage, and residential mobility, when assessing neighborhood effects. Recidivism studies to-date have stopped short of considering place-based policing strategies as structural neighborhood factors that might influence recidivism, though enforcement approaches that frequently focus on disadvantaged and high-crime neighborhoods, such as SQF and OMP, have been shown to influence other individual outcomes including stress, civic participation, and perceptions of the legitimacy of police (Gau & Brunson, 2010; Fratello, Rengifo & Trone, 2013; Geller, Fagan, Tyler & Link, 2014; Lerman & Weaver, 2014). Second, many of the previous studies discussed are limited in their models of individual risk, which consist of criminal history and demographic factors. The present study seeks to address these limitations.

Individual Risk: The Risk-Need-Responsivity Model

As noted in the introduction, a rich body of academic literature provides a theoretical basis for understanding individual risk for criminal recidivism. Not to be confused with pure behavioral theories of criminal motivation (e.g.., rational choice theory), which date back to positivist schools of the 18th century, criminal risk prediction is a newer science rooted in the practical need to manage correctional populations through the creation of actuarial schemes based on the grouped behavior of prior offenders (Harcourt, 2007; Monahan & Skeem, 2014). Since its inception with the use of actuarial tables to inform parole release in the 1930s, this field of research has undergone multiple "generations" (Andrews & Bonta, 2007; Schwalbe, 2007) and ultimately has distinguished itself through superior capacity to predict and manage risk when compared with traditional professional discretion models (Dawes, Faust, & Meehl, 1989; Grove & Meehl, 1996).

Beginning with the resurgence of rehabilitative perspectives in the late 1980s, actuarial risk assessment in criminology has become strongly associated with the priorities of therapeutic intervention and risk reduction, culminating in the Risk-Need-Responsivity (RNR) model (Cullen & Jonson, 2011). Developed in the late 1980s by Canadian psychologists Don Andrews and James Bonta, RNR is at its core a rehabilitative theory of crime prevention which encompasses three basic principles: (1) the *risk principle,* which asserts that criminal behavior can be reliably predicted and that correctional intervention should focus on the higher risk offenders; (2) the *need principle,* which highlights the importance of criminogenic needs (needs that can be statistically tied to recidivism) for the delivery of therapeutic intervention; (3) and the *responsivity principle,* which describes how the correctional treatment should be provided (Andrews & Bonta,1990; Andrews, Bonta & Wormith, 2006). Specifically, RNR posits eight central factors for predicting recidivism, described in Table 1 below (referred to hereinafter as the "Central Eight" risk model).

Table 1. Central Eight Predictors of Criminal Risk	
Risk Domain	**Common Measures by Domain**
Criminal History	Prior adult and juvenile arrests; Prior adult and juvenile convictions; arrest warrants & open cases; Prior and current charge characteristics.
Antisocial Attitudes	Patterns of antisocial thinking which typically reflect the following primary constructs: (1) Lack of empathy; (2) Externalization of blame; (3) Entitlement; (4) Attitudes supportive of violence.
Antisocial Personality Pattern	Impulsive behavior patterns; lack of consequential thinking.
Criminal Peer Networks	Peers involved in drug use, criminal behavior and/or with a history of involvement in the justice system.
School or Work Deficits	Poor past performance in work or school (lack of a high school diploma; history of firing or suspension); Alienation from informal social control via work or school (e.g., chronic unemployment).
Family Dysfunction	Unmarried; Recent family or intimate relationship stress; Historical lack of connection with family or intimate partner.
Substance Abuse	Duration, frequency and mode of current substance use; history of substance abuse or addiction; self-reported drug problems.
Lack of Pro-social Leisure Activities	Isolation (time spent alone) or lack of pro-social recreational activities.
Note: Domains and sample items developed based on extensive review of several comprehensive, fourth generation risk-need assessment systems, including the LSI-R (Andrews & Bonta, 1990), the COMPAS (Brennan & Dietrich, 2007), and the ORAS (Latessa, Lemke, Makarios & Smith, 2010). See Schwalbe, 2007 for a review of juvenile risk assessment instruments.	

Additionally, RNR constitutes the foundation for multiple risk assessment systems that have generated a separate literature of validation studies and meta-analyses (e.g., Gendreau, Little & Goggin, 1996; Brennan & Dietrich, 2009; Smith, Cullen & Latessa, 2009).[3] This literature has consistently supported the validity of the Central Eight risk model for predicting general recidivism in a variety of populations, including women (Smith et al., 2009), juveniles (Schwalbe, 2007), and the mentally ill (Bonta, Law & Hanson, 1998). Based on this robust body of literature, RNR and the Central Eight model have been broadly accepted as foundational to evidence-based correctional practice in the U.S. and elsewhere (Andrews & Bonta, 2010; Cullen & Jonson, 2011; Rempel, 2014).

Relevant to the present research, the Central Eight model of risk prediction has historically been examined primarily in custodial and felony offender populations, leaving the predictors of criminal risk—in particular dynamic factors such as substance abuse, criminal networks, and criminal thinking—poorly understood in the general criminal court population. Two notable exceptions have emerged in recent years, including a study by Krista Ghering and Patricia Van Voorhis (2014) of a small pretrial population in Ohio composed largely of individuals charged with misdemeanor offenses. Gherig and Van Voorhis found that both factors integral to the RNR model (e.g., criminal history, substance abuse) *and* other dynamic need variables not central to the RNR model such as homelessness, mental illness, and trauma, were significant predictors of new arrest. Second, a recent study by the Center for Court Innovation (CCI)—the first to specifically consider risk and need in a purely misdemeanor defendant population—revealed similar findings. Specifically, while the integrity of the RNR model was upheld in the sample, residential instability—in particular homelessness—was also found to be a

[3] RNR is at least partially the foundation for the majority of comprehensive risk assessment systems in widespread use, including the LSI-R, the Ohio Risk Assessment System (ORAS) and the COMPAS.

strong predictor of new arrest. Additionally, other factors integral to the Central Eight model, such as criminal thinking and criminal peer networks, were less important to understanding risk in this population (Rempel et al., 2018).[4]

The RNR model provides a theoretical basis for understanding the individual risk factors that influence recidivism in the present study (see *Appendix D* for the specific risk model used in the study). However, the overarching goal of the current research is to examine recidivism patterns as an ecological phenomenon wherein individual recidivism is considered both a function of individual risk factors and neighborhood-level risk factors. The remainder of the literature review summarizes the existing literature regarding neighborhood effects on crime in two specific areas: (1) social disorganization theory and social ecology perspectives more generally, and (2) policing strategies such as OMP and SQF, which are designed to aggressively enforce criminal codes in higher crime neighborhoods (Golden & Almo, 2004; Geller, 2015). Such strategies are only two examples within the diverse genre of proactive policing, however, which also includes problem-solving approaches, community-oriented policing, and situational crime prevention strategies (National Academies of Sciences, Engineering & Medicine, 2018). While these types of police efforts also frequently focus on higher crime neighborhoods, because the present study is concerned with the effects of exposure to police *enforcement* activity on individual arrest patterns, other types of proactive policing are explicitly excluded from the study.

[4] Drawing on the same data, the researchers also found that homelessness was a significant predictor of re-arrest in a mixed felony/misdemeanor population, suggesting that housing may be an important general criminogenic need factor, despite the fact that housing instability is not included in the original RNR model.

Neighborhood Effects

Origins of ecological theory

Ecological perspectives in criminology are over a century old. Nineteenth century "cartographic criminologists," for example, analyzed crime patterns across European nations and associated the spatial distributions of crime with socioeconomic factors such as literacy rates, population density, and wealth distribution (Cahill, 2011). More specifically, crime as a micro-geographic or "neighborhood" phenomenon dates back to the Chicago School of sociology in the early 20th century and can be attributed to that school's interest in the social consequences of rapid urbanization (Sampson et al., 2002). Early Chicago School leaders Ernest Burgess and Robert Park defined neighborhoods as "collections of both people and institutions occupying a spatially defined area influenced by ecological, cultural, and sometimes political forces" (Park, 1916, 147–154), and ultimately mapped Chicago's neighborhoods as concentric "zones" emanating from the City's center. Park and Burgess theorized that as the central business district grew, affluent residents moved outward leaving an unstable zone conducive to social disorder (Park & Burgess, 1925; Kubrin, 2009).

The first empirical test of neighborhood effects on crime came with the work of Shaw and Mckay (1942), who applied Park and Burgess' "zone theory" to understanding patterns of juvenile delinquency in Chicago by studying the geographic patterns of juvenile court cases filed in 1920, 1930, and 1940, respectively. Ultimately, the researchers determined that delinquency rates were higher in neighborhoods with particular characteristics, specifically high rates of poverty, residential mobility, and racial heterogeneity. A key conclusion from Shaw and McKay's work was that delinquency in Chicago's industrial zones remained high even as the demographic characteristics (e.g., ethnicity) of the populations in these neighborhoods changed drastically (Shaw & McKay, 1942). The possibility that certain areas of a city could produce high rates of deviance, despite substantial turnover in the population of the individuals in the community, challenged prevailing individualistic notions of criminality and ultimately gave rise to social disorganization theory (Kubrin, 2009).

Social disorganization theory & the evolution of ecological perspectives

Social disorganization can be defined as the inability of residents of a community or neighborhood to realize shared goals, including the goal of local control over crime and deviance (Bursik, 1988; Kubrin & Weitzer, 2003; Sampson, 2012). Inherent to the original formulation of social disorganization is the premise that highly *disorganized* neighborhoods share particular structural characteristics, including high rates of poverty, racial heterogeneity, and high residential mobility (Shaw & McKay, 1942; Kubrin, 2009). It is a common misconception, however, that social disorganization theory posits a direct relationship between macro-level community characteristics and crime. Rather, Shaw and McKay theorized that objective neighborhood-level characteristics such as poverty and residential mobility weakened the collective ability of residents to control crime, thereby leading to higher crime in disorganized areas. Indeed, specification of the intermediate mechanisms linking community level characteristics with crime patterns is an ongoing venture in criminology (Sampson, 2012), even as a growing literature suggests a direct "ecological" effect of exogenous community characteristics on crime rates (Pratt & Cullen, 2005).

Despite strong support during the 1940s and 1950s, social disorganization theory ultimately fell into disfavor for several reasons. Importantly, subsequent attempts to replicate Shaw and McKay's findings failed, leading to the critique that the theory of criminogenic "places" was a relic of a particular period of urbanization (Bursik, 1986; Wright, 2010). At the same time, developments in forensic psychology and survey methodology shifted the focus of criminology back toward individual theories of criminal behavior, such as rational choice or control theories (Bursik, 1986; Sampson, 2011; 2012). These advances simultaneously gave rise to methodological concerns regarding the dangers of making individual inferences based on aggregate-level data (e.g., see Robinson, 1950). Indeed, following this shift, even those studies accounting for environmental factors tended to view neighborhoods merely as "opportunity structures" that facilitated or deterred criminally prone individuals (Bursik, 1986; Cohen & Felson, 1979).

Beginning in the late 1980s, however, new theoretical work buoyed a significant resurgence in ecological perspectives on crime (Massey, 2001). In particular, William Julius Wilson's seminal 1987 work *The Truly Disadvantaged* argued that the flight of wealthy families and businesses from urban centers has resulted in the geographic clustering of social problems (crime, unemployment, family disruption) among an urban underclass, spurring a new generation of neighborhood effects research. Subsequently, numerous studies have supported Wilson's thesis by empirically linking structural neighborhood characteristics with an array of negative outcomes, including violent victimization (Sampson, 1986; Rountree et al. 1994) and crime (e.g., Sampson et al., 1997; Peterson, Krivo, & Harris, 2000; Rosenfeld, Messner, & Baumer, 2001; Veysey & Messner, 1999). Previously discarded, ecological perspectives now constitute the foundation for an array of "place-based" crime prevention strategies (Eck & Guerette, 2012).

This resurgent body of ecological research has also resulted in conceptual advances over the early work of the Chicago School (Sampson et al., 2002; Kubrin, 2009; Wright, 2010). Specifically, structural correlates of crime beyond the three originally indicated in Shaw & McKay's model (i.e., residential instability, poverty, racial heterogeneity) have been hypothesized and tested. Support has emerged for selected new variables, including family disruption (Sampson, 1986; Sampson & Grove, 1989) and neighborhood unemployment (Sampson 1987; 1995). Beginning in the 1990s, sociologists have frequently employed concentrated disadvantage indices--which combine indicators of neighborhood-level disadvantage such as household income, unemployment rates, residential turnover and percentage of single-headed households-- as independent variables in multi-level studies. Concentrated disadvantage is now a well-accepted proxy measure for neighborhood socioeconomic status across the social sciences. Specific to criminology, early studies showed concentrated disadvantage to be a robust predictor of violent crime (e.g., Sampson et al., 1997), victimization (e.g., Peterson & Krivo,1999), and youth delinquency (e.g., Rosenfeld, Bray & Egley,1999). A more recent meta-analysis of 31 macro-level predictors of crime, which aggregated effect sizes across over 200 studies, ranked concentrated disadvantage among the strongest predictors of crime (Pratt & Cullen, 2005). In short, the use of concentrated disadvantage in the present study is well-supported in the prior literature.

Contextual effects research

Early studies of neighborhood effects typically focused on aggregate neighborhood outcomes (e.g., violent crime rates in disorganized communities are higher than in organized communities). The emergence of multi-level statistical modeling techniques has increased the number and rigor of ecologically informed studies that specifically examine the influence of neighborhood context on individual behavior and allow for the disentanglement of individual and environmental influences in regression models (Bryk & Raudenbush, 1992; Sampson et al., 2002; Kubrin & Weitzer, 2003). In recent decades, multi-level regression modeling has been used to isolate the effects of neighborhood context on adolescent cognitive development (Elliot et al., 1996); crime victimization (Rountree et al., 1994); violent crime (Sampson et al., 1997); and the effects of neighborhood incarceration rates on adolescent educational outcomes (Hagan & Foster, 2012). Described by Kubrin and Weitzer (2003) as "contextual effects" research, a basic premise of these studies is that individual action is determined to some extent by social forces in the immediate environment (Kubrin & Weitzer, 2003, 391). This advance is critical to social disorganization and social ecology perspectives alike, given longstanding critiques that neighborhood effects on crime amount to little more than the natural result of geographic concentrations of criminally prone individuals (Sampson et al, 2002; Wright, 2010; Sharkey & Faber, 2014).

As detailed previously, a number of recent studies have examined the contextual effects of neighborhood on recidivism specifically, with mixed results. Motivated by the documented importance of neighborhood environment to the successful reintegration of former prison inmates and parolees (Visher, LaVigne & Travis, 2004), the bulk of existing multi-level studies define recidivism conservatively-- either as a new conviction or a re-incarceration--rather than as a new arrest (for exceptions, see Kubrin & Stewart, 2006; McNeeley, 2017). This definition makes intuitive sense for examining neighborhood context as an aspect of prisoner reentry, but may underestimate the effect of neighborhood factors on recidivism more generally, as many individuals spend limited time incarcerated and may be frequently arrested and processed without formal conviction (see Geller, 2015). In short, re-arrest more adequately represents recidivism when it is defined as any new involvement in the justice system (i.e., the use of conviction excludes police encounters that do not result in a formal conviction as instances of justice system re-involvement).

The decision to examine re-arrest versus reconviction as an outcome measure may be particularly crucial to understanding recidivism among misdemeanor defendants. This is because a unique aspect of the misdemeanor population (when compared with felony or prison populations) is the tendency to rapidly cycle in and out of correctional institutions with or without a formal conviction (e.g., Kohler-Hausmann, 2014; Geller, 2015), but to *typically* be situated in the community and at risk for new arrest. The present research examines neighborhood concentrated disadvantage on re-arrest specifically. It also extends it to more explicitly consider policing as a neighborhood-level contextual risk factor, for reasons considered in the next section of this literature review.

Neighborhood-focused policing and the study of recidivism

One aspect of neighborhood context that has yet to be considered in the empirical literature on crime and re-arrest outcomes, but that is intuitively important for understanding this relationship, is the neighborhood distribution of formal social control-- specifically policing. Indeed, this gap has been noted in recent scholarship (Kubrin & Weitzer, 2003; Onifaade et al., 2011), but remains understudied. Research suggesting that individual exposure to formal social control-- via probation or other forms of community supervision-- can increase recidivism lends credence to the theory that neighborhood-focused policing might influence recidivism (Kubrin & Stewart, 2006; Wright, 2010; Ayoub & Pooler, 2015).

The concept of neighborhood-focused policing practice as a potential risk factor for individual recidivism is also compelling in light of the shift toward OMP in a number of U.S. cities over the last thirty years. Scholars have traced this trend to the development and widespread endorsement of "Broken Windows Theory" (Wilson & Kelling, 1982), which argues that neighborhoods characterized by high rates of lower-level crime and disorder are breeding grounds for violent crime, as the primary impetus for the growth in order maintenance strategies (Roberts, 1999; Trettien, 2006; Harcourt, 2009). Given the NYPD's early adoption of the

Broken Windows perspective in 1993 (Greene, 1999), as well as the roll out of Operation Impact in 2003, New York City has been the site of multiple studies regarding the impact of enforcement-oriented neighborhood policing on crime.[5] This research has produced equivocal findings, with some studies attributing New York's "great crime decline" in part to these proactive enforcement tactics (e.g., see Smith & Purtell, 2007; Weisburd, Telep & Lawton, 2014) and others finding moderate or null effects (e.g., see Harcourt & Ludwig, 2006; Harcourt, 2009). More recently, however, even research identifying empirical support for OMP strategies has simultaneously expressed concern regarding the potential that such strategies strain the relationship between police and communities (Weisburd et al., 2014) and several local studies have documented the negative individual and social and health impacts of SQF in New York City (e.g., see Geller et al. 2014; Lerman & Weaver, 2014).

A general neighborhood orientation in law enforcement is not necessarily new to American policing, which has traditionally been distributed via neighborhood precinct (Walker & Katz, 2005). Moreover, as discussed in Chapter 1, neighborhood-focused proactive policing strategies may take diverse forms (Braga, Welsh & Schnell, 2015; National Academies of Sciences, Engineering and Medicine, 2018). However, OMP is historically unique for its explicit emphasis on the enforcement of low-level criminal codes through increased misdemeanor arrest and aggressive street policing (Kelling & Coles, 1997). Additionally, OMP is by design focused on high-crime neighborhoods (Smith & Purtell, 2007; Harcourt, 2009), and therefore inexorably leads to the uneven distribution of policing across neighborhoods, with greater policing in historically disadvantaged areas. This effect has, once again, been documented in the case of

[5] Operation impact involved deployment of higher proportions of new police recruits in crime hotspots. Recruits were encouraged to conduct investigatory stops (SQF) and aggressively enforce misdemeanor criminal codes pursuant to an order maintenance policing strategy (Golden & Almo, 2004).

New York City. Citywide statistics dating back to the implementation of OMP show the highest concentration of both misdemeanor arrest and street stop activity in neighborhoods that also feature high rates of poverty, unemployment, family disruption and other indicators of social disorganization (Fagan et al., 2009). The geographic concentration of police enforcement activity in disadvantaged areas has also been documented outside of New York, specifically in Washington, D.C. (Kane, Gustfson & Bruell, 2013) and Chicago (Kane-Willis, Aviles, Bazon & Narloch, 2014).

With respect to the present study, the geographic concentration of police enforcement activity in multiple cities supports the thesis that a neighborhood-level police "supervision effect" could interact with other factors to predict recidivism. In other words, existing data suggests it is realistic to expect that an individual released to a neighborhood that is subject to more aggressive enforcement strategies such as OMP or SQF would have a higher likelihood of re-arrest, net of individual risk factors, compared with one who is released to a neighborhood not subject these strategies (Office of the New York State Attorney General, 2013). This represents a potentially important gap in the literature, given that variance in formal social control has largely been unaccounted for in neighborhood effects research to date.

Focus on misdemeanor defendants

Although rarely acknowledged in the political and popular discourse on criminal justice, high rates of misdemeanor arrest and recidivism are critical drivers of mass incarceration in the United States. Indeed, misdemeanor defendants make up the vast majority of the more than 12 million jail admissions each year, and recent research suggests that chronic cycling through jails is the norm, rather than the exception in this population (Rempel et al., 2018; Olson & Huddle, 2013). The causes and consequences of chronic justice system involvement among individuals charged with low-level crimes are otherwise poorly understood. That research which does exist tends to *either* view misdemeanor recidivism patterns as a function of individual risk (e.g., Rempel et al., 2018) *or* as a function of broader social forces, such as shifts toward the proactive enforcement of low-level crime or the increasing collateral consequences of conviction associated with get tough on crime policy (e.g., Howell, 2009; Natapoff, 2012, 2015).

While precise national data on misdemeanor arrests are unavailable, they likely approach 10 million annually (Natapoff, 2012). As documented by the National Center for State Courts, recent statistics from thirteen states suggest a minor drop in criminal court caseloads overall (-2%) but a significant *increase* (13%) in the number of misdemeanor cases (LaFountain et al., 2010). Misdemeanor caseloads carried by public defender offices have also nearly doubled in recent decades, with caseloads in some cities now averaging over 2,000 (Baruchowitz et al., 2009). Finally, this fundamental shift in the focus of the justice system is supported by national jail statistics, which show that local jail admissions—the majority of which are for misdemeanor offenses-- have more than doubled since 1983 and now outpace annual prison admissions by 19:1 (Subramaninan et al., 2015).

New York City's trends in misdemeanor arrest have recently been studied in detail by researchers at John Jay College and appear to adhere closely to national trends discussed above. Indeed, since 1990, and in the midst of significant drops in crime and felony arrest, the raw numbers of misdemeanor arrests in the five boroughs have increased more than 100% from approximately 125,000 in 1990 to more than 250,000 annually in recent years (Chauhan, Fera, Welsh, Balazon & Misshula, 2014). These statistics suggest a significant paradigm shift in the focus of local policing, court, and correctional resources over the last several decades, notwithstanding a decrease in misdemeanor arrests observed in the last three years (Chauhan, Tomascak, Cuevas, Hood & Lu, 2018).[6]

Scholars tracking recent trends in misdemeanor case processing have raised specific concerns about the causes and consequences of the system's focus on lower-level offenses. Empirical research suggests a confluence of causal factors, including the widespread uptake of OMP tactics in the 1990s (Harcourt, 2009); increasing criminalization of public nuisance behavior (e.g., see Baruchowitz et al., 2009; Stuntz, 2011); and the hardening of barriers to social reintegration for convicted individuals associated with get tough on crime policy (Natapoff, 2012).[7] Ironically, even short-term involvement in the justice system has been shown to increase vulnerability to new arrest among previously low-risk individuals and groups (Lowenkamp et al., 2013), suggesting that trend toward enforcement against minor offenses may in fact be exacerbating the problem it was intended to solve.

Despite the important policy-level trends described above, misdemeanor offending patterns-- like criminal offending patterns more generally-- are not driven solely by enforcement efforts, but also by the significant underlying clinical and social service needs of individuals. For example, an in-depth analysis of a sample of 473 defendants repeatedly admitted to jails in New York City between 2008 and 2013 found exceptionally high rates of substance abuse (>90%) and significant rates of mental illness (28%) in the studied group, which was alone responsible for more than 10,000 arrests over the 5-year period (Subramanian et al., 2015). Further evidence of significant untreated clinical needs and chronic justice system involvement is found in several other recent studies of misdemeanor and jail populations (e.g., Freudenberg et al., 2008; Gehring & Van Voorhis, 2014; Rempel et al., 2018), leading some individuals to become colloquially

[6] Recent decreases may be in part explainable by a 2014 legal challenge to SQF tactics by the NYPD (*See Floyd v. City of New York* , 959 F.Supp.2d 540 (S .D.N.Y. 2013).
[7] Examples of statutes relevant to criminalization include laws against sleeping in a cardboard box in NYC or feeding the homeless in Florida (Baruchowitz et al. 2009).

labeled "frequent flyers" by correctional professionals.

In short, although misdemeanor crime and arrests play an increasingly key role in driving mass incarceration, there has been little prior inquiry into the potential drivers of high rates of recidivism among misdemeanor defendants when compared to felony defendants. Indeed, the majority of contextual studies of recidivism focus on prison populations and utilize reconviction as a proxy for recidivism, largely overlooking the problem of lower-level defendants cycling in and out of local jails often without a formal conviction (Kohler-Hausmann, 2014). By separately examining the combined effects of individual and neighborhood-level risk factors on re-arrest among individuals charged with misdemeanor and felony offenses, the present research begins to address this gap.

Theoretical Framework

This research draws primarily on two existing theoretical perspectives: (1) Risk-Need-Responsivity theory; and (2) Ecological theory as explicated in the social disorganization and neighborhood effects literatures. In keeping with the RNR model, it is anticipated that individual recidivism patterns are predictable based on the "Central Eight" model of individual risk. It is simultaneously expected, however, that the likelihood of new arrest will also be influenced by each individual's neighborhood context. In keeping with social disorganization theory, it is expected that individuals residing in neighborhoods characterized by high levels of concentrated disadvantage will have a higher likelihood of re-arrest, net of individual risk factors. Additionally, neighborhood-based policing tactics are expected to influence the likelihood of recidivism, with individuals in neighborhoods characterized by proactive law enforcement strategies (i.e., high rates of SQF and "discretionary" misdemeanor arrests) will have a higher probability of re-arrest, net individual risk factors.

Until very recently, the academic study of recidivism has focused primarily on understanding how specific characteristics of individuals--e.g., prior criminal history, employment, drug use, and personality traits--may predispose them to new arrests or convictions. More recent work considers neighborhood context as a contributing, or in some cases competing, factor in this basic model. While the present research replicates this approach by testing the effects of neighborhood concentrated disadvantage and policing tactics before and after controlling for known individual risk factors, it also includes some exploratory analyses in an effort to move beyond this dichotomy. Specifically, it explores the interaction between neighborhood characteristics and cumulative individual risk score, as well as a variety of potential interactions between neighborhood factors and established individual risk factors (i.e., criminogenic needs, demographic factors, criminal history factors).

Chapter 3

Methodology

This research is guided by the thesis that individual recidivism patterns are an ecological phenomenon, influenced simultaneously by individual and environmental risk factors. This proposition is tested by examining the distinctive effects of three variables on the odds of re-arrest in a sample of defendants charged with misdemeanor or felony offenses: (1) individual risk based on a set of demographic, criminal history and criminogenic needs factors; (2) neighborhood concentrated disadvantage based on U.S. census data; and (3) neighborhood policing tactics based on New York City Police Department (NYPD) historical data regarding rates of SQF and arrests on select misdemeanor charges in 22 precincts across Brooklyn and one precinct in Manhattan. Given the specific research interest in the influence of neighborhood factors on re-arrest among defendants charged with misdemeanors, all analyses are repeated separately on subsamples of defendants whose top arrest charge at the time of data collection was a misdemeanor (first subsample) or a felony (second subsample).

Drawing on the research questions laid out in the introduction, this study seeks to test the following hypotheses:

H1: Neighborhood concentrated disadvantage will be positively related to re-arrest, net of individual-level risk.

H2: Neighborhood proactive police enforcement tactics will be positively related to re-arrest, net of individual-level risk.

H3: Defendants with misdemeanor charges will be more vulnerable to the effects of neighborhood-level factors on re-arrest, when compared with those charged with a felony.

H4: Higher individual risk scores will interact with neighborhood factors to increase the likelihood of re-arrest.

Chapter 3 begins by describing the setting and the data collection methods for the research, followed by a description of the study sample and operationalization of key variables. The chapter concludes by providing details of the analytic strategy.

Study Setting

This study draws on a sample of misdemeanor and felony defendants who were arrested in Brooklyn, New York and are current residents of one of the five boroughs of New York City. Less than 10% original sample resided in one of the City's boroughs other than Brooklyn at the point of data collection, so Brooklyn specifically is considered the "setting" of the study. With more than 2.5 million residents, Brooklyn is New York City's largest borough and is home to a diverse overall population and a wide range of neighborhood contexts in terms of characteristics relevant to the study (crime rates, socio-demographics, economic characteristics and neighborhood level policing tactics).[8] This level of neighborhood diversity makes Brooklyn an ideal setting for the research, which aims to understand the unique environmental and individual factors which contribute to criminal recidivism in urban environments.

Data Collection

This research merges data from several existing sources. The study relies partly on existing, individual-level data collected by the Center for Court Innovation (CCI) under the auspices of a Bureau of Justice Assistance grant to develop and validate a short risk and need assessment tool for high-volume criminal courts (Picard-Fritsche et al., 2018). These data were collected via one-on-one interviews in a sample of approximately 1000 pre-arraignment

[8] Median family income in Brooklyn ranges from under $35,000 in lower-income neighborhoods to over $100,000 in wealthier areas (www.city-data.com). Over the 7-year period immediately preceding (2010-2014) and including (2015-2016) this study, neighborhood SQF rates ranged from 102 per 10,000 residents in the 66th precinct to 1,250 per resident in the 73rd Precinct (NYPD, 2017).

defendants in Brooklyn criminal court, utilizing a brief, actuarial risk-need assessment tool developed in 2014 (*see Appendix A* for the full interview instrument utilized in the study).[9] As seen in the interview instrument, the assessment tool measures demographic, criminal history, and criminogenic needs variables, drawing heavily on Risk-Need-Responsivity theory. Distinct from the BJA-funded study-- which focused on individual-level risk-- the current research utilizes the risk assessment data collected by CCI in combination with data regarding neighborhood of residence collected from the same sample, pursuant to a unique interest in in the effect of neighborhood context on individual recidivism. Specifically, study participants were asked to self-report either street address, neighborhood of residence, or both, during the course of their interviews. Where participants volunteered street address data, these data were used to place individuals in census tracts that were then matched to neighborhood police precincts. In the 35% of cases where address-level data were not volunteered, research assistants used a pre-existing list of neighborhood precincts in New York City to "match" individual defendants' self-reported neighborhood to their home precinct (*see Appendix B* for a copy of the list used to match neighborhoods with precincts).[10]

Data regarding neighborhood precinct characteristics were collected from two distinct sources. First, data used to construct indicators of concentrated disadvantage are based on U.S. Census American Community Survey Data (2015) retrieved via NYC Infoshare, a website dedicated to aggregating census data at different geographic levels in New York City.[11] Second,

[9] All fieldwork protocols developed for the CCI study were subject to approval by the CCI IRB and the DOJ human subjects officer. All protocols for data protection in the present study were approved by the CUNY IRB board.
[10] Where there was ambiguity in terms of the appropriate match between self-reported neighborhood and precinct (e.g., individuals reporting their neighborhood as "Flatbush" could be assigned to the 67th or 70th precincts) *and* there was no reported census tract, defendants were assigned proportionally to a precinct based on the distribution of that neighborhood's sample that reported *both* street address and neighborhood.
[11] See www.infoshare.org

indicators of police enforcement draw on publicly available reports of precinct-level SQF activity and misdemeanor arrests, published annually by the New York City Police Department (New York City Police Department, 2017). Finally, outcome data (re-arrest data) were provided by the New York State Division of Criminal Justice Services (DCJS) as a component of the BJA individual risk assessment study. Prior to analysis, individual risk assessment data were linked with DCJS data using pseudo-identifiers assigned to each participant and these data were subsequently matched to NYPD and Census data using precinct numbers associated with each individual. In other words, the final datasets used for analysis included one dataset that contained individual risk assessment data for each defendant, as well an identifier for precinct and policing and concentrated disadvantage indices for each defendant. A second dataset included original and indexed variables regarding neighborhood socioeconomic context and policing aggregated to the precinct level.

Sampling

Individual sample

The individual-level data draws on an original interview sample of 1047 defendants. This sample was created using a purposive sampling frame of all individuals arrested and detained on any charge (felony or misdemeanor) in the jurisdiction of Kings County (Brooklyn), NY between May 2015 and December 2015. Data collection was conducted 2-3 days per week, during which times all defendants awaiting arraignment in the Brooklyn criminal court holding facility were eligible to participate. Days and times of field research were selected specifically to gain as diverse a sample as possible while not interfering with the normal court process. A subsample that included all of the original research participants for whom valid criminal history data and valid data regarding home precinct could be obtained were retained for the present study.[12]

Demographic and criminal history characteristics for the final individual-level sample are displayed in Table 3.1 below. As shown, the study sample was relatively young (mean age of 32), largely male (83%), and disproportionately black or Hispanic (92%) when compared with New York City as a whole.[13] While the felony and misdemeanor defendant subsamples were similar in terms of demographic characteristics, several significant differences were found between them in terms of socioeconomic characteristics and criminal history.[14] Specifically, misdemeanor defendants were more likely to report current homelessness (9% vs 5%, $p<.01$) and drug use (40% vs. 34%, $p<.10$). Conversely, defendants with current felony charges had more serious criminal histories, with a larger percentage having at least one prior felony arrest (68% vs. 60%, $p<.05$) or felony conviction (28% vs. 25%, $p<.10$). Finally, misdemeanor defendants were more likely to have a current property offense (44% vs. 29%, $p<.001$) or drug offense (14% vs. 9%, $p<.05$) as their top arrest charge.

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[12] Specifically, 86 individuals whose top arraignment charge was less than a misdemeanor (violation level) were dropped as full criminal history is sealed by DCJS on these cases. An additional 17 individuals were dropped from the analysis for reporting home neighborhoods that could not be matched to a precinct (e.g., "Kings Highway" or "Downtown Brooklyn"). A final 60 cases were dropped for reporting residence outside of New York City or in a precinct with fewer than 10 other study participants.
[13] As of the 2015, The city of New York is 53% black or Hispanic (http://worldpopulationreview.com/us-cities/new-york-city-population/).
[14] Across all analyses, the definition of statistical significance was broadened to include p-values up to .10 in order to detect notable differences in the smaller subsamples (i.e., the felony subsample) and to detect effects that are "approaching" statistical significance.

Table 3.1. Study Sample Statistics			
	Full Sample	Misdemeanor Subsample	Felony Subsample
Total Sample Size	884	550	334
Demographics			
Average Age	32	32	33
Male	82%	82%	84%
Race			
Black/African American	68%	69%	67%
White/Caucasian	7%	6%	10%
Hispanic/Latino	24%	24%	23%
Other	1%	1%	0%
High School Diploma/GED	63%	63%	64%
Employed at time of arrest	61%	60%	63%
Housing			
Permanent Housing	88%	86%	92%
Long-term Shelter	4%	5%	3%
Homeless**	8%	9%	5%
Current Drug Use+	37%	40%	34%
Criminal History			
Any Prior Arrest	79%	79%	79%
Misdemeanor Arrest	74%	74%	75%
Felony Arrest*	63%	60%	68%
Any Prior Conviction	43%	40%	46%
Misdemeanor Conviction	37%	36%	41%
Felony Conviction+	26%	25%	28%
Violent Felony Conviction	13%	12%	14%
Instant Case			
Arrest Severity			
Misdemeanor	62%	100%	
Felony	38%		61%
Violent Felony	14%		39%
Arrest Charge Type			
Property***	39%	44%	29%
Drug*	12%	14%	9%
Other[1]	49%	42%	52%

***p<.001 **p<.01 *p<.05 +p<.10

[1] Other charges include the following major categories: DWI, domestic violence, resisting arrest, assault and weapons charges.

Neighborhood sample

This research seeks to understand whether two specific aspects of an individual's neighborhood of residence —concentrated disadvantage and level of police enforcement activity -- influences their likelihood of a new arrest over a one-year period. While there remains significant conceptual debate in the literature regarding the proper parameters of neighborhood as a unit of analysis (e.g., Sampson et al., 2002; Sampson, Morenoff, & Gannon-Rowley, 2012; Sharkey & Faber, 2014), the lion's share of recent neighborhood effects research has relied on census tracts or counties (e.g., see Kubrin & Stewart, 2006; Mears et al., 2008; Tillyer & Vose, 2011). As Sharkey and Faber discuss in a recent review of neighborhood effects methodology (2014), the definition of neighborhood in existing studies may be driven by theoretical (i.e., which definition is the most conceptually salient proxy for neighborhood given the study questions) or empirical (i.e., level of data available to test hypotheses) considerations.

For a mix of theoretical and empirical reasons, the present research utilizes police precinct as a proxy for neighborhood. The use of census tracts as the primary unit of analysis was rejected for several reasons: (1) census tract information was available for only 65% of the individual research participants; (2) the use of census tract would have reduced the individual sample size per neighborhood to less than ten per "neighborhood," threatening the validity of the planned multi-level analytic approach; and (3) data relevant to policing are not publicly available at the census tract level. Amongst potential larger units of analysis considered for the study (Precinct, Public Use Microdata Area (PUMA), Neighborhood Tabulation Area ("NTA")), precinct is also the most theoretically salient unit of analysis with respect to measuring the influence of neighborhood policing tactics.

Table 3.2 displays the distribution of the individual-level sample into neighborhood precincts. The final neighborhood-level sample included all but one precinct in Brooklyn (the 94th precinct had fewer than 10 individual research participants) and one precinct in Manhattan (the 28th precinct in Harlem). As the table suggests, individuals in the interview sample were not evenly distributed across neighborhood precincts. Indeed, the top four precincts in the study accounted for more than 40% of the total individual sample. *Appendix C* maps the sample across all the studied precincts, further illustrating this uneven distribution.

Table 3.2. Distribution of Individual-level Sample by Precinct (N=884)

Precint #/Neighborhood Name	Final Sample (#)	Final Sample (%)
28-Central Harlem	12	1%
66 - Borough Park	12	1%
78 - Park Slope	12	1%
61 - Sheepshead Bay	19	2%
63 - Flatlands/Mill Basin	18	2%
68 - Bay Ridge	19	2%
71 - Flatbush	17	2%
72 - Sunset Park	15	2%
76 - Carroll Gardens/Red Hook	13	2%
84 - Brooklyn Heights	17	2%
62 - Bensonhurst	23	3%
88 - Fort Greene	23	3%
60 - Coney Island	35	4%
90 - Williamsburg	32	4%
69 - Canarsie	42	5%
81 - Brownsville	41	5%
70 - Kensington	55	6%
77 - Crown Heights	58	7%
83 - Bushwick	63	7%
67 - East Flatbush	73	8%
73 - Ocean HIll-Brownsville	78	9%
79 - Bedford-Stuyvesant	84	10%
75 - East New York	123	14%

One important drawback of defining neighborhood as police precinct is a potential loss of variance in the neighborhood-level data, given that there are a likely a greater number of naturally occurring neighborhoods in the sample then there are formally designated precincts. This lack of specificity at the neighborhood level could obscure important findings regarding the key neighborhood-level independent variables if there is significant variance within precincts in levels of concentrated disadvantage (e.g., see null results of county-level studies in Tillyer and Vose (2011) and Mears et al., 2008) or police enforcement activity.[15] Additionally, while the methodological literature is equivocal on the minimum number of higher-level units (e.g., neighborhoods) needed to support multi-level analyses, it is generally agreed that small samples may pose a threat to the integrity of multi-level models (e.g., Mass & Hox, 2005; Gelman, 2006; Johnson, 2010). That said, the current study includes 23 precincts, which easily exceeds the minimum of ten recommended in recent scholarly literature on multilevel models (Luke, 2004; Johnson, 2010).

Key Variables

Because the research relies solely on existing data, the primary pre-analytic work involved the use of raw data to operationalize key variables of interest. Key variables include individual (Level 1) and neighborhood (Level 2) variables. Specifically, three independent variables and one outcome variable were operationalized: Individual Risk (Level l), Neighborhood Concentrated Disadvantage (Level 2), Policing Tactics (Level 2), and Any Re-arrest over one year following intake into the study (Level l, outcome variable).

[15] One-way ANOVA models showed statistically significant variance between precincts with respect to both the concentrated disadvantage and policing index scores used for this study.

Individual risk

Drawing on an actuarial risk model developed for the original BJA research (*see Appendix D* for a detailed summary of this model), individual risk is defined primarily by the cumulative risk score of each individual in the sample.[16] The final actuarial model covers a range of factors that prior research has shown to be predictive of re-arrest, including demographic variables (age and gender), criminal history, employment and education problems, residential instability, and substance abuse. Bivariate correlation, scaling, and regression techniques were used to isolate the variables measured in the original interview instrument that were most of predictive of re-arrest over one year for inclusion in the final model. Variables included as factors in the final model were assigned a weight based on the strength of their association with re-arrest and summed to create a cumulative risk score. As shown in *Appendix D*, possible risk scores range from 0-33 with higher scores indicating greater risk.[17]

Table 3.3 summarizes the risk score distribution in the current sample. Risk scores ranged from a low of two to a high of 23. The median risk score for individuals in the sample was 11, while the mean was slightly higher at 11.19. Compared with felony defendants, risk scores were, on average, nearly one point higher among misdemeanor defendants (11. 51 vs. 10.67, p<.01).

[16] Some models in the analyses rely on individual constituent variables in the risk model, described in detail in Chapter 4.
[17] For details regarding the development and validation of the individual risk model, see Picard-Fritsche, Rempel, Kerodal & Adler (2018). *The Criminal Court Assessment Tool: Development and Validation.* New York: Center for Court Innovation.

Table 3.3. Study Sample Risk Statistics			
	Full Sample	Misdemeanor Subsample	Felony Subsample
Total Sample Size	884	550	334
Mean Risk Score**	11.19	11.51	10.67
Median Risk Score	11.00	11.00	11.00
Minimum Risk Score	2.00	3.00	2.00
Maximum Risk Score	23.00	23.00	22.00

Note: General Risk Score is measured as a continuous variable ranging from 0-33.
***p<.001 **p<.01 *p<.05 +p<.10

Neighborhood concentrated disadvantage

Drawing on 2015 American Community Survey data that is publicly available at the precinct level, a neighborhood concentrated disadvantage index was constructed. Census variables that were available at the precinct level and potentially relevant to concentrated disadvantage included: (1) precinct unemployment rates; (2) percent of the precinct population that is under 18 years old; (3) percent female-headed households in the precinct; and (4) median household income. In keeping with approaches prior neighborhood effects literature (e.g., Sampson et al., 1997; Kubrin & Stewart, 2006; Tillyer & Vose, 2011), factor analysis was utilized to distill multiple variables into one concentrated disadvantage index. Such indices reduce the threat of multicollinearity between related variables and facilitate parsimonious multi-level models. One factor representing all four candidate variables emerged from this analysis.[18] The factor had an Eigen value of 2.63 and explained approximately 66% of the variance in the underlying variables. The standardized score produced by the factor analysis was used as the independent variable representing concentrated disadvantage in all subsequent analyses.

[18] Factor loadings for all four candidate variables exceeded .6.

Neighborhood policing context

Level of formal social control (i.e., policing) within a particular neighborhood is an intuitively important factor in understanding recidivism from an ecological perspective, although to-date it has been understudied in the empirical literature. For purposes of the present research, four variables drawn from publicly available NYPD reports were used to represent proactive police enforcement tactics: (1) historic rates of SQF activity in each precinct (2010-2016); (2) historic rates of "proactive" misdemeanor arrest activity in each precinct (2010-2016); (3) rates of SQF in each precinct specific to the study tracking period (2015-2016); and (4) "proactive" misdemeanor arrest rates in each precinct specific to the study tracking period (2015-2016).[19] SQF was used in this analysis as part of the policing index because it was explicitly included as one component of *Operation Impact*, a proactive policing strategy launched by the NYPD in 2003. It is worth noting here that prior studies have not typically utilized SQF activity as an indicator of OMP tactics (see Braga, Welsh & Schnell, 2015 for a review of this research). This preference makes sense, given that SQF often serves an explicit function unrelated to disorder policing (i.e., the detection of illegal weapons) and many stops do not result in arrest. It is therefore possible that the use of SQF as an indicator of police enforcement may dilute or confuse the policing index in the current study. To explore this possibility, key analyses were repeated utilizing an index of misdemeanor arrests alone (see *Appendix E*).

[19] Annual reports published by the NYPD produce aggregate numbers of misdemeanor arrests broken down by charge and precinct (*see* http://www1.nyc.gov/site/nypd/stats/crime-statistics/historical.page). These reports identify arrests in the following charge categories as related to the implementation of "proactive" policing tactics: (1) Misdemeanor Possession of Stolen Property; (2) Misdemeanor Dangerous Drug Charges; (3) Misdemeanor Dangerous Weapons; (4) Intoxicated/Impaired Driving; and (5) Criminal Trespass. This definition was replicated for the purposes of calculating the neighborhood policing index in the present study.

Rates of SQF and misdemeanor arrest were highly correlated in the precincts studied, in keeping with prior research regarding SQF and misdemeanor arrests in New York City (New York State Office of the Attorney General, 2013; MacDonald, Fagan & Geller, 2016). Because preliminary bivariate analyses suggested high inter-correlation between the selected proactive policing variables, factor analysis was utilized to combine the variable into an index of proactive policing. One factor representing three of the four candidate variables emerged from this analysis.[20] The factor had an Eigen value of 2.67 and explained approximately 88% of the variance in the underlying variables. The standardized score produced by the factor analysis was used as the independent variable representing neighborhood policing in all subsequent analyses.

Recidivism

The outcome to be understood is recidivism, which prior studies have operationalized in a variety of ways including re-arrest, re-conviction, or re-incarceration over a particular tracking period. For the current study, any re-arrest was selected as indicator of recidivism, which theoretically captures a broader sample of new offenses compared to other official measures. On the other hand, re-arrest is vulnerable to critique as a measure of criminal offending, as many people who are arrested are never convicted. While none of the commonly used measures of recidivism is a perfect approximation of new criminal activity, re-arrest is the most appropriate measure of for the present research, since a measure such as conviction or incarceration might underestimate re-involvement in the justice system and could fail to adequately capture neighborhood differences in policing on recidivism.

The present research uses any re-arrest (yes/no) over a one-year tracking period to

[20] The factor loading for SQF rates over the tracking period (2015-2016) was less than .6, whereas loadings for the other 3 variables exceeded .8. Two-year SQF was therefore dropped from the index.

distinguish recidivists from non-recidivists. To accomplish this, a standard one-year tracking variable was created that ended at 12 months following the date when the final interview was conducted for the individual-level study (December 29, 2015). Actual tracking periods for individuals in the study ranges from a minimum of 12 months to a maximum of 17 months. Differences in time exposed to re-arrest are controlled for in all analyses. Table 3.4 displays the average re-arrest rate and time to re-arrest for the full, misdemeanor, and felony defendant samples. As shown, 49% of the full sample was re-arrested over the tracking period, with approximately 256 days elapsing between study intake and re-arrest. The misdemeanor defendant sample had significantly higher rates of new arrest for any charge (51% vs. 46%, p<.05), as well as new arrests on a misdemeanor charge (39% vs. 26%, p<.05). Rates of new arrest on a felony charge were equivalent in the two groups, as was average time to new arrest.

Table 3.4. Study Sample Recidivism

	Full Sample	Misdemeanor Subsample	Felony Subsample
Total Sample Size	884	550	334
Any Re-arrest*	49%	51%	46%
Misdemeanor Re-arrest*	34%	39%	26%
Felony Re-arrest	27%	26%	28%
Violent Felony Re-arrest	9%	9%	10%
Average time to re-arrest	255.88	254.3	264.9

***p<.001 **p<.01 *p<.05 +p<.10

Control variables

All analyses control for individual defendants' time exposed to re-arrest (i.e., time in the community) within their tracking period by subtracting length of jail or prison sentence from the tracking period for those who were sentenced to jail (available in DCJS data).[21] However, pretrial detention lengths are not available in DCJS data, so tracking periods may be moderately overestimated for those defendants who were held on bail pending trial.[22] Given significant bivariate associations observed between race and re-arrest at the individual level, race/ethnicity acts as a control variables in the multivariate models.[23] At the neighborhood level, the racial make-up of precincts (e.g., % black, % Hispanic, % white) was not found to be significantly related to re-arrest, and so was excluded from the final models.

Data Analysis

The present research employed multilevel modeling using HLM (Version 6) software to test the hypothesized relationships between individual risk, neighborhood context, and recidivism. Multi-level models are considered the appropriate methodology when a researcher is simultaneously examining the effects of independent variables associated with different units of analysis (e.g., individual and neighborhood) and the individual data are "nested" within the higher order unit (Bryk & Raudenbush, 1992; Luke, 2004; Johnson, 2010). If data are nested, the use of traditional regression methodology to estimate contextual effects on individual outcomes (e.g., the disaggregation of neighborhood characteristics to the individual level and use of ordinary least squares regression) can lead to the incorrect assumption of randomly distributed errors across the individual-level data. In turn, this increases the likelihood of "Type 1" errors

[21] This control variable will assume the average 67% time served on NYC jail sentences. It should be noted that this approach is necessarily flawed, as data regarding the actual release date of participants given a jail sentence will not be available.
[22] In 2015, 70% of cases arraigned in New York City were released at arraignment (within 24 hours of arrest). A substantial majority of misdemeanor cases were also disposed at arraignment, suggesting that pretrial detention times would not have a significant impact on the tracking period for this study (see CJA annual report: http://www.nycja.org/).
[23] Other relevant individual demographic characteristics—i.e. age and gender—are included in the individual risk model.

where the researcher infers differences in individuals that are actually a function of context. Multi-level modeling approaches control for the influence of context by separately estimating the intercepts and/or slopes of the individual data within each higher order unit (in this case neighborhood precinct) and introducing a unique error term for nested data.

The rationale for the use of multi-level modeling in the current research case is both theoretical and empirical. Theoretically, it draws on the robust body of prior research indicating that individual criminal behavior and arrest patterns are influenced by neighborhood context (LaVigne, Mamalian, Travis, & Visher, 2003; Kubrin & Stewart, 2006; Fagan et al. 2009). Additionally, two of the three independent variables to be tested (police enforcement activity, concentrated disadvantage) are characteristics of the neighborhood in which individuals reside rather than of the individuals themselves, making multi-level modeling the statistically appropriate approach for the present study.[24] Finally, as Table 3.2 above demonstrated, there are substantial differences in the number of individuals in the sample nested within each precinct, and multi-level models provide the added advantage of dealing well with small within-group sample sizes by utilizing "borrowing power" to better estimate group-level means (Johnson, 2010). For the current study, therefore, group-level statistics for those precincts containing a small number of individuals will be more reliable as a result of the multi-level modeling approach.

Utilizing HLM 6 software, a series of two-level logistic regression models were estimated to test the premise that neighborhood context has a significant effect on recidivism patterns in the study sample.[25] First, an unconditional model was specified to determine whether

[24] This approach specifies degrees of freedom models testing precinct-level effects to reflect the number of neighborhood precincts in the sample (N=23) rather than the number of individuals in the sample (N=884).
[25] A Bernoulli distribution was specified to account for the non-normal distribution of the binomial outcome variable (i.e., re-arrested vs. not re-arrested).

there was significant variation in the average log odds of recidivism by precinct. Second, a means-as-outcomes model was examined to isolate the effects of the precinct-level independent variables (concentrated disadvantage index, neighborhood policing index) on mean recidivism rates in each precinct. A third and fourth model were then specified to test the effects of precinct-level independent variables on the individual odds of recidivism, net of individual risk. Specifically, the third model controls for each individual's cumulative risk score, while the fourth model examines the unique influence of key demographic and needs related risk factors (e.g., unemployment, homelessness, substance abuse) when separated from criminal history variables in the model. All four models are repeated separately on the misdemeanor and felony subsamples, pursuant to the third hypotheses regarding the potentially unique influence of neighborhood factors on individuals with misdemeanor charges. Finally, a random coefficients model was estimated which allowed for cumulative risk scores to vary by precinct, in order establish a basis for the proposition that precinct-level factors influence the interaction between individual risk scores and recidivism.

Chapter 4 presents results for each of the a priori hypotheses described above, as well as findings from an additional analysis regarding the relationship between neighborhood context and individual risk score. The additional analysis grew out of a desire to further understand the relatively modest results regarding the relationship between neighborhood context and re-arrest over the study tracking period, despite the uneven distribution of the original sample by neighborhood. The chapter concludes with an exploratory analysis of how recent changes in policing practice may have influenced the results.

Chapter 4

Findings

This chapter presents findings from an empirical investigation of the effects of neighborhood context on individual recidivism in a mixed sample of misdemeanor and felony defendants arrested in Brooklyn, New York. Specifically, it explores the relative influence of proactive police enforcement tactics and concentrated disadvantage—measured at the neighborhood precinct level—on the probability of re-arrest, after controlling for individual risk as measured by a summary risk score. Bivariate and multi-level regression models are employed to test four a priori hypotheses laid out in the study. A fifth analysis disaggregates criminal history factors from other individual risk factors contributing to the risk score (e.g., gender, age, homelessness), in order to assess for a potential relationship between neighborhood context and re-arrest when individual risk is not defined primarily by individual criminal history. The chapter concludes with an exploratory analysis of the relationship between neighborhood context and individual risk scores. This final analysis also considers whether recent shifts in neighborhood policing tactics in New York City could explain some unanticipated findings in the study.

Table 4.1 presents descriptive statistics for the independent and dependent variables included in the main analyses. Statistics are also presented separately for misdemeanor and felony subsamples, with several significant differences worth noting. On average, misdemeanor defendants in the sample were more likely to have been re-arrested over the one-year tracking period, and had higher individual risk scores when compared to defendants with a current felony charge. A current misdemeanor charge was also associated with living in a neighborhood characterized by more police enforcement activity.

Table 4.1. Descriptive Statistics for Study Variables

	Full Sample (N=884)				Misdemeanor Subsample (N=550)				Felony Subsample (N=334)			
	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum
Dependent Variable												
Recidivism (0=no 1=yes)*	0.49	0.50	0.00	1.00	0.51	0.50	0.00	1.00	0.46	0.50	0.00	1.00
Independent Variables												
Individual [1]												
Risk Score (0-33)**	11.19	4.00	2.00	23.00	11.51	4.02	3.00	23.00	10.67	3.91	2.00	22.00
Black/African American (0=no 1=yes)	0.68	0.47	0.00	1.00	0.69	0.46	0.00	1.00	0.67	0.47	0.00	1.00
Latino (0=no 1=yes)	0.24	0.43	0.00	1.00	0.24	0.43	0.00	1.00	0.23	0.42	0.00	1.00
Days at Risk for Re-arrest	500.85	65.59	377.00	549.00	503.40	65.55	383.00	669.00	496.65	65.53	377.00	617.00
Neighborhood												
Concentrated Disadvantage Index	0.47	0.52	-1.18	1.18	0.47	0.54	-1.18	1.18	0.48	0.48	-1.18	1.18
Policing Index*	0.28	0.93	-1.26	2.50	0.34	0.94	-1.26	2.50	0.18	0.89	-1.26	2.50

***p<.001 **p<.01 *p<.05 +p<.10

[1] Risk score accounts for age and gender (See Appendix E).

Table 4.2 displays bivariate correlations between the study variables. A relatively strong bivariate relationship (.392, $p<.01$) was detected between individual risk score and probability for re-arrest, supporting the contention that individual risk factors such as age, criminal history, and criminogenic needs are predictive of recidivism. No other significant relationships between the dependent and independent variables were detected, indicating limited preliminary support for a relationship between neighborhood-level factors and re-arrest over the one-year tracking period. Correlations between independent variables (e.g., race, time at risk for re-arrest, risk score) were relatively modest with the exception of a strong correlation between the concentrated disadvantage and neighborhood policing indices (.515, $p<.01$).[26] A modest but statistically significant relationship (.082, $p<.05$) was found between the neighborhood policing index and individual risk score, suggesting potential for an indirect relationship between neighborhood policing tactics and recidivism.

The final variable included in the correlation matrix represents individual top charge of misdemeanor (as opposed to felony). Having a top charge that is a misdemeanor is positively correlated with individual risk score (.102, $p<.01$). A positive correlation was also detected between misdemeanor charge and neighborhood policing index (.084, $p<.05$), suggesting preliminary support for the theory that higher levels of police enforcement activity increase the probability of misdemeanor arrest in some neighborhoods. In turn, it is reasonable to infer that residents of such neighborhoods may be at generally greater risk for a new arrest, net of individual level predictors of recidivism.

[26] Neighborhood-level indices are entered separately into all multivariate models to increase degrees of freedom at level 2 and avoid issues of multicollinearity.

Table 4.2. Bivariate Correlations among Study Variables								
	Re-Arrest	**Individual Risk Score**	**Concentrated Disadvantage Index**	**Neighborhood Policing Index**	**Recidivism Tracking Period**	**Black/African American**	**Hispanic/ Latino**	**Misdemeanor (Current Charge)**
Re-Arrest	1	.392**	-0.018	0.039	0.018	-0.048	0.014	0.054
Individual Risk Score	.392**	1	0.026	.082*	0.023	-0.018	0.032	.102**
Concentrated Disadvantage Index	-0.018	0.026	1	.551**	0.017	.103**	-0.035	-0.015
Neighborhood Policing Index	0.039	.082*	.551**	1	0.008	.167**	-.092**	.084*
Recidivism Tracking Period	0.018	0.023	0.017	0.008	1	.233**	-.147**	0.05
Black/African American	-0.048	-0.018	.103**	.167**	.233**	1	-.817**	0.016
Hispanic/Latino	0.014	0.032	-0.035	-.092**	-.147**	-.817**	1	0.011
Misdemeanor (Current Charge)	0.054	.102**	-0.015	.084*	0.05	0.016	0.011	1

***p<.001 **p<.01 *p<.05 +p<.10

Note: The definition of statistical significance was broadened to include p-values up to .10 in order to detect notable differences in the smaller subsamples (i.e., the felony subsample) and to detect effects that are "approaching" statistical significance.

Neighborhood Context & Re-arrest

Drawing on the full sample of misdemeanor and felony defendants, Tables 4.3 and 4.4 display results from a series of multi-level models addressing the first two of the study hypotheses:

H1: Neighborhood proactive police enforcement tactics will be positively related to re-arrest, net of individual-level risk.

H2: Neighborhood concentrated disadvantage will be positively related to re-arrest, net of individual-level risk.

As displayed in Table 4.3. Model 1, an unconditional, random effects model was specified to assess for variance in the mean odds of re-arrest between precincts, with non-significant results (χ^2=13.994, p>.500). Based on this finding, it was anticipated that precinct-level factors would have a modest—if any—impact on individual re-arrest outcomes. To confirm this, two "means-as-outcomes" models were created to test the influence of the neighborhood policing and concentrated disadvantage indices on re-arrest, respectively, without controlling for individual-level risk. As shown in Model 2, a higher level of police enforcement activity was found to have a modest, but statistically significant, overall effect on recidivism. Specifically, for every unit increase in the neighborhood policing index, the odds of re-arrest for defendants residing in that precinct increased by nine percent (OR= 1.09, P<.05). Conversely, concentrated disadvantage was found to have no significant influence on individual odds for a new arrest (Model 3).

Table 4.3 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

	Model 1				Model 2				Model 3			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	-0.041	0.054	0.960	(.858, 1.107)	-0.064	0.055	0.937	(.837, 1.105)	-0.022	0.058	0.978	(.868, 1.103)
Individual Level												
Total Risk Score[1]												
Black/African American												
Latino/Hispanic												
Days at Risk for Re-Arrest												
Neighborhood Level												
Policing Index					0.085	0.035	1.09*	(1.011, 1.172)				
Concentrated Disadvantage Index									-0.068	0.130	0.934	(.760, 1.149)
Random Effects												
Variance Component	0.0003				0.0003				0.0003			
Chi-Square	13.934				12.590				13.660			
Model Fit												
Deviance	2849.820				2703.930				2849.546			
Parameters Estimated	2				3				3			

N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.

***p<.001 **p<.01 *p<.05 +p<.10

Table 4.4 presents two additional models that test the same neighborhood indices while controlling for individual risk score, individual race, and days at risk for re-arrest. As expected based on bivariate analyses, individual risk score is a relatively strong predictor of re-arrest, with every unit increase in risk score increasing the odds of re-arrest by approximately 25 percent. Individual race was also a significant factor in predicting re-arrest in the sample, with black and Latino defendants *less* likely to be re-arrested compared to their white counterparts ($p<.10$).[27] Days at risk for re-arrest had no significant effect on re-arrest.

Importantly, the effect of neighborhood policing on recidivism shown in Table 4.3 becomes non-significant once individual risk score is introduced into the model, while the effect of concentrated disadvantage further weakens. After controlling for individual risk, neighborhood concentrated disadvantage and proactive police enforcement tactics do not exert a significant influence on individual odds for re-arrest. This finding suggests that defendants with certain individual characteristic (e.g., younger age, more significant criminal history, presence of criminogenic needs) are at a relatively higher risk for re-arrest irrespective of their neighborhood context. The premises laid out in the first two hypotheses can therefore be rejected, at least for the defendant sample as a whole.

[27] White defendants in the sample had significantly higher re-arrest rates (59% vs. 51% of Hispanics and 48% of African Americans), despite no racial differences in average risk scores. Exploring reasons for these differences is challenging given the low sample size of white defendants (N=71).

Table 4.4 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.554	0.297	1.741	(.938, 3.230)	0.553	0.291	1.738	(.950, 3.3183)
Individual Level								
Total Risk Score	0.228	0.019	1.255***	(1.211, 1.302)	0.229	0.019	1.257***	(1.212, 1.304)
Black/African American	-0.689	0.318	0.502*	(.269, .937)	-0.637	0.300	0.53*	(.288, .970)
Latino/Hispanic	-0.578	0.338	0.561+	(.289, 1.087)	-0.550	0.333	0.577+	(.300, 1.109)
Arrest Tracking Period	0.001	0.001	1.000	(.999, 1.003)	0.001	0.001	1.000	(.999, 1.003)
Neighborhood Level								
Policing Index	0.049	0.056	1.050	(.935, 1.180)				
Concentrated Disadvantage Index					-0.099	0.124	0.905	(.699, 1.173)
Random Effects								
Variance Component	0.000				0.000			
Chi-Square	14.282				13.955			
Model Fit								
Deviance	2698.050				2697.947			
Parameters Estimated	7				7			

N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.

***p<.001 **p<.01 *p<.05 +p<.10

Isolating Effects by Charge Severity

A growing body of scholarship suggests that rapid cycling of misdemeanor defendants through jails has been a key driver of mass incarceration in recent years (e.g., see Natapoff, 2012; Chauhan et al., 2014; Geller, 2015). One possible explanation for this trend is the increased surveillance of misdemeanor crime brought about by order maintenance policing practices that are typically focused on economically disadvantaged areas (e.g., see Howell, 2009). The next set of analyses explore this contention in the current sample:

> H3: Defendants with misdemeanor charges will be more vulnerable to the effects of neighborhood-level factors on re-arrest, when compared with those charged with a felony.

In order to test for a potential unique influence of neighborhood policing and neighborhood concentrated disadvantage on re-arrest among defendants with misdemeanor charges, the regression models initially conducted on the full sample were re-run separately in the misdemeanor and felony subsamples.[28] Results of these analyses are displayed in Tables 4.5 through 4.8 beginning on page 56.

Misdemeanor defendants

The unconditional model remained nonsignificant for misdemeanor defendants (χ^2=16.96, p>.500), while some modest differences were observed in the mean outcomes analyses. Specifically, the predictive strength of neighborhood policing on the odds of re-arrest increased modestly while losing some of its statistical significance (OR=1.12, p=.14). The effect of concentrated disadvantage on the odds of re-arrest remained small and nonsignificant. As

[28] The misdemeanor subsample, which includes 550 individuals nested in 23 precincts, accounts for 62% of the full sample. The felony subsample (334 individuals nested in 23 precincts) accounts for 38% of the full sample.

shown in Table 4.6, individual risk score continues to far outweigh both neighborhood-level and other individual-level factors in the misdemeanor sample (OR=1.24, p<.001).

Felony defendants

As in the full and misdemeanor samples, the unconditional model in the felony subsample showed no significant variance in re-arrest between individual precincts (χ^2=25.407, p>.500). Further, when isolated from the full sample, probability of re-arrest among felony defendants was driven primarily by individual risk. Shown in Table 4.7, the policing and concentrated disadvantage indices had no significant effect on re-arrest outcomes for felony defendants, even before individual risk factors were introduced into the model. Further, Table 4.8 shows that the predictive power of individual risk score is modestly higher in the felony subsample relative to the misdemeanor subsample. Specifically, after controlling for neighborhood-level factors, the odds of re-arrest increased by 28% for every unit increase in risk score (OR=1.28, p<.001) amongst felony defendants, compared with a 24% increase among misdemeanor defendants (OR=1.24, p<.001). Interestingly, living in a neighborhood characterized by high concentrated disadvantage appears to *decrease* the odds of re-arrest among felony defendants (OR=.72), although this result did not reach statistical significance.

Overall, the analyses comparing misdemeanor and felony defendants in the current sample is inconclusive. Although the results suggest that neighborhood policing exerts some influence over recidivism among misdemeanor defendants, whereas neighborhood factors showed little importance for predicting re-arrest among felony defendants, neither of these findings achieved statistical significance.

Table 4.5 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Misdemeanor Subgroup

	Model 1				Model 2				Model 3			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.042	0.089	1.043	(.871, 1.252)	-0.005	0.074	0.994	(.853, 1.159)	0.043	0.077	1.040	(.890, 1.221)
Individual Level												
Total Risk Score												
Black/African American												
Latino/Hispanic												
Arrest Tracking Period												
Neighborhood Level												
Policing Index					0.149	0.096	1.160	(.950, 1.418)				
Concentrated Disadvantage Index									0.041	0.076	1.007	(.679, 1.493)
Random Effects												
Variance Component	0.001				0.001				0.000			
Chi-Square	16.962				14.383				16.961			
Model Fit												
Deviance	1773.027				1770.350				1773.029			
Parameters Estimated	2				3				3			

***p<.001 **p<.01 *p<.05 +p<.10

N=550 individuals nested in 23 Precincts

Table 4.6 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Misdemeanor Subgroup

	Model 4				Model 5			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.663	0.368	1.938	(.902, 4.167)	0.658	0.353	1.931	(.922, 3.998)
Individual Level								
Total Risk Score	0.217	0.213	1.242***	(1.191, 1.295)	0.022	0.021	1.244***	(1.194, 1.296)
Black/African American	-0.680	0.373	.506+	(.244, 1.055)	-0.065	0.365	.523+	(258 1.079)
Latino/Hispanic	-0.714	0.420	.489+	(.215, 1.17)	-0.070	0.414	0.497+	(.221, 1.124)
Arrest Tracking Period	0.000	0.000	1.000	(.998, 1.004)	0.000	0.000	1.001	(.998, 1.004)
Neighborhood Level								
Policing Index	0.110	0.123	1.116	(.867, 1.444)				
Concentrated Disadvantage Index					0.060	0.205	1.060	(.693, 1.629)
Random Effects								
Variance Component	0.0009				0.0001			
Chi-Square	14.601				15.609			
Model Fit								
Deviance	1683.310				1684.440			
Parameters Estimated	7				7			

***p<.001 **p<.01 *p<.05 +p<.10

Table 4.7 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Felony Subgroup

	Model 1				Model 2				Model 3			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	-0.188	0.119	0.824	(0.647, 1.061)	-0.194	0.117	0.823	(0.659, 1.061)	-0.152	0.138	0.860	(0.664, 1.173)
Individual Level												
Total Risk Score												
Black/African American												
Latino/Hispanic												
Arrest Tracking Period												
Neighborhood Level												
Policing Index					-0.005	0.142	0.954	(0.710, 1.282)				
Concentrated Disadvantage Index									-0.158	0.236	0.854	(0.503, 1.310)
Random Effects												
Variance Component	0.034				0.024				0.010			
Chi-Square	25.407				25.188				24.479			
Model Fit												
Deviance	1073.96				1073.85				1073.26			
Parameters Estimated	2				3				3			

***p<.001 **p<.01 *p<.05 +p<.10

N=334 individuals nested in 23 Precincts

Table 4.8. Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Felony Subgroup

	Model 4				Model 5			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	-0.213	0.133	1.397	(0.611, 1.067)	0.396	0.395	1.485	(0.689, 1.195)
Individual Level								
Total Risk Score	0.243	0.043	1.275***	(1.171, 1.387)	0.251	0.044	1.285***	(1.179, 1.401)
Black/African American	-0.691	0.469	0.501	(.199, 1.261)	-0.630	0.441	0.532	(.224, 1.267)
Latino/Hispanic	-0.332	0.436	0.717	(.304, 1.694)	-0.337	0.424	0.689	(.300, 1.587)
Arrest Tracking Period	0.001	0.002	1.000	(.995, 1.005)	0.000	0.002	1.000	(.996, 1.005)
Neighborhood Level								
Policing Index	-0.006	0.160	0.995	(.611, 1.343)				
Concentrated Disadvantage Index					-0.326	0.225	0.722	(.424, 1.047)
Random Effects								
Variance Component	0.049				0.002			
Chi-Square	23.873				20.696			
Model Fit								
Deviance	1011.02				1008.97			
Parameters Estimated	7				7			

***p<.001 **p<.01 *p<.05 +p<.10

N=334 individuals nested in 23 Precincts

Interaction: Neighborhood Context & Risk Score

The next analysis examines the possibility that neighborhood factors such as police enforcement activity and concentrated disadvantage influence the *form* of the relationship between individual risk score and recidivism. It is possible, for example, that high risk individuals are at even greater risk for re-arrest when they reside in "high risk" neighborhoods (e.g., see Onifaade et al., 2011) *or* that individual risk factors operate independently of context (e.g., see Tillyer & Vose, 2011).

The concept that individual risk scores and neighborhood factors might interact to affect recidivism in the current sample is laid out in the study's fourth hypothesis:

> H4: Higher individual risk scores will interact with neighborhood factors (policing, concentrated disadvantage) to increase the likelihood of re-arrest.

Drawing on the full sample of defendants, a random coefficients model was specified to test this premise. The random coefficients approach differs from the previous hierarchical models presented in that allows it for random variance by precinct in the *slop*e of the relationship between risk score and re-arrest over the tracking period, in addition to allowing the model intercepts to vary.[29] The unconditional model presented in Table 4.9 (Model 1) indicates that there was no significant variance found between precincts in terms of strength of individual risk score as a predictor of new arrest (χ^2=14.05, p>.500), suggesting that neighborhood-level factors would be unlikely to have a strong influence on the relationship between individual risk scores and re-arrest.

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[29] Prior models shown were random intercept models, which allowed for random variance in the mean of the outcome variable by precinct, but held the coefficients of predictor variables constant across precincts.

Two full regression models, also included in Table 4.9, largely confirm this finding. As shown in Model 2, a cross-level interaction term between individual risk score and neighborhood policing had no independent effect on the odds of re-arrest. Similarly, no significant interaction was found between risk score and level of neighborhood concentrated disadvantage, displayed in Model 3. Given the null findings regarding the anticipated *positive* interaction between neighborhood factors and re-arrest, the fourth hypothesis was rejected.

However, a separate, unanticipated finding arose from this analysis that is noteworthy. As shown in Model 2, inclusion of the interaction term between individual risk score and the neighborhood policing index resulted in an *increase* in predictive strength and statistical significance of the policing index (OR=1.39, $p<.10$), when compared with prior models. This change suggests that the impact of neighborhood policing on odds of re-arrest is, after all, partly contingent on individual risk score, but not in the originally expected way. Rather than higher risk scores interacting with a high levels of proactive policing to increase the odds of re-arrest, this analysis shows that individuals at the *lower* end of the risk spectrum are more vulnerable to the effects of neighborhood policing on recidivism.[30] An increase in the predictive strength of concentrated disadvantage for lower risk defendants was also observed in Model 3, though this finding did not reach statistical significance (OR=1.52, p=.189).

Tables 4.10 and 4.11 repeat the random coefficients analysis separately in the misdemeanor and felony subsamples. As shown in Table 4.10 (Model 2), the results for the misdemeanor subsample largely follow that of the full sample, with the neighborhood policing index exerting a relatively strong and statistically significant effect on recidivism for misdemeanor defendants at the lower end of the risk spectrum (OR=1.37, $p<.10$). As displayed

[30] Higher odds of re-arrest applied only to individuals with risk scores in the lowest 10% of the risk spectrum.

in Table 4.11, while the effect of the policing index on lower risk felony defendants was actually stronger than that observed among misdemeanor defendants, it did not reach statistical significance (OR=1.61, p=.195). Finally, the effect of concentrated disadvantage index on recidivism among lower risk defendants did not reach statistical significance in either of the subsamples, though the effect size was large in both groups.[31]

Ultimately, while these findings contradict the original hypothesis regarding the relationship between risk score, neighborhood context, and re-arrest, they nonetheless support the broader concept that proactive enforcement tactics contribute to a "criminogenic" environment for some individuals. In effect, they suggest that living in a highly policed area *could* act as a gateway back into the criminal justice system for individuals otherwise at low risk for a new arrest. Moreover, this finding appears to be more reliable among defendants with current misdemeanor charges, suggesting that low risk individuals in "high risk" environments may be drawn into the system as the result of relatively minor offense.

[31] Results are difficult to interpret, as large effect sizes and lack of significance may be an artifact of small within precinct sample sizes after controlling for both charge severity and risk level.

Table 4.9. Neighborhood Factors and the Risk-Recidivism Relationship

Random Coefficients Model

	Model 1				**Model 2**				**Model 3**			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
	-0.0407	0.07355	0.96009	(.844, 1.092)	0.494	0.315	1.638	(.851, 3.156)	0.436	0.283	1.549	(.858, 2.789)
Individual Level												
Total Risk Score					0.24	0.02	1.27***	(1.213, 1.322)	0.25	0.02	1.29***	(1.231, 1.341)
Black/African American					-0.71	0.32	0.49*	(.261, .932)	-0.66	0.31	0.515*	(.278, .958)
Latino/Hispanic					-0.61	0.35	0.55+	(.261, .932)	-0.57	0.34	0.56+	(.289, 1.001)
Arrest Tracking Period					0.00	0.00	1.00	(.999, 1.003)	0.00	0.00	1.00	(.999, 1.003)
Risk Score x Policing Index					-0.03	0.02	0.97	(.277, 1.077)				
Risk Score x Concentrated Disadvantage Index									-0.05	0.02	0.95	(.911,1.001)
Neighborhood Level												
Policing Index					0.33	0.19	1.39+	(.933, 2.077)				
Concentrated Disadvantage Index									0.42	0.31	1.52	(.797, 2.900)
Random Effects												
Variance Component (Random Intercept Model)	0.00				0.00				0.00			
Chi-Square	14.05				14.63				14.29			
Variance Component (Random Slopes Model)	0.00				0.00				0.00			
Chi-Square	18.14				16.87				16.69			
Model Fit												
Deviance	2703.93				2696.78				2696.68			
Parameters Estimated	5.00				10.00				10.00			

***p<.001 **p<.01 *p<.05 +p<.10

N=884 individuals nested in 23 Precincts

Table 4.10. Neighborhood Factors and the Risk-Recidivism Relationship

Random Coefficients Model (Misdemeanor Subsample)

	Model 1				Model 2				Model 3			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
	0.00586	0.089	1.06	(.881, 1.276)	0.602	0.389	1.152	(.813, 4.107)	0.602	0.342	1.826	(.895, 3.724)
Individual Level												
Total Risk Score					0.22	0.02	1.27***	(1.186, 1.327)	0.23	0.02	1.26***	(1.196, 1.323)
Black/African American					-0.70	0.38	0.49*	(.237, 1.060)	-0.67	0.37	0.52*	(.248, 1.0640
Latino/Hispanic					-0.73	0.43	0.55+	(.208, 1.117)	-0.73	0.42	0.48+	(.213, 1.095)
Arrest Tracking Period					0.00	0.00	1.00	(.998, 1.004)	0.00	0.00	1.00	(.998, 1.004)
Risk Score x Policing Index					-0.02	0.02	0.97	(.945, 1.020)				
Risk Score x Concentrated Disadvantage Index									-0.02	0.02	0.95	(.932, 1.022)
Neighborhood Level												
Policing Index					0.32	0.27	1.37+	(.813, 4.107)				
Concentrated Disadvantage Index									0.35	0.43	1.41	(.573, 3.489)
Random Effects												
Variance Component (Random Intercept Model)	0.02				0.00				0.02			
Chi-Square	16.45				15.02				17.04			
Variance Component (Random Slopes Model)	0.03				0.00				0.00			
Chi-Square	19.26				19.14				18.99			
Model Fit												
Deviance	1687.00				1682.84				1683.84			
Parameters Estimated	5				10				10			

***p<.001 **p<.01 *p<.05 +p<.10

N=550 individuals nested in 23 Precincts

Table 4.11. Neighborhood Factors and the Risk-Recidivism Relationship

Random Coefficients Model (Felony Subsample)

	Model 1				Model 2				Model 3			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
	-0.187	0.126	0.829	(.638, 1.079)	-0.274	0.141	0.759	(.567, 1.018)	-0.636	0.301	0.529	(.283, .991)
Individual Level												
Total Risk Score					0.266	0.044	1.31***	(1.190, 1.431)	0.371	0.058	1.45***	(1.285, 1.634)
Black/African American					-0.738	0.465	0.478	(.191, 1.195)	-0.738	0.446	0.478+	(.198, 1.151)
Latino/Hispanic					-0.401	0.436	0.669	(.284, 1.580)	-0.444	0.438	0.641+	(.270, 1.522)
Arrest Tracking Period					0.000	0.002	1.001	(.996, 1.005)	0.001	0.001	1.001	(.995, 1.005)
Risk Score x Policing Index					-0.051	0.031	0.949	(.894, 1.009)				
Risk Score x Concentrated Disadvantage Index									-0.196	0.087	0.955	(.270, 1.522)
Neighborhood Level												
Policing Index					0.477	0.356	1.611	(.768, 3.378)				
Concentrated Disadvantage Index									1.588	0.934	4.890	(.701, 34.17)
Random Effects												
Variance Component (Random Intercept Model)	0.035				0.020				0.004			
Chi-Square	19.620				20.013				17.857			
Variance Component (Random Slopes Model)	0.071				0.007				0.009			
Chi-Square	23.877				24.170				26.419			
Model Fit												
Deviance	1013.38				1008.52				1003.50			
Parameters Estimated	5				10				10			

***p<.001 **p<.01 *p<.05 +p<.10

N=334 individuals nested in 23 Precincts

Disaggregating Individual Risk

Next, in order to gain a more nuanced understanding of how individual- and neighborhood-level risk factors contribute to re-arrest in the current sample of defendants, another series of regression models were specified. These models disaggregate the demographic and criminogenic needs factors from the criminal history factors in the original risk model, and explore whether considering these types of risk factors separately might result in a shift in the observed influence of neighborhood context on re-arrest. Results are presented in Tables 4.12 through 4.19, beginning on page 70.

Demographic and criminogenic needs factors

Despite a rich body of prior literature documenting the importance of criminogenic needs (e.g., substance abuse, unemployment, homelessness) to understanding recidivism, few prior studies have specifically considered how such needs variables might interact with neighborhood-level factors to affect the probability of re-arrest. Indeed, the present study has relied thus far on a summary measure of individual risk that includes *both* criminal history and criminogenic needs variables. One drawback of this approach is that--as in most existing risk assessment tools--criminal history variables carry disproportionate weight in the underlying risk algorithm utilized for this research.

Table 4.12 (Model 1) examines the extent to which demographic and criminogenic needs factors in the original risk model independently influence odds of re-arrest in the full sample, as well as whether the relative influence of the neighborhood policing index changes after criminal history variables are removed from the model. As shown, each of the non-criminal history variables contributing to the original risk score exert a significant influence on the odds of re-arrest, with homelessness, male gender, and current drug use having the strongest effects.

Additionally, the influence of neighborhood police enforcement activity did retain statistical significance (OR=1.10, p<.05) in this model, unlike in previous models controlling for total risk score. As in prior models, concentrated disadvantage had no significant effect on the likelihood of re-arrest.

The analysis presented in Table 4.12 suggests that neighborhood-level policing tactics influence re-arrest after controlling for individual demographic and criminogenic needs factors, but falls short of demonstrating the independence of policing as a risk factor in a scenario where this type of risk is defined more holistically. To strengthen this analysis, a risk score was created by summing the weights of each of the risk factors included the non-criminal history model. A logistic regression analysis (not shown) confirmed that this score is a significant predictor of re-arrest in the current sample (OR=1.33, p<.001), although its predictive accuracy is relatively weak when compared with the original risk score utilized in prior analyses.[32] A second multi-level model (Table 4.13, Model 1) demonstrates that the neighborhood policing index *is* an independent predictor of re-arrest, after controlling for a non-criminal history risk score (OR=1.09, p<.05). Also shown in Table 4.13 (Model 2), after controlling for this risk score, the concentrated disadvantage index continued to have no effect on odds of re-arrest. Tables 4.14 and 4.15 repeat this analysis for separately for the misdemeanor and felony defendant subsamples, respectively. As shown in Table 4.14, findings for the misdemeanor subsample are similar to the those for the full sample, though the influence of the neighborhood policing index loses significance (OR=1.14, p<.181). For the felony subsample, neither of the neighborhood-level factors proved important for predicting re-arrest after controlling for individual risk based on demographics and criminogenic needs factors (see Table 4.15).

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[32] The demographic and needs based risk score achieved an AUC of .630, compared with the AUC of. 743 achieved by the original risk score that includes criminal history, criminogenic need, and demographic factors.

Criminal history factors

The next set of analyses explore the relationship between individual criminal history, neighborhood-level risk factors, and re-arrest. Table 4.16 shows the influence of each of the criminal history variables included in the original risk model on odds of re-arrest, while controlling for neighborhood police enforcement (Model 1) and concentrated disadvantage (Model 2). Most of the original criminal history variables retained predictive power, with prior misdemeanor and felony convictions being the strongest individual predictors in both models. In contrast to findings from the non-criminal history risk analysis, Model 1 suggests that neighborhood policing is *not* an independent predictor of re-arrest (OR=1.027, p=.768) after controlling individual criminal history variables. As in prior analyses, neighborhood-level concentrated disadvantage also did not exert a significant influence on re-arrest in the criminal history based risk model.

In order to further assess whether neighborhood-level factors influence re-arrest after controlling for individual criminal history, a "criminal history score" was computed by summing the weights of each of the risk factors included the criminal history model. A logistic regression analysis (not shown) confirmed that this risk score is a significant predictor of odds for re-arrest in the current sample (OR=1.23, p<.001). As with the score based on needs and demographic factors , the predictive accuracy of the criminal history only model was found to be weak when compared to the original model containing all types of risk factors.[33] Table 4.17 (Model 1) confirms that neighborhood-level police enforcement is *not* an independent predictor of re-arrest after accounting for the criminal history risk score, and that neighborhood concentrated disadvantage also does not predict re-arrest after controlling for individual criminal history

[33] The criminal history risk score achieved an AUC of .686, compared with the AUC of. 743 achieved by the original risk score that includes criminal history, criminogenic need, and demographic factors.

(Table 4.17, Model 2). Tables 4.18 and 4.19 repeat this analysis for separately for the misdemeanor and felony defendant subsamples, respectively, with null findings for both subsamples regarding the influence of neighborhood factors on re-arrest after controlling for criminal history. Findings from the disaggregation of demographic, criminogenic needs and criminal history variables in the original risk model present a more nuanced picture of the relationship between individual and neighborhood-level risk factors than is often found in multi-level studies of recidivism. Specifically, demographic and needs factors appear to operate independently of neighborhood policing as predictors of re-arrest in the current sample, whereas criminal history and neighborhood policing are inter-related. These effects appear to be stronger for individuals currently charged with a misdemeanor offense compared to those charged with a felony offense, though this finding is not statistically significant. In summary, the aggregation of criminal history and non-criminal history variables into a summary risk score may have ultimately obscured a real relationship between neighborhood context and recidivism in the current sample.

Table 4.12. Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Needs and Demographic Factors

	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	-0.391	0.387	0.676	(.302, 1.515)	-0.412	0.385	0.661	(.354, 1.238)
Age	-0.013	0.006	.986*	(.975, .997)	-0.013	0.006	.987*	(.975, .999)
Gender (Male)	0.625	0.180	1.87***	(1.300, 2.640)	0.609	0.189	1.84***	(1.267, 2.670)
Homeless/Shelter	0.920	0.239	2.51***	(1.563, 4.106)	0.945	0.240	2.57***	(1.605, 4.124)
Education (No HS diploma/GED)	0.202	0.094	1.22+	(.997, 1.472)	0.213	0.149	1.240	(.923, 1.628)
Unemployed	0.225	0.129	1.25+	(.971, 1.618)	0.229	0.140	1.257	(.928, 1.658)
Current Drug User	0.361	0.119	1.43**	(1.139, 1.821)	0.364	0.145	1.44*	(1.083, 1.915)
Black/African American	-0.607	0.356	0.545+	(.263, 1.204)	-0.583	0.270	.558*	(.328, .948)
Hispanic	-0.544	0.352	0.581	(.286, 1.136)	-0.519	0.289	0.595+	(.337, 1.050)
Arrest Tracking Period	0.000	0.001	1.000	(.999, 1.003)	0.001	0.001	1.001	(.999, 1.003)
Policing Index	0.097	0.041	1.10*	(1.103, 1.203)				
Concentrated Disadvantage Index					-0.056	0.135	0.945	(.714, 1.251)
Random Effects								
Variance Component	0.000				0.001			
Chi-Square	12.148				13.195			
Model Fit								
Deviance	2795.930				2797.420			
Parameters Estimated	12				12			

***p<.001 **p<.01 *p<.05 +p<.10

N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.

Table 4.13 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Needs and Demographic Factors Risk Score

	Model 1				**Model 2**			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.532	0.320	1.702	(.876, 3.311)	0.517	0.316	1.677	(0.868, 3.242)
Individual Level								
Dynamic Risk Score	0.284	0.028	1.328***	(1.255, 1.405)	0.287	0.029	1.332***	(1.259, 1.409)
Black/African American	-0.673	0.344	0.510*	(.260, 1.001)	-0.608	0.340	0.544+	(.279, 1.063)
Latino/Hispanic	-0.575	0.344	0.563+	(.286, 1,106)	-0.538	0.345	0.584	(.297, 1.063)
Arrest Tracking Period	0.001	0.000	1.000	(.099, 1.003)	0.001	0.001	1.001	(.999, 1.003)
Neighborhood Level								
Policing Index	0.087	0.039	1.09*	(1.005, 1.184)				
Concentrated Disadvantage Index					-0.053	0.097	0.948	(.774, 1.161)
Random Effects								
Variance Component	0.000				0.000			
Chi-Square	12.087				12.900			
Model Fit								
Deviance	2797.042				2798.173			
Parameters Estimated	7				7			

***p<.001 **p<.01 *p<.05 +p<.10

N=884 individuals nested in 23 Precincts

Table 4.14 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Needs and Demographic Factors Risk Score (Misdemeanor Subsample)

	Model 1				Model 2			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.630	0.370	1.877	(.870, 4.054)	0.613	0.357	1.845	(.877, 3.883)
Individual Level								
Dynamic Risk Score	0.314	0.039	1.368***	(1.267, 1.478)	0.318	0.039	1.374***	(1.274, 1.484)
Black/African American	-0.648	0.385	0.532+	(.245, 1.116)	-0.580	0.378	0.559	(.266, 1.177)
Latino/Hispanic	-0.745	0.420	0.474+	(.208, 1.075)	-0.704	0.420	0.494+	(.216, 1.129)
Arrest Tracking Period	0.001	0.001	1.001	(.999, 1.004)	0.001	0.038	1.001	(.998, 1.004)
Neighborhood Level								
Policing Index	0.133	0.109	1.142	(.911, 1.433)				
Concentrated Disadvantage Index					0.022	0.190	1.022	(.688, 1.521)
Random Effects								
Variance Component	0.001				0.000			
Chi-Square	14.488				16.173			
Model Fit								
Deviance	1731.180				1733.090			
Parameters Estimated	7				7			

***p<.001 **p<.01 *p<.05 +p<.10

N=550 individuals nested in 23 Precincts

Table 4.15 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Needs and Demographic Factors Risk Score (Felony Subsample)

	Model 1				Model 2			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.337	0.484	1.401	(.511, 3.840)	0.345	0.482	1.413	(.518, 3.855)
Individual Level								
Dynamic Risk Score	0.212	0.060	1.236***	(1.097, 1.394)	0.213	0.061	1.238***	(1.097, 1.397)
Black/African American	-0.730	0.531	0.481	(.169, 1.371)	-0.687	0.518	0.503	(.181, 1.395)
Latino/Hispanic	-0.262	0.505	0.768	(.284, 2.078)	-0.261	0.503	0.769	(.286, 2.075)
Arrest Tracking Period	0.000	0.002	1.000	(.996,1.004)	0.000	0.002	1.000	(.996, 1.004)
Neighborhood Level								
Policing Index	0.043	0.183	1.004	(.713, 1.530)				
Concentrated Disadvantage Index					-0.107	0.240	0.897	(.544, 1.482)
Random Effects								
Variance Component	0.071				0.052			
Chi-Square	27.901				27.143			
Model Fit								
Deviance	1059.734				1059.660			
Parameters Estimated	7.000				7.000			

***p<.001 **p<.01 *p<.05 +p<.10

N=334 individuals nested in 23 Precincts

Table 4.16. Hierarchical Logistic Regression Models Predicting Odds of Re-arrest								
Criminal History Factors								
	Model 1				**Model 2**			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
	0.850	0.422	2.340	(.974, 5.625)	0.865	0.432	2.383	(1.002, 5.670)
Individual Level								
Current Felony Drug, Misdemeanor Property, or Weapons Charge	-0.272	0.099	0.756**	(.674, .925)	-0.278	0.098	0.756**	(.624, .918)
Prior Felony Convictions (last three years)	0.720	0.246	2.05**	(1.236, 3.207)	0.688	0.242	1.99**	(1.236, 3.207)
Prior Misemeanor Convictions	0.341	0.049	1.37***	(1.244, 1.507)	0.315	0.049	1.37***	(1.244, 1.512)
Ten or more misdmeanor convictions	0.729	0.546	2.073	(.709, 6059)	0.730	0.551	2.076	(.703, 6.132)
Prior Jail or Prison Sentence	0.369	0.172	1.45*	(1.030, 2.029)	0.374	0.169	1.45*	(1.042, 2.030)
Number of warrants for failure to appear in court	0.112	0.076	1.118	(.963, 1.300)	0.118	0.077	1.126	(.968, 1.310)
Number of currently open cases	0.222	0.095	1.25*	(1.036, 1.503)	0.219	0.093	1.25*	(1.037, 1.496)
Black/African American	-0.650	0.320	.522*	(.278, .978)	-0.596	0.315	.551+	(.297, 1.023)
Hispanic	-0.488	0.342	0.614	(.314, 1.201)	-0.452	0.339	0.636	(.326, 1.329)
Arrest Tracking Period	0.001	0.001	1.001	(.999, 1.003)	0.001	0.001	1.001	(.999, 1.003)
Neigborhood Level								
Policing Index	0.028	0.053	1.027	(.921, 1.147)				
Concentrated Disadvantage Index					-0.015	0.141	0.859	(.676, 1.091)
Random Effects								
Variance Component	0.001				0.000			
Chi-Square	15.156				13.872			
Model Fit								
Deviance	2719.010				2717.970			
Parameters Estimated	13				13			
***p<.001 **p<.01 *p<.05 +p<.10								
N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.								

Table 4.17 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Criminal History Risk Score

	Model 1				Model 2			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.537	0.298	1.711	(.921, 3.179)	0.534	0.294	1.706	(.924, 3.152)
Individual Level								
Risk Score	0.209	0.017	1.232***	(1.192, 1.273)	0.211	0.016	1.235***	(1.196, 1.277)
Black/African American	-0.680	0.325	0.506*	(.267, 0.960)	-0.616	0.319	0.540+	(.289,1.011)
Latino/Hispanic	-0.491	0.611	0.611	(.317, 1.181)	-0.451	0.332	0.637	(.332, 1.222)
Arrest Tracking Period	0.001	0.001	1.001	(1.000, 1.003)	0.001	0.001	1.001	(1.000, 1.003)
Neighborhood Level								
Policing Index	0.051	0.046	1.052	(.955, 1.159)				
Concentrated Disadvantage Index					-0.135	0.107	0.872	(.697, 1.093)
Random Effects								
Variance Component	0.000				0.000			
Chi-Square	14.040				13.201			
Model Fit								
Deviance	2740.890				2740.360			
Parameters Estimated	7				7			

***p<.001 **p<.01 *p<.05 +p<.10

N=884 individuals nested in 23 Precincts

Table 4.18 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Criminal History Risk Score (Misdemeanor Subsample)

	Model 1				Model 2			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.658	0.369	1.930	(.895, 4.171)	0.649	0.360	1.913	(.905, 4.047)
Individual Level								
Risk Score	0.215	0.028	1.241***	(1.173, 1.313)	0.218	0.028	1.244***	(1.177, 1.316)
Black/African American	-0.682	0.387	0.506+	(.236, 1.082)	-0.627	0.381	0.534+	(.252, 1.131)
Latino/Hispanic	-0.634	0.419	0.530	(.232, 1.209)	-0.596	0.414	0.550	(.244, 1.244)
Arrest Tracking Period	0.002	0.001	1.001	(.999, 1.005)	0.002	0.001	1.001	(.999, 1.004)
Neighborhood Level								
Policing Index	0.094	0.111	1.098	(.872, 1.384)				
Concentrated Disadvantage Index					-0.025	0.195	0.975	(.649, 1.466)
Random Effects								
Variance Component	0.001				0.003			
Chi-Square	15.159				15.914			
Model Fit								
Deviance	1703.390				1704.280			
Parameters Estimated	7				7			

***p<.001 **p<.01 *p<.05 +p<.10

N=550 individuals nested in 23 Precincts

Table 4.19 Hierarchical Logistic Regression Models Predicting Odds of Re-arrest

Criminal History Risk Score (Felony Subsample)

	Model 1				Model 2			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.347	0.402	1.414	(.613, 3.265)	0.412	0.400	1.511	(.656, 3.480)
Individual Level								
Risk Score	0.203	0.025	1.225***	(1.165, 1.288)	0.208	0.024	1.231***	(1.175, 1.291)
Black/African American	-0.711	0.432	0.490+	(.209, 1.151)	-0.665	0.416	0.513	(.226, 1.167)
Latino/Hispanic	-0.280	0.409	0.755	(.338, 1.691)	-0.306	0.406	0.735	(.331, 1.638)
Arrest Tracking Period	0.001	0.002	1.001	(.996, 1.005)	0.001	0.002	1.001	(.996, 1.005)
Neighborhood-level								
Policing Index	-0.025	0.172	0.974	(.680, 1.396)				
Concentrated Disadvantage Index					-0.311	0.246	0.732	(.439, 1.222)
Random Effects								
Variance Component	0.047				0.008			
Chi-Square	25.787				23.588			
Model Fit								
Deviance	1029.630				1028.430			
Parameters Estimated	7.000				7.000			

***p<.001 **p<.01 *p<.05 +p<.10

N=334 individuals nested in 23 Precincts

Neighborhood Context: Predicting Individual Risk Score

Both the bivariate and multivariate models presented thus far suggest that some relationship exists between individual risk for re-arrest—as represented by summary risk scores--and neighborhood policing tactics. This relationship was first detected in the modest but statistically significant relationship between neighborhood-level police enforcement tactics and individual risk scores (see Table 4.2). A related finding emerged again in the multivariate analyses disaggregating the influence of dynamic and static risk factors in the context of neighborhood-level proactive policing tactics, which showed higher levels of police enforcement activity remained a significant predictor of re-arrest after removing criminal history variables from the individual model. In order to further explore this phenomenon, a final series of regression models were created that specified *individual risk score* as the outcome of interest, with individual race, time at risk for re-arrest, and neighborhood-level factors entered as the independent variables.

Beginning on page 81, results of this analysis for the full sample of defendants are presented in Table 4.20, and for the misdemeanor and felony subsamples in Tables 4.21 and 4.22, respectively. With respect to the full sample, average defendant risk score *does* vary significantly by precinct (χ^2=43.100, p<.01), as shown in the unconditional model (Model 1). This model reveals that error terms in regression lines representing risk scores are systematically correlated by precinct (i.e., average risk scores skew higher in some precincts than others). Model 2 shows that higher levels of neighborhood police enforcement activity are associated with higher average risk scores (*b* =.467, p<. 01), whereas concentrated disadvantage is not significantly related to risk score. As shown in Table 4.21, results for the misdemeanor subsample largely follow that of the full sample, with average defendant risk scores varying significantly by precinct (χ^2=39.034, $p<.01$) and neighborhood policing associated with higher risk scores (b =.477, $p<.10$). Conversely, shown in Table 4.22, while risk scores among felony defendants also varied significantly by precinct (χ^2=35.216, $p<.05$), neighborhood policing was *not* associated with higher risk scores. On the other hand, concentrated disadvantage was associated with higher risk scores (b=1.207*,* $p<.10$) in the felony population.[34]

Results of this final analysis are somewhat counterintuitive and suggest a more complex relationship between neighborhood context and re-arrest than was initially contemplated at the outset of the study. Specifically, the finding that neighborhood police enforcement activity is associated with higher individual risk scores seems to contradict the earlier null findings regarding the relationship between policing and actual re-arrest over the study tracking period. This could be explained by changes in local police practice over time. In short, it is possible that lower overall levels of police enforcement activity during the study tracking period (2015- 2016) mitigated the influence of policing on re-arrest in the current sample, while historically higher levels of police enforcement activity nonetheless played a role in driving up average risk scores in some neighborhoods.

This possibility is explored in Figures 4.1 and 4.2, beginning on page 84, which compare trends in SQF activity and "proactive" misdemeanor arrests—in five of the 23 precincts under study over the four years prior to the study ("criminal history" period) and the two years during which the sample was tracked for re-arrest ("recidivism tracking" period). The sample neighborhoods shown were purposefully selected to represent diversity in terms of historic levels of proactive policing tactics. Specifically, Brownsville (73rd precinct) and East Harlem (28th

[34] Results comport with several prior analyses which suggest that concentrated disadvantage is a more important indicator in the felony subsample, though taken together these results do not suggest a reliable pattern of influence of concentrated disadvantage (e.g., the concentrated disadvantage index sometimes appears to increase, and sometimes appears to decrease probability of re-arrest).

precinct) have historically high levels of proactive policing, when compared with East Flatbush (67th precinct) with historically moderate levels of proactive policing, and Kensington (70th Precinct), and Borough Park (66th precinct) with relatively low levels. These figures indicate that, indeed, substantial drops in both SQF activity and "proactive" misdemeanor arrests were observed across the five precincts in the year just prior to the recidivism tracking period for the present study, with particularly sharp drops in SQF activity in Brownsville and East Harlem. Notably, these drops coincide with the conclusion of the *Floyd v. City of New York* case in late 2013, which required the NYPD to undergo an independent review of SQF practices in the wake of allegations that the practice is racially biased (Meares, 2014).

While these figures are descriptive and therefore not conclusive, they provide relevant context for interpreting some contradictory findings emerging from the research. One possible interpretation is that historically high rates of police enforcement activity have driven up average risk scores in some precincts over time, thereby exerting an *indirect* influence on re-arrest. Such a finding would suggest that—at least in the current sample—an individual risk model which incorporates criminal history factors cannot be wholly individual, since it is partially influenced by policing practices at the neighborhood level.

Table 4.20. Hierarchical Linear Regression Model Predicting Individual Risk Score

	Model 1		Model 2		Model 3	
	b	S.E.	b	S.E.	b	S.E.
Intercept (y0)			11.132	0.442	11.073	0.472
Individual Level						
Black/African American			-0.123	0.525	0.010	0.534
Latino/Hispanic			0.246	0.500	0.311	0.504
Arrest Tracking Period			0.002	0.001	0.002	0.001
Neighborhood Level						
Policing Index			0.467*	0.204		
Concentrated Disadvantage Index					0.168	0.389
Random Effects						
Variance Component (level 2)	0.403		0.325		0.404	
Chi-Square	43.100**		36.935*		42.543**	
Variance Component (level 1)	15.653		15.638		15.693	
Model Fit						
Deviance			4958.219		4961.270	
Parameters Estimated			2.000		2.000	

***p<.001 **p<.01 *p<.05 +p<.10

N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.

Intraclass correlation coefficient for unconditional model =.025.

Table 4.21. Hierarchical Linear Regression Model Predicting Individual Risk Score						
Misdmeanor Subsample						
	Model 1		**Model 2**		**Model 3**	
	b	S.E.	b	S.E.	b	S.E.
Intercept (y0)	11.491	0.224	11.400	0.659	11.370	0.654
Individual Level						
Black/African American			0.000	0.693	0.184	0.696
Latino/Hispanic			-0.032	0.743	0.094	0.750
Arrest Tracking Period			0.000	0.003	0.001	0.002
Neighborhood Level						
Policing Index			0.477+	0.237		
Concentrated Disadvantage Index					-0.195	0.418
Random Effects						
Variance Component (level 2)	0.405		0.592		0.514	
Chi-Square	39.034**		34.431*		38.897	
Variance Component (level 1)	15.860		15.879		15.900	
Model Fit						
Deviance	3089.200		3094.800		3097.900	
Parameters Estimated	2		2		2	

***p<.001 **p<.01 *p<.05 +p<.10

N=550 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.

Intraclass correlation coefficient for unconditional model =.025.

Table 4.22. Hierarchical Linear Regression Model Predicting Individual Risk Score

Felony Subsample

	Model 1		Model 2		Model 3	
	b	S.E.	b	S.E.	b	S.E.
Intercept (y0)			10.753	0.863	10.533	0.882
Individual Level						
Black/African American			-0.478	0.790	0.010	0.534
Latino/Hispanic			0.572	0.829	0.311	0.504
Arrest Tracking Period			0.002	0.003	0.002	0.001
Neighborhood Level						
Proactive Policing Index			0.351	0.327		
Concentrated Disadvantage Index					1.027+	0.281
Random Effects						
Variance Component (level 2)	0.633		0.673		0.533	
Chi-Square	35.216*		34.717*		31.256+	
Variance Component (level 1)	14.688		14.644		14.612	
Model Fit						
Deviance	1853.570		1857.190		1853.720	
Parameters Estimated	2		2		2	

***p<.001 **p<.01 *p<.05 +p<.10

N=334 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.

Intraclass correlation coefficient for unconditional model =.041.

Figure 4.1. SQF Rates in selected Precincts (2010-2016)

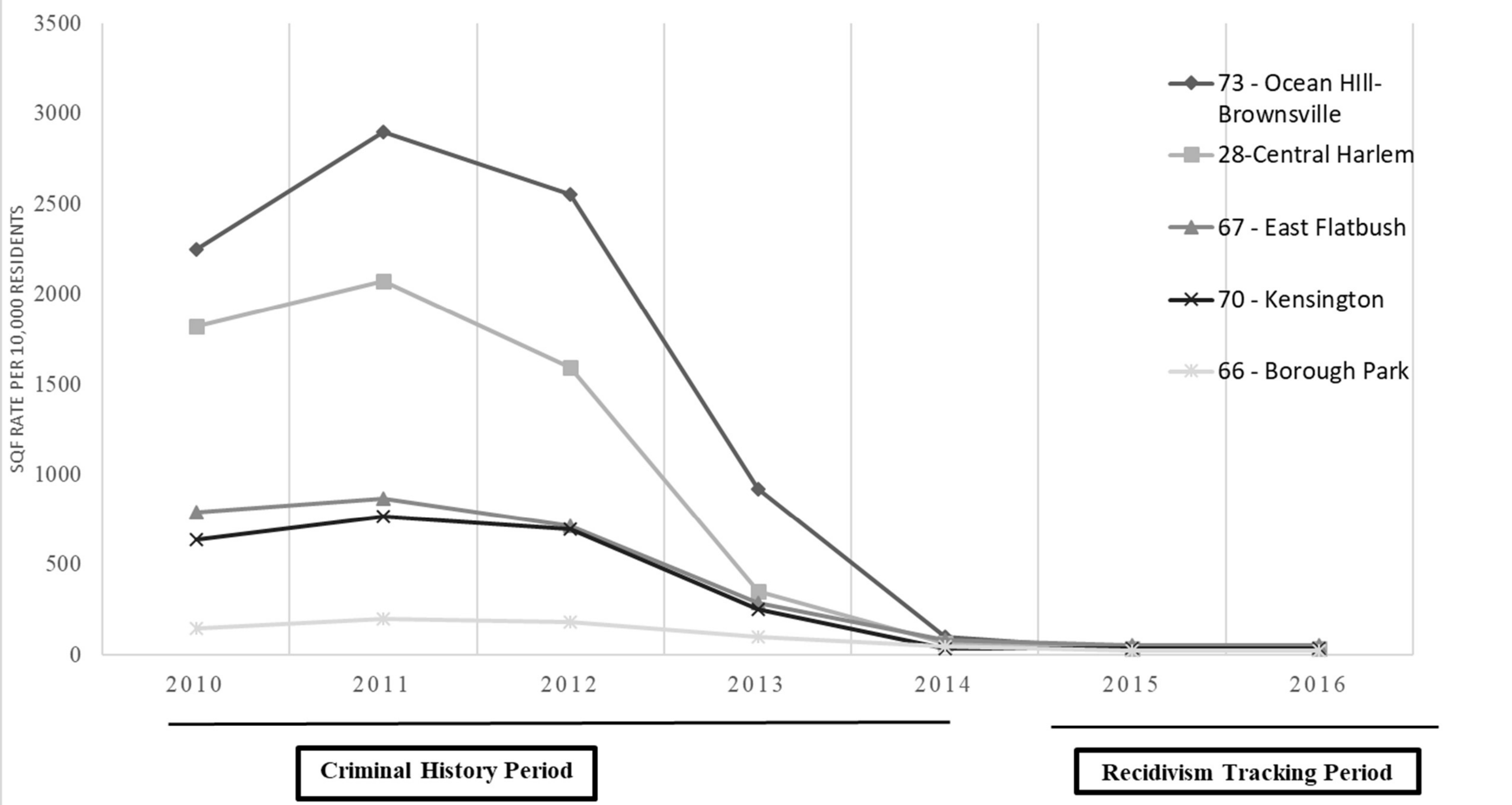
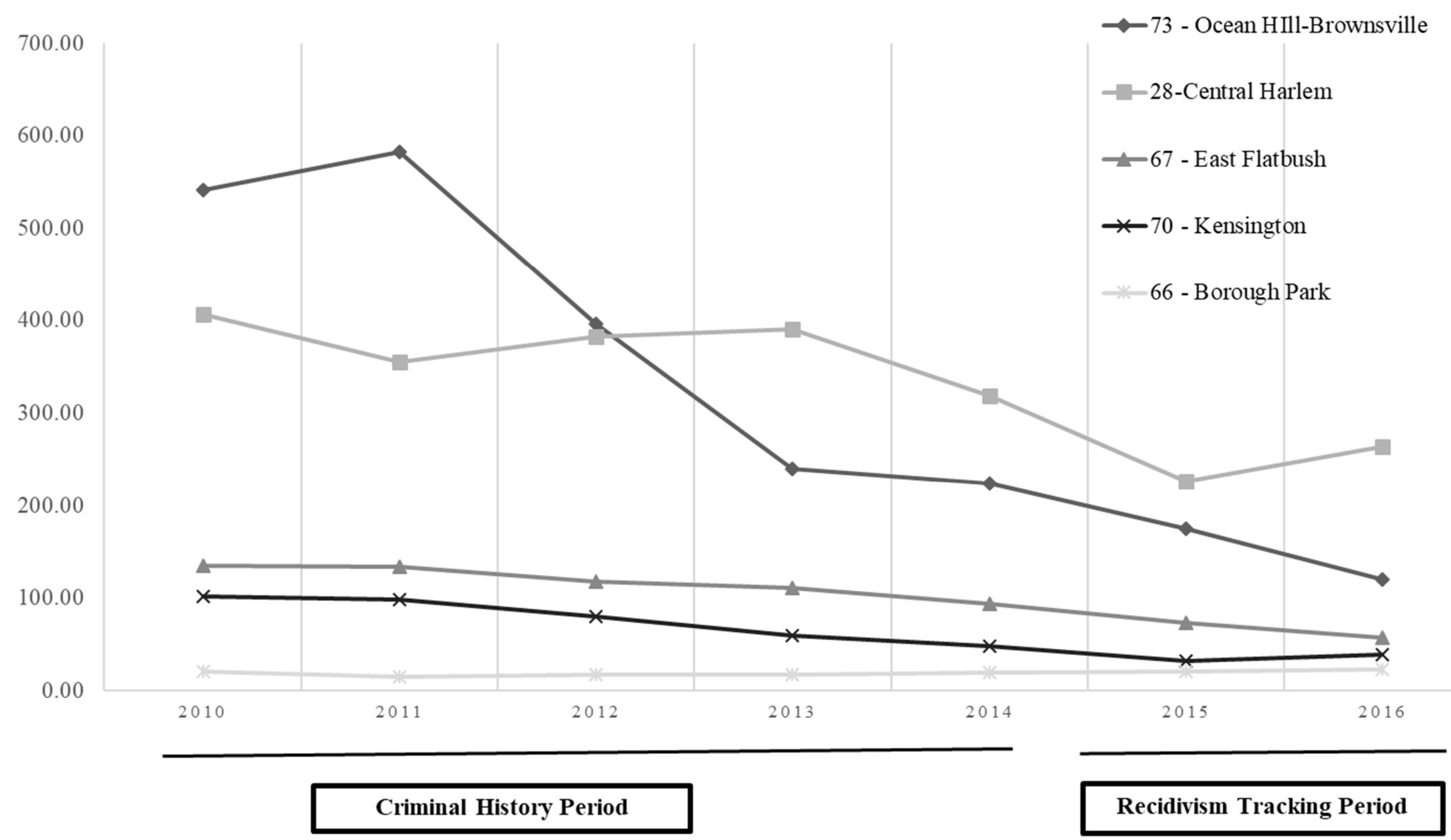


Figure 4.2. Proactive Misdemeanor Arrest Rates in Selected Precincts (2010-2016)



Neighborhood context and "false positives"

Results from the prior analyses regarding the influence of neighborhood environment on risk score caution against viewing individual risk factors as a phenomenon independent of environment. Instead, they support a more complex perspective, in which neighborhood context plays a role in shaping individual risk profiles and, in turn, recidivism. The implications of this finding for individuals should not be underestimated: specifically, it suggests that residents of certain neighborhoods may be collectively assessed as higher risk for recidivism, though they may not *actually* have a higher probability of re-arrest. A final analysis explored this possibility in the current sample by examining whether individuals from precincts with high levels of neighborhood police enforcement activity or concentrated disadvantage were more likely to be labeled as "high risk," despite not being re-arrested over the tacking period. Specifically, this analysis isolated all defendants who scored in the top one-third of the individual risk score range *but were not rearrested* over the one-year tracking period, and investigated whether neighborhood factors might predict this "false positive" status. Results are displayed in Table 4.23. Similar to prior logistic models predicting new arrest, false positive rates did not vary significantly across precincts (χ^2=16.815, p>.500). Nonetheless, as shown in Model 2, higher levels of police enforcement activity were found to be a significant predictor of false positive status (OR=1.17, p<.10). This suggests that neighborhood of residence could be affecting individual risk scores in a way that has real policy implications (e.g. a scenario where "high risk" status influences release or sentencing decisions). Finally, while neighborhood concentrated disadvantage also appears to increase the odds of a "false positive," this finding did not reach statistical significance.

Table 4.23 Hierarchical Logistic Regression Models Predicting "False Positive" Risk Scores

	Model 1				Model 2				Model 3			
	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.	b	S.E.	Exp (b)	C.I.
Intercept (γ0)	-2.050	0.098	0.129	(.105, .158)	-3.330	0.743	0.036	(.008, .168)	-3.312	0.581	0.043	(.013, .147)
Individual Level												
Black/African American					1.007	0.621	2.738	(.811, 9.245)	1.049	0.621	2.856+	(.870, 9.78)
Latino/Hispanic					1.112	0.608	3.041	(.923, 10.023)	1.123	0.595	3.076+	(.923, 10.023)
Arrest Tracking Period					0.000	0.001	1.000	(.998, 1.003)	0.000	0.001	1.000	(.998, 1.003)
Neighborhood Level												
Policing Index					0.165	0.090	1.179+	(.978, 1.422)				
Concentrated Disadvantage Index									0.210	0.169	1.233	(.868, 1.755)
Random Effects												
Variance Component	0.002				0.008				0.001			
Chi-Square	16.815				13.685				15.231			
Model Fit												
Deviance	2252.900				2245.732				2246.856			
Parameters Estimated	2				6				6			

Note: "False positive" is defined as having a risk score in the to 30% of the total risk range for all defendants (13 and up) but not being rearrested over the tracking period. 100 defendants (11.4% of the total sample) fell into this group.

***p<.001 **p<.01 *p<.05 +p<.10

N=884 individuals nested in 23 Precincts

Chapter 5

Discussion

The last decade has witnessed unprecedented efforts to reform the criminal justice system and stem the tide of mass incarceration in the United States. Persistently high rates of recidivism among justice-system involved individuals, however, present a significant obstacle to the success of these efforts. Thirty years of research in the fields of social psychology and criminology has produced a shared understanding of the individual characteristics that drive recidivism, but less is known regarding whether or how recidivism is influenced by social environment. The present research adds to a growing body of scholarship which views recidivism as an ecological phenomenon, co-produced by individual and environmental risk factors. Specifically, this research draws on individual risk assessment interviews conducted with nearly 900 defendants in New York City, combined with publicly available U.S. Census and NYPD data in 23 neighborhood precincts, to assess the relative importance of six factors for predicting re-arrest: criminal history, demographics, criminogenic needs, neighborhood concentrated disadvantage, and neighborhood policing tactics.

Key Findings

Individual risk

The results presented here conform to a robust body of existing research which demonstrates that individual characteristics-- particularly criminal history, gender, age, and criminogenic needs such as substance use, homelessness, and unemployment-- are relatively strong and consistent predictors of recidivism. Single point increases in a summary risk score combining these risk factors increased the odds of re-arrest by 24 to 28 percent in the current sample. Further, disaggregation of criminal history and criminogenic needs factors demonstrated that criminogenic needs are independently predictive of re-arrest. Ultimately, the neighborhood-level factors included in the study exerted little-to-no moderating influence on the relationship between individual risk score and recidivism, leading to the conclusion that certain key individual characteristics are predictive of recidivism irrespective of environment. One exception is the finding that neighborhoods characterized by high levels of police enforcement activity may be "criminogenic" for some individuals who are not *already* at high risk for arrest based on individual traits such as criminal history or criminogenic needs.

Neighborhood concentrated disadvantage

Contrary to expectations, this study found little-to-no independent relationship between neighborhood concentrated disadvantage and recidivism. One exception to this is that in some analyses of the felony subgroup, precinct levels of concentrated disadvantage appear to influence outcomes. Specifically, *lower* risk felony defendants appear more vulnerable to new arrest if they reside in a disadvantaged area, though this finding did not reach significance. Perhaps related, concentrated disadvantage predicts higher risk scores among felony--but not misdemeanor--defendants. One interpretation of this finding is that neighborhood socioeconomic status has some relationship to the likelihood of re-arrest in the felony defendant population. This interpretation is plausible, given equivocal and population specific findings from recent studies regarding concentrated disadvantage and recidivism in prior research (e.g., see Huebner & Pleggenkuhle, 2015; McNeeley, 2017). Another possible explanation is that the use of police precinct as a proxy for neighborhood obscured the relationship between neighborhood socioeconomic disadvantage and recidivism, which might have been detected with a finergrained analytic approach (e.g., where census tract is used as a proxy for neighborhood). In short, the null findings could be a result of a design limitation in the present study.

Neighborhood policing

Findings regarding the impact of neighborhood-police enforcement tactics on recidivism were decidedly more mixed. A preliminary "means-as-outcomes" analysis suggested that residents of neighborhoods characterized by more proactive police enforcement activity had significantly higher odds of re-arrest. The effect was modest, however, and disappeared after individual risk score was introduced into the model. The latter finding led to the initial conclusion that individual risk factors strongly outweigh neighborhood policing tactics in determining likelihood for re-arrest. Further analyses presented a more nuanced picture, however. For example, a random coefficients model suggested that defendants on the lower end of the risk spectrum are more likely to be re-arrested if they reside in a high police enforcement neighborhood. Additionally, neighborhood policing was found to predict re-arrest after controlling for a dynamic risk score that excludes criminal history variables, suggesting that individual criminogenic needs and policing tactics operate independently as predictors of re-arrest in the current sample. Finally, the neighborhood policing index was positively associated with higher individual risk scores. Taken together, these findings support the premise that proactive police enforcement contributes to a "criminogenic" environment, though not via the direct relationship originally hypothesized.

Misdemeanor defendants

With respect to the theory that individuals with misdemeanor charges may be more vulnerable to the effects of neighborhood context on recidivism, results were also mixed. An initial bivariate analysis suggested a relationship between residing in a neighborhood with greater police enforcement activity and current misdemeanor charge. More importantly, in several of the multi-level models, the effect size of neighborhood policing on recidivism *increased* when misdemeanor defendants were isolated from the full sample, though these results fell short of statistical significance. Finally, neighborhood policing tactics such as OMP and SQF appear to contribute to higher risk scores among misdemeanor defendants specifically, suggesting that individuals who commit lower level offenses in these neighborhoods may be historically more vulnerable to arrest, and to the accumulation of criminal history, than those in neighborhoods with less police activity. Conversely, levels of neighborhood concentrated disadvantage exerted little influence on re-arrest or risk among individuals with current misdemeanor charges. Ultimately, findings suggest that neighborhood environment--and particularly levels of police enforcement activity--should not be ignored in studies of misdemeanor crime and recidivism.

Neighborhood context and risk score

A final exploratory analysis led to a surprising, and seemingly contradictory, finding. While neighborhood context was not strongly predictive of re-arrest over the one-year tracking period studied, it nonetheless appears to have played a role in shaping *risk for re-arrest* over time. Specifically, a regression model specifying individual risk score as the dependent variable of interest revealed that defendants (and particularly misdemeanor defendants) residing in areas with high levels of police enforcement activity had --on average--significantly higher risk scores. Neighborhood policing had less of an influence on risk scores among felony defendants, whereas higher levels of concentrated disadvantage did increase risk scores in this subgroup. This finding suggests the possibility of an indirect relationship between neighborhood context and recidivism in some precincts. A subsequent analysis of trends in stop-question-frisk events (SQF) and misdemeanor arrests in several of the studied precincts showed a precipitous drop in SQF and misdemeanor arrests just before the recidivism tracking period for the present study and may provide a partial explanation for these counterintuitive findings. In short, it is possible that declines in police activity specifically during the study period effectively obscured a real relationship between neighborhood context and recidivism in prior time periods.

Limitations

Several methodological limitations related to the definition of neighborhood in in the present study are worth noting. First, because police precinct is an imperfect proxy for neighborhood, this definition may prevent the detection of variance in neighborhood-level variables that occur within, rather than across, precincts. This challenge was noted by Tillyer & Vose (2011) in their recent county-level study of the effects of concentrated disadvantage on recidivism in Iowa. While precinct is likely a more precise proxy for neighborhood than county, it is still possible that variance in concentrated disadvantage or policing tactics were unaccounted for in the present research.

Second, it is assumed by the researcher that the neighborhood each individual respondent reported at the time of their arrest is their neighborhood for the purposes of tracking re-arrest, even though that individual may well have moved over the course of the one-year tracking period. While documenting the residential mobility patterns of the study sample over time was outside the scope of the present research, interview data suggests that the sample was relatively stable in terms of neighborhood of residence. Specifically, the average interview respondent reported having lived in their current neighborhood for 10 years, and less than ten percent of respondents reported having lived in their current neighborhood for less than a year. It should also be emphasized that the present research measures the influence of characteristics of an individual's *home* neighborhood-- rather than the neighborhood in which they were arrested-- on the likelihood of recidivism. A recent study of misdemeanor arrest patterns in New York City suggests that as many as half of such arrests occur outside the arrestee's residential neighborhood (Warner, Lu, Fera, Balazon & Chauhan, 2016), so a study of neighborhood of arrest characteristics could produce different results.

Third, there are limitations related to sample sizes that are likely affecting the findings. The small Level 2 sample size (N=23) may introduce bias into model parameter estimates (McNeish & Stapleton, 2016). The same study in a citywide sample of precincts, for example, could produce different results. The relatively small sample of individual defendants with a current felony charge (N=331) could also reduce the reliability of findings in this subsample.

Finally, there are limitations in terms of conclusions that may be drawn from the study findings, which are only a partial explanation of recidivism in a specific time and place. In particular, contextual factors such as neighborhood concentrated disadvantage or local policing strategies are likely to be qualitatively different in other areas of the country. As this study has also clearly shown, environmental changes such as major policy shifts can have a significant impact on the salience of ecological theory for explaining individual outcomes, so a similar study in New York City during a different time period might produce different results. Therefore, while the results of this study are theoretically relevant to other large urban jurisdictions, particularly those employing order maintenance policing tactics, they should not be considered empirically generalizable.

Policy Implications

Over 10 million arrests for criminal offenses are made in the United States each year, and significant recidivism among released individuals is a widely acknowledged driver of overburdened criminal courts, jails, and community-based correctional programs. The primary purpose of this research was to achieve a more nuanced understanding of recidivism in a contemporary urban context in the United States. In that regard, the findings largely confirm established models of individual risk for explaining recidivism risk (e.g., the RNR model), and thus support the continuation of efforts to reduce recidivism through interventions with a focus on clinical treatment and human services. However, they also caution against the presumption that criminal behavior is unrelated to environment, with specific implications for policy in two areas: enforcement oriented policing tactics and the use of actuarial risk models to predict recidivism.

Enforcement oriented policing

The proactive enforcement of lower level criminal codes to reduce "disorder" in high crime neighborhoods has been widespread in cities across the United States since the early 1990s (Roberts, 1999; Mears, 2014). Parallel to ongoing debates regarding the efficacy of these strategies for reducing more serious criminal activity, an emerging body of research documents the negative consequences of OMP and SQF for individuals and communities, including the erosion of perceptions police legitimacy; reduced civic engagement; increased self-reported criminal behavior; and negative health and psychological consequences (Geller et al., 2014; Goff, 2018). Critics contend that proactive policing strategies such as OMP, originally intended to increase safety in poor neighborhoods, may ultimately do more harm than good (e.g., see Harcourt, 2009; Howell, 2009).

The present study contributes to this body of work by empirically demonstrating that proactive police enforcement tactics can result in higher odds for re-arrest for individual defendants, independent of established risk factors such as unemployment, substance abuse, and housing instability. The finding that these tactics have a particularly strong influence on individuals at the *lower* end of the risk spectrum (i.e., those without significant criminal histories) is key here, as it suggest that individuals living in OMP neighborhoods may be more likely than others to become caught in a cycle of release and re-arrest with its attendant collateral consequences, despite a relatively low individual propensity for criminal behavior. This finding complicates prior research suggesting that aggressive enforcement strategies have net public safety benefits (e.g., see Weisburd et al., 2014). Specifically, while focused enforcement tactics may provide short-term crime reductions, they may also have criminogenic effects on low-risk individuals in particular neighborhoods, who may inadvertently become caught in a broader policing net. Finally, this research dovetails with a more recent study of proactive policing broadly which suggests that community problem solving (e.g., police-community partnerships) and situational crime prevention strategies (e.g., drug market interventions) are *more* effective at reducing neighborhood crime than enforcement-oriented tactics such as OMP (Braga et al., 2015). Braga and colleagues found that the benefits of enforcement tactics are limited, while the current research points to important trade-offs in terms of recidivism reduction and community safety.

Actuarial risk assessment tools

Risk assessment tools that combine factors such as criminal history, criminogenic needs, and demographics into actuarial models that predict recidivism—such as the one examined in the present study-- are in widespread use by jurisdictions across the country.[35] While such tools have been shown to improve discretionary decisions hinging on the estimation of individual risk for recidivism (e.g., pretrial release, level of probation supervision), they are also the topic of

[35] Recent research suggests there are as many as 60 different risk assessment systems in use by jurisdictions across the United States (see Picard-Fritsche, Rempel, Tallon, Adler & Reyes, 2017).

significant controversy. At the heart of this controversy are questions regarding whether these models are truly fair in the sense that they measure *only* individual propensity for recidivism, or whether they also reflect arbitrary (e.g., race) or structural factors beyond an individual's control (e.g., policing practice). Indeed, strong critics of risk assessment have suggested that some of the factors commonly included in risk assessment tools act as proxies for race or socioeconomic status (e.g., see Harcourt, 2007; Starr, 2014). Overall, findings from the present study largely support prior research regarding the accuracy of risk assessment models for predicting individual outcomes. At the same time, they provide a measure of support for critics of their use. Drawing on the current NYC example, it appears that proactive police enforcement practices can result in significantly higher risk scores for residents of particular neighborhoods, supporting the contention that risk scores are, indeed, not entirely a function of individual traits. Given the reality that aggressive police enforcement often disproportionately occurs in largely minority neighborhoods, these findings may also have implications for recent debates regarding risk assessment tools and racial bias in criminal justice.

Research Implications

The present research makes an important contribution to the growing body of scholarship regarding neighborhood context and recidivism, as it is one of the first efforts to empirically examine the relationship between neighborhood policing practices and individual risk for recidivism. The finding that neighborhood policing tactics may influence individual recidivism patterns -- at least in the NYC context-- suggests that this relationship could benefit from further study in other cities. Additionally, the finding that neighborhood context may affect recidivism differently depending on how individual risk is defined (i.e., based on criminal history versus demographic or needs factors) presents an interesting new research question: is it possible that individual criminal histories are accumulated partly as a function of individual propensity *and* partly as a function of social environment? In particular with respect to lower-level charges, future research regarding contextualized pathways into justice system involvement is needed. If contextual or neighborhood factors are influencing these pathways, community interventions or changes in policing policy should be considered. Additionally, future research on actuarial assessment tools should carefully consider the finding that reliance on criminal history variables could produce biased outcomes, while simultaneously obscuring important relationships between social environment, individual needs, and individual risk. There is a tinge of irony in this last finding, as criminal history measures have traditionally been viewed as the "objective" components of risk assessment when compared to needs and demographic factors. This study calls that assumption into question.

Conclusion

Drawing on a robust body of research demonstrating that neighborhood context matters in the study of crime, it was initially anticipated that recidivism among New York City defendants would be directly influenced by contextual factors such as neighborhood concentrated disadvantage and proactive policing. The findings ultimately paint a more complex picture. First and foremost, they suggest recidivism is *largely* a matter of individual risk, with factors such as younger age, longer criminal history, unemployment, and drug use driving justice system involvement across neighborhoods. At the same time, they caution against the presumption that neighborhood context is irrelevant to the study of recidivism. At least in New York City, individual risk profiles appear to be partly shaped by structural factors that differ by neighborhood, and changes in such factors may reduce recidivism risk independent of individual traits. This latter finding suggests that policy strategies to reduce recidivism will be stronger if they focus simultaneously on addressing individual criminogenic needs and structural neighborhood characteristics, such as policing practice, that may exacerbate risk for justice system involvement.

Appendix A. Interview Instrument

CCI Risk and Need Assessment Study

Administrative Information
[Research assistants should write or enter the following information into the tablet before beginning the survey]

Research Assistant Initials: ________________

Study ID:________________

Interview Date:__________________

Section I. Criminal Record Review

		Circle One	Points
R1	Top arrest charge involves a drug offense that is NOT a marijuana offense.	No Yes	
R2.	Top arrest charge involves a property offense (e.g. petit larceny, criminal possession of stolen property).	No Yes	
R3.	Prior felony conviction(s), past three years.	No Yes	
R4.	Number of prior misdemeanor or violation convictions in the past three years.	Zero One Two Three+	
R5.	Ten or more misdemeanor or violation convictions in past three years.	No Yes	
R6.	Any prior sentence to jail or prison.	No Yes	
R7.	Number of warrants for failure to appear in court.	Zero One Two Three+	

R8.	Number of currently open cases.	Zero One Two Three+

Section II. Background Questions

		Circle One
A1a.	What is your sex?	Male Female Transgender
A2.	How old are you?	__ __ years
A3a.	Do you live in NYC? If so, what neighborhood do you live in?	____________________________ (a list of NYC neighborhoods will be provided to match against)
A3b.	How many years have you lived in this neighborhood?	__ __years
A4a.	What is your race? (select all that apply)	Black/African-American White/Caucasian Asian/Pacific Islander Native American/Alaska Native Other________________
A4b.	Are you Hispanic/Latino?	Yes/No

Section III. Defendant Interview (Risk-Need Questions)

		Circle One
R9.	Have you either graduated high school or received a GED?	No Yes Refusal
R10.	Have you ever been employed? (not including illegal activities). [IF NO, SKIP TO R12]	No Yes Refusal
R11a.	Were you either employed (not including illegal activities), attending school, or attending a vocational training program at the time of your arrest?	No Yes Refusal
R11b.	Have you ever been fired from a job?	No Yes Refusal
R12.	How would you describe your current living situation (the place you were living at the time of your arrest)? (Choose one) Homeless (on the streets, in a car, in a drop-in shelter) Living in a long-term shelter (transitional housing) Living in a halfway house Living with friends or family Living in an apartment, house, or room (own/rent) Living in public housing Other Refusal	
R13.	How long have you been at your current address? (Choose one) Less than 1 year 1-3 years 4 or more years Refusal	
R14.	Are you married or do you currently have a steady girlfriend or boyfriend?	No Yes Refusal
R15.	Have you been through a break-up or divorce in the last year?	No Yes Refusal
R16.	Do you have any children under the age of 18?	No Yes Refusal
R17a.	Have you ever drank alcohol?	Yes No

		Refusal
R17b.	Have you ever used drugs (like weed, pills, meth cocaine, heroin, etc.)? [IF NO, SKIP TO R20]	Yes No Refusal
R18.	How old (in years) were you when you first used drugs? Less than 10 years 10 to 14 years old 15 to 19 years old 20 to 24 years old 25 or older Refusal	
R19.	About how often do you <u>currently</u> use drugs? About every day (five or more times a week) One or a few times per week One or a few times per month Only a few times each year Not currently using Refusal	
R20.	About how often do you currently have four or more drinks of an alcoholic beverage in a single day? About every day One or a few times per week One or a few times per month Only a few times each year Not currently drinking alcohol Refusal	
Now, I have just a few questions about your attitudes and behavior. I am going to read a statement and you tell me whether you agree or disagree. There are no right or wrong answers, just give your best answer.		
R21.	When I am very sad, I tend to do things that cause problems in my life. (Choose one) Strongly Agree Agree Neutral Disagree Strongly Disagree Refusal	
R22.	When I am really excited, I tend to not think of the consequences of my actions. (Choose one) Strongly Agree Agree Neutral	

	Disagree Strongly Disagree Refusal
R23.	The trouble with getting close to people is that they start making demands on you. (Choose one) Strongly Agree Agree Neutral Disagree Strongly Disagree Refusal
R24.	Some people must be beaten up or treated roughly just to send them a clear message. (Choose one) Strongly Agree Agree Neutral Disagree Strongly Disagree Refusal

Section IV. Defendant Interview (Continued)

		Circle One
N1.	Have you ever been in a hospital for emotional or mental health problems?	No Yes Don't know Refusal
N2.	Do you currently feel that other people know your thoughts and can read your mind?	No Yes Don't know Refusal
N3.	Have there recently been a few weeks where felt sad or empty most of the time?	No Yes Don't know Refusal
N4.	In the past few weeks, have there been some days where you have had a lot more energy than normal?	No Yes Don't know Refusal

N5.	In the past month, how often have you had repeated disturbing memories, thoughts, or images of a stressful experience? (Choose one) Not at all A little bit Moderately Quite a bit Extremely Refusal
N6.	In the past month, how often have you felt very upset when something reminded you of a stressful experience? (Choose one) Not at all A little bit Moderately Quite a bit Extremely Refusal
Procedural Justice Questions.	
P1.	Looking back on the incident that led to this case, how fair was your treatment by the police? Very Fair Somewhat Fair Neutral Somewhat Unfair Very Unfair Refusal
P2.	If you have ever been to a criminal court before, think about the last time you were in court. How fair was your treatment by the court (Probes: Did you feel the court treated you with respect? Did you understand everything that happened in your case?) Very Fair Somewhat Fair Neutral Somewhat Unfair Very Unfair Refusal

	Thank you! Is there anything else you would like to tell me?

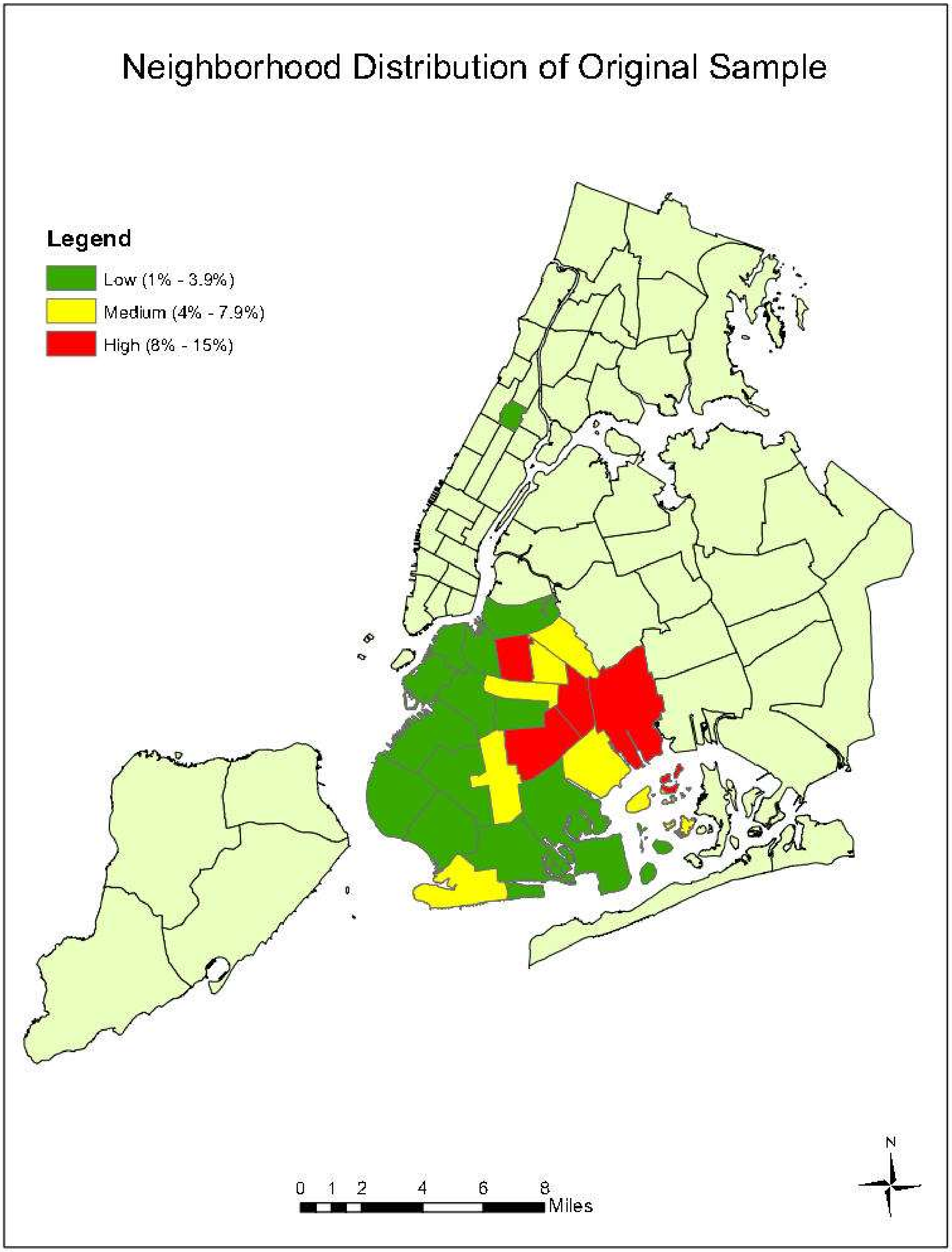
Appendix B. List of Neighborhood Precincts

Precinct Number	Borough	Neighborhood
1	Manhattan	Tribeca/Wall Street
5	Manhattan	Chinatown/Little Italy
6	Manhattan	Greenwich Village
7	Manhattan	Lower East Side
9	Manhattan	East Village
10	Manhattan	Chelsea
13	Manhattan	Gramercy Park
14	Manhattan	Midtown South
17	Manhattan	Midtown
18	Manhattan	Midtown North
19	Manhattan	Upper East Side
20	Manhattan	Upper West Side/Central Park
23	Manhattan	East Harlem
24	Manhattan	Upper West Side
25	Manhattan	East Harlem
26	Manhattan	Morningside Heights
28	Manhattan	Central Harlem
30	Manhattan	Harlem
32	Manhattan	Harlem
33	Manhattan	Washington Heights
34	Manhattan	Washington Heights/Inwood
40	Bronx	Mott Haven/Melrose
41	Bronx	Hunts Point
42	Bronx	Tremont
43	Bronx	Soundview
44	Bronx	Morris Heights
45	Bronx	Schuylerville
46	Bronx	University Heights
47	Bronx	Eastchester
48	Bronx	Fordham

49	Bronx	Baychester
50	Bronx	Riverdale
52	Bronx	Bedford Park
60	Brooklyn	Coney Island
61	Brooklyn	Sheepshead Bay
62	Brooklyn	Bensonhurst
63	Brooklyn	Flatlands/Mill Basin
66	Brooklyn	Borough Park
67	Brooklyn	East Flatbush
68	Brooklyn	Bay Ridge
69	Brooklyn	Canarsie
70	Brooklyn	Kensington
71	Brooklyn	Flatbush
72	Brooklyn	Sunset Park
73	Brooklyn	Ocean Hill-Brownsville
75	Brooklyn	East New York
76	Brooklyn	Carroll Gardens/Red Hook
77	Brooklyn	Crown Heights
78	Brooklyn	Park Slope
79	Brooklyn	Bedford-Stuyvesant
81	Brooklyn	Brownsville
83	Brooklyn	Bushwick
84	Brooklyn	Brooklyn Heights
88	Brooklyn	Fort Greene
90	Brooklyn	Williamsburg
94	Brooklyn	Greenpoint
100	Queens	Rockaway
101	Queens	Far Rockaway
102	Queens	Richmond Hill
103	Queens	Jamaica Business District
104	Queens	Ridgewood/Middle Village/Glendale
105	Queens	Queens Village
106	Queens	Ozone Park

107	Queens	Fresh Meadows
108	Queens	Long Island City
109	Queens	Flushing
110	Queens	Elmhurst
111	Queens	Bayside
112	Queens	Forest Hills
113	Queens	Jamaica
114	Queens	Astoria
115	Queens	Jackson Heights
120	Staten Island	St. George
121	Staten Island	Graniteville
122	Staten Island	New Dorp
123	Staten Island	Tottenville

Appendix C. Map of Original Sample Distribution by Precinct



Appendix D. Individual Risk Model

Original Risk Model: The Criminal Court Assessment Tool[1]

Final CCAT-S Risk Factors	Response Options	Weight (Multiplier)
Weapons charge	0,1	1
Felony drug charge	0,1	3
Misdemeanor property charge	0,1	2
Prior felony conviction	0,1	1
Prior misdemeanor (or violation) conviction in past 3 years	0,1,2,3	1
Ten or more prior misdemeanor (or violation) convictions in past 3 years	0,1	3
Prior jail or prison sentence	0,1	2
Prior case with failure to appear	0,1	2
Current open case	0,1	2
Age (>60=0, 50-59=1, 40-49=2, 30-39=3, 25-29=4, 20-24=5, <19=6)	0,1,2,3,4,5,6	1
Ages 16-24	0,1	1
High school degree / GED (HS degree/GED=0, no HS degree /GED=1)	0,1	1
Currently employed legally, in school, or in vocational training program (unemployed=1, employed / in school=0)	0,1	1
Currently homeless or living in a shelter	0,1	3
Current drug use (not currently using or only a few times/year vs. using)	0,1	1
Male gender	0,1	1

[1] The Criminal Court Assessment Tool is an actuarial risk model developed by researchers at the Center for Court Innovation as part of a BJA funded study to examine risk and need in a criminal court population in New York City. Raw risk scores for the model range from 0-33. Performance indicators for the model are strong by industry standards (AUC=.743). Details regarding the development and validation of the tool are available at: https://www.courtinnovation.org/publications/C-CAT_validation.

Appendix F. Additional Analysis: Alternative Policing Index

As mentioned in Chapter 3, the use of SQF activity as a partial proxy for proactive police enforcement tactics is not a traditional measure of OMP and could theoretically dilute the effects of a more traditional measure, such as rate of misdemeanor arrests or summons issued in each precinct.[36] Additionally, it is fair to argue that the inclusion of SQF rates is redundant, and a measure representing discretionary misdemeanor arrests alone would capture the majority of enforcement activity related to SQF (most arrests resulting from stop activity in NYC are for lower level charges). On the other hand, some new arrests resulting from SQF could have fallen into felony charge categories or into misdemeanor categories not labeled as "proactive" by the NYPD. To examine whether an index of "proactive" misdemeanor arrests alone would have performed differently, several of the key analyses related to the effect of neighborhood policing on re-arrest were repeated using a revised index that excluded SQF rates from the index. As shown below, revision of the neighborhood policing index had no measurable impact on the mean effect of neighborhood policing on individual recidivism (OR=1.09, $p<.05$), displayed in Table 1, or on the effect of policing on recidivism after controlling for individual risk score (OR=1.05, NS), shown in Table 2. Finally, use of the revised policing index had little to no effect on the influence of neighborhood policing index on individual risk score (b=.482, $p<.05$), displayed in Table 3.

[36] As a reminder, the present study included only those misdemeanor arrest categories explicitly labeled in NYPD Compstat reports as associated with "proactive" policing tactics. These included (1) Misdemeanor Possession of Stolen Property; (2) Misdemeanor Dangerous Drug charges; (3) Misdemeanor Dangerous Weapons charges; (4) Intoxicated/Impaired Driving; and (5) Criminal Trespass, While likely very imperfect, this choice was made explicitly as a way to avoid the inclusion of large numbers of arrests related to calls for service (which are by definition *not* proactive) or related to actual differences in misdemeanor crime rates by neighborhood. Rates of police summons activity were not available by precinct for the study period.

Table 1. Revised Policing Index and Recidivism				
Mean Outcomes Model				
	b	S.E.	Exp (b)	C.I.
Intercept (y0)	-0.064	0.055	0.937	(.837, 1.105)
Individual Level				
Total Risk Score[1]				
Black/African American				
Latino/Hispanic				
Days at Risk for Re-Arrest				
Neighborhood Level				
Misdemeanor Arrest Index[1]	0.085	0.039	1.09*	(1.003, 1.180)
Concentrated Disadvantage Index				
Random Effects				
Variance Component	0.0003			
Chi-Square	12.781			
Model Fit				
Deviance	2848.650			
Parameters Estimated	3			
N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.				
***p<.001 **p<.01 *p<.05 +p<.10				

Table 2. Revised Policing Index and Recidivism				
Model Controlling for Individual Risk				
	b	S.E.	Exp (b)	C.I.
Intercept (y0)	0.554	0.297	1.741	(.938, 3.230)
Individual Level				
Total Risk Score	0.228	0.021	1.256***	(1.205, 1.309)
Black/African American	-0.688	0.290	0.505*	(.286, .984
Latino/Hispanic	-0.575	0.308	0.562+	(.307, 1.030)
Arrest Tracking Period	0.001	0.001	1.000	(.999, 1.003)
Neighborhood Level				
Misdemeanor Arrest Index	0.046	0.087	1.046	(.874, 1.254)
Concentrated Disadvantage Index				
Random Effects				
Variance Component	0.000			
Chi-Square	14.346			
Model Fit				
Deviance	2698.144			
Parameters Estimated	7			

N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean cente

***p<.001 **p<.01 *p<.05 +p<.10

Table 3. Revised Policing Index and Individual Risk Score

	b	S.E.
Intercept (y0)	11.132	0.442
Individual Level		
Black/African American	-0.123	0.525
Latino/Hispanic	0.246	0.500
Arrest Tracking Period	0.002	0.001
Neighborhood Level		
Misdemeanor Arrest Index	0.482*	0.216
Random Effects		
Variance Component (level 2)	0.337	
Chi-Square	37.544*	
Variance Component (level 1)	15.636	
Model Fit		
Deviance	4958.219	
Parameters Estimated	2	

***p<.001 **p<.01 *p<.05 +p<.10

N=884 individuals nested in 23 Precincts; All non-binary independent variables are mean centered.

Intraclass correlation coefficient for unconditional model =.021

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