Offender Recidivism and Neighborhood Environments

By

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Abstract

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The huge increase in the number of incarcerated people in the United States since 1980 has led to an unprecedented number of offenders returning to just a few disadvantaged inner-city neighborhoods. These offenders return with health problems, illiteracy, and little support from the justice system. Unfortunately, almost half return to prison or jail within three years, only to be released again with fewer job prospects and weaker ties to their community.

Using data on 38,411 felony convictions in Brooklyn over a 17½ year period, this dissertation examined the relationship between offender recidivism and neighborhood environments by examining the following research questions: (a) *do recidivism hot spots exist?*, (b) *what are the social and physical characteristics of recidivism hot spots?*, and (c) *how important is the effect of local environment on recidivism as compared to traditional individual-level characteristics?*

The first analysis confirmed the existence of six recidivism hot spots in Brooklyn. The second analysis focused on the characteristics of these recidivism hot spots, with the final regression model indicating that increased recidivism was significantly related to areas with fewer churches, fewer foreign born residents, fewer single parent households, fewer working mothers, and increased residential mobility. This model was significant at the .00001 level and accounted for 46.2% of the variability in tract-level recidivism.

The last analysis compared traditional individual-level variables to neighborhood-level variables using a multi-level model (offenders within census tracts). The final model contained six significant individual-level variables and two significant neighborhood-level variables, percent in poverty and density of all offenders, indicating that multiple neighborhood-level variables in the same model can have a significant affect on recidivism. Finally, the predictive power of a significant neighborhood-level variable (length of criminal career) was compared with that of a significant individual-level variable (poverty), and results indicated that a one year increase in the criminal career of an offender increases the of having a recidivism event by 66.96%, while a 10% increase in percent in poverty in a tract increases the odds of having a recidivism event by 4.4%. These results indicate that environment has a significant and measurable effect on recidivism.

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CHAPTER 1

Introduction, Literature Review, and Research Questions

Introduction

The number of people incarcerated in the United States has been increasing at an alarming rate. Between 1980 and 2000, the correctional population grew from 1.84 million to 6.47 million people – roughly 3.1% of adults in the United States (Beck and Glaze, 2001). With so many people entering the criminal justice system each year researchers have become increasingly interested in the issues of offender reentry and offender recidivism.

Reentry refers to the process of incarcerated offenders leaving prison and jail and returning to live in the community. Recidivism refers to an offender committing a crime after being convicted and punished for committing a previous crime. While often studied separately, reentry and recidivism represent two sides of the same coin – if an offender returns home without adequate planning and services he or she will be at greater risk of committing another crime. Conversely, after committing another crime the offender will be incarcerated, only to reenter society once again after serving his or her time. This vicious cycle of *reentry* → *recidivism* → *incarceration* has claimed the freedom of millions of people, and without a better understanding of this process, and a society-wide commitment to solve this problem, it will continue unabated.

Since a disproportionate number of poor minorities are incarcerated (as will be discussed below), this cycle of *reentry* → *recidivism* → *incarceration* has a much greater impact on poor, minority, urban neighborhoods. Much like the people being incarcerated and returned, disadvantaged neighborhoods themselves become caught within this vicious cycle. Large numbers of young men leave from disadvantaged neighborhoods for prison and jail and then return some time later with criminal records, substance abuse problems, mental

illness, and health problems. This large pool of "unemployable" ex-offenders has a huge effect on the social fabric of the community (Clear et al., 2001; Travis, 2001). The *reentry → recidivism → incarceration* cycle can also be seen as a migration pattern of young, minority males from the inner city to jails and prisons and then back to the inner-city. Visualizing this process as a migration pattern emphasizes the fact that the same group(s) of people, from the same low-income neighborhoods, are moving in and out of the criminal justice system on a regular basis.

This research study focuses on the identification and description of high-recidivism areas, or *recidivism hot spots*, in Brooklyn, New York. The specific research questions being asked are:

1. Do recidivism hot spots exist?
2. What are the characteristics of high-recidivism areas?
3. How important is the effect of the local environment on recidivism as compared to traditional individual-level characteristics?

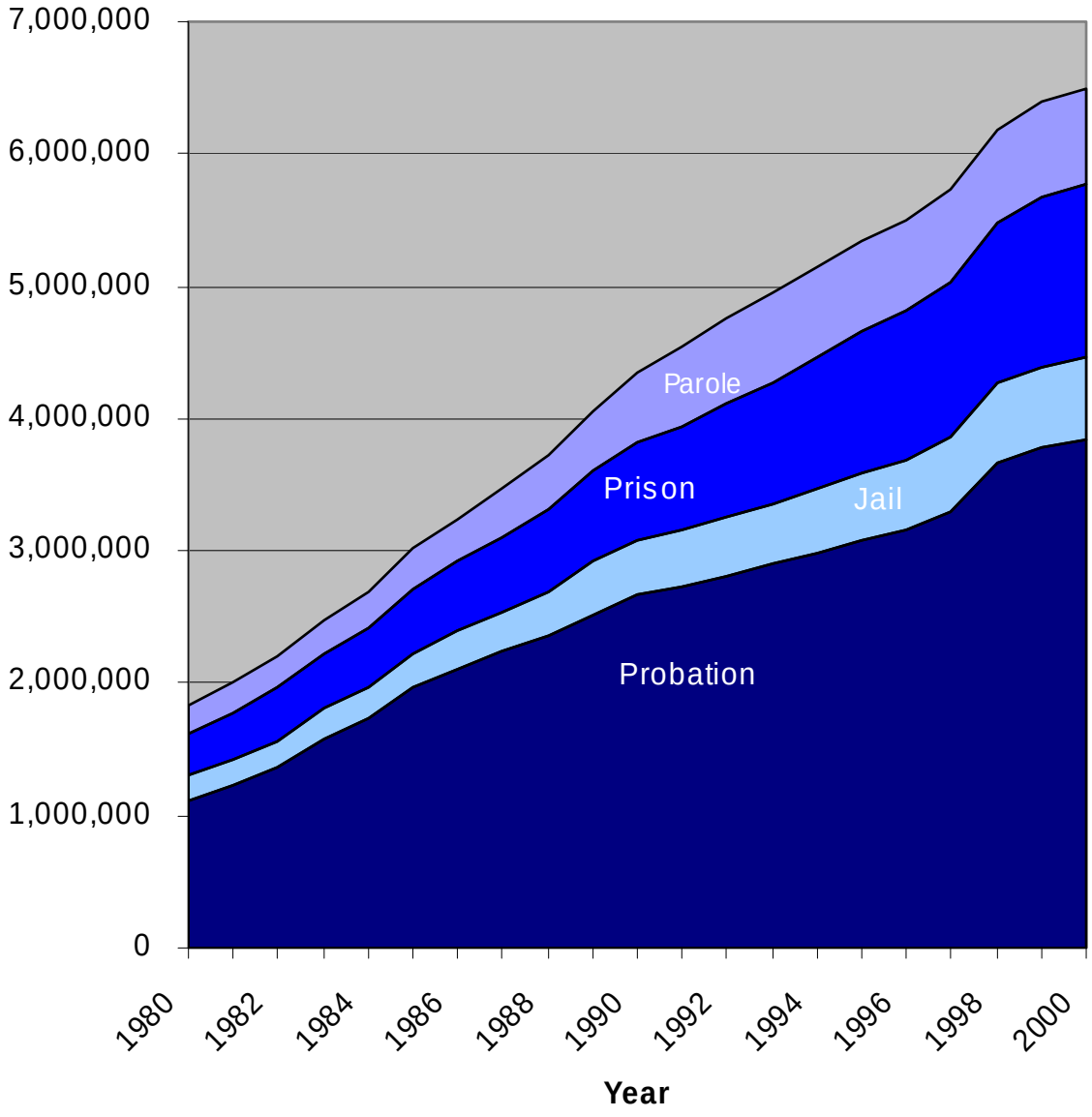
This research study investigates if the *density* of recidivists, as compared with the density of nonrecidivists, fluctuates across neighborhoods and attempts to better understand the neighborhood characteristics of areas with high rates of recidivism. In addition, a comparison between traditional, individual-level predictors of recidivism will be compared with neighborhood-level variables in order to assess the relative importance of environment on recidivism. Information on how local environments affect recidivism rates can be very helpful in reducing the rate of recidivism and slowing the cycle of *reentry → recidivism → incarceration.* This information can also be used to develop better reentry programs, to offer incentives and financial help to offenders who would like to relocate, and provide policy makers with information necessary to alter the environmental triggers and causes of recidivism events.

The Incarceration Culture, USA

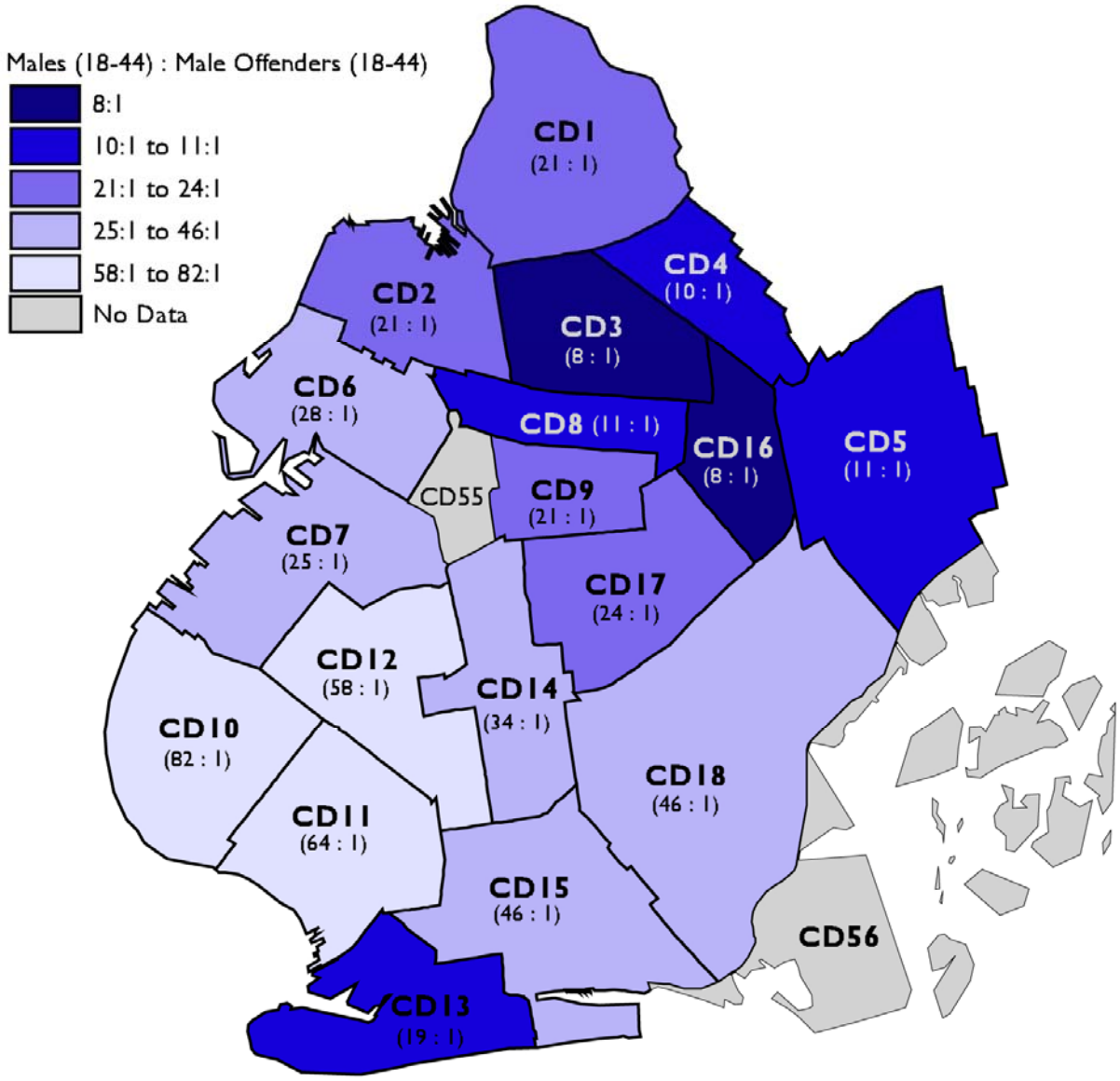
The Unites States incarcerates individuals at an astounding rate. As mentioned above, between 1980 and 2000 the correctional population grew from 1.84 million to 6.47 people – a 250% increase in the number of people under correctional supervision (Beck and Glaze, 2001; see Figure 1, below). This means that 3.1% of the adult population in the United States is under some form of correctional supervision. In 1999, 1 in every 110 men (1 in every 29 African-American males) was sentenced to at least one year of incarceration. This is more than four times the rate of incarceration in 1973 (Travis et al., 2001). Between 1995 and 2001 incarceration rates increased from 411 per 100,000 residents to 470 per 100,000 residents (Harrison and Beck, 2002).

The effects of such huge rates of incarceration are not randomly distributed throughout the country. Residents from poor, minority communities are much more likely to be involved in the criminal justice system and so our nation's love affair with incarceration has a very disproportionate impact on poor, inner-city neighborhoods. In a spatial analysis conducted by the author, the number of prison and jail admissions in Brooklyn Community Districts was mapped[1], and the ratio of male offenders age 18 to 44 was compared with the ratio of all males age 18 to 44 (see map 1, below). In the poorest neighborhoods of Brooklyn, between one out of eight and one out of eleven males age 18 to 44 was admitted to jail or prison in one year. Other neighborhoods in Brooklyn had very different ratios, but the average ratio was about one in forty and the smallest ratio was one in 82.

Figure 1: Correctional Populations in the US, 1980 to 2000 (based on Beck and Glaze, 2001)



Map 1: Ratios of All Males Age 18 to 44 and Male Offenders Age 18 to 44 (Brooklyn, New York)



These numbers would be even more polarized if race were included in the analysis. According to Donziger (1996), on any given day, one in ten African-American males aged 18 to 34 are incarcerated and one in three African-American males are under some form of correctional supervision (Donziger, 1996, p.35). In 2001, 46% of all inmates were African-American and 36% were Hispanic, even though African-Americans represent only 12.3% of

the population and Hispanics represent only 12.5% of the population (Harrison and Beck, 2002; U.S. Census Bureau, 2000). In addition, 10% of African-American non-Hispanic males age 25 to 29 were in prison on December 31st, 2001 (Harrison and Beck, 2002), and "29% of black males born today can expect to serve time in prison in their lifetimes" (Mauer, 2001). These staggering statistics illustrate a major crisis that disproportionately affects poor, inner-city African-American and Hispanic communities.

Why This Increase?

The huge increase in incarceration rates in the United States has been attributed to many factors. The following are most often discussed:

- "Mandatory sentences" and "three strikes and your out" legislation that began to emerge in the 1970's greatly increased the number of offenders sentenced to long amounts of time in prison and jail (Tonry, 1999).
- The "war on drugs", started by President Reagan, combined with harsh mandatory sentences caused a huge influx of non-violent drug offenders into the criminal justice system (Mauer, 2001).
- The politicization of crime starting in the mid 1960's, the growing conservative political climate of the 1980's, and an increase in the disparity between rich and poor created a "tough on crime" atmosphere in the United States that many politicians took advantage of in order to get elected (Mauer, 2001).
- The rate of parolees who successfully complete their parole terms has decreased sharply, from 70% in 1985 to 45% in 1998. The "tough on crime" atmosphere means that parolees who commit minor offenses, such as smoking marijuana, are readmitted to prison for long periods of time. Parole revocations account for over one-third of prison admissions (Travis et al., 2001).

Reentry

Offender reentry has become a major issue due to the large number of offenders returning from prison and jail with little or no assistance. As the number of people admitted to prison and jail increases, there will be a corresponding increase in the number of offenders released back into the community and a decrease in the available resources to deal with this

crisis as resources are redirected away from rehabilitation services in order to incarcerate the increasing prison population. The number of prisoners released each year has increased from 147,895 in 1977 to 585,000 in 2000. In 1998, approximately 25% of released offenders were convicted of a violent crime and 32% were convicted of a drug-related crime (Travis et al., 2001).

In 2001, over 50,000 people in New York City returned home from jail after at least 1 week of incarceration.[2] Even being incarcerated for such a short period of time can mean large life changes. For example, how does someone explain to their boss at work why they have been absent for a week or two? Also, being admitted to jail means going through a humiliating series of events and being exposed to unpleasant and dangerous living conditions.

In addition to the negative affects of incarceration, returning offenders also have much higher incidents of health problems and mental disorders. In 1997, almost 25% of all individuals with HIV or AIDS in the United States were released from a correctional facility that year. That same year, approximately one-third of all people with hepatitis C and tuberculosis were released from a correctional facility. These rates are five to ten times higher than found in the general population (Hammett et al., 2001). Estimates of the prevalence of mental illness among incarcerated individuals varies widely but research indicates that approximately 15% of returning offenders have a serious mental illness, such as schizophrenia, bipolar disorder, or major depression (Lurigio, 2001). In addition to these problems, returning offenders have high rates of drug abuse, unemployment, illiteracy, and homelessness (Travis et al., 2001).

To make matters worse, many prisoners are released without any reentry planning or participation in prison programs. A survey of prisoners in 1997 who were to be released from prison within the next 12 months found that only 27% participated in vocational programs, only 35% participated in educational programs, and only 13% participated in prerelease programs. In addition, 66% of the offenders had children and 67% did not complete high school (Lynch and Sabol, 2001). Many prisoners return home with high levels of stress and anxiety and without enough guidance from the justice system. They often lack necessary pieces of identification, health care, family support, and housing (Travis et al., 2001).

Just as the increase in incarceration rates disproportionately affected poor, minority inner-city neighborhoods, problems related to returning offenders also affect a small number of urban neighborhoods. This means that the effects of a large number of offenders returning home from jail and prison (including any services that they might need and crimes that they might commit) are concentrated within a small geographic area. Such a spatial concentration places a huge strain on existing services and a huge strain on the social fabric of the community as a whole (Clear et al., 2001; Lynch and Sabol, 2001).

Recidivism

Offender recidivism is defined as an offender committing a crime after being convicted of a previous crime (Maltz, 1984). The Bureau of Justice Statistics (BJS) conducted a study of recidivism among prisoners released in 1983 and found that "62.5% were rearrested for a felony or serious misdemeanor, 46.8% were reconvicted, and 41.4% returned to prison or jail" (Beck and Shipley, 1989, p. 1). A second, very thorough study was conducted by BJS of recidivism among prisoners released in 1994. This study found that

67.5% were rearrested within three years of release and 46.9% were reconvicted of a new crime. The rearrest rate varied by the type of offense committed by the individual, race, and gender. Property offenders (73.8%) were more likely to be rearrested than drug offenders (66.7%) and violent offenders (61.7%). Men (68.4%) were more likely to be rearrested than women (57.6%); and blacks (72.9%) were more likely to be rearrested than whites (67.2%). The first year after release accounted for almost two-thirds of all of the recidivism over the three year period (Langan and Levin, 2002).

The BJS study of released prisoners involved 272,111 inmates – approximately two-thirds of all prisoners released in 1994. The 183,675 prisoners who were rearrested (67.5% of the total) were charged with 744,480 new crimes. This represents an average of 4 new crimes for each recidivist. In addition, the 272,111 prisoners in the study had been arrested for 4.1 million charges prior to entering prison. This means that the offenders involved in the study were charged with 4.9 million crimes prior to and after being released from prison in 1994, for an average of 17.9 charges per offender. In reality, a small number of offenders were responsible for a large number of the 4.1 million arrest charges. About 6.4% of the prisoners were each charged with at least 45 offenses before and after their release, accounting for 14% of all charges. About 24% of the prisoners were each charged with at least 25 offenses before and after their release, accounting for 52% of all charges. Using a rough estimate, the prisoners released in 1994 accounted for 4.7% of all arrests in the United States between 1994 and 1997 (Langan and Levin, 2002).

These numbers illustrate the incredible persistence of criminal behavior as well as the inability of incarceration to deter such behavior. Numerous studies have shown that offenders sentenced to other types of sanctions, from probation to community service, also have high

rates of recidivism. Latessa and Travis (1991) found that about 30% of probationers and halfway house residents were *convicted* of a new crime within three years of being sentenced[3]. Muiluvuori (2001) in a study conducted in Finland found that 60.5% of offenders sentenced to community service, and 66.7% of offenders sentenced to prison reoffended within 5 years of program completion. Benedict and Huff-Corzine (1997) found a recidivism rate of 31% among male property offenders on probation and report rates for probationers from other research (for both violent and property offenders) of 65%. May (1999), in a study in England, found *reconviction* rates of probationers and offenders on community service to be between 43% and 58%, depending on the type of sanction. Heilbrun et al. (2000) found a parole violation rate of 73% and a reoffending rate of 40% among juveniles on parole in Virginia. Frederick (1999), in a study of youth discharged from the New York State Division for Youth, found that 81% of males and 45% of females were rearrested within 36 months of release.

Many research studies focus on the characteristics of recidivists versus non-recidivists. Table 1 summarizes the main characteristics of recidivists that have been found to be statistically significant by researchers. The order of the variables in this table also indicates the approximate importance of each variable, with age being very important and IQ having less importance.

Table 1: Primary characteristics found to be significantly related to recidivism.

Characteristic	Source
age (youthfulness)	Zamble and Quinsey, 1997; Stanz and Tewksbury, 2000; Frederick, 1999; Archwamety and Katsiyannis, 2000; May, 1999; Mears et al., 2008
number of previous arrests or convictions	Zamble and Quinsey, 1997; Tollett and Benda, 1999; Stanz and Tewksbury, 2000; Gray et al., 2001; Frederick, 1999; Cottle et al., 2001; May, 1999; Kubrin and Stewart, 2006; Mears et al., 2008
age at first arrest/offense	Zamble and Quinsey, 1997; Grey et al., 2001; Martinez, 1997;

	Frederick, 1999; Archwamety and Katsiyannis, 2000; Myner et al., 1998; Cottle et al., 2001; Miller and Ohlin, 1985;
Alcohol/drug abuse	Zamble and Quinsey, 1997; Frederick, 1999; Myner et al., 1998; Cottle et al., 2001; May, 1999
Lack of education	Zamble and Quinsey, 1997; Grey et al., 2001; Myner et al., 1998; Mears et al., 2008
Gender (male)	Tollett and Benda, 1999; Grey et al., 2001; Cottle et al., 2001; May, 1999; Miller and Ohlin, 1985; Kubrin and Stuart, 2006
Race (non-white)	Tollett and Benda, 1999; Heilbrun et al., 2000; Grey et al., 2001; Martinez, 1997; Cottle et al., 2001; Miller and Ohlin, 1985; McGovern et al, 2009; Kubrin and Stewart, 2006; Mears et al., 2008
Parental Drug/Alcohol abuse	Tollett and Benda, 1999; Myner et al., 1998;
Being a gang mamber	Tollett and Benda, 1999; Myner et al., 1998;
Offense Type (robbery, burglary, assault, etc.)	Stanz and Tewksbury, 2000; Grey et al., 2001; Myner et al., 1998; Cottle et al., 2001;
Employment	Grey et al., 2001; May, 1999
IQ	Archwamety and Katsiyannis, 2000; Cottle et al., 2001;

While many studies (such as the ones listed in Table 1) have looked at the characteristics of recidivists, this study is concerned with the neighborhood context of recidivism and how one's neighborhood environment contributes to or deters recidivism. Very few studies have addressed this relationship and the few studies that do allocate only a small amount of space and effort to this topic. Zamble and Quinsey (1997), in their book *The Criminal Recidivism Process*, believe that current research on recidivism places too much emphasis on static predictors, such as offense history, age, or past substance abuse. These variables, defined by past events, are unchanging or very slow to change and provide little information to those planning programs to reduce recidivism. While current research can be used to select groups of offenders who are more likely to reoffend, program planners and managers require information about specific life events and conditions that "trigger" recidivism. This "leads to the conclusion that we must redirect attention from general determinants of recidivism (except to identify high-risk groups of offenders for concentrated

attention) to questions of how to reduce or prevent it in the community" (p.4). The next part of this literature review will focus on research that looks at the relationship between neighborhood/place and recidivism.

Recidivism & Environment Literature

The first research study on the relationship between neighborhood environment and recidivism was conducted by Gottfredson and Taylor (1986). The authors hoped to improve upon the prediction of recidivism by considering the socio-environmental context of the offenders neighborhood. In order to test their ideas, the authors gathered extensive information about 500 subjects released from state prisons into any of 90 random Baltimore neighborhoods over a two-year period (October 1978 to October 1980). Offense data were gathered 14 months after the release of the last inmate (the authors used an arrest as a measure of recidivism). Within the 90 neighborhoods, a random sample of 20% of blocks was selected for assessment for a total of 1,102 blocks and an average of 12 blocks per neighborhood. The blocks were assessed for land use, appearance, building types, incivilities, and social climate. The authors created two factors based upon these assessments: social and physical incivilities; residential versus nonresidential land use. Their initial findings showed that environmental measures did not significantly affect recidivism. They concluded that "the socio-environmental variables we have explored here have little to do with release outcomes" (p.146).

The authors then decided to investigate the person-environment interaction in an effort to examine a more complex relationship between environment and recidivism. In examining the interaction between *criminal history* and environment, they found that "bad risk offenders" (offenders with a more extensive criminal history) engage in more serious

offenses when in "bad environments" (high scores on the incivilities scale) and engage in less serious offenses in good environments. In examining the interaction between *post-release situation* (financial need, skills, employment status, wages) and environment, they found a contradictory result – that good risk offenders do better in good environments, while bad risk offenders do significantly worse in good environments, possibly due to an increase in criminal opportunities in good environments. The authors believe that these results are consistent with a "differential surveillance hypothesis", that greater formal surveillance in bad environments targets offenders with more extensive criminal records. But when criminal history is ignored good risk offenders do better in good environments, while bad risk offenders do worse in good environments due to greater opportunities.

Up to this point, the authors have analyzed the relationship between specific neighborhood characteristics and recidivism. The authors decided to change their approach, and instead investigate if an offender's neighborhood environment as a whole has an effect on recidivism. Their statistical approach to this question was to create a variable that acted as a "dummy variable" for each neighborhood. Results showed that this general "environmental effects" variable was significantly related to recidivism.

This study has two main limitations, both of which were discussed by the authors. First, the authors did not include census data in their analysis because the 1980 census had not been released to researchers at the time of the research. This is a significant problem due to the large amount of information that could have been added about each neighborhood. Second, the authors did not study any qualitative neighborhood characteristics, such as social networks, neighborhood attachment, fear of crime, informal social control, etc. The authors

acknowledge that these types of variables could be more important than the easily observable variables included in this study.

Kubrin and Stewart (2006) believe that recidivism studies have largely ignored the role neighborhood characteristics play in influencing recidivism. The authors note that "notably absent from recidivism studies are measures reflecting the neighborhood contexts in which former prisoners live. [Previous] studies fail to document the types of communities ex-offenders are released into and treat neighborhood context as constant, and therefore irrelevant, for understanding recidivism" (p. 166). Their study analyzed the extent to which census tract socioeconomic status accounts for variation in reoffending behavior using a sample of 5,002 ex-offenders in Multnomah County, Oregon (Portland and its surrounding area). The authors mapped the release address of offenders on community supervision and linked this address to the appropriate census tract.

The analysis included individual-level data on each offender (age, race, gender), offense characteristics, a neighborhood disadvantage construct made up of several 2000 Census variables (poverty, median family income, unemployment, and people on public assistance), and a measure of concentrated affluence or poverty. The operational definition of recidivism for this analysis was a new arrest within a 12-month period, but the authors did not indicate that any other measure was available to them. A multi-level model was used to analyze individual offenders with neighborhoods. Results indicate that neighborhood disadvantage has a significant and positive relationship with recidivism after controlling for individual-level characteristics. In addition, individuals living in tracts with more affluent families relative to poor families were less likely to recidivate.

This study has several limitations, but the largest and most serious is the use of arrest as the operational definition of recidivism. The authors go to great lengths to justify this decision, but there is no way that a person arrested of a crime can be assumed to be guilty of a crime. Innocent people can be arrested as a result of incorrect or fabricated information from witnesses, insufficient evidence, racial bias, socioeconomic bias, police error, etc., and as a result it is irresponsible for criminal justice researchers to use an arrest as the definition of reoffending. A second limitation, this one noted by the authors themselves, is the focus on socio-economic status as the only characteristic of the neighborhood environment used in this analysis. While income and poverty are no doubt important characteristics, several key variables were missing that would have given the analysis more depth, such as residential mobility, single parent households, race, education levels, and amount of social services. A third limitation is that recidivism was defined to be within a 12 month period of time. Therefore, anyone who committed another crime 2 or three years later would not be included in this study. This is obviously a limitation of the available data, but this short time period has important ramifications for the validity of this research. In spite of these shortcomings, this study is one of the first large scale recidivism studies to specifically focus on the neighborhood context of recidivism and it does a good job laying the groundwork for future research.

Mears et al. (2008) analyzed the relationship between social ecology and recidivism using data on all males released from Florida prisons from January 1988 to June 2001 (N = 49,420). The authors defined recidivism as "a new felony that resulted in correctional supervision [or incarceration] any time within 2 years after release" (p. 312). The analysis included individual-level data on each offender (age, race, and criminal history) and county-

level "social ecology" variables (resource deprivation, racial segregation, and criminal justice system resources). The variable resource deprivation is a factor made up of median family income, female-percent headed households, percent in poverty, and percent receiving public assistance. The geographic unit of analysis for this study was counties, and the authors argue that "counties do not constitute communities by some definitions, but they do reflect the social ecological context to which offenders return…" (p. 315). Hierarchical generalized linear modeling (HGLM) was used for the analysis. Results indicate that the county-level variable "resource deprivation" has mildly significant relationship (.05 level) with both violent reconviction and drug reconviction, but no relationship with property reconviction. The measure of county-level racial segregation was not related to any of the measure of recidivism. The authors also found that higher levels of racial segregation led to higher drug and property recidivism.

The Mears et al. study suffers from one very severe methodological flaw: the use of counties as the geographic unit of analysis. Counties are extremely large geographic areas housing very diverse populations, and county level data will hide all of this geographic variability by producing one value representing all of the diversity of the county. Individuals are influenced by their immediate neighborhood environments, and by no means would any researcher consider a county a neighborhood environment. It is obvious that the researchers only had access to county level data and did their best with what they had, but this flaw calls into question all of the results of this research analysis. A second limitation of this study is the use of only two environment variables, resource deprivation and racial segregation. With all of the interesting and important variables available from the census, it would have been easy to include more environment variables in the analysis. However, the authors do use an

excellent operational definition of recidivism, a felony conviction within 2 years of release. This more strict definition of recidivism ensures that most minor charges and arrests are not included in the analysis as recidivism events.

One very interesting study of the relationship between environment and recidivism was conducted by Kirk (2009) in New Orleans in the aftermath of hurricane Katrina. The author used the mass relocations that occurred as a result of hurricane Katrina as a natural means to analyze the relationship between residential change and recidivism. Kirk believes that a change in the residential location of a released offender can have a positive impact on recidivism by reducing interactions with criminal peers and reducing familiar triggers and opportunities that lead to drug use and/or offending.

Kirk's analysis uses several samples of prisoners released from Louisiana correctional facilities, and specifically focused on offenders who resided in the areas hardest hit by Katrina: Orleans Parish, Jefferson Parish, Plaquemines Parish, St. Bernard Parish, and St. Tammany Parish. The author created three separate cohorts of prison releasees, two control cohorts released prior to Katrina and one cohort released after Katrina. Race, income, unemployment, and fair market rent data at the ZIP Code and Parish levels were used to control for and assess changes in social and economic conditions ("parish" is the word for "county" in Louisiana), and a binary "re-incarceration" variable was used as the dependent variable to identify offenders who were re-incarcerated within 1 year of release. Individual-level data as well as data on the Louisiana criminal justice system were also used in the analysis. Two variables were used to measure residential change: a binary variable indicating if the parolee has moved to a different parish from where they were originally convicted, and

variable measuring the distance of this migration using the distance between the centroid of the original parish of residence and the centroid of the new ZIP Code of residence.

Results indicate that hurricane Katrina did lead to the residential displacement of significantly more ex-prisoners. In addition, offenders who moved to a different parish after Katrina "were significantly and substantially less likely to be re-incarcerated within one year of release from prison" (p.496). Kirk took the analysis a step further by separating his sample into two groups, new commitments to prison and parole revocations. Kirk found that both groups were significantly less likely to be re-incarcerated after moving to a new residential location. The author believes that this is mainly due to the severing of ties with criminal peers, and suggests that policy makers should make an effort to help returning prisoners relocate their residential addresses in order to reduce recidivism.

There are a few limitations of this study. First, the author used very large geographic units (parishes/counties) as the "origin" addresses. This means that if an ex-prisoner relocated to the opposite end of the parish he or she would be coded as living in the same residential location. In addition, all of the contextual demographic and economic data was at the ZIP Codes or parishes level, and data at this level is much less specific and much more "watered down" by the large size and population of the geography than data at the census tract level. Second, the variables used to control for an understand the social and environmental characteristics of the ZIP Codes and parishes was small and omitted several key variables, such as single parent households, residential mobility, and any data on the characteristics of the physical environment, such as housing density and vacancy rates. It would be interesting to see how these variables would affect the author's models. Third, the author defines recidivism as a re-incarceration within one year of release. This relatively

short time period does not pride for enough time to fully assess this long term problem. In spite of these limitations, this is an excellent and very timely analysis of the relationship between residential environment and recidivism.

May (1999), in a study of reconviction following a community sentence[4] in England found "considerable differences in the reconviction rates of the six areas in the study" (p. x[5]). Table 2 below shows the six areas analyzed in the study and the reconviction rates for each area. The reconviction rate ranges from 49% to 64% for probationers, and from 34% to 48% for those on community service.

Table 2: Reconviction rates by area and sentence type (from May, 1999, p.9)

Area	Probation	Community Service
Cheshire	64%	48%
Dorset	54%	41%
Lincolnshire	57%	46%
Nottinghamshire	49%	44%
Oxon & Bucks	50%	44%
NE London	50%	34%

Frederick (1999) conducted a study of 9,477 juvenile offenders who were discharged from the New York State Division for Youth (DFY) from 1991 to 1995 and reported recidivism rates by geographic area. Recidivism was defined in two ways, (1) arrested for any felony or misdemeanor within 30 months of discharge, and (2) arrested for a violent felony offense within 30 months of discharge. Table 3 summarizes his findings. These data show similar recidivism rates within most boroughs of New York City, with the exception of Staten Island, and much lower rates for youth living in the suburbs of New York City, especially for violent felony arrests.

Table 3: Recidivism by Geographic Area, New York City Boroughs and New York State (from Frederick, 1999, p.8)

Geographic Area	Arrested within 30 Months	Arrested for Violent Felony within 30 Months
Bronx	76%	49%
Brooklyn	77%	54%
Manhattan	75%	41%
Queens	71%	39%
Staten Island	68%	47%
NYC Suburban	60%	29%
Non-NYC Urban	76%	38%
Rest of State	69%	24%

Stanz and Tewksbury (2000) examined variables that are associated with successful completion or recidivism of offenders sentenced to a home incarceration program in Kentucky. The authors included the zip code of the offender in the analysis to see if residential location affected recidivism rates. Results indicated that "the location where the offender lives is also a statistically significant predictor of successful completion ($p = .001$). Participants in the traditionally high-crime, low-income, predominately minority west end of Jefferson County have a 2.09 greater odds of failing to successfully complete the program."

Miller and Ohlin (1985) discussed research they conducted on a cohort of youth involved in the Massachusetts criminal justice system during a time of reform of the youth correctional system. Since the state is divided into seven administrative districts, the authors reported recidivism rates for each district using two different measures of recidivism: reappearance in court, and probation/incarceration. Table 4 reports their results. The recidivism rate across regions ranges from 54% to 85% for a court appearance, and from 40% to 65% for a sentence of probation or incarceration.

Table 4: Recidivism Rates for Boys in the 1974 Massachusetts Sample (from Miller and Ohlin, 1985, p.69)

Recidivism Criteria	*Region*						
	1	*2*	*3*	*4*	*5*	*6*	*7*
Court Appearance	73%	75%	54%	68%	80%	85%	69%
Probation or Incarceration	58%	45%	40%	52%	65%	64%	50%

It is important to keep in mind that Frederick (1999), May (1999), Stanz and Tewksbury (2000), and Miller and Ohlin (1985) are looking at large geographic areas, and within each larger area there will be additional variations between places. These studies, as well as that of Gottfredson and Taylor (1986), Kubrin and Stewart (2006), Mears et. Al (2008), and Kirk (2009), addressed the relationship between geographic location and recidivism. However, none of these studies discussed or put forth a thorough definition and description of a recidivism "hot spot" or thoroughly examined the characteristics of high-recidivism areas using a comprehensive group of census variables. The fact that previous research has found geographic variations in recidivism rates is a good sign given the nature of this research study. In spite of this, a much more thorough analysis of the relationship between place and recidivism and of the existence and characteristics of recidivism hot spots must be conducted in order to better understand the recidivism process.

This study will put forth an argument for the existence of recidivism "hot spots", attempt to describe their characteristics, and assess if neighborhood-level "environment" variables influence recidivism after controlling for individual-level characteristics of the offender. Just as crime researchers have defined and examined the characteristics of crime hot spots, this research will define and examine the characteristics of recidivism hot spots and attempt to quantify the unique contribution that environmental variables have on recidivism. If individuals from particular neighborhoods are more likely to recidivate, then it

is possible that environmental characteristics could contribute to or deter recidivism. Such information could be used to design interventions that reduce recidivism.

Research Questions

The purpose of this research is to answer the following questions:

1. Do recidivism hot spots exist?
2. What are the characteristics of high-recidivism areas?
3. How important is the effect of the local environment on recidivism as compared to individual-level variables?

While several researchers have commented on the need to understand the community effects of recidivism, only a small number of studies have specifically examined some of the neighborhood-level characteristics that contribute to recidivism. While these study did an excellent job introducing the topic and addressing some of the major issues, there were several methodological flaws, as discussed above, that severely reduced the usefulness of the research. One of the biggest issues with previous studies is the lack of availability of a substantial criminal justice data set, and as a result past studies were forces to use huge geographic areas (e.g., counties) or inappropriate operational definitions of recidivism (e.g., an arrest). This study benefits from having the single most impressive criminal justice data set ever used for an analysis of recidivism (see Chapter 2 below for more details), allowing for a more comprehensive and in depth analysis of the relationship between environment and recidivism.

Since reentry and recidivism represent two sides of the same coin, answering these recidivism related questions has important implications for work in reentry. The lack of services and support provided to returning offenders, as well as the specific local characteristics of the offenders neighborhood (e.g., lack of resources, gang activity, access to

drugs, a culture of violence, incivilities, etc.), have a direct impact on the recidivism rates of offenders in the community. Any research that can be used to slow this *reentry → recidivism* cycle and prevent some offenders from recidivating could save the jail and prison systems millions of dollars, and, more importantly, save individuals, families, and communities from the large negative impacts of incarceration.

Theoretical Perspective

Spatial Distribution of Crime Theories

Why do some neighborhoods have more crime than other neighborhoods? Many theories concerning the relationship between crime and place have been postulated, so many that it is often difficult to weed out the most promising and valid theories from the collection. The following is a brief review of the most popular or promising theories related to the spatial distribution of crime that also apply to the spatial distribution of offenders.

Social Disorganization Theory

The most famous theory related to the geography of crime and offenders is social disorganization theory developed by Shaw and McKay in the 1920's. Shaw and McKay argue that neighborhoods characterized by poverty, high ethnic diversity, and high residential mobility (residents live in the area for a short amount of time) will suffer from a lack of social organization. In other words, "social disorganization refers to the inability of a community structure to realize the common value of its residents and maintain effective social controls" (Sampson and Groves, 1989, p. 777). Individuals living in such an area will lack social ties (e.g., friendships with neighbors), and the neighborhood as a whole will suffer

from a lack of participation in community organizations and informal neighborhood supervision. For example, in areas with low social organization the residents of the community exert less control over unsupervised teenagers. Neighbors will be less likely to know the teenagers and the families of the teenagers, and therefore less likely to intervene when neighborhood teens behave badly (Henry and Einstadter, 1988; Sampson and Groves, 1989).

Defensible Space Theory

Jane Jacobs and Oscar Neumann developed a theory based upon the idea that the physical design of the environment, such as the size of buildings, has an effect on the amount social contact among residents and social control levels of the neighborhood (Perkins et al., 1993; Greenberg and Rohe, 1984). Jacobs believed that designing neighborhoods with multiple land-uses, such as residential and commercial buildings existing side-by-side, building large sidewalks for children to play, and designing street blocks that encourage people to sit outside and socialize will ensure that the area has a constant flow of people throughout the day and night. This will increase the number of "eyes on the street" and informal surveillance, thus reducing crime. (Greenberg and Rohe, 1984). In addition, Neumann felt that real barriers (e.g., a brick wall), symbolic barriers (e.g., low bushes), territorial markers, outside lighting, outside seating, small buildings, and easily surveyable surroundings act to increase the amount of territorial control, social interaction, and informal social control exercised by residents, thus decreasing crime (Taylor and Harrell, 1996; Brantingham and Brantingham 1993; Perkins et al., 1993; Taylor et al., 1984). Furthermore, large, multiple-unit buildings hinder surveillance by residents, increase the number of people using an area, and decrease social interaction and neighbor identification (Sampson, 1983).

Strain Theory

According to this theory originally developed by Robert Merton, economically disadvantaged individuals have a large gap between their desires and the means to achieve such desires. Due to the importance of material goods and the positive attention and status they bring, poor individuals will seek other means to attain the goods they desire, such as theft or robbery (Akers, 1997). Cohen (*in* Akers, 1997) agreed with the basic premise of this theory but he felt that strain was caused by the inability to gain status and acceptance in conventional society rather than by the inability to obtain material items. Delinquent subcultures develop in response to frustrations caused by this strain and the normative behaviors in these subcultures are the opposite of the conventional standards. Cloward and Ohlin (1960) adapted this theory to produce a social opportunity theory of delinquency. They felt that delinquency was an act of rebellion against blocked social opportunities but they believe that in order to become an offender the individual must experience a deviant learning environment. Also, just because *legitimate* opportunities are unavailable does not mean that *illegitimate* opportunities are available. Individuals experience unequal access to illegitimate opportunities, and the available opportunities determine the types of illegal behavior in the area (Akers, 1997; Weatherburn and Lind, 2001).

Relative Deprivation Theory

According to this theory, cities and neighborhoods in which a low-income population lives in close proximity to a high-income population will suffer from high crime rates. The poor population, seeing the wealth and possessions of the rich, will be motivated to commit crimes because of emotional frustration as a result of being unable to purchase desired goods that, in turn, "create latent animosities that foster crime and violence" (Sampson, 1985, p. 8;

Brantingham and Brantingham, 1980). This view is similar to the process described in strain theory. While quite plausible, this theory has not received the same amount of attention as the theories mentioned above.

Differential Association Theory

Edward Sutherland developed Differential Association Theory in the pages of his criminology textbook, with the final version of his theory appearing in the 1947 edition (Sutherland, 1947). His theory states that criminal behavior is learned through interactions with other people, primarily within intimate personal groups. Specifically, the individual learns favorable or unfavorable definitions of the legal code and he or she becomes delinquent if they accumulate "an excess of definitions favorable to violation of law over definitions unfavorable to violations of law" (p. 6-7). Sutherland believes that those exposed to criminal beliefs and behavior from a young age, more frequently, for a longer duration, and with greater intensity are much more likely to become offenders (Akers, 1997; Sutherland, 1947).

An Epidemic Model of Offender Population Growth

In their book, *Delinquent-Prone Communities*, Weatherburn and Lind (2001) provide compelling evidence for their "epidemic model of offender population growth", a model that does an excellent job of explaining why offenders concentrate in particular geographic areas. The authors begin their argument with a discussion of theories related to the economic and stress induced motivations for offender behavior. These theories attempt to explain why crime and offenders concentrate in poor, minority areas. Weatherburn and Lind feel that these theories alone do not adequately explain the relationship between economic stress and crime. Here are some of the anomalies mentioned by the authors (pp. 26-27):

1. They do not adequately explain why economic stress increases violent offending.
2. Delinquent behavior often develops at a young age, before the child has entered the labor market and occasionally even before the child has entered school. Many economic theories of crime predict a later onset of delinquency.
3. Studies examining the relationship between economic stress and crime have often found non-significant and sometimes negative results.

Weatherburn and Lind provide a strong argument that poor parenting acts as a mediating variable between economic stress and delinquency. Parents who experience higher levels of economic stress are more likely to neglect or abuse their children or engage in harsh, erratic disciplinary practices. Such behavior from parents increases the likelihood that the children will more strongly associate with peers, increasing the chances of that child associating with those already involved in crime, and therefore increasing his or her likelihood of becoming an offender. In disadvantaged areas (where more juveniles are engaged in delinquent acts) the chances of a neglected or abused child becoming a delinquent are greater due to the higher chances of the juvenile coming in contact with those already involved in criminal activities. This model adequately explains why economic stress influences both property and violent crime, and why delinquent behavior can begin at such a young age.

A "Positive Feedback" Model of Recidivism Hot Spots

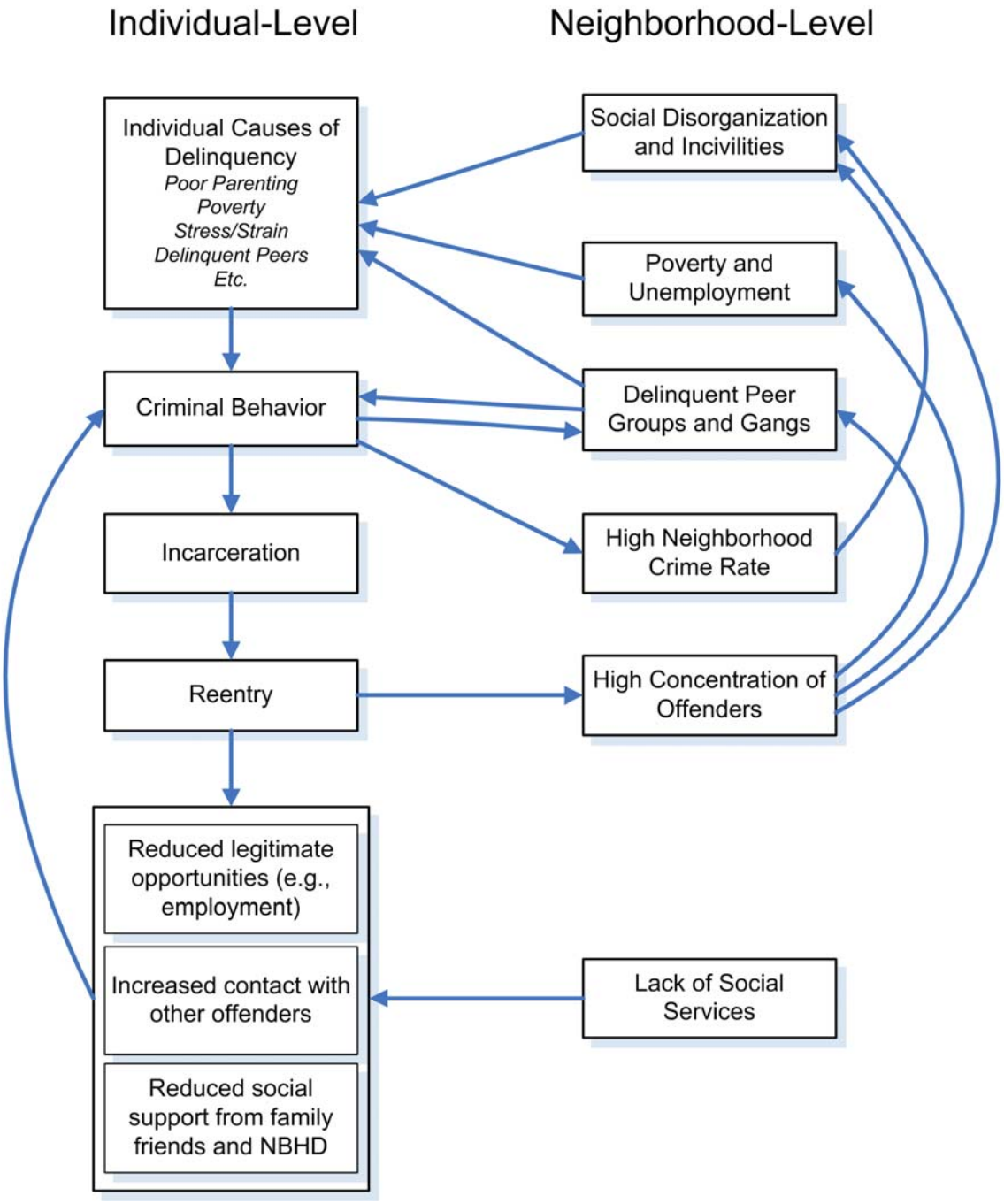
While the theories above are very useful for helping us understand the possible causes of delinquent behavior or the reasons why crime and offenders are concentrated in specific locations, they do not specifically address offender recidivism or the complex mechanisms that contribute to the formation of recidivism hot spots. Using the above theories, a basic

model of recidivism hot spots has been developed and will be tested using the available data. This model draws upon differential association theory, strain theory, social disorganization theory, the model of offender population growth put forward by Weatherburn and Lind (2001), as well as the research literature on offender recidivism and reentry and the spatial analysis of crime (see *Figure 2* below).

There are many competing theories related to the development of delinquency, but since this model is concerned with recidivism and not the development of delinquency, we can place all individual causes of delinquency in a "black box". Within this black box are all of the personal experiences (e.g., poor parenting, abuse, differential association, strain) and other causes (e.g., genetic, dietary) of the development of criminal behavior. In addition to the individual causes of criminal behavior the model includes several neighborhood-level variables that are believed to have an effect on criminal behavior and recidivism. These include social disorganization and incivilities, neighborhood poverty and unemployment levels, the presence of delinquent peer groups or gangs, the crime rate of the neighborhood, high concentrations of offenders, and a lack of social services.

The diagram in *Figure 2* illustrates the relationships between the variables in the model. Each arrow in the diagram represents a positive[6] relationship between variables. The model states that the individual causes of delinquent behavior lead to criminal activity but that the presence of delinquent peers significantly increases the strength of this relationship. At an individual-level, criminal behavior leads to incarceration and reentry from prison or jail, but it also affects neighborhood-level variables, such as the crime rate, the presence of delinquent peer groups, and neighborhood social disorganization. These neighborhood-level variables in turn have a powerful effect on the individual causes of offending behavior.

Figure 2: A "Positive Feedback" Model of Recidivism Hot Spots



In addition, individual-level incarceration and reentry lead to several individual-level issues, such as reduced legitimate opportunities, increased contact with other offenders, reduced contact with and support from family and friends, and an increase in stress and strain, but also increase the neighborhood-level concentration of offenders, and this in turn

increases neighborhood gang activity, poverty, and social disorganization. The absence of social services for ex-offenders combine with the individual-level reentry issues to make it difficult for the offender to obtain legitimate employment, reduce social ties with family and friends, increases contact with like-minded offenders, and increases the overall chances of recidivism.

The model puts the initial emphasis on the individual causes of delinquent behavior, but also illustrates a complex relationship between several neighborhood characteristics and the development of delinquency and subsequent recidivism. In the model, neighborhood conditions contribute directly to the development of delinquency, but they also act indirectly through the increased concentration of offenders that naturally happens in areas with high rates of incarceration and reentry. This cycle of *incarceration → reentry → recidivism*, the same cycle discussed at the beginning of this chapter, leads to more social disorganization, poverty, crime, and delinquent gangs.

The model can be used to predict the characteristics of recidivism hot spots. Using this model, neighborhoods with high social disorganization, poverty and unemployment should have a high number of offenders, and recidivism hot spots should be related to (a) the number of offenders living in the area (more offenders = more delinquent peers = increased recidivism), (b) a lack of social services. The next chapter will discuss the data and methodology employed by this research study.

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[1] Admissions data from NYC DOC and NYS DCJS for 1 year of admissions.

[2] The number is based upon research conducted by the author using admission and release data from the New York City DOC.

[3] There are several operational definitions of recidivism, ranging from an arrest to a crime conviction. The BJS studies discussed above report data using several of the definitions, but most studies define recidivism using only one operational definition. This study uses several operational definitions of recidivism (see *Operational Definition of Recidivism and "Hot Spots"* below)

[4] The sentence could be probation, community service, or a combination of the two.

[5] This quote was taken from the summary at the front of the report. The summary is on pages vii to xi.

[6] Positive does not refer to "good", but to the direction of the relationship. The relationship between s*hoe size* and *height* is an example of a statistically positive relationship, since as one value increases the other value tends to increase, and as one decreases the other tends to decrease. *Temperature* and the *number of people wearing gloves* is an example of a negative relationship since as one increases the other value tends to decrease, and vice versa.

CHAPTER 2

Methodology

Data

Corrections Data

The main data set for this study has been provided by the New York City Department of Correction (DOC) and consists of every admission to the New York City Jail system from July of 1994 to June of 2003[7]. These data represent 1,070,769 admissions to jail by 407,272 people in New York City for a nine year period[8]. Since this file represents admissions, and not individuals, a single individual could be admitted many times each year. Some of these admissions represent individuals who are sentenced to jail or prison after being convicted of a crime and other admissions represent detainees on or awaiting trial, detainees who will be released without being charged, or parole violators awaiting trial.

Each jail admission entry contains a New York State ID (NYSID) number that acts as a unique identifier of each individual being admitted. This number is assigned to each person at the time of their first interaction with city or state departments of correction and it remains unchanged throughout his or her life. The NYSID can be thought of as a social security number for offenders in New York State. The NYSID number allows every person to be identified across each of their admissions to jail providing an accurate way to group admissions by person.

Information on the gender, race, date of birth, high charge (the most severe charge associated with the admission), category and class (e.g., "A" misdemeanor or "C" felony) of the high charge, admission date, and street address is associated with each admission in the data table. The street address is the address of the individual at the time of admission. In addition, there is a yes/no field called "Prior Felony Conviction" that indicates if the person

being admitted has ever had a prior felony conviction. A final field indicates the status at admission of the inmate – detainee, jail sentenced, parole violator, or newly sentenced state prisoner.

A second data set contains information on 1,982,602 discharges from jail from January of 1986 to June of 2003. This file links to the admissions file using a Book and Case Number. The Book and Case Number is a unique number assigned to each admission to jail – a person who has been admitted to jail three times will have three different Book and Case Numbers, one for each admission. This file does not contain address information, and so addresses can only be used from the admissions files. The discharge file provides information on the admission date, sentence date (if the person was convicted of the crime), discharge date, status at discharge (detainee, jail sentenced, parole violator, newly sentenced state prisoner), high charge, the category and class (e.g., "A" misdemeanor or "C" felony) of the high charge, and the discharge reason (e.g., sentence expired, transferred to a state facility, time served, bail paid). The discharge file does not have any additional demographic information about the inmate but does repeat the date of birth, race, and gender data that are also in the admissions file.

Since the admissions file with addresses starts in July of 1994, any discharges that do not link with the admissions file will not contain an address. Discharges will be used to develop valuable criminal history information for each individual who has an address in the admissions file. This historical information will allow for an accurate count of the number of admissions and convictions for each offender between 1986 and 2003.

The discharge file provides important information about the sentencing of offenders to jail or prison. Using a combination of the *Sentence Date*, *Discharge Status*, and *Discharge*

Reason, each discharge linked to an admission to jail or prison can be identified. Also, using a combination of *Sentence Date* and *crime category and class*, each discharge linked to a felony or misdemeanor conviction can be identified. Two new binary variables were added to the discharge table after identifying these different types of admissions: Fel_Conv (felony conviction) and Mis_Conv (misdemeanor conviction). In addition, an *age at admission* field was calculated using *date of birth* and *admission date*.

The discharge file was joined to the admissions file using the common book and case number. All admissions/discharges that did not have a sentence date (an indicator of a conviction) were removed[9] as were all discharges for any individual NOT in the admissions file. These discharges did not link to anyone with an address and so they could not be used for this study. A law code table with information on each specific charge was also joined to the admission/discharge table. This table has information on the specific name, degree, class (A, B, C, D, or E), level (misdemeanor or felony), and general category (violent, property, public order) of the crime. Also, a binary field was created for offenders with only one admission but who also have a "Y" in the *prior felony conviction* field. These offenders will be labeled as recidivists because they have been convicted of an earlier offense but it was too far in the past to be included in the discharge files (they only go back to 1986).

In addition, first time offenders who were never released or who were released with less than one year of time "in the community" before the end of the data set (06/30/2003) were removed from the data set. These offenders did not have enough time in the community in order to accurately label them as recidivists or non-recidivists. In total, there were 7,415 first-time offenders discharged from jail after 06/30/2002. Since the discharge file contains data on jail discharges there are no discharge dates for offenders admitted to prison.[10]

Therefore, an estimated discharge date was calculated for each prisoner using median minimum sentence length data from the New York State Division of Criminal Justice Services (DCJS). This file provided average sentence length by crime category (violent felony vs. non-violent felony) and class (A, B, C, etc.). Using this information, an estimated prison discharge date was calculated and used to select 9,201 first time offenders discharged from prison after 06/30/2002. These offenders were removed from the data set.

Since the operational definition of recidivism will be a felony conviction, the next step was to select all felony convictions from the file of admissions and save this as a separate file. There were 241,898 admissions that ended as a felony conviction in the data set. These admissions represent 142,124 different people.

For several reasons, Brooklyn was chosen as the area to be studied for this research project. While many of these reasons will be discussed later in this chapter, one important reason to choose one borough of New York City (as opposed to the entire city) was to have a manageable data set that can be accurately geocoded[11] to a New York City street map. Using a file with the entire city would introduce a large amount of geocoding error that would significantly reduce the accuracy and validity of the research. Therefore, all felony convictions that occurred while the individual was living in Brooklyn were selected from this larger data set. In total, there were 41,444 admissions that resulted in a felony conviction in Brooklyn. This represents 33,471 people. The following tables provide summary information on these 33,471 offenders.

Table 5: Gender of Brooklyn Felony Offenders

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	3199	9.6	9.6	9.6
	Male	30272	90.4	90.4	100.0
	Total	**33471**	**100.0**	**100.0**	

Table 6: Race/Hispanic Information

Race and Hispanic

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Black	21842	65.3	65.3	65.3
	White	1869	5.6	5.6	70.8
	Hispanic	9572	28.6	28.6	99.4
	Other	187	.6	.6	100.0
	Total	**33470**	**100.0**	**100.0**	
Missing	System	1	.0		
Total		**33471**	**100.0**		

Table 7: Frequency of Felony Convictions

All Felony Convictions

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	15052	45.0	45.0	45.0
	2.00	11597	34.6	34.6	79.6
	3.00	4569	13.7	13.7	93.3
	4.00	1634	4.9	4.9	98.2
	5.00	472	1.4	1.4	99.6
	6.00	126	.4	.4	99.9
	7.00	20	.1	.1	100.0
	9.00	1	.0	.0	100.0
	Total	**33471**	**100.0**	**100.0**	

Table 7 contains frequency information on Felony Convictions in Brooklyn. These totals were calculated by adding the total number of felony convictions per NYSID number with the prior felony conviction binary variable. This variable could only be determined to be a 1 if the total number of convictions was 1 and the prior felony conviction flag was "Yes."

This means that the person has only one conviction, but it is indicated that they have had at least 1, and possibly more, prior felony conviction(s). If someone had two convictions and a "Yes" in the prior felony conviction variable it was not possible to accurately determine if the "Yes" referred to a conviction in the existing file or to a conviction before the file date. In this file, 1,608 people were identified as a recidivist using this prior felony conviction variable because without this variable it would have appeared as if these individuals only had one conviction.

Table 7 indicates that 45% of offenders are non-recidivists, 34.6% have one recidivism event, and 13.7% have two recidivism events. Since the data deal with felony convictions, there is a limit to the number of serious crimes an individual can commit due to the months or years of incarceration imposed by the judicial system for such crimes. While the maximum number of felony convictions for these offenders is 9, the maximum number of total convictions, both felony and misdemeanor, is 62, and the maximum number of admissions to jail is 80.

It is interesting to note that these 33,471 people have had a total of 231,226 admissions to jail – an average of almost 7 admissions per offender – over the 17 year period covered by the data. Of these admissions, 60,146 resulted in a felony conviction and 38,802 resulted in a misdemeanor conviction. The remaining admissions did not end in a conviction (see Table 8 below).

Table 8: Admission, Felony Conviction, and Misdemeanor Conviction Descriptives

Conviction and Admission Information on Brooklyn Felony Offenders

	Total Jail Admissions	Felony Convictions	Misdemeanor Convictions
N	33471	33471	33471
Minimum	1	1.00	.00
Maximum	80	9.00	60.00
Sum	231226	60146.00	38802.00
Mean	6.91	1.7970	1.1593
Std. Dev.	6.109	.99593	2.86665

Prison Admissions from DCJS, Calendar Year 2003

An additional data set containing all admissions to prison in New York State in the calendar year 2003 was combined with the jail admissions data to create an even more complete picture of offender recidivism in Brooklyn. Since the DOC jail admissions data ends in the middle of 2003, these data provide an additional 6 months of prison admissions that can be used to supplement the other felony conviction data.

There were 26,024 prison admissions in 2003 in New York State and 3,646 of these were from Brooklyn addresses. There are two main admission type categories, new commitments versus revocations. A new commitments is when an individual is convicted and sentenced based on a new crime while a revocation is when an individual is on parole and is sent back to prison as a result of a parole violation. Since revocations are not new offenses they have been removed from the analysis leaving a total of 2,266 new commitments. Using this file any additional prison admissions (recidivism events) were documented in the data and any new prison admissions from Brooklyn are added.

Census Data

As noted in the literature review, the greatest methodological flaw with Gottfredson and Taylor (1986) involved their decision not to use any of the 1970 census data in their research as well as the lack of available 1980 census data. Without the very detailed information provided by the census, their assessment of neighborhood characteristics was flawed. In addition, Kubrin and Stewart (2006), Mears et. al. (2008), and Kirk (2009) all omitted several key census variables from their analyses, and this flaw will be corrected in this analysis. This research study has the benefit of using data that fits well with the 2000 Census data releases.

In August of 2002, the Census Bureau released "Summary File 3", a very detailed set of data from the 2000 Census. The 2000 Census provides information on over 15,000 variables related to people, families, households, and housing that are available at many different levels of geography. The most detailed data are available at the block-group level or larger[12], while some basic data are still made available at the block-level. Detailed data are not available at the block-level in order to prevent any single individual or family from being identified using census data.

This research study will utilize many important variables from the 2000 Census at the tract-level.[13] Some of these variables will include race, age, income, poverty, unemployment, household composition, housing density, vacancy rate, length at current residence (a measure of residential mobility), and religion. The census will be used to understand the social, economic, and physical characteristics of neighborhoods.

In addition to using 2000 Census data, historical census data were also incorporated into the study. Historical data provide an understanding of the past characteristics of the area

and how local conditions have changed in the last ten to twenty years. Snapshot data provided from one census does not provide enough information to completely assess neighborhood conditions. Neighborhoods undergoing gentrification are very different from those on the decline, yet the snapshot data could be identical. A product produced by GeoLytics called "CensusCD Neighborhood Change Database 1970-2000" will be used to extract historical census data. This product provides census data from 1970 to 2000 normalized to the 2000 census tract boundary[14].

The initial variables used in the analysis have been drawn from the spatial analysis of crime literature (Swartz, 2000), previous research on recidivism and environment, and from the experience of the author.

Social Services and Religious Institutions

The department of city planning provides spatial information on the locations of many important social services throughout the city, such drug treatment centers and public day care locations. The locations of such services can provide important contextual information about a given location and will be included in the analysis. Accurate data on local social services were obtained from the New York City Nonprofits Project database of over 6,000 New York City nonprofit organizations.

The locations of religious institutions (churches and synagogues) will be mapped using a digital phone book file. Many companies sell digital phone book files that allow users to search and export the names and addresses of facilities and establishments under a particular phone book heading, such as "churches". The entries can be exported into a table file (.dbf), and then imported into mapping software and geocoded.

Public Housing

Public housing information was obtained when the author worked with Thomas Kamber and Baruch College School of Public Affairs to map the locations of publicly funded housing in New York City. The file is quite complete and shows the locations of many different types of public housing (NYCHA, HPD, HUD large projects, small section 8 buildings, etc.), the number of housing units in each building, and the date of construction.

Crime Data

The crime rate of each area will also be included in the analysis. There are many studies analyzing the spatial distribution of crime but very few that look at the relationship between crime hot spots and offender residences. This study incorporates local crime rates as a control variable. It is possible that the only difference between high-recidivism areas and low-recidivism areas is that high-recidivism areas have high rates of crime. The inclusion of these data ensure that we are not simply conducting yet another analysis of the characteristics of crime hot spots.

The crime data used in this study come from the New York City Police Department and includes the addresses of almost 150,000 major crimes in Brooklyn from 1995 to 1997. The crime data are from the middle of the time period being examined and therefore provide valuable insight into relative crime rates across areas. Even if the exact crime rates are not the same throughout the nine year study period covered by the admissions files and address information, the relative rates across areas will likely remain unchanged.

Summary of Independent Variables

The following table summarizes the variables that were included in the analysis. Information on the unit of geography, the time period of the data, and the data source are also included in the table. Variables listed in italics have been calculated by the author using available data and were not included in the original file. The address-level data listed below will be aggregated to the tract level for analysis.

Table 9: Summary List of Independent Variables

Name	Variables	Unit	Time Period	Source
Jail Admissions (variables in file from DOC)	Admission Date, Offense Charge, DOB (Age), Gender, Race, Hispanic (Y/N), Address, Prior Felony Conviction, Admission Type (Detainee, Jail Sentenced, Parole Violator, State Prisoner), *Admissions per Person*, *Density of Offenders, Offender Residential Mobility, severity of crimes*	Individual (Address)	July 1994 – June 2003	NYC DOC
Jail Discharges	Admission Date, Sentence Date, Discharge Date, Discharge Code (e.g., Sentence Expired, Time Served, Paroled, Dismissed, Death, Escaped, Transfer to Prison, etc.)	Individual (Address)	July 1994 – June 2002	NYC DOC
Prison Admissions	Admission Date, Admission Type (New Commitments), Offense Charge, Address	Individual (Address)	CY 2003	NYS DCJS
Census Data	Race (and *ethnic diversity*), age, poverty, income, education level, unemployment, household composition (single parents, 1 person households), housing density, vacancy rate, residential mobility, religion, primary language, *income inequality*	Census Tract	2000	US Census Bureau
Facilities and Establishments	Religious institutions (churches and synagogues), social service agencies (drug treatment, family counseling, food bank, etc.), public day care, community development organizations	Address		NYC Nonprofit Project; NYC Facilities File; Phone Book CD

Public Housing	Address of housing, number of units, operating agency, type of housing	Address	1940 – 2000	Housing Project with Thomas Kamber and Baruch College
Crime Data	Offense Type (assault, robbery, burglary, etc.), Address, *Crime Category (Violent or Property Crime)*	Address	1995 – 1997	NYPD

Geocoding

Using computer mapping technology, each address will be *geocoded* to a street map of Brooklyn. Geocoding represents the mapping of addresses contained in a table and involves a comparison between the information contained in an address with information contained in a table that is linked to a street map. The street map contains a table with information on the starting and ending street numbers for each street segment. For example, if the address of the offender is 150 Smith Street, the software will locate all of the street segments for Smith Street and then locate the segment with addresses that start at 90 and end at 170. The software will then interpolate the location of the address along that street segment and place a point at that location.

The geocoding process is as follows. First, any entries missing an address are deleted from the address file. In the large, city-wide jail admission file, there were 157,859 blank addresses, 22,110 addresses that indicated “Homeless”, 3,041 addresses that simply said “Downstate”, and another 7,664 that said “YMCA”, “None”, “Undomiciled”, or “N/A”. Second, the entire data table was geocoded and any addresses that did not match will exported and “cleaned” using database software, such as Microsoft Access, or the table manipulation capabilities of ArcGIS mapping software. The cleaning process involves correcting common spelling mistakes, correcting missing spaces, removing apartment

numbers that prevent a match, and looking for any other common problems that can be fixed. Once cleaned, the table of unmatched addresses will be geocoded again and any positive matches will be appended to the first set of data. The geocoding process creates a point for every address with a match to the street map. Each point is linked to the data contained in the table. Points can be selected and queried just as admissions in the original data table can be selected and queried.

The beginning part of the geocoding process is done automatically by the mapping software while the later stages involve tedious data cleaning and interactive geocoding by the researcher. The average address table (using "dirty" NYC addresses from government sources) will have about 80% to 85% of addresses geocoded correctly, although the data can be "cleaned" and manipulated in order to increate the success rate to perhaps 90%. After carefully cleaning and interactively mapping the Brooklyn address data, the final hit rate was a very good 92.68%, for a total of 38,411 successful address matches and 3,033 unsuccessful matches.

Geographic Unit of Analysis

The data provided by the DOC provide a unique opportunity to analyze the relationship between neighborhood characteristics and recidivism. Since each admission contains an address that is updated each time the individual is admitted to jail, and since each person is identified by a unique NYSID number, it is possible to identify all admissions for each offender, and then map where they lived at the time of each admission. The resulting file will contain a point for each admission into jail. This will allow for a spatial analysis of recidivism rates using any of a number of geographic levels, such as blocks, census tracts, zip

codes, community districts, or counties – a file containing points can be aggregated to any boundary file using mapping software.

This study will analyze recidivism using census tracts. New York City census tracts encompass an area of about six to ten city blocks and have an average population of 3,612 people (sd = 2,463), with the largest tract having a population of 24,500 people. There are 2,217 tracts in New York City and 783 tracts in Brooklyn. Using census tracts makes for an easier and "cleaner" analysis due to the thousands of census variables available at the tract level. As a result, census tracts have been the geographic unit of choice for spatial researchers. Tracts have often been referred to as "neighborhoods" in research papers even though they represent areas that are smaller than what is considered a neighborhood (at least in New York City). Even a small neighborhood in New York is composed of 5 to 8 census tracts. For example, while there are 2,217 tracts in New York City, there are about 245 neighborhoods (according to the New York City Department of City Planning). Normal daily activities, such as shopping or walking to the subway, will often take a person through two or three adjacent census tracts surrounding their home. In this study, census tracts will be used as (a) a means to compare this research with similar research on the spatial analysis of crime, (b) a measure of what we will consider to be a "small neighborhood" that surrounds an individual's home (and often includes a block or two in each direction, although not always), and (c) a good measure of the characteristics of one's immediate residential environment.

Operational Definition of Recidivism

This study will employ the following operational definition of recidivism: a felony conviction, regardless of sentence length. Past research studies have used several different

operational definitions of recidivism ranging from an arrest to a felony conviction. Using conviction as the operational definition of recidivism reduces the chances that other factors, such as racial profiling or mistaken identity, were responsible for any individual being arrested and charged for committing a crime. A felony conviction is the best measure of recidivism because the necessary legal process necessary to convict an individual will "weed out" many erroneous arrests. Also, as noted above, over 30% of all admissions to prison are parole revocations. The majority of these revocations are due to parole violations, not new felony offenses, and as a result these revocations will correctly not be considered recidivism events.

Therefore, in this study a recidivism event occurs if it is at least the second time the individual has been convicted of a felony during the 17½ year period covered by the data or if the field "prior felony conviction" in the admissions table is marked with a "yes", indicating that the individual has been arrested and convicted of a serious crime in the past, and he or she has a second, more recent, felony conviction in the admissions file.

The calculation of the number of offenders (the denominator in the above equations) is complicated by the fact that the admissions file covers a nine year period and some offenders will live in different census tracts during this time. What should be done if one person has an address point in multiple areas? Should some of the points be ignored or should we count the point in each area?

If an offender has lived in four different neighborhoods (i.e., census tracts) over the nine year period it is very difficult to decide which neighborhood is the most important and which points can be deleted. Even if they live in the area for a short time, their decision to live in that area and their subsequent rearrest when living in that area represent important

information. Therefore, if an offender has lived in four different neighborhoods, then the offender will be counted once for each of the four neighborhoods. This means that the number of offenders in each neighborhood is really the number of offenders who *have ever lived* in the neighborhood over the nine year period. The same technique will be used to calculate the number of recidivists who have ever lived in each area.

Another issue that must be addressed is the fact that every recidivist was a nonrecidivist when he or she committed their first offense. Since we are interested in the neighborhood environment at the time of a recidivist event, one cannot simply label a person as a recidivist and call every address linked to that person a recidivist address. Instead, each geocoded point must be conceived as either a recidivism address or nonrecidivism address (or 1st offense address). This means that every first offense will be labeled a nonrecidivist address and every subsequent address will be labeled a recidivist address. An offender with four felony convictions will have one nonrecidivism address and three recidivism addresses linked to them.

Analysis Procedure

The purpose of this study is to analyze spatial variations in recidivism, not the number of recidivists. The number of recidivists in a given area does not have much meaning unless the number of total offenders in that area is also known. Offenders concentrate in particular areas, and recidivists, as offenders, also live in these areas. The high correlation between the residential addresses of recidivists and offenders means that a more complex technique must be used to identify recidivism hot spots.

For this research study, the number of recidivists must be compared to the total number of offenders in order to identify areas with more than the expected number of recidivists. In order to conduct this analysis, a baseline number of offenders must be developed for every geographic level. This number will be the total number of people who have been convicted of a felony from each area for the nine year period of the admissions data. All other numbers will be reported as a proportion of this number.

Spatial Join and Data Aggregation

The points (and their associated data) created during the geocoding process were aggregated to the tract level. In order to do this, the mapping software performs a *spatial join* between the point file and the census tract basemap. The spatial join allows the point data to be aggregated to the tract or zip code level such that each point will be linked to the tract or zip code that it intersects. This also means that the number of points within each tract can be summarized and a new field added to the table of each tract or zip code with information about the points with its boundaries. For example, a spatial join will allow us to calculate the number of felony convictions or the average age at time of arrest of offenders within each census tract in New York City.

In addition, several different queries can be created using the conviction data and the information from these queries linked to the polygons. For example, individuals with a felony conviction value greater than 1 can be identified and only these admissions linked to the polygons. This would create a field of felony recidivists for each tract.

Anticipated Results

Even though the results of this study appear in later chapters, it is interesting and important to see the results that were anticipated before the study was conducted. It was anticipated that recidivism hot spots exist, and, similar to crime hot spots, that most hot spots are closely related to the socio-economic status (SES) of the area (Kubrin and Stewart, 2006; Swartz, 2000). Also, as stated in the Positive Feedback Model of Recidivism Hot Spots described earlier, it was expected that hot spots will have a high concentration of offenders, few social services, and access to criminal opportunities (e.g., close proximity to wealthier areas). It is very possible that recidivism hot spots differ from crime hot spots since most offenses occur at least some distance from the residential address of the offender. While the distance between crime locations and offender residences is often small, it could have a large effect on the locations of offenders and recidivism hot spots.

It is anticipated that the more surprising result of this research will be the comparison of the relative importance of local environment with the importance of "traditional" recidivism variables, such as age, race, criminal history, etc. (Miller and Ohlin, 1985; Myner et al., 1998; Tollett and Benda, 1999; Zamble and Quinsey, 1997). While these variables have been shown to consistently have a significant relationship with recidivism, it is quite possible that some environmental variables have an even greater impact on recidivism thereby changing how criminal justice researchers conceive of recidivism as a concept. More importantly, this information will alter how criminal justice agencies plan offender reentry and offender supervision – if environmental variables have a significant effect on recidivism, then criminal justice agencies could concentrate services in high recidivism areas as well as identify ways to alter the characteristics of the offender's environment to reduce recidivism.

[7] The DOC did not consistently enter address data into the database prior to July, 1994.

[8] In New York State, Prison is for offenders sentenced to over one year of incarceration and jail is for offenders sentenced to one year or less of incarceration. In addition, jails act as a general holding cell for detainees, parole violators, and newly sentenced state prisoners.

[9] As stated below, the operational definition of recidivism will be a felony conviction – the most strict definition possible.

[10] We know if a convicted offender was discharged from jail and sent to prison, but there is no information on when this offender was discharged from prison.

[11] Geocoding is the process of matching a street address in a data table to a location on a digital street map and then placing a point on this location that represents the address. See discussion of geocoding later in this chapter.

[12] In New York City, a block-group is approximately 3 or 4 blocks, and a census tract contains about 3 to 6 block-groups.

[13] See "Units of Analysis" below for an explanation of why Tracts were chosen.

[14] The US Census Bureau changes census tract boundaries in response to population changes at the time of each decennial census. Therefore, it is necessary to choose a common boundary if data from all years are to be compared.

CHAPTER 3

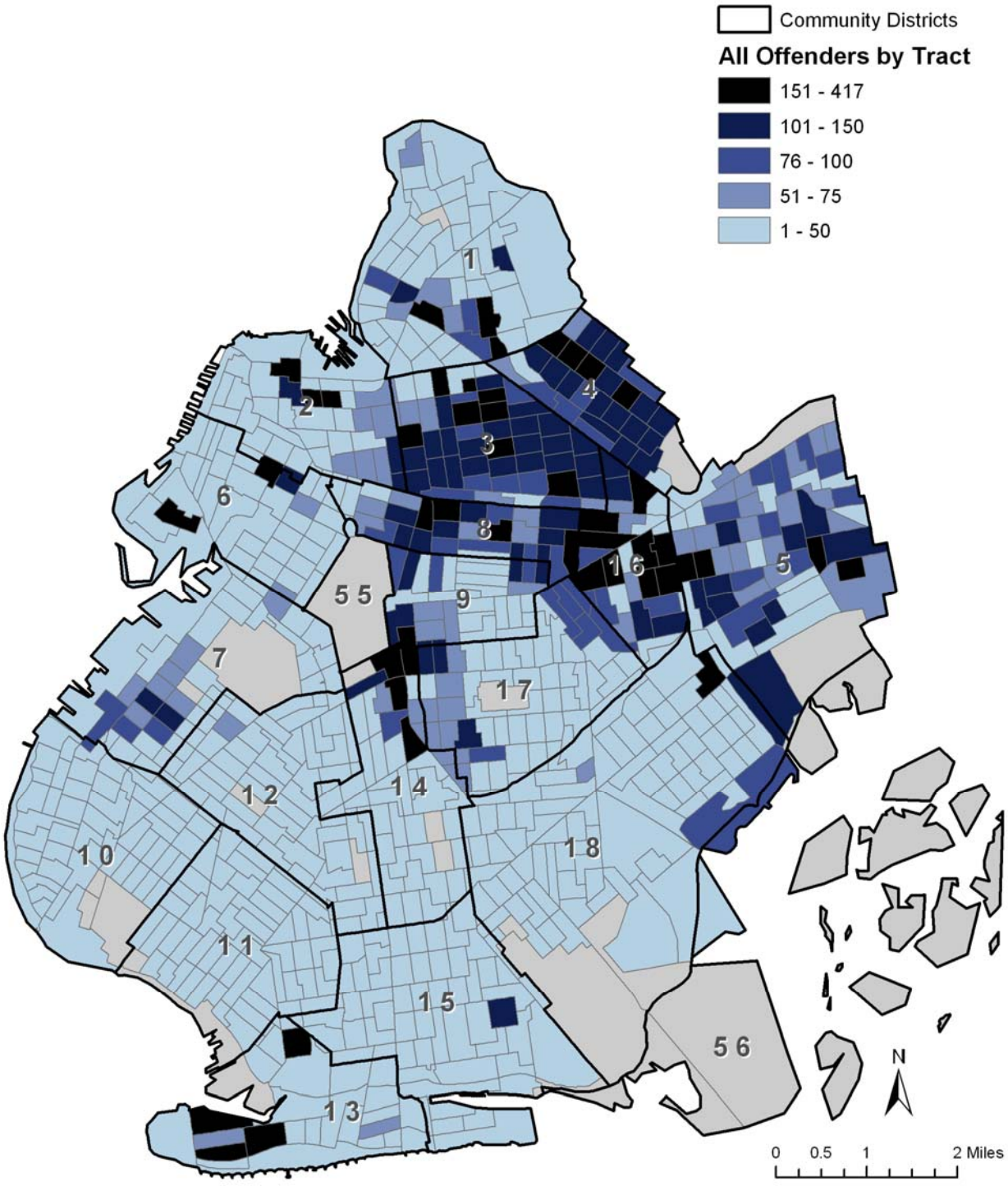
Do Recidivism Hot Spots Exist?

A New Definition of Recidivism Hot Spots

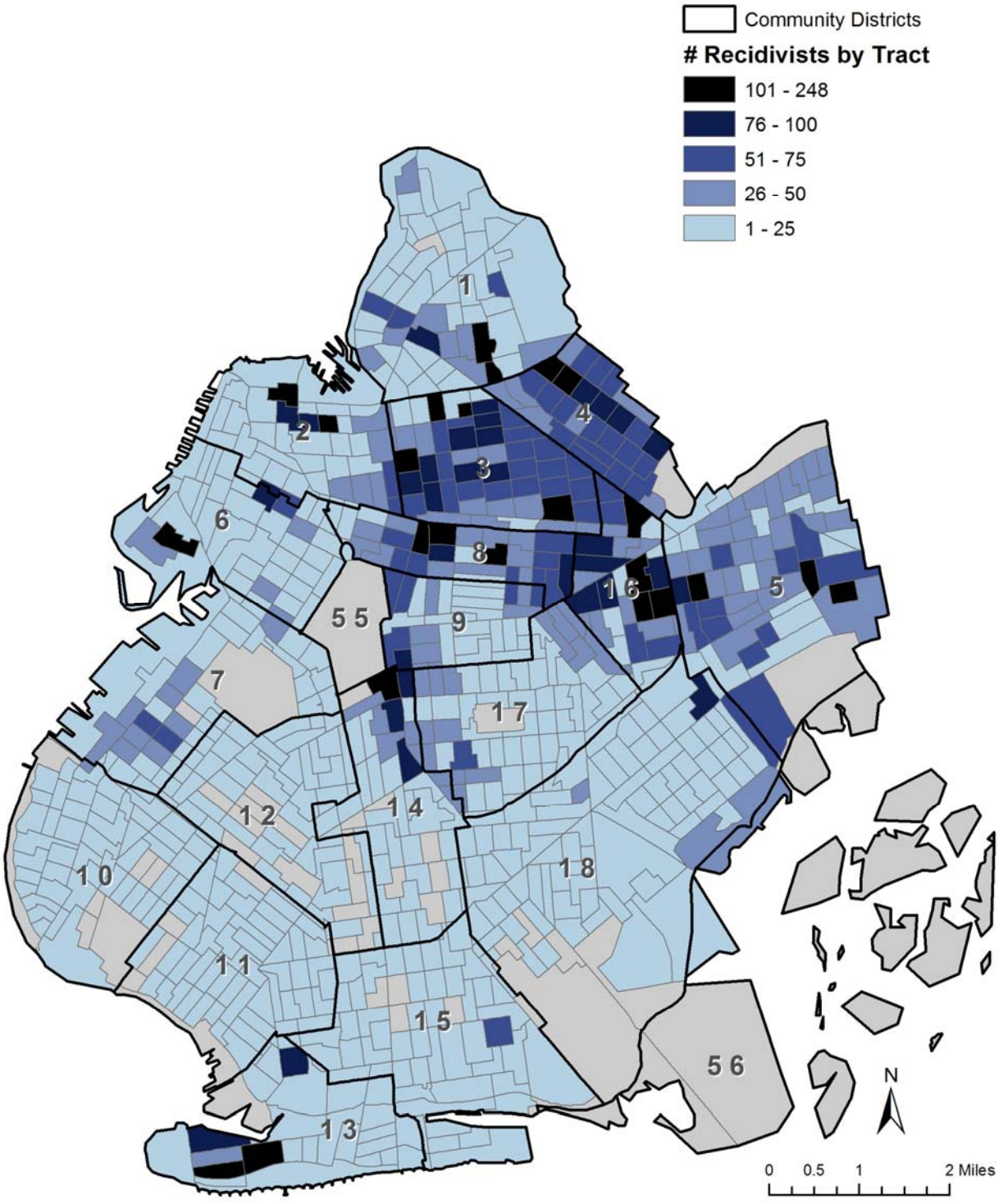
While several studies have shown some spatial variation in the rate of recidivism, no research has specifically investigated and mapped the existence of recidivism hot spots. This chapter will discuss an analysis of recidivists and recidivism hot spots in Brooklyn, New York using data on 41,444 felony convictions (representing 33,471 people) in Brooklyn from July 1994 to June 2003 and historical data on convictions going back to January of 1986.

The operational definition of recidivism hot spots seems obvious – areas with high numbers of recidivists. Unfortunately this definition does not work. Since all offenders are highly concentrated in specific neighborhoods, high recidivist areas are very similar to high offender areas (see Map 2 and Map 3 below). In fact, the correlation between number of offenders per tract and number of recidivists per tract is .992, a value significant at the .0000000000000001 level. Since high offender areas and high recidivist areas are so similar, can recidivism hot spots exist? The answer to this question is yes. As mentioned in Chapter 2, because offender addresses obviously concentrate in specific geographic areas, and since recidivists will also concentrate in these areas, it is necessary to use some calculation that takes into account the relationship between recidivists and nonrecidivists to determine the existence of a recidivism hot spot. This is not as simple as it seems, as initial attempts to develop an operational definition using this method uncovered methodological problems in the calculated values and the maps produced using these values.

Map 2: Number of Offenders per Tract



Map 3: Number of Recidivists by Tract

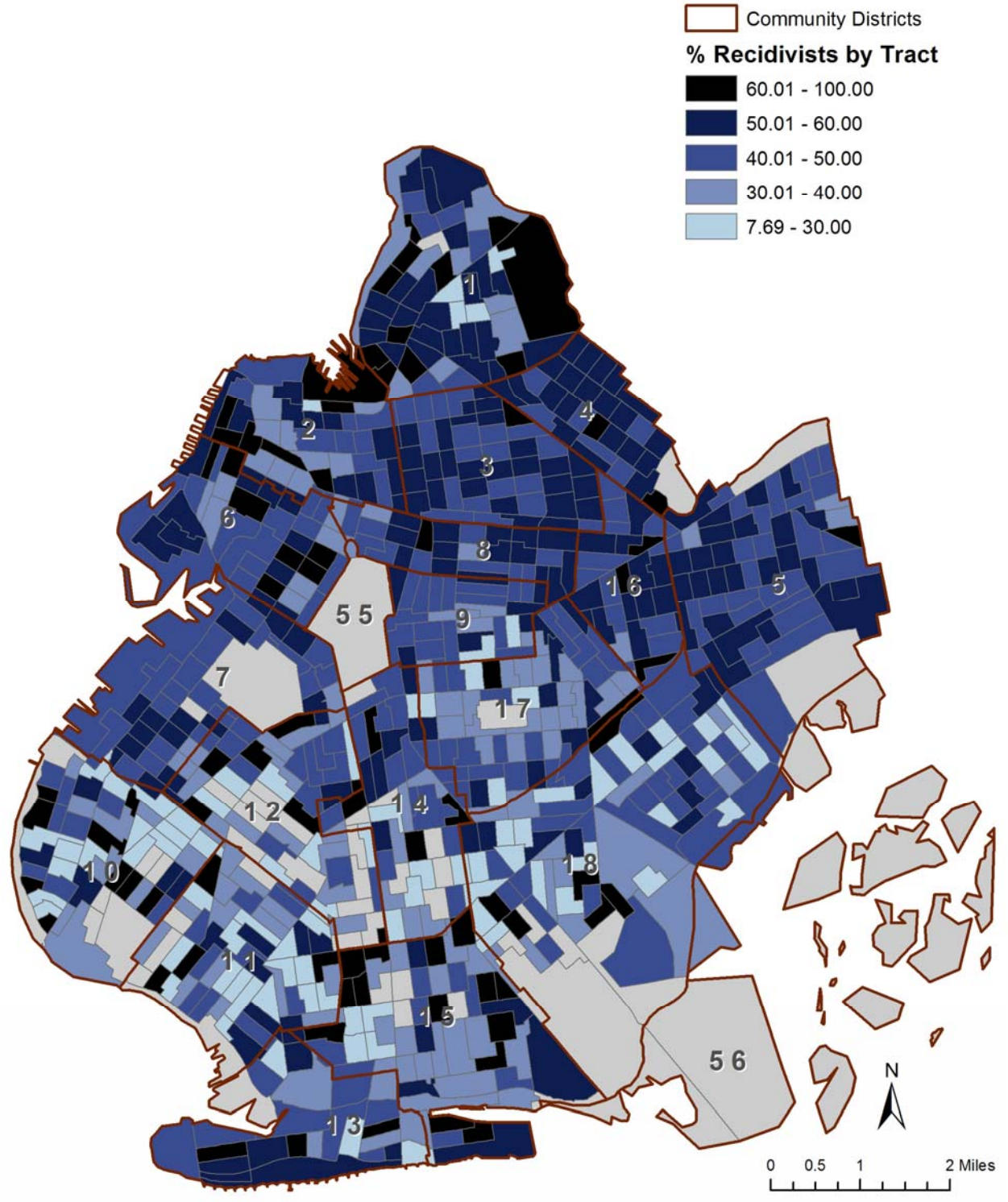


The first attempt to develop an operational definition of recidivism hot spots was to map the percentage of recidivists per tract:

*(# Recidivists / # Offenders) * 100 = % Recidivists per Census Tract*[15]

While this initially seems to be a viable definition, a closer examination at the final calculated values and the map produced using this technique uncovered a serious problem (see Map 4 below). As can be seen in Map 4, tracts in Community Districts 10, 11, and 12, 15 and 18 that have very few offenders and recidivists in Map 2 and Map 3 have very high percentages of recidivists using this technique. This is due to the fact that many areas with less than 10 or 15 offenders have a high percentage of recidivists. As a result, these areas appear to be hot spots but actually have too few recidivists to be classified as such. This problem is inherent in any formula that calculates a rate or percentage and so a different technique must be used that does not calculate a percentage or rate.

Map 4: Percent Recidivists by Tract

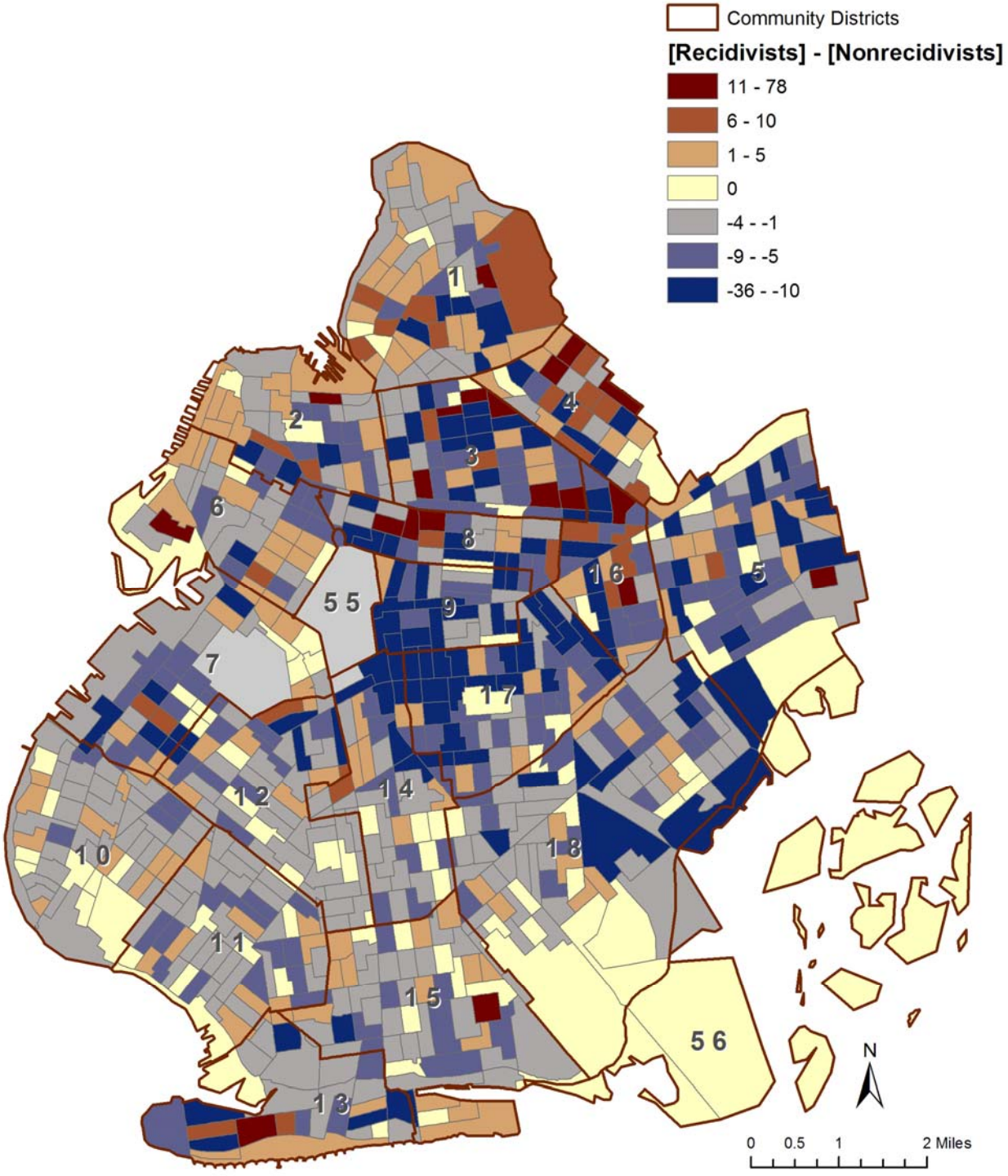


The next attempt was to create a variable using the following formula:

[# of Recidivists] – [# of Nonrecidivists] = Surplus or Deficit of Recidivists per Tract

This creates a variable highlighting the differences between number of recidivists and number of nonrecidivists per tract. This formula makes sense given the fact that recidivists and nonrecidivists both add up to the total number of offenders per tract. Therefore, recidivists and nonrecidivists are "of the same unit of measure" in a conceptual sense and can be manipulated with this in mind. Also, since the number of recidivists and nonrecidivists in Brooklyn is approximately equal we would expect some areas with more recidivists and some with more nonrecidivists. This formula also solves the major flaw with the previous variable – areas with few offenders cannot have extreme values using this technique (see Map 5). While this is not a percentage or ratio, the formula creates a value that reflects surplus or deficit of number of recidivists per tract and highlights areas that have more recidivists than nonrecidivists.

Map 5: Number of Recidivists minus Nonrecidivists



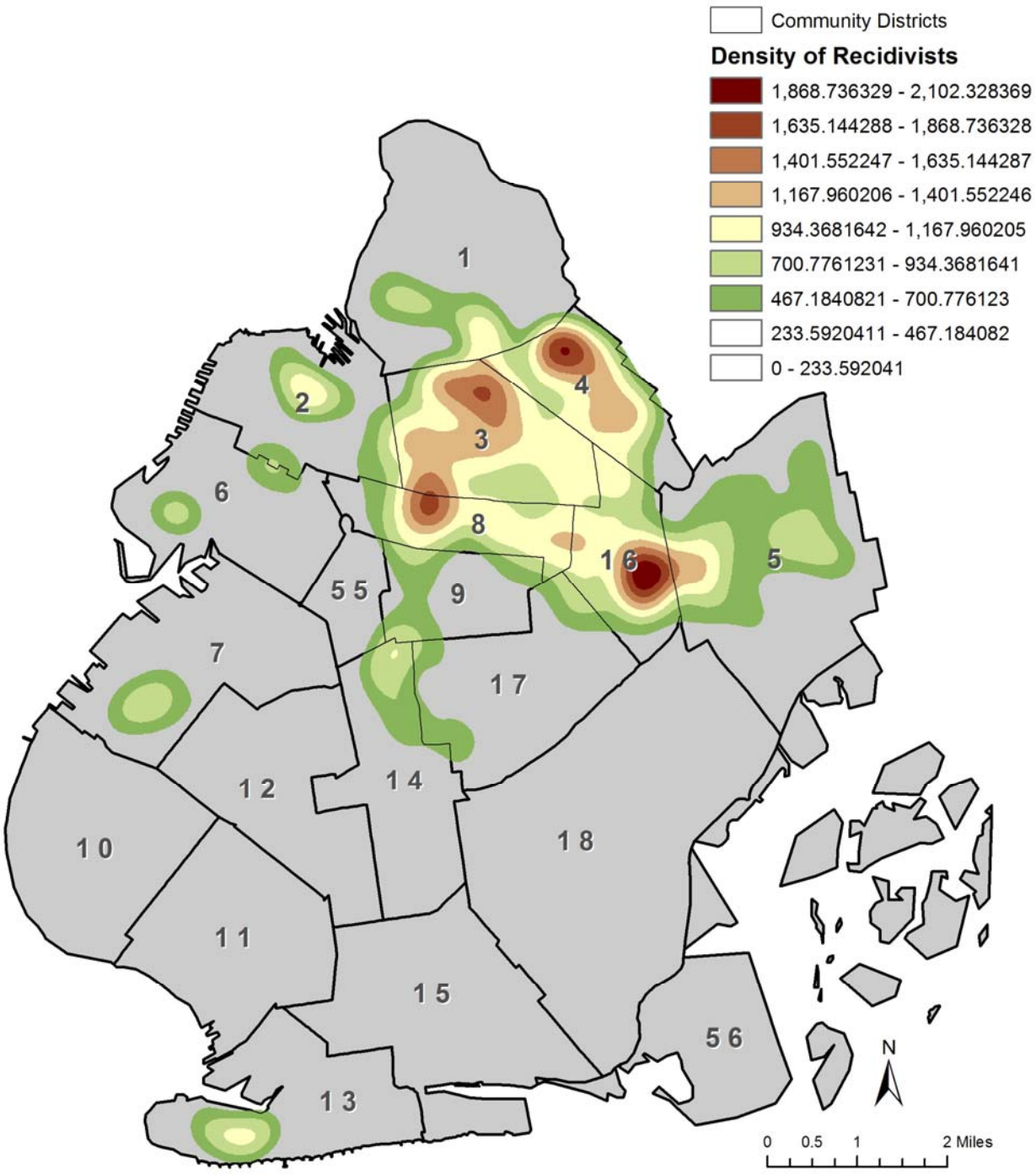
A problem facing both of the previous techniques is their reliance on the arbitrary boundaries of census tracts. Since the original geocoded file contained address-level points, it is possible to use these points to create a density map of recidivists (see Map 6 below). This

density map is created using a technique called Kernel Smoothing (McLafferty et al., 2000). To create this map, the mapping software places a grid over the entire surface of Brooklyn with each square grid cell measuring 50 feet on a side.[16] Starting from the center of each cell, the software counts the number of points within a specified distance of each grid cell. The distance, called the "bandwidth", is specified by the user and has an important effect on the density values created: the larger the bandwidth the lower the density values and the more uniform the map. A small bandwidth is more similar to the original set of points, while a large bandwidth will smooth out the points and create a more uniform density surface. The key is to use a bandwidth value that is realistic to the residents of the area being studied. In this case, a bandwidth of 0.5 miles (2,640 feet, about 10 city blocks) was used. To most residents of Brooklyn, the characteristics of the 0.5 miles surrounding their home has a noticeable impact on their life as most residents routinely walk this distance when shopping or going to the subway.

To create Map 6, every geocoded recidivism address was selected and saved in a separate file and, using this file, the software counted the number of recidivists within 0.5 miles of the center of each grid cell and weighted those points closer to the center of the cell with a higher value than those farther from the center. Then, the software calculated the density of points within the circle and assigned this value to the cell. This was done for every one of the 2.6 million grid cells placed on top of Brooklyn and the same point can be used in the density calculation of thousands of different grid cells although the point will have more weight if it is closer to the center of the cell (McLafferty, et al., 2000). The final density value is given in a unit of measure chosen by the user, such as recidivists per square mile,

recidivists per square kilometer, or recidivists per square foot. Recidivists per square mile was used for this Map 6, although the unit selected has no effect on the look of the map.

Map 6: Density of Recidivists

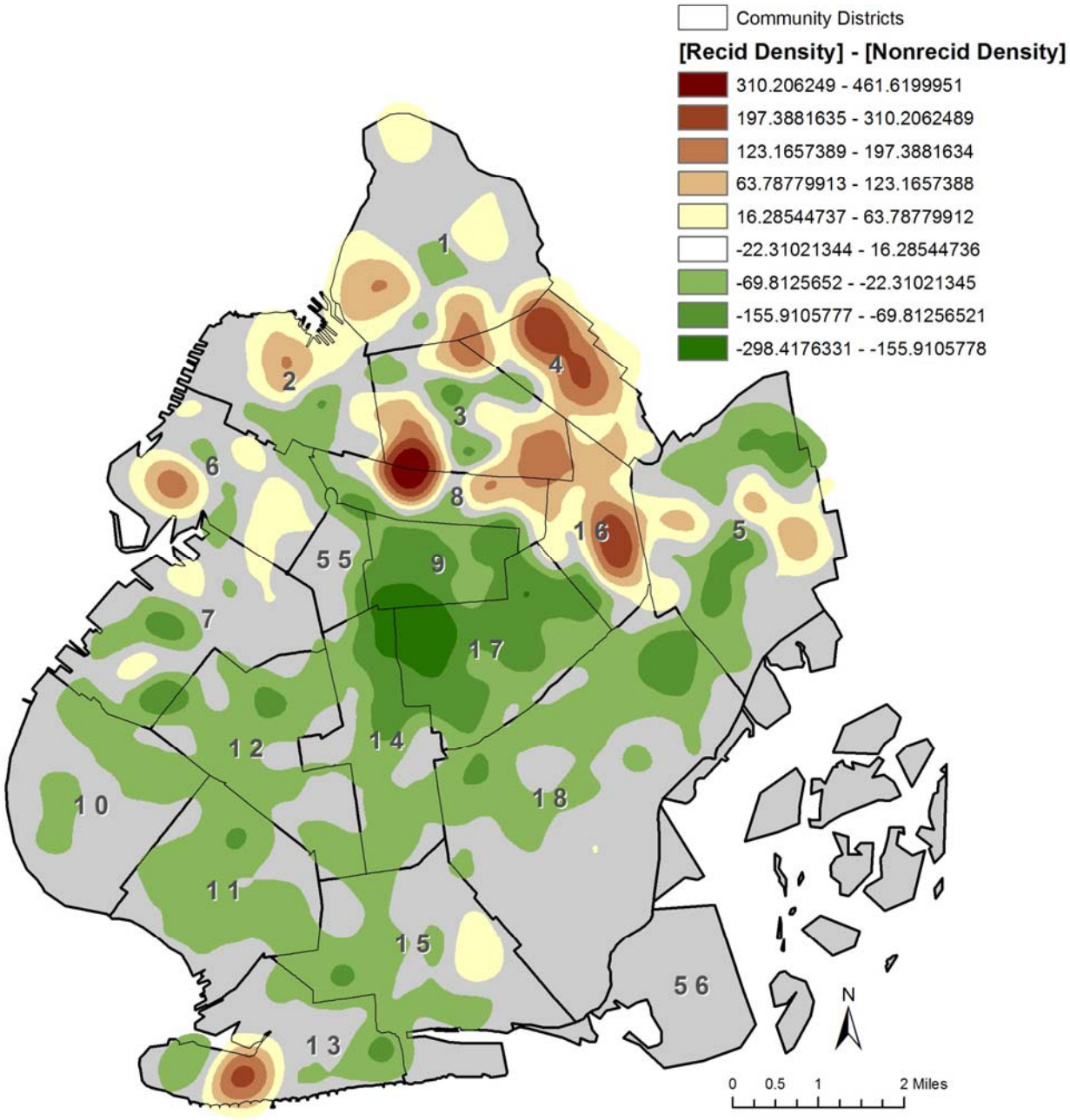


Map 6 was used as a simple illustration of kernel smoothing but it cannot be considered a recidivism hot spot map for the same issues as Map 3 – this is a map of the number of recidivists and it does not take into account the number of nonrecidivists or offenders in each area. In order to create a meaningful map of recidivism hot spots a nonrecidivist density map must be subtracted from the recidivist density map shown above using the same formula as that for Map 5. The will create a map highlighting areas where the density of recidivists is greater than the density of nonrecidivists and vice versa. The ability to conduct calculations using density maps makes them very useful tools for spatial analysis. In order to conduct this calculation a density map was created using all nonrecidivism addresses and the mapping software used this map to subtract the density of nonrecidivists from the density of recidivists for each overlapping grid cell.[17] The product of this calculation is Map 7 (see Map 7 below).

In Map 7, dark green areas are areas where the density of recidivists is much lower than the density of nonrecidivists and dark red areas are areas where the density of recidivists is much higher than the density of nonrecidivists. These areas correspond to recidivism cold spots and hot spots. Map 7 does an excellent job illustrating the location of recidivism hot spots by solving all three of the methodological problems associated with previous attempts:

1. Areas with very few offenders or recidivists cannot become a hot spot using this technique since these areas, by definition, will have low density values
2. The final value takes into account the number of nonrecidivists in each area
3. Arbitrary census tract boundaries do not influence the results

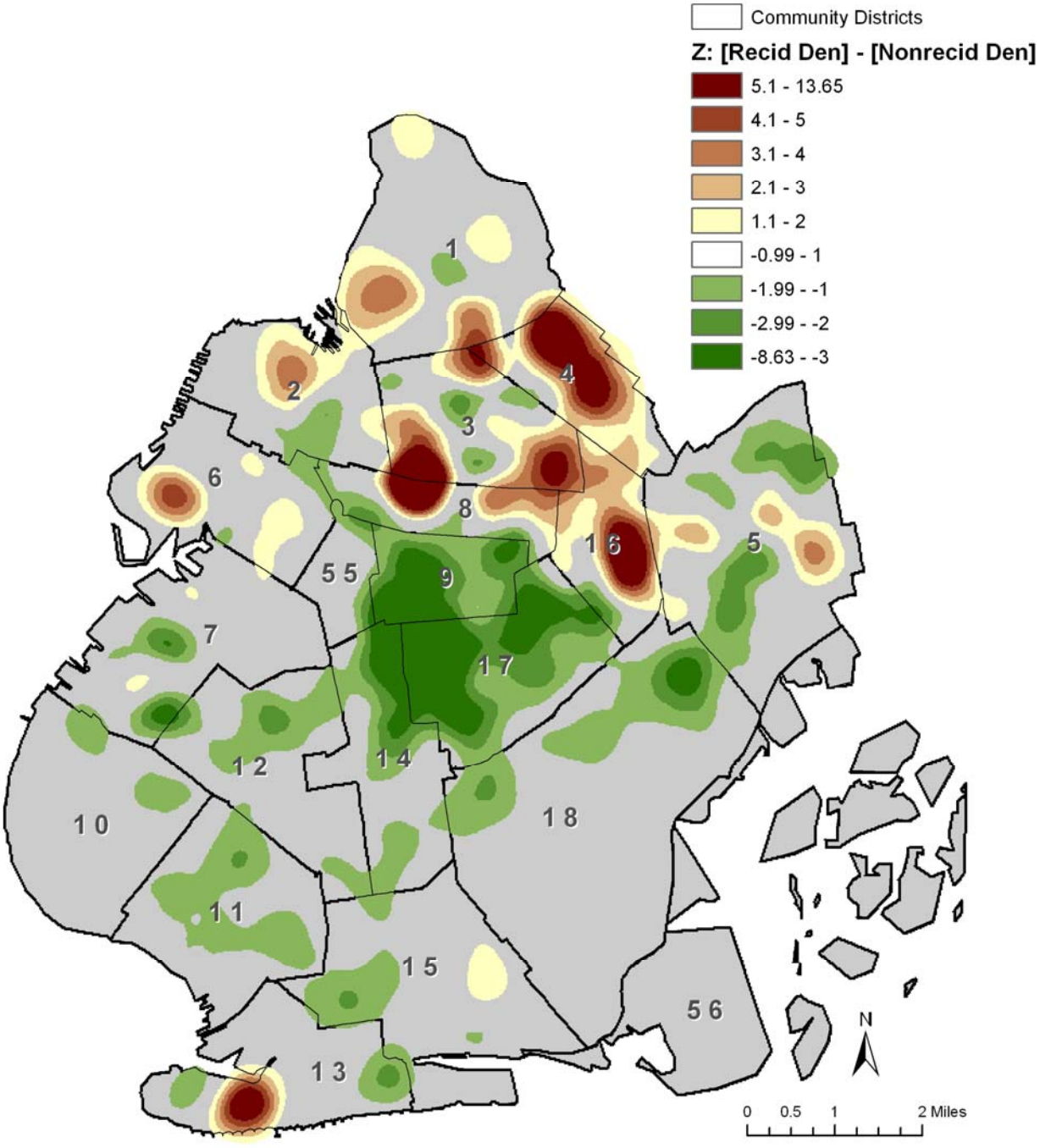
Map 7: Density of Recidivists minus Density of Nonrecidivists



The calculation used to create Map 7 will be the basis for the operational definition of recidivism hot spots and cold spots and will be used to analyze the characteristics of high recidivism areas in the next chapter. Due to of the arbitrary nature of the unit of measure used to calculate density, and in order to make the interpretation of these density values easier, Z-Scores for the density value of each grid cell were calculated using the mean and standard

deviation of the cells (mean = -3.9, SD = 34.12). Even though the primary technique for the identification of hot spots is visual (Harries, 1999), it seems that using Z-Scores can at least help to quantify the concept of a recidivism hot spot. Map 8 was produced using these Z-Score values (see map 8 below).

Map 8: Z-Score of Density of Recidivists minus Density of Nonrecidivists



Using Map 8, a recidivism hot spot is defined as an area where:

[Density of Recidivists] – [Density of Nonrecidivists] > 5 Standard Deviations from the Mean

This is a very conservative definition of a recidivism hot spot yet it still yields the identification of six distinct hot spots in Brooklyn:

1. A large hot spot in Community District 4
2. A small hot spot intersecting the northern boarder of Community District 3 and the western boarder of Community District 4
3. A large hot spot intersecting the southwest corner of Community District 3 and the northern boarder of Community District 8
4. A small hot spot in the southeast corner of Community District 3
5. A large hot spot in Community District 16
6. A medium sized hot spot in Community District 13

Since several recidivism hot spots have been identified in Brooklyn, the answer to research question #1 (*Do recidivism hot spots exist?*) is yes, recidivism hot spots do exist. The next chapter will use several data sources to better understand the neighborhood characteristics related to high levels of recidivism.

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[15] The number of recidivists in the tract is actually "the number of recidivists who have ever lived in each census tract", and the number of offenders is "the number of offenders who have ever lived in each census tract."

[16] The size of the grid cell is determined by the user. The smaller the cells, the smoother the map and the more calculations needed by the mapping software. Fifty foot grid cells are quite small, but create a much nicer looking map.

[17] Since the same grid cell size, bandwidth, and units of measure were used these maps were in exactly the same units and could therefore be accurately used together to calculate a new variable.

CHAPTER 4

What are the Characteristics of High Recidivism Areas?

Variables Used in the Analysis

Independent Variables

After proving the existence of recidivism hot spots and illustrating the spatial differences in recidivism across Brooklyn, the next step is to address research question 2 by analyzing the characteristics of recidivism hot spots using data from a variety of sources. At this stage, the focus is on an understanding of the neighborhood-level variables related to high recidivism areas and so individual-level data from the offender data will not be used in this part of the analysis. The data sources used to identify the characteristics of high recidivism areas include (for a more detailed discussion of these data sources see Chapter 2):

- 2000 Census Data (US Census Bureau)
    - An initial set of over 30 variables were used from the 2000 census, including data on race, age, income, education, employment, poverty, household composition, country of birth, language, residential mobility, occupancy status, and structural density.
- Crime Data from 1995 to 1997 (NYPD)
    - 148,144 crimes in Brooklyn from January 1995 to December 1997. Crime types include assaults, auto theft, burglary, grand larceny, homicide, rape, robbery. The crime data was geocoded to a digital street map of Brooklyn, and density maps were created using these points (cell size = 50', bandwidth = ½ mile). The mean density of (1) all crime, (2) violent crime, and (3) property crime was calculated for

- Locations of Public Housing Units in Brooklyn (File created for public housing analysis conducted by Thomas Kamber and Charles Swartz in 2000)
    - 7,364 public housing addresses from NYCHA, HPD, NYS Division of Housing and Urban Renewal, and HUD with additional information on the number of housing units at each address. The public housing addresses were geocoded using a digital street map of Brooklyn and density maps were created using these points (cell size = 50', bandwidth = ½ mile). The mean density of (1) all public housing addresses weighted by the number of units per building and (2) public housing addresses with over 49 housing units weighted by the number of units per building was calculated for each census tract and used as independent variables.
- Locations of Churches and Synagogues (Digital Phone Book)
    - Addresses of 1,669 churches and 178 synagogues in Brooklyn. The church and synagogue addresses were geocoded to a digital map of Brooklyn and density maps were created for each of the files (cell size = 50', bandwidth = ½ mile). The mean density of churches and synagogues was calculated for each census tract and used as independent variables.
- Locations of Social Services (NYC Nonprofits Project and NYC Department of City Planning Facilities File)

    - 847 social services in Brooklyn from the NYC Department of City Planning Facilities File and 409 social services from the NYC Nonprofits Project database. The social service addresses were geocoded to a digital map of Brooklyn and density maps were created for each of the files (cell size = 50', bandwidth = ½ mile). The mean density of social services was calculated for each census tract.
- The density of all offenders in each census tract will also be used as an independent variable. As stated in chapter 2 in the positive feedback model of recidivism hot spots, it is predicted that areas with high number of offenders also have high levels of recidivism.

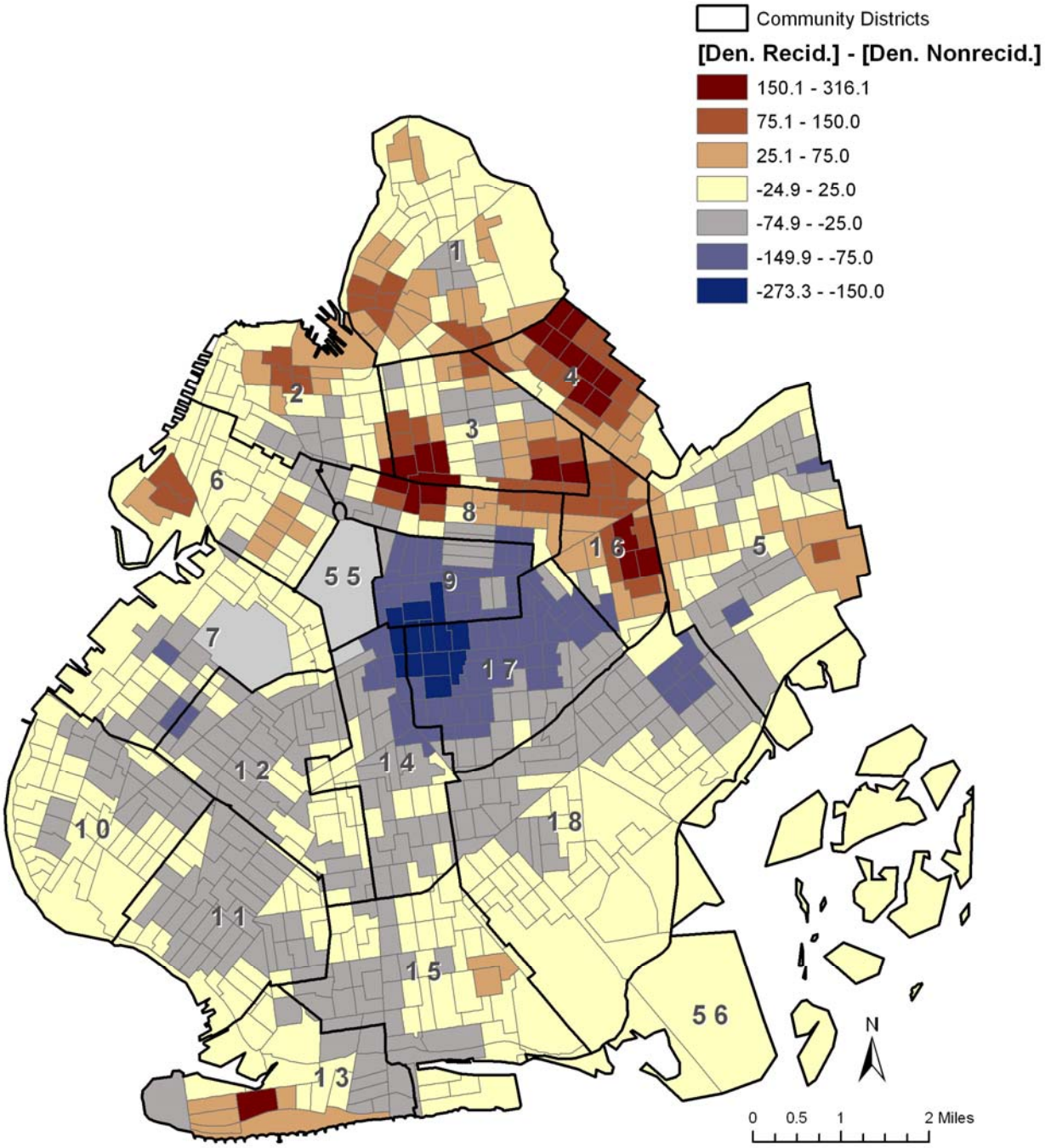
Before conducting the analysis, each of the independent variables were examined for extreme skewness and/or kurtosis and normality using descriptive statistics and histograms in SPSS. Skewness was not a problem for any of the variables but kurtosis was an issue for nine independent variables. Two variables had slightly high kurtosis (average density of public housing and percent teen males; 3.6 to 3.7), four variables had medium high levels (percent Asian, percent living in a different house in 1995, percent elderly, and per capita income; 4.5 to 8), and three variables had very high values (percent unemployed, percent vacant housing, and percent of households with over 1.5 occupants per room; 18.4 to 21.9). These variables were transformed using square root and natural log transformations. The square root transformations did a much better than the log transformations in "fixing" the kurtosis although the new values were worse for percent teenage males and percent living in a different house in 1995. As a result, the original values for these two variables will be used in the analysis.

Dependent Variable

The dependent variable used in the analysis of the characteristics of high recidivism areas will be the same variable used to identify recidivism hot spots in the previous chapter: the density of recidivists minus the density of nonrecidivists. The density difference values depicted in Map 7 (in chapter 3) can be transferred to census tracts by taking the mean density value for each tract. This will allow for an examination of the characteristics of high and low recidivism areas using census data and any other data that can be aggregated to the tract level. Map 9 was produced using the average difference in density per census tract as calculated for Map 7 in the previous chapter (see Map 9 below). As can be seen, all of the hot spots described at the end of the previous chapter are clearly visible in this census tract map, therefore adding to the validity of this approach.

The dependent variable and all of the independent variables were combined into one large data table and brought into SPSS for analysis. The initial analysis involved analyzing the correlations between the dependent variable and all of the independent variables. The variables with the highest correlation with the dependent variable include[18]: density of all offenders (.478), density of public housing (.486), percent Hispanic (.328), density of social service facilities (.237), percent single parent households (.227), percent foreign born (-.458), percent of households with income under $20K (.344), percent with public assistance income (.417), percent in poverty (.366), percent Hispanic males age 10 to 24 (.303), percent vacant housing (.247). See below for a more detailed discussion of correlations.

Map 9: Average Density Difference per Census Tract



Correlations

The following table provides data on the means and standard deviations of the independent variables as well as bivariate correlations (Pearson's r) between the independent variables and the dependent variable (see Table 10 below). The first nine variables were created in the same manner as the dependent variable – geocoded points were used to create a density map in ArcGIS and the average density value per census tract was calculated using this density map. A cell size of 50 feet and a bandwidth of 0.5 miles were used in each of these density calculations.

Table 10: Correlations between Independent Variables and Dependent Variable (* = p ≤ .01)**

Variable Name	Mean	Standard Deviation	Correlation with Dep Var	P Value
Den of Diff (DEPENDENT VARIABLE)	-10.45	66.91	n/a	n/a
Density of All Offenders***	726.73	752.51	0.478	0.000
Density of All Crimes	2,510.17	1,204.55	0.064	0.073
Density of Violent Crime***	1,031.72	799.81	0.200	0.000
Density of Property Crime***	1,478.45	533.46	-0.155	0.000
Density of Public Housing***	2,202.63	3,035.47	0.486	0.000
SQRT Density of Public Housing***	36.40	29.64	0.454	0.000
Density of Churches***	30.32	27.74	0.176	0.000
Density of Synagogues***	3.12	5.60	-0.107	0.003
Density of Social Service Facilities***	15.06	12.59	0.237	0.000
% White NH***	37.34	34.13	-0.109	0.002
% Black	34.00	36.08	-0.034	0.344
% Asian***	7.44	10.07	-0.140	0.000
SQRT % Asian***	2.13	1.70	-0.150	0.000
% Hispanic***	19.47	21.06	0.328	0.000
% Teen Males	4.98	2.01	0.059	0.103
% Teenagers	9.70	3.34	0.069	0.054
% of POP Black Males Age 10 to 24	3.96	4.44	-0.013	0.727
% of POP Hispanic Males Age 10 to 24***	2.56	3.11	0.303	0.000
% of POP White NH Males Age 10 to 24***	3.33	3.71	-0.100	0.005
% Elderly***	11.68	6.33	-0.106	0.003
SQRT % Elderly***	3.29	0.92	-0.130	0.000
% in 1 person HH***	26.23	10.10	0.093	0.010
SQRT % 1 person HH	5.02	1.04	0.071	0.051
% in 5+ person HH	16.13	8.73	0.002	0.954
% Single Parent HH***	13.73	10.28	0.227	0.000
% Speak Only English	54.77	21.95	-0.011	0.757
% Foreign Born***	36.26	15.69	-0.458	0.000
% living in different house in 1995	37.35	10.00	0.040	0.270
% no High School Diploma***	31.15	14.16	0.267	0.000
% with MA or PhD*	6.63	5.92	-0.085	0.018
% Prof. and Management Occ.***	31.45	14.43	-0.118	0.001
% Unemployed***	10.87	8.12	0.283	0.000
SQRT % Unemployed***	3.10	1.12	0.244	0.000
% HHs with income under $25K***	39.06	15.19	0.332	0.000
Median HH Income***	$35,381	$15,455	-0.222	0.000
% with public assistance income***	8.79	7.42	0.417	0.000
Per Capita Income***	$17,463	$9,317	-0.099	0.006
SQRT Per Capita Income***	127.61	34.37	-0.131	0.000
% in Poverty***	23.22	13.39	0.366	0.000
% Vacant Housing***	5.66	4.59	0.247	0.000
SQRT % Vacant Housing***	2.18	0.95	0.199	0.000
% over 1.5 occupants per room	6.76	4.96	-0.017	0.636
SQRT % over 1.5 occupants per room	2.40	1.01	-0.024	0.509
% Building with 20 or more units	26.99	26.87	-0.018	0.625
% Building with 50 or more units	15.71	20.33	0.003	0.924

Of the density independent variables, only one variable is not significantly correlated with spatial variations in recidivism: density of all crimes. This is a very interesting and unexpected result that does not support the positive feedback model of recidivism hot spots described in chapter 1. This discrepancy can be explained by looking at the correlations between property crime and violent crime and the dependent variable. Even though both of these crime variables are significantly related to recidivism, the density of violent crime has a significant positive correlation while the density of property crime has a significant negative correlation. When combined to calculate the density of all crime, these variables cancel each other out and cause the density of all crime to be non-significant. Given these results, areas with a high density of violent crime are conceptually and spatially different than areas with a high density of property crime. Therefore, the variable density of all crime must be dropped from the analysis since it does not accurately capture the complexity of the relationship between crime and recidivism.

The density of public housing and the square-root-transformed density of public housing both have a significant and positive relationship with recidivism. The density of churches also has a significant and positive relationship while the density of synagogues has a significant and negative relationship. This can be explained by the large number of churches located in underprivileged areas of Brooklyn. The density of social services has a positive relationship with recidivism most likely indicating that social services are located in poor, high offender areas.

Five race/ethnicity variables were used in the analysis. Percent white non-Hispanic has a significant and negative relationship with recidivism while percent black is not significantly related to recidivism. Given the strong relationship between percent black and

crime (r = .549), and the even higher relationship between percent black and violent crime (r = .667; with property crime, r = .233), it is very surprising that percent black is not significantly related to recidivism. Percent Asian and the square-root-transformed percent Asian both have a significant and negative relationship with recidivism and percent Hispanic has a significant and positive relationship with recidivism.

It is interesting to note that the variables percent teenagers and percent teen males are not significantly related to recidivism – both of these variables have been significant predictors of crime in other studies (Swartz, 2000). This is most likely due to the fact that this study uses two or more felony convictions as the operational definition of a recidivism event. Such a strict definition of recidivism means that, by definition, an individual must be convicted of a serious crime, serve his or her sentence, and then commit another crime after being released. The length of time required to enter and exit the criminal justice system for a serious crime makes it difficult for teenagers to commit two felony convictions in a short period of time. On the other end of the age spectrum, percent elderly has a significant and negative relationship with recidivism.

Even though the percentage of teenage males is not related to recidivism, the percent Hispanic males age 10 to 24 has a significant and positive relationship with recidivism and the percent white non-Hispanic males age 10 to 24 has a significant and negative relationship with recidivism. Percent black males age 10 to 24 does not have a relationship with recidivism. The direction and strength of these relationships are very similar to the relationship between the dependent variable and the variables percent white non-Hispanic, percent Hispanic, and percent black.

Several household composition variables were included in the analysis. Percent one person households has a significant and positive relationship with recidivism while the square-root-transformed version of the variable is not significant. Percent 5 or more person households is not significantly related to recidivism but percent single parent households has a significant and positive relationship with recidivism.

The variables percent foreign born and percent who speak only English were included in the analysis as a measure of the number of people from different cultures. These variables were significantly correlated with each other at the .01 level yet only percent foreign born was correlated with the dependent variable (at the .01 level). Percent who speak only English was not at all correlated with the dependent variable.

Residential mobility is a common and important variable in the spatial analysis of crime literature (Swartz, 2000). The census variable *percent living in a different house in 1995* is used as the operational definition of residential mobility. In this analysis residential mobility was, surprisingly, not related to the spatial distribution of recidivism. It is interesting to think of high recidivism areas as also having stable, longtime residents.

Many education and income variables were also included in the analysis. Percent without a high school diploma has a significant and positive relationship with recidivism and percent with an MA or PhD has a slightly less significant and negative relationship with recidivism. This variable is the only variable that is significant at the .05 level – all other significant variables are significant at the .01 level. An interesting variable is the percent of those with professional and management occupations. By focusing on the level of employment instead of education, this variable captures those who have good jobs, good incomes, but possibly less education. This variable has a negative and significant relationship

with recidivism. Percent unemployed (and the square-root-transformed percent unemployed), a very important and often used variable, has a significant and positive relationship with recidivism.

Percent of households with income under $25K has a significant and positive relationship with recidivism while median household income and per capita income both have significant and negative relationships with the dependent variable. Percent with public assistance income has one of the strongest significant and positive relationships with recidivism (r = .417) and percent living in poverty also has a significant and positive relationship with the dependent variable. It is interesting to see the consistency in the relationship between the income and education variables and the dependent variable. All but one of these variables are significant at the .01 level and all correlations are in the expected direction

Finally, several housing variables from the census were also included in the analysis with only one variable being significant. Percent vacant housing (and the square root transformation of the variable) has a significant and positive relationship with recidivism. Percent of units with over 1.5 occupants per room (a measure of close living conditions), percent of buildings with over 20 or more housing units, and percent with 50 or more housing units (both measures of structural density) were not related to recidivism.

Regression Analyses

Building upon the information provided by the correlations in the above section, several regression analyses were conducted in stages using the previously described variables. When working with real-world data, it is very difficult to develop complex and

accurate statistical models due to the high correlations among the various independent variables. Therefore, this analysis will be a series of four separate regression analyses, with three analyses focusing on a smaller piece of the entire puzzle and a final analysis that attempts to combine all of the above.

The first analysis, stage 1, examined the relationship between several control variables and the dependent variable. The second analysis, stage 2, involved the analysis of the relationship between the characteristics of the built environment and recidivism hot spots while controlling for the variables from stage 1. The third analysis, stage 3, probed the relationship between the characteristics of the social environment and recidivism hot spots while controlling for the variables from stage 1. A final analysis, stage 4, attempted to create an overall model using the control variables, the characteristics of the built environment, and the characteristics of the social environment. This multi-stage process will help to better understand the many complex relationships among the different sets of variables.

Stage 1 Regression Analysis (Control Variables)

The first regression analysis will focus on the control variables. These variables will be included in every subsequent regression model. The initial list of candidates includes density of all offenders, density of violent crime, and two variables related to the economic conditions of the area: percent in poverty and per capita income. These variables control for the number of offenders living in a tract (more offenders means more potential recidivists, and therefore must be controlled in order to identify variables related to recidivism, not number of offenders), the amount of crime in a tract, and the economic conditions of the tract. Race variables are normally present as control variables in spatial analysis of crime

research but race did not emerge as a consistent and important predictor of recidivism (as seen in the above correlations, Table 10 above).

Table 11: Stage 1 Independent Variable Correlations (Control Variables)

Correlations

	Pearson Correlation			
	Av Density Recid minus Density Nonrecid - DEP VAR	Av Density of All Offenders	Av Density of Violent Crime	% in Poverty
Av Density Recid minus Density Nonrecid - DEP VAR				
Av Density of All Offenders	.478**			
Av Density of Violent Crime	.200**	.886**		
% in Poverty	.366**	.627**	.499**	
Per Capita Income	-.131**	-.407**	-.315**	-.766**

**. Correlation is significant at the 0.01 level (2-tailed).

Table 11 is a correlation table of these independent variables. Since density of offenders is highly correlated with density of violent crime (r = .886) these variables need to be combined into a single factor or one of the variables needs to be removed from the analysis in order to deal with possible multicollinearity problems. Initially, a factor was created by combining these two variables into an overall "Neighborhood Safety" factor. After some preliminary analyses using this factor, it because evident that the factor behaved too differently from the individual variables to be used in the analysis. As a result, one of the variables will be used as an overall indicator of neighborhood safety. Since density of offenders is a much more important control variable for this study, the density of violent crime will be removed from the analysis. In addition, percent in poverty will be used to control for the economic conditions of the area.

Therefore, the control variables included in stage 1 analysis are density of all offenders and percent in poverty. A regression analysis was conducted that included these

control variables and the dependent variable. This model has an R Square of 0.238, and an adjusted R Square of 0.236. This model is significant at the .0001 level (see table 12 below). Table 13 contains information on the independent variable regression coefficients and the significance level of the variable (see Table 13 below). In this model both independent variables have a significant relationship with the dependent variable. Looking at the Standardized Beta coefficient, Density of Offenders has the strongest relationship with the dependent variable (beta = .415), with percent in poverty having the weaker relationship the dependent variable in this model (beta = .106). As would be expected, areas with a higher density of offenders and more people in poverty have more recidivism.

Table 12: ANOVA Summary Table, Regression Stage 1 (Control Variables)

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	830283.20	2	415141.598	119.927	.000000[a]
	Residual	2651598.1	766	3461.616		
	Total	3481881.3	768			

a. Predictors: (Constant), % in Poverty, Av Density of All Offenders

b. Dependent Variable: Av Density Recid minus Density Nonrecid - DEP VAR

Table 13: Regression Coefficients, Regression Stage 1 (Control Variables)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-49.820	4.261		-11.692	.000
	Av Density of All Offenders	.037	.004	.415	10.252	.000
	% in Poverty	.533	.204	.106	2.620	.009

a. Dependent Variable: Av Density Recid minus Density Nonrecid - DEP VAR

Stage 2 Regression Analysis (Built Environment)

The stage 2 analysis will build upon the stage 1 analysis by adding several variables that focus on the characteristics of the built environment: density of public housing, density of churches, density of social service facilities, and percent vacant housing. These variables were chosen for both statistical and conceptual reasons – each of these variables has a significant relationship with the dependent variable and each represents an important characteristic of the physical environment. Table 14 contains the bivariate Pearson correlation coefficients of all of the desired independent variables, the control variables, and the dependent variable. This table indicates that there several potential multicollinearity issues, such as between Density of Offenders and the density of public housing (r = .786) and between Density of Offenders and the density of churches (r = .743). A close examination of the multicollinearity diagnostics will be important in order to identify any potential problems (see Table 15 below).

Table 14: Stage 2 Correlations (Built Environment)

	Pearson Correlation					
	Av Density Recid minus Density Nonrecid - DEP VAR	Av Density of All Offenders	% in Poverty	SQRT Av Density of Public Housing	Av Density of Churches	Av Density of Social Service Facilities
Av Density Recid minus Density Nonrecid - DEP VAR						
Av Density of All Offenders	.478**					
% in Poverty	.366**	.627**				
Density of Public Housing	.454**	.786**	.646**			
Av Density of Churches	.176**	.743**	.401**	.565**		
Av Density of Social Service Facilities	.237**	.590**	.393**	.601**	.611**	
% Vacant	.199**	.425**	.272**	.324**	.456**	.260**

**. Correlation is significant at the 0.01 level (2-tailed).

Table 15 presents the regression coefficients of the stage 2 model. The model itself is significant at the .00001 level, and the model R Square is .317 (adjusted R Square = .312). Collinearity diagnostics in SPSS did not indicate a problem with multicollinearity (Tolerance, VIF, Eigenvalues, Condition Index). Since the concentration of social service facilities was not significant (p = .721), a regression model with this variables removed was conducted, and the results indicated no change in R Square or in the significance of the coefficients after this variable is removed.

This model has several interesting results. First, when taking into account the characteristics of the physical environment, such as the density of public housing units or the presence of vacant housing units, Percent in Poverty is no longer significant. (p = .651). This suggests that, when controlling for offender rates, the built environment has more of an influence on recidivism than neighborhood economic conditions. It is also possible that the

characteristics of the physical environment mediate the relationship between SES and recidivism – SES appears to have a significant relationship with recidivism but this relationship disappears when characteristics of the built environment are taken into effect (see Table 15 below).

Table 15: Regression Coefficients, Regression Stage 2 (Physical Environment and Control Variables)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-47.031	6.001		-7.838	.000
	Density of All Offenders	.054	.006	.602	9.671	.000
	% in Poverty	.093	.205	.018	.453	.651
	Density of Public Housing	.386	.121	.171	3.182	.002
	Density of Churches	-.989	.119	-.409	-8.287	.000
	Density of Social Service Facilities	.080	.223	.015	.358	.721
	% Vacant	4.633	2.419	.065	1.916	.056

a. Dependent Variable: Av Density Recid minus Density Nonrecid - DEP VAR

A second, equally interesting result is the fact that the density of churches has a positive correlation with recidivism in a bivariate correlation (see Table 14 above), yet has a strong negative relationship with recidivism in this multivariate model (see Table 15 above). This indicates that churches are located in underprivileged areas which would explain the initial positive correlation between churches and recidivism but, after controlling for neighborhood safety, economic conditions, public housing units, and vacancy rates, the presence of churches is associated with reduced recidivism. These results hint at the positive impact that churches possibly have on low income, high offender communities.

Third, results indicate that, after controlling for poverty and neighborhood Safety, the density of social service facilities does not have a significant relationship to recidivism (p = .721). This is somewhat surprising especially since the correlation between social services and the dependent variable was significant at the .01 level. This result could possibly be due to this variables correlation with density of churches. After removing density of churches and calculating a new regression model, density of social service facilities becomes significantly and positively related to the dependent variable (p = .01). This new model has an R Square of .256. The change in R Square after removing density of social services and then density of churches from the model is a good indicator of the importance of each variable to the overall analysis. As mentioned above, removing density of social services from the analysis results in no change in R Square while removing density of churches results in a .061 drop in R Square (.317 - .256 = .061). Therefore, density of churches appears to be the more important of the two explanatory variables but it is important to keep in mind that density of social services does have a relationship with recidivism after density of churches is removed.

The density of public housing has a significant positive relationship to recidivism. Results indicate that areas with a higher density of public housing have more recidivists. Perhaps this means that public housing in some way contributes to or encourages criminal activity due to the physical design of public housing structures, high population densities in large public housing complexes, or the concentration of ex-offenders in a small spatial area. It is beyond the scope of this study to identify the exact reasons for this relationship but hopefully this research will encourage others to examine this important relationship.

After controlling for SES and neighborhood safety, the percentage of vacant housing in an area has a slightly significant and positive relationship with recidivism – areas with

more vacant housing have higher levels of recidivism. The amount of vacant housing is an indicator of the desirability or undesirability of an area especially in New York City where residents must find more affordable areas due to very high rents. Therefore, these results could be rephrased as: areas that are less desirable have more recidivism.

Stage 3 Regression Analysis (Social Environment)

The stage 3 analysis builds upon the stage 1 analyses by adding several variables that focus on the characteristics of the social environment: percent foreign born, percent living in a different house in 1995 (aka, residential mobility), percent single parent households, percent one person households, and percent working mothers (working women with children under the age of 18). Also, percent in poverty will be used as a control variable along with density of offenders. Table 16 contains the Pearson correlations among the variables used in this stage of the analysis (see Table 16 below). As can be seen, there are some possible multicollinearity issues due to high correlations between percent in poverty and percent single parent households and between percent single parent households and density of all offenders. The high correlation between the two control variables (percent in poverty and density of all offenders) has already been investigated and is not a problem in these models.

Table 16: Stage 3 Correlations (Social Environment)

	Pearson Correlation						
	Av Density Recid minus Density Nonrecid - DEP VAR	Density of All Offenders	% in Poverty	% Foreign Born	% living in different house in 1995	% Single Parent HH	% 1 person HH
Av Density Recid minus Density Nonrecid - DEP VAR							
Av Density of All Offenders	.478**						
% in Poverty	.366**	.627**					
% Foreign Born	-.458**	-.284**	-.171**				
% living in different house in 1995	.040	.053	-.050	.084*			
% Single Parent HH	.227**	.741**	.605**	-.118**	.054		
% 1 Person HH	.071	-.056	-.167**	-.213**	.128**	-.293**	
% working mothers	-.257**	-.163**	-.549**	.089*	.124**	-.086*	.172**

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Two notable variables missing from the analysis are percent Black and percent Hispanic, variables often found to be significant in spatial analysis of crime studies. Percent Black and percent Hispanic were not included in this regression model after an initial series of analyses indicated that these variables have an erratic and difficult to understand relationship with the spatial distribution of recidivism. As described in Table 10 above, percent black is not correlated with the dependent variable in a bivariate analysis and percent Hispanic has a positive relationship with recidivism, significant at the .01 level. When included in a regression analysis with just the two control factors, percent black has a significant and negative relationship with recidivism – areas with more Blacks have lower levels of recidivism. When percent Hispanic is included in a model with only the two control factors it has a significant and positive relationship with recidivism. In a model with (1) the

control factors, (2) percent Hispanic, and (3) percent Black, percent Black continues to be significant and negative and percent Hispanic is no longer significant. Several other models involving these variables and the other independent variables were conducted and the results indicate that there is no consistent relationship between race and recidivism. In addition, an analysis of the individual-level data on recidivism (which will be discussed in the next chapter) does not support the results found using these aggregated values. As a result of all of these different issues, race variables were not included in this statistical model.

Table 17 presents the regression coefficients of the stage 3 model. The model itself is significant at the .00001 level and the model R Square is .400 (adjusted R Square = .394). Collinearity diagnostics in SPSS indicated that there is not a problem with multicollinearity in this model (Tolerance, VIF, Eigenvalues, Condition Index). Since percent in a one person household is not significant, an additional regression model was created with this variable removed from the analysis. This new model had the same R Square and there was no change in the significance levels of the coefficients.

Table 17: Stage 3 Regression Analysis (Social Environment)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	35.992	16.643		2.163	.031
	Density of All Offenders	.043	.004	.488	10.290	.000
	% in Poverty	.357	.242	.071	1.477	.140
	% Foreign Born	-1.447	.133	-.333	-10.863	.000
	% living in different house in 1995	.578	.203	.083	2.852	.004
	% Single Parent HH	-1.562	.323	-.237	-4.833	.000
	% 1 Person HHs	-.639	2.122	-.010	-.301	.763
	% working mothers	-.592	.159	-.139	-3.724	.000

a. Dependent Variable: Av Density Recid minus Density Nonrecid - DEP VAR

Results indicate that, after controlling for poverty and the density of offenders, percent foreign born has the strongest relationship with the spatial distribution of recidivism. Areas with higher populations of foreign born residents are significantly less likely to be recidivism hot spots. These results suggest that foreign populations moving to Brooklyn take with them some important traditional values and that these values have a protecting influence on the area. This can also be seen in the correlations in Table 16 above. In this table percent foreign born has a moderate negative correlation with poverty (r = -.171) and single parent households (r = -118), indicating that foreign born populations live in areas with less poverty and fewer single parent households but has a stronger negative correlation with density of offenders (r = -.284) and the spatial distribution of recidivism (r = -.458), indicating that these areas have significantly less offenders and recidivism events. So even though foreign born residents are in poorer areas, their traditional values are associated with fewer single parent households and a fewer offenders and recidivism.

Residential mobility (percent living in a different house in 1995) has a significant and positive relationship with the dependent variable. This variable has been an important explanatory variable in many spatial analysis of crime studies (Swartz, 2000) and it continues to be an important predictor of recidivism. Areas with highly mobile residents are significantly more likely to be recidivism hot spots than areas with more stable residents and larger households. This variable, along with single parent households, is an indicator of the amount of informal social control and the strength of the social bonds of a community. Residents in areas with a high population turnover rate and few intact families have a difficult time developing the important social bonds that help to deter crime and reduce recidivism.

A very interesting variable that was used in this analysis is percent working mothers. This variable was included because it was hypothesized to have a positive relationship with crime, delinquency, and recidivism due to mothers being away from home and unable to supervise their children. In reality the opposite is true – it has a negative and significant relationship with recidivism after controlling for poverty and the density of offenders. In addition, the bivariate correlations indicate that it is negatively related to both poverty and density of offenders – areas with more working mothers have less poverty and fewer offenders. Given the expense of living in New York City, mothers from both single parent and two parent families often work and this extra income could allow these families to afford housing in safer, wealthier communities.

Stage 4 Regression Analysis (Physical and Social Environment)

The stage 4 analysis will combine the control variables from stage 1 with the most promising variables from the stage 2 analysis (the physical environment) and stage 3 (the social environment) into a single model. Density of public housing and density of churches were selected from the stage 2 analysis. Percent foreign born, percent single parent households, and percent working mothers were selected from the stage 3 analysis.

Table 18: Stage 4 Independent Variable Correlations

Pearson Correlations

	Av Density Recid minus Density Nonrecid - DEP VAR	Av Density of All Offenders	% in Poverty	Density of Public Housing	Av Density of Churches	% Foreign Born	% Single Parent HH	% working mothers
Av Density Recid minus Density Nonrecid - DEP VAR								
Av Density of All Offenders	.478**							
% in Poverty	.366**	.627**						
Density of Public Housing	.454**	.786**	.646**					
Av Density of Churches	.176**	.743**	.401**	.565**				
% Foreign Born	-.458**	-.284**	-.171**	-.407**	-.192**			
% Single Parent HH	.227**	.741**	.605**	.599**	.495**	-.118**		
% working mothers	-.257**	-.163**	-.549**	-.201**	-.012	.089*	-.086*	
% living in different house	.040	.053	-.050	-.018	.025	.084*	.054	.124**

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 18 is a correlation table of these independent variables. This table contains several interesting correlations. First, the density of public housing has a strong positive correlation with percent single parent households and a significant negative correlation with percent working mothers indicating that single parents are more likely to live in or near public housing and mothers in or near public housing are less likely to be employed than mothers living in areas with less public housing. Even more interesting, both density of

public housing and density of churches have significant negative correlations with percent foreign born, indicating that foreign born populations do not use public housing as much as other populations and they live in areas with fewer churches.

Table 19 presents the regression coefficients of the stage 4 model. The model is significant at the .00001 level and the model R Square is .462 (adjusted R Square = .456). The stage 2 model had an R Square of .317 and the stage 3 model had an R Square of .400, so this combined physical and social model manages to improve in explanatory power over models that focus on just one of these dimensions of the environment.

Table 19: Stage 4 Regression Analysis (Both Physical and Social Environment)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	34.291	12.993		2.639	.008
	Av Density of All Offenders	.072	.006	.812	12.897	.000
	% in Poverty	.372	.241	.074	1.542	.123
	Density of Public Housing	.008	.110	.003	.071	.943
	Av Density of Churches	-.919	.099	-.379	-9.319	.000
	% Foreign Born	-1.388	.131	-.319	-10.609	.000
	% Single Parent HH	-1.876	.286	-.285	-6.563	.000
	% working mothers	-.398	.150	-.093	-2.653	.008
	% living in different house in 1995	.494	.191	.071	2.591	.010

a. Dependent Variable: Av Density Recid minus Density Nonrecid - DEP VAR

Results indicate that, after controlling for poverty and the density of offenders, density of churches and percent foreign born have the strongest relationship with the spatial distribution of recidivism. Areas with more churches and more foreign born residents are significantly less likely to be recidivism hot spots providing even more evidence that traditional and religious values may have an important impact on recidivism.

In addition, areas with *fewer* single parents, *fewer* working mothers, and higher levels of residential mobility also have higher rates of recidivism. Tracts with higher numbers of working mothers tend to have less poverty and fewer offenders, so this result makes sense, and the negative relationship between single parent households and recidivism is most likely due to the fact that single parents in Brooklyn work hard to support their families and after controlling for poverty single parents tend to live in areas with fewer recidivists.

Surprisingly, after controlling for characteristics of the social environment, the density of public housing ceases to have a significant relationship with recidivism hot spots. This indicates that the relationship between public housing and recidivism is more complex than first thought and the physical presence of public housing is not in itself enough to increase recidivism rates of an area.

Summary

The goal of this chapter is to better understand the characteristics of recidivism hot spots. In order to answer this question several data sources were used as independent variables including census data, crime data, locations of public housing units, locations of churches, locations of social services, and data on felony convictions to jail and prison (the density of offenders in census tracts). Four separate analyses were conducted in order to better understand the complex relationships between the control variables (density of offenders and poverty) and the characteristics of the physical and social environments of census tracts. Conducting separate analyses made it easier to understand the unique contribution of physical and social variables, allowed more control over issues of

multicollinearity, and allowed for a more accurate selection of the most important variables included in the combined stage 4 model.

Results of the stage 2 physical environment model indicate that, after controlling for density of offenders and poverty, areas with more public housing units have more recidivism while areas with more churches have less recidivism. Results of the stage 3 social environment model indicate that, after controlling for density of offenders and poverty, areas with more foreign born residents have less recidivism and areas with more working mothers and more single parent households also have less recidivism. Results of the final stage 4 combined model indicate that, after combining the most important physical and social characteristics together in one model, the density of public housing is no longer significant and areas with a high density of churches, high percent foreign born, and high percentage of single parent households all have lower recidivism.

The US Census Bureau collects data on thousands of data variables, but there are still very important types of data that they do not collect, such as crime data, health data, mental health data, public housing data, or criminal justice data (e.g., felony or misdemeanor convictions). The US Census is extremely expensive and time consuming, so it is understandable that they cannot collect data requested by every researcher. However, the above list represents core areas that effect the health and well being of every American and should be included in the US Census.

One limitation of this analysis is the use of census data from only one year, 2000. The mapped criminal justice data spanned 10 years, and the criminal history data spanned 17.5 years, It would be very interesting to look at this data over time to see if there is a temporal aspect to the relationship between neighborhood environments and recidivism. Many New

York City neighborhoods changed drastically in the 10 years represented by the felony admission addresses in my study, so a closer look at these changes over time and how they relate to recidivism could be useful.

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[18] All of the following correlations are significant at the .01 level

CHAPTER 5

How Important is Environment?

Introduction

This chapter will examine the strength of the relationship between the characteristics of offender's local environment and recidivism. Previous chapters have illustrated the existence of recidivism hot spots and identified the most important characteristics of the local environment as related to recidivism. This chapter aims to put the previous chapters into perspective by directly comparing the strength of the relationship between environment and recidivism with the strength of the relationship between traditional individual-level characteristics and recidivism.

This is perhaps the most important analysis of this research study because it places all of the previous results into perspective. Just because we can create a regression model that shows a relationship between foreign born residents and recidivism does not mean that this variable is more important than an offenders' demographic characteristics or individual criminal history. It is quite possible that individual characteristics have a much stronger predictive relationship than environmental characteristics and that placing both types of variables into the same statistical model will reveal that the environmental characteristics are useless when looking at the entire picture of recidivism. On the other hand, if characteristics of the environment have as much or more predictive power as individual characteristics then there is a very strong argument to consider the environment when releasing and supervising offenders in the community.

The goal of this analysis is to compare the relative predictive power of individual-level versus neighborhood-level variables. This not intended to be a comprehensive multi-level analysis of recidivism but rather an assessment of the relative importance of

"neighborhood environment" as a concept in comparison to the personal characteristics of the offender. If environmental variables have a significant effect on recidivism after the inclusion of individual-level variables in the model, then environmental variables still have an influence on recidivism even after controlling for individual-level characteristics. If social and/or physical neighborhood characteristics can withstand this test, then policy makers and criminal justice professionals can no longer ignore the environment of the offender when attempting to reduce recidivism.

The ecological fallacy has clearly shown that researchers must be cautious of aggregate results (Liu, 2007; Steel and Holt, 1996). Most research on the spatial analysis of crime only looks at aggregated data because it is very difficult for any researcher to obtain individual-level crime and criminal justice data. This analysis is very fortunate due to its ability to include individual-level data in the analysis and such an analysis should provide valuable insight into the relative contributions of neighborhood-level and individual-level characteristics.

A multi-level model will be used in order to conduct an analysis using variables at both the neighborhood and individual levels. A multi-level analysis allows variables at different levels to be included in the same model and compared across levels. Levels are groupings that are nested within each other, such as children in classes or schools: children in the same class are more likely to be similar than children in different classes just as children in the same school are more likely to be similar than children in different schools. Our two-level analysis looks at offenders, many with multiple admissions in the file, within census tracts. The file containing all offenders with a felony conviction in Brooklyn is used for the analysis and the dependent variable is "recidivism address", a binary variable that indicates if

the address represents a recidivism or a non-recidivism address (1 or 0 respectively). The Proc GENMOD (General Linear Model) procedure in SAS was used with the "repeated" statement which generates the Generalized Estimating Equation (GEE) multi-level analysis.

Independent and Dependent Variables

As discussed, this multi-level analysis has two distinct sets of independent variables: individual-level variables that from the DOC jail admissions file and the neighborhood-level variables discussed in detail in chapter 4. These individual-level independent variables attempt to emulate the highly cited variables listed in Table 1 in chapter 1 of this paper using the available data contained in the DOC data files. The following individual-level variables were used in this portion of the analysis:

- gender (1 = male, 0 = female)
- black (1 = black, 0 = not black)
- hispanic (1 = Hispanic, 0 = not Hispanic)
- Age at first conviction (age_first_conv) – the age at which the offender was convicted of his or her first felony or misdemeanor.
- The criminal career time span (crimespan) - the number of years between the oldest and most recent conviction.

In addition, several variables focusing on the total number of admissions and/or convictions an offender has had throughout their career are also used:

- Total number of jail admissions regardless of whether there was a conviction (all_adm).
- Total number of convictions both felony and misdemeanor (all_conv).
- Total number of felony convictions (fel_conv).
- Total number misdemeanor convictions the offender has had during his or her criminal career (mis_conv). This is an indicator of the number of minor offenses the person has committed during their criminal career.
- Number of admissions to jail that did not result in a conviction (non_conv_adm) – this is the total number of admissions minus the number of felony or misdemeanor convictions. Represents the number of times the person was arrested and admitted to jail but not convicted of any crime. An indicator of how many times the person has interacted with the criminal justice system but not convicted.

- Felony convictions outside of Brooklyn (non_brooklyn_fel) – total number of felonies committed by the offender minus the number that are in Brooklyn. Another indicator of the breadth of his or her criminal career.

The dependent variable for this analysis is the binary variable "is_recid". If this variable has a value of 1, then the admission is at least the second felony conviction of the offender and represents a recidivism event. If the value is 0 then it is the first felony conviction for that individual and it is not a recidivism event.

Table 20 contains the bivariate correlations between the first set of independent variables and the dependent variable. Results indicate that age at first conviction and crimespan have the strongest relationship between the dependent variable – individuals who start their criminal careers at a younger age have higher rates of recidivism and individuals with longer criminal careers have higher rates of recidivism. In addition, there is a possible multicollinearity issue between Black and Hispanic (r = -.870).

Table 20: Correlations between the first set of Independent Variables

Correlations

	is Recidivism (DEP VAR)	gender	black	hispanic	Age at first conviction
is Recidivism (DEP VAR)	1				
gender	.045**	1			
black	.004	-.020**	1		
hispanic	.025**	.024**	-.870**	1	
Age at first conviction	-.136**	-.125**	-.067**	.015**	1
crimespan	.569**	.018**	.037**	-.014**	-.115**

**. Correlation is significant at the 0.01 level (2-tailed).

Table 21 contains the bivariate correlations between the several measures of total number of admissions and convictions listed above and the dependent variable. As expected, all of the correlations are significant and all are positive. The strongest correlations are between the total number of convictions and the total number of misdemeanor convictions (r

= .937), the total number of jail admissions and the number of admissions that did not result in a conviction (r = .880), the total number of jail admissions and the total number of convictions (r = .874), the total number of jail admissions and the total number of misdemeanor convictions (r = .792), and the total number of felony convictions and the number of admissions that took place outside of Brooklyn. These are extremely high correlations due to the mathematical overlap between the variables and, as a result, these variables cannot be placed in the same model.

Table 21: Correlations between the various Admission & Conviction Variables

Correlations

	Recidivism Address	Total Jail Admissions	Total Convictions	Felony Convictions	Misdemeanor Convictions	non_conv_ adm
is Recidivism (DEP VAR)	1					
Total Jail Admissions	.325**	1				
Total Convictions	.276**	.874**	1			
Felony Convictions	.594**	.508**	.484**	1		
Misdemeanor Convictions	.109**	.792**	.937**	.198**	1	
non_conv_adm	.295**	.880**	.537**	.409**	.457**	1
non_brooklyn_fel	.596**	.382**	.338**	.720**	.141**	.332**

**. Correlation is significant at the 0.01 level (2-tailed).

An additional bivariate correlation analysis containing all of the individual-level independent variables in tables 20 and 21 was conducted and is presented in Table 22. Results indicate that almost all of the correlations are significant and, most notably, cimespan has a strong positive relationship between all of the independent variables listed in Table 21 ranging from a low of .358 with number of misdemeanor convictions to a high of .586 with the number of felony convictions outside of Brooklyn. Age at first conviction has significant negative correlations with all of the Table 21 variables.

Table 22: Correlations between all Invidivual-Level Variables

Correlations

	is Recidivism (DEP VAR)	gender	black	hispanic	Age at first conviction	crimespan	Total Jail Admissions	Total Convictions	Felony Convictions	Misdemeanor Convictions	non_conv_adm
is Recidivism (DEP VAR)	1										
gender	.045**	1									
black	.004	-.020**	1								
hispanic	.025**	.024**	-.870**	1							
Age at first conviction	-.136**	-.125**	-.067**	.015**	1						
crimespan	.569**	.018**	.037**	-.014**	-.115**	1					
Total Jail Admissions	.325**	-.026**	.070**	-.060**	-.111**	.543**	1				
Total Convictions	.276**	-.072**	.069**	-.060**	-.087**	.486**	.874**	1			
Felony Convictions	.594**	.022**	.003	.029**	-.216**	.533**	.508**	.484**	1		
Misdemeanor Convictions	.109**	-.087**	.073**	-.074**	-.023**	.358**	.792**	.937**	.198**	1	
non_conv_adm	.295**	.025**	.054**	-.045**	-.108**	.466**	.880**	.537**	.409**	.457**	1
non_brooklyn_fel	.596**	.048**	-.013**	.041**	-.134**	.586**	.382**	.338**	.720**	.141**	.332**

**. Correlation is significant at the 0.01 level (2-tailed).

Selecting variables to include in the individual-level model is complicated and confounded by the fact that some of the variables are so closely related to the very definition of recidivism that they might wrongly inflate or confuse the model. For example, total number of felony convictions can only have a non-zero value if the individual has had more than one felony conviction. Since the operational definition of a recidivism event for this analysis is a second felony conviction, this variable is too close to the operational definition and exhibits too much conceptual overlap to be used in the analysis. As a result, only those variables from Table 21 that do not contain the felony admissions represented in the individual-level data will be used. This means that total number of admissions (all_adm), total number of convictions (all_conv), and total felony convictions (fel_conv) will not be used in subsequent models. While the dependent variable for this stage of the analysis would mathematically allow for the inclusion of these variables it makes conceptual sense to keep them out of further models.

Preliminary Individual-Level Logistic Regression

These initial multi-level models will look at individual variables separately from environment variables using binary logistic regression. The goal is to get a sense of how the variables behave on their own before bringing them together into a unified multi-level model. An initial set of logistic regressions were used to identify the most important individual-level variables to include in the multi-level model. Initial models included the variables gender, black, Hispanic, age_first_conv, and crimespan and at least one of the remaining variables from Table 21. The best model contained all of these individual-level variables (see Table

23). The Cox & Snell R Square of this model is .473, and the Nagelkerke R Square is .631 indicating that this model has a high degree of predictive power.

Table 23: Individual-Level Logistic Regression

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
gender	-.022	.051	.190	1	.663	.978
black	.136	.064	4.491	1	.034	1.146
hispanic	.205	.068	9.120	1	.003	1.227
age_first_conv	-.018	.002	114.109	1	.000	.982
crimespan	.375	.007	3171.224	1	.000	1.454
mis_conv	-.157	.007	581.558	1	.000	.854
non_conv_adm	.029	.005	31.431	1	.000	1.030
non_brooklyn_fel	2.350	.031	5667.277	1	.000	10.484
Constant	-1.550	.097	257.753	1	.000	.212

Results from this model indicate that all variables, except for gender, have a significant relationship to the dependent variable. The most interesting result from this analysis is the direction of the mis_conv variable (total number of misdemeanor convictions). Offenders with more misdemeanor convictions are less likely to have a felony conviction recidivism event. This result is most likely related to the very strict operational definition of recidivism used for this study. Some offenders are chronic misdemeanor offenders who commit the occasional felony or receive a felony conviction for a large number of misdemeanor offenses. These results suggest that these offenders are less likely to be convicted of a felony offense. The variables listed in Table 23 will be used in the multi-level analysis. Even though gender was not significant in this model it will still be included as a control variable as a result of its prominence in the recidivism literature.

Multi-Level Analyses

Multi-Level Analysis: Step A

Two distinct approaches will be conducted in this multi-level analysis. First, Step A will add all of the individual-level variables discussed in the preceding section to the multi-level model along with one neighborhood-level variables to see if the neighborhood-level variable is significant after controlling for individual characteristics. This simple approach will provide valuable information regarding the ability of neighborhood-level variables to rise above the predictive power of individual-level variables to add value to the multi-level model. Second, in Step B, a more comprehensive model will be "built" in stages. This model will combine several individual-level variables with the most promising neighborhood-level variables in order to evaluate how multiple neighborhood-level variables influence the model.

Table 24: Baseline Multi-Level Model, Individual-Level Variables Only

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		-2.2827	0.0823	-2.4441	-2.1214	-27.72	<.0001
gender	1	-0.0669	0.0533	-0.1714	0.0376	-1.25	0.2096
black	1	0.1035	0.0634	-0.0206	0.2277	1.63	0.1022
hispanic	1	0.175	0.0666	0.0445	0.3054	2.63	0.0086
mis_conv		-0.8816	0.039	-0.9581	-0.8051	-22.59	<.0001
non_conv_adm		0.0482	0.0062	0.0361	0.0603	7.83	<.0001
non_brooklyn_fel		2.3161	0.0374	2.2428	2.3894	61.93	<.0001
age_first_conv		-0.0181	0.0017	-0.0214	-0.0148	-10.77	<.0001
crimespan		0.4068	0.0096	0.3881	0.4255	42.55	<.0001

This first series of multi-level models (Step "A") includes several models that contain all of the individual-level variables shown in Table 23 and one environment variable. Table 24 above shows the results of a multi-level model containing only individual-level variables

– this will be used as a baseline from which to measure the impact of the addition of a neighborhood-level variable to the model. This model is extremely similar to the logistic regression model shown in Table 23, with the only difference being that the variable black is was significant at the .05 level in the logistic regression but is not significant in the multi-level model in Table 24.

The first of these models is shown in Table 25. This model uses all of the individual-level variables and one neighborhood-level variable, percent in poverty. Results indicate that, even after controlling for many important individual-level characteristics, poverty has a significant positive relationship with the dependent variable ($p < .0001$). It is interesting to note that, after adding percent in poverty to the model, the individual-level variable Hispanic is no longer significant.

Table 25: Multi-Level Model Step A, #1: Percent in Poverty

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		-2.401	0.087	-2.5716	-2.2304	-27.59	<.0001
gender	1	-0.0575	0.0533	-0.162	0.047	-1.08	0.2808
black	1	0.0401	0.065	-0.0873	0.1674	0.62	0.5375
hispanic	1	0.114	0.0679	-0.0191	0.2471	1.68	0.0933
mis_conv		-0.8844	0.039	-0.9609	-0.8079	-22.66	<.0001
non_conv_adm		0.0482	0.0062	0.0361	0.0603	7.83	<.0001
non_brooklyn_fel		2.3155	0.0374	2.2421	2.3888	61.88	<.0001
age_first_conv		-0.0178	0.0017	-0.0211	-0.0145	-10.56	<.0001
crimespan		0.4068	0.0096	0.3881	0.4255	42.59	<.0001
poverty		0.005	0.0011	0.0028	0.0072	4.4	**<.0001**

The second model in this series is very similar to the first, except that density of public housing was used instead of percent in poverty (see Table 26 below). The results of this model are identical to the results of the poverty model: density of public housing has a significant positive relationship with the dependent variable ($p < .0001$) and, after adding density of public housing, the variable Hispanic is no longer significant.

Table 26: Multi-Level Model Step A, #2: Density of Public Housing

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		-2.3468	0.0836	-2.5106	-2.183	-28.08	<.0001
gender	1	-0.0615	0.0533	-0.166	0.043	-1.15	0.2486
black	1	0.0118	0.0666	-0.1188	0.1424	0.18	0.8596
hispanic	1	0.1135	0.068	-0.0197	0.2467	1.67	0.0949
mis_conv		-0.8842	0.039	-0.9606	-0.8079	-22.69	<.0001
non_conv_adm		0.0481	0.0062	0.036	0.0602	7.79	<.0001
non_brooklyn_fel		2.3154	0.0374	2.2421	2.3887	61.88	<.0001
age_first_conv		-0.018	0.0017	-0.0212	-0.0147	-10.69	<.0001
crimespan		0.4064	0.0096	0.3877	0.4251	42.55	<.0001
public_housing		0.0023	0.0005	0.0013	0.0032	4.47	**<.0001**

The third model in this series includes all of the prior individual-level variables and the percent foreign born (see Table 27 below). This variable was shown to be very important in explaining the characteristics of recidivism hot spots in the previous chapter. Results indicate that percent foreign born has a significant and negative relationship with the dependent variable (p = .0033).

Table 27: Multi-Level Model Step A, #3: Percent Foreign Born

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		-2.1657	0.091	-2.344	-1.9875	-23.81	<.0001
gender	1	-0.062	0.0534	-0.1666	0.0425	-1.16	0.2449
black	1	0.066	0.0646	-0.0606	0.1926	1.02	0.307
hispanic	1	0.1498	0.0671	0.0183	0.2814	2.23	0.0256
mis_conv		-0.8848	0.039	-0.9612	-0.8083	-22.69	<.0001
non_conv_adm		0.0483	0.0062	0.0362	0.0604	7.82	<.0001
non_brooklyn_fel		2.3145	0.0374	2.2412	2.3878	61.89	<.0001
age_first_conv		-0.018	0.0017	-0.0213	-0.0147	-10.72	<.0001
crimespan		0.4064	0.0096	0.3877	0.4252	42.54	<.0001
foreignborn		-0.0029	0.001	-0.0048	-0.0009	-2.93	**0.0033**

The forth model in this series includes all of the prior individual-level variables and the neighborhood-level variable density of all offenders (see table 28 below). Again, this

variable has a significant and positive relationship with the dependent variable ($p < .0001$), and the addition of this variable causes the variable Hispanic to no longer be significant.

Table 28: Multi-Level Model Step A, #4: Density of All Offenders

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates							
Parameter		**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept		-2.3315	0.0832	-2.4946	-2.1684	-28.02	<.0001
gender	1	-0.0597	0.0533	-0.1642	0.0448	-1.12	0.2629
black	1	-0.0026	0.067	-0.1339	0.1287	-0.04	0.9691
hispanic	1	0.089	0.0688	-0.0458	0.2238	1.29	0.1956
mis_conv		-0.8839	0.039	-0.9604	-0.8074	-22.66	<.0001
non_conv_adm		0.048	0.0062	0.036	0.0601	7.79	<.0001
non_brooklyn_fel		2.317	0.0374	2.2437	2.3904	61.89	<.0001
age_first_conv		-0.018	0.0017	-0.0213	-0.0147	-10.74	<.0001
crimespan		0.4066	0.0096	0.3878	0.4253	42.53	<.0001
den_all_offenders		0.0001	0	0.0001	0.0001	4.79	**<.0001**

In addition to the four models shown above, several other models were generated using additional neighborhood-level variables. Here is a summary of those results:

- Percent living in a different house in 1995: Was not significant when added to the model.
- Vacant housing units: Was not significant when added to the model.
- Density of all crime: Was not significant when added to the model.
- *Density of violent crime: Was significant at the .05 level ($p = .0291$) (positive relationship).
- Density of property crime: Was not significant when added to the model.
- Percent black: Was not significant when added to the model.
- *Percent Hispanic: Was moderately significant at the .05 level ($p = .0523$) (positive relationship).
- *Median household income: Was significant at the .001 level ($p < .0001$) (negative relationship).

- Percent of housing units in buildings with 10 or more units: Was not significant when added to the model.
- Density of churches: Was not significant when added to the model.
- *Percent one parent households: Was significant at the .001 level (p = .0003) (negative relationship)
- *Of women with children, % of women with children under 18 who work: Was significant at the .01 level (p = .0009) (negative relationship).

The results of the Step A models show that many neighborhood-level variables have a significant relationship with recidivism when added to models with many key individual-level variables. This is an important first step to show that environment can have an effect on recidivism. The following Step B analysis will work to build a model combining the key individual-level variables with the neighborhood-level variables from Step 4 of the previous chapter and the significant variables from the Step A analyses above.

Multi-Level Analysis: Step B

The following individual-level variables will be used for this series of models: number of misdemeanor convictions (mis_conv), number of non-conviction admissions (non_conv_adm), age at first conviction (age_first_conv), and the length of the offender's criminal career (crimespan). Gender, black, and Hispanic will not be used initially because they were either not significant or marginally significant in most of the previous models, and number of felony convictions outside of Brooklyn (non_brooklyn_fel) will not be used because it is too close conceptually to the operational definition of recidivism used to identify recidivism events. The significant neighborhood-level variables from the Step A models will be used in these Step B models as well as the key variables identified in the neighborhood-

level analysis of the previous chapter. We will first present and briefly review the results of each model but a more comprehensive analysis will wait until later in the chapter after all of the models have been presented. Please note that neighborhood-level variables have been bolded in the following tables to make them easier to identify and the bolding does not indicate that the variables are significant.

Table 29 contains the first of the Step B multi-level models. The individual-level variables in this model are number of misdemeanor convictions (mis_conv), number of non-conviction admissions (non_conv_adm), and age at first conviction (age_first_conv). The neighborhood-level variables in the model are the control variables used in the previous chapter: percent in poverty (poverty) and density of all offenders (den_all_offenders). Results indicate that all of the individual-level variables are significant at the .001 level, and percent in poverty is also significant at the .001 level. Density of offenders is not significant.

Table 29: Multi-Level Model Step B, #1

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-0.856	0.1467	-1.1435	-0.5686	-5.84	<.0001
mis_conv	0.4762	0.1417	0.1984	0.754	3.36	0.0008
non_conv_adm	0.1704	0.029	0.1137	0.2272	5.88	<.0001
age_first_conv	-0.0417	0.0047	-0.051	-0.0325	-8.86	<.0001
poverty	0.0138	0.0026	0.0087	0.0189	5.32	**<.0001**
den_all_offenders	-0.0001	0.0001	-0.0002	0	-1.75	**0.0796**

Table 30 displays almost the same model as Table 29, except that the length of criminal career (crimespan) individual-level variable has been added. Similar to the other individual-level variables, crimespan is significant at the .001 level. Also, adding crimespan has caused density of all offenders to become significant at the .05 level.

Table 30: Multi-Level Model Step B, #2

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-1.9142	0.042	-1.9965	-1.832	-45.6	<.0001
mis_conv	-0.9446	0.0322	-1.0077	-0.8816	-29.37	<.0001
non_conv_adm	0.0841	0.0052	0.0738	0.0943	16.08	<.0001
age_first_conv	-0.0196	0.0015	-0.0225	-0.0168	-13.4	<.0001
crimespan	0.5128	0.0084	0.4964	0.5293	61.18	<.0001
poverty	0.0048	0.0011	0.0026	0.007	4.29	**<.0001**
den_all_offenders	0	0	0	0.0001	2.21	**0.0273**

Tables 31 through 34 display the results of adding a new neighborhood-level variable in each step. First, percent foreign born was added to the model in Table 31. Even though this variable was significantly related to recidivism in the previous tract analysis, after controlling for individual level traits this variable is no longer significant (p = .3856).

Table 31: Multi-Level Model Step B, #3

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-1.8702	0.0663	-2.0002	-1.7402	-28.2	<.0001
mis_conv	-0.9454	0.0322	-1.0085	-0.8824	-29.38	<.0001
non_conv_adm	0.0841	0.0052	0.0738	0.0943	16.08	<.0001
age_first_conv	-0.0196	0.0015	-0.0225	-0.0168	-13.4	<.0001
crimespan	0.5128	0.0084	0.4963	0.5292	61.17	<.0001
poverty	0.0044	0.0012	0.002	0.0068	3.59	**0.0003**
den_all_offenders	0	0	0	0.0001	2.02	**0.0434**
foreign_born	-0.0008	0.001	-0.0027	0.001	-0.87	**0.3856**

Next, percent one parent households was added to the model in Table 32. Percent in poverty (p < .0001) and density of offenders (p = .0108) both remain significant in this model, but percent foreign born (p = 04577) and percent one parent households (p = .0698) are not significant.

Table 32: Multi-Level Model Step B, #4

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-1.8599	0.0665	-1.9902	-1.7295	-27.97	<.0001
mis_conv	-0.9459	0.0322	-1.009	-0.8828	-29.39	<.0001
non_conv_adm	0.0841	0.0052	0.0738	0.0943	16.09	<.0001
age_first_conv	-0.0198	0.0015	-0.0226	-0.0169	-13.46	<.0001
crimespan	0.5127	0.0084	0.4963	0.5292	61.18	<.0001
poverty	0.0057	0.0014	0.003	0.0085	4.07	**<.0001**
den_all_offenders	0.0001	0	0	0.0001	2.55	**0.0108**
foreign_born	-0.0007	0.001	-0.0026	0.0012	-0.74	**0.4577**
one_parent_hhs	-0.0035	0.0019	-0.0073	0.0003	-1.81	**0.0698**

Next, density of public housing was added to the model in Table 33. Percent in povery ($p < .0001$) and density of offenders ($p = .0096$) again remain significant, but percent foreign born ($p = .3524$), percent one parent households ($p = .0709$) and density of public housing ($p = .5531$) are all non-significant.

Table 33: Multi-Level Model Step B, #5

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-1.8417	0.0731	-1.9851	-1.6984	-25.18	<.0001
mis_conv	-0.9458	0.0322	-1.0089	-0.8828	-29.39	<.0001
non_conv_adm	0.0841	0.0052	0.0738	0.0943	16.09	<.0001
age_first_conv	-0.0198	0.0015	-0.0227	-0.0169	-13.46	<.0001
crimespan	0.5127	0.0084	0.4963	0.5292	61.18	<.0001
poverty	0.006	0.0015	0.0031	0.0088	4.09	**<.0001**
den_all_offenders	0.0001	0	0	0.0001	2.59	**0.0096**
foreign_born	-0.001	0.0011	-0.0031	0.0011	-0.93	**0.3524**
one_parent_hhs	-0.0035	0.0019	-0.0073	0.0003	-1.81	**0.0709**
den_public_housing	-0.0004	0.0007	-0.0017	0.0009	-0.59	**0.5531**

Next, percent working mothers was added to the model in Table 34. The addition of this variable caused percent in poverty to go from highly significant ($p < .0001$) to non-significant ($p = .1987$). Such a large shift is most likely due to the high correlation between percent in poverty and percent working mothers ($r = -.549$, see Table 16 above). Density of all offenders remains significant ($p = .0069$), and percent foreign born ($p = .3947$), percent

one parent households (p = .254), and density of public hosing (p = .9156) all remain non-significant in this model. Percent working mothers has a significant negative relationship with recidivism in this model (p = .0081), indicating that areas with more working mothers have less recidivism than areas with fewer working mothers.

Table 34: Multi-Level Model Step B, #6

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-1.6057	0.1163	-1.8335	-1.3778	-13.81	<.0001
mis_conv	-0.9444	0.0322	-1.0074	-0.8813	-29.36	<.0001
non_conv_adm	0.0839	0.0052	0.0736	0.0941	16.05	<.0001
age_first_conv	-0.0198	0.0015	-0.0227	-0.0169	-13.47	<.0001
crimespan	0.5126	0.0084	0.4962	0.529	61.16	<.0001
poverty	0.0025	0.002	-0.0013	0.0064	1.29	**0.1987**
den_all_offenders	0.0001	0	0	0.0001	2.7	**0.0069**
foreign_born	-0.0009	0.0011	-0.0031	0.0012	-0.87	**0.3847**
one_parent_hhs	-0.0023	0.002	-0.0062	0.0016	-1.14	**0.254**
den_public_housing	-0.0001	0.0007	-0.0014	0.0012	-0.11	**0.9156**
working_moms	-0.0036	0.0013	-0.0062	-0.0009	-2.65	**0.0081**

For the next model all of the individual-level variables that were removed from the model have been added back in as control variables (see Table 35). The variables added back to the model are gender, black, and Hispanic, all binary variables. All of the individual-level variables except for black have a significant relationship with recidivism while the only significant neighborhood-level variable is density of all offenders (p = .0202). Adding back all of the individual-level variables sheds light on the relative predictive power of each group of variables. It is obvious from these models that individual-level predictors are heartier and more resilient predictors and that neighborhood-level predictors are much more likely to fluctuate and dip in and out of significance from model to model. This is most likely due to high levels of multicollinearity among neighborhood-level variables. The final two models attempt to deal with this issue by removing some of the neighborhood-level independent

variables in an effort to reduce multicollinearity. All of the individual-level variables will be left in the model as control variables.

Table 35: Multi-Level Model Step B, #7

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-1.8809	0.1315	-2.1387	-1.6231	-14.3	<.0001
gender	0.1073	0.0463	0.0165	0.1981	2.32	0.0206
black	0.0609	0.0622	-0.0611	0.1828	0.98	0.328
hispanic	0.2176	0.0612	0.0976	0.3377	3.55	0.0004
mis_conv	-0.9337	0.032	-0.9965	-0.871	-29.15	<.0001
non_conv_adm	0.0834	0.0052	0.0732	0.0937	15.97	<.0001
age_first_conv	-0.0193	0.0015	-0.0222	-0.0163	-12.85	<.0001
crimespan	0.5123	0.0084	0.4958	0.5287	61.09	<.0001
poverty	0.0024	0.002	-0.0014	0.0062	1.22	**0.2215**
den_all_offenders	0.0001	0	0	0.0001	2.32	**0.0202**
foreign_born	-0.0012	0.0011	-0.0033	0.001	-1.06	**0.2899**
one_parent_hhs	-0.0017	0.002	-0.0056	0.0023	-0.82	**0.4145**
den_public_housing	0.0003	0.0007	-0.001	0.0017	0.5	**0.6165**
working_moms	-0.0022	0.0014	-0.0049	0.0005	-1.62	**0.1046**

Two neighborhood-level variables were removed in the next model, percent foreign born and density of public housing (see Table 36). These variables were removed because they performed poorly in the previous models. Removing these variables had almost no effect on the significance levels of the individual-level variables but percent in poverty went from being non-significant in Table 35 to being marginally significant in this latest model (p = .04). Percent one parent households and percent working mothers remain non-significant in this model.

Table 36: Multi-Level Model Step B, #8

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-1.9588	0.1173	-2.1886	-1.729	-16.71	<.0001
gender	0.1069	0.0463	0.0161	0.1976	2.31	0.021
black	0.0697	0.0618	-0.0513	0.1908	1.13	0.2587
hispanic	0.2195	0.0612	0.0995	0.3395	3.59	0.0003
mis_conv	-0.9326	0.032	-0.9954	-0.8699	-29.12	<.0001
non_conv_adm	0.0835	0.0052	0.0732	0.0937	15.98	<.0001
age_first_conv	-0.0193	0.0015	-0.0222	-0.0163	-12.85	<.0001
crimespan	0.5124	0.0084	0.496	0.5288	61.1	<.0001
poverty	0.0036	0.0018	0.0002	0.007	2.05	**0.04**
den_all_offenders	0.0001	0	0	0.0001	2.94	**0.0033**
one_parent_hhs	-0.002	0.002	-0.006	0.0019	-1.01	**0.3145**
working_moms	-0.002	0.0014	-0.0047	0.0007	-1.48	**0.14**

In the next model, both percent of one parent households and working mothers were removed from the model in order to reduce the multicollinearity among the neighborhood variables and because they were not significant in the previous model. This model contains all of the individual-level variables and only two neighborhood-level variables, percent in poverty (p = .0001) and density of offenders (p = .0106), both of which are significant (see Table 37). Again, it is interesting to note that removing two neighborhood-level variables from the model has very little to no impact on the individual-level variables.

Table 37: Multi-Level Model Step B, #9

Analysis Of GEE Parameter Estimates Empirical Standard Error Estimates						
Parameter	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Z**	**Pr > |Z|**
Intercept	-2.0906	0.0795	-2.2465	-1.9347	-26.29	<.0001
gender	0.1075	0.0463	0.0167	0.1982	2.32	0.0203
black	0.0402	0.0597	-0.0769	0.1573	0.67	0.501
hispanic	0.2067	0.0607	0.0877	0.3256	3.41	0.0007
mis_conv	-0.9328	0.032	-0.9956	-0.8701	-29.13	<.0001
non_conv_adm	0.0836	0.0052	0.0734	0.0938	16.01	<.0001
age_first_conv	-0.0192	0.0015	-0.0222	-0.0163	-12.84	<.0001
crimespan	0.5126	0.0084	0.4962	0.529	61.12	<.0001
poverty	0.0044	0.0011	0.0022	0.0066	3.88	**0.0001**
den_all_offenders	0	0	0	0.0001	2.55	**0.0106**

Relative Predictive Power of Individual and Neighborhood-Level Variables

In addition to the significance or non-significance of variables, the results of the GENMOD procedure can be translated into a value that represents the effects of a one unit change in the independent variable on the odds of the occurrence of the dependent variable. For example, using the values from Table 37, a one year increase in the criminal career of an offender (crimespan) increases his or her odds of having a recidivism event by 66.96%. In addition, Hispanics are 1.22 times more likely to have a recidivism event and an increase of one misdemeanor conviction reduces the odds of having a recidivism event by 154%. In contrast, a 1% increase in the percent in poverty in a census tract results in a 0.44% increase in the odds of an individual having a recidivism event.[19] Since a 1% increase in percent in poverty is a very small change, a more reasonable value would be a 10% increase. Thus, a 10% increase in percent in poverty results in a 4.4% increase in the odds of an offender having a recidivism event. To put this into specific perspective, all Brooklyn census tracts were divided into deciles based on percent in poverty and the mean values calculated for the lowest and highest deciles (N = 76 census tracts in each decile). The mean value for the lowest decile was 4.9% in poverty and the mean value for the highest decile was 50.8% in poverty for a 45.9% difference. This difference would translate into a 20% increase in the odds of an offender having a recidivism event. This is still not close to the 66.96% increase for every year of criminal history but it is substantial nonetheless. Another example is percent foreign born from Table 27 above. This variable was significant at the .01 level (p =

.0033), and a 10% decrease in percent foreign born in a census tract increases the odds of having a recidivism event by 2.9%.

As can be seen in these examples, changes in the values of individual-level variables have a greater effect on ones odds of being a recidivist than changes in the values of neighborhood-level variables but the combined effect of dozens of neighborhood-level variables would add up to a substantial amount of predictive power if it was possible to more accurately measure these variables.

Summary

The goal of this multi-level analysis was to answer the following research question: How important is the effect of the local environment on recidivism as compared to traditional individual-level characteristics? The first step in answering this question was to conduct a binary logistic regression analysis using only the individual-level variables in order to understand the relationships among the individual-level variables and recidivism. The results indicate that all of the individual-level variables, except for gender, have a significant relationship with the dependent variable.

Next, a series of multi-level analysis were conducted using the SAS GENMOD (General Linear Model) procedure with the GEE multi-level analysis (General Estimating Equation). A multi-level model is an ideal tool to answer the above questions because it allows for an analysis of variables nested in different levels to be analyzed in the same model such as children within classrooms within schools. Our analysis looked at offenders within multiple felony convictions within census tracts.

The results of the multi-level models were very interesting. After controlling for several important individual-level variables (gender, black, Hispanic, number of misdemeanor convictions, number of non-conviction admissions, age at first conviction, and length of ones criminal career), some neighborhood-level variables did have a significant effect on recidivism. However, while individual-level variables have a consistent and powerful relationship with recidivism, neighborhood-level variables have an inconsistent and unstable relationship in the models. Due to multicollinearity, adding and removing neighborhood-level variables from the multi-level model had large unpredictable effects on the neighborhood-level variables in the model but did not affect the individual-level variables.

In the first set of multi-level models a single environment variable was added to a model containing several individual-level variables in order to identify which neighborhood-level variables have a significant relationship with recidivism after controlling for individual-level characteristics. The following neighborhood-level variables were significant: percent in poverty, density of public housing, percent foreign born, density of all offenders, density of violent crime, percent Hispanic, median household income, percent one parent households, and percent working mothers.

In the second set of multi-level models the goal was to build the best model containing several key individual-level and neighborhood-level variables. This task proved difficult due to the high predictive power of the individual-level variables and the high degree of multicollinearity among the neighborhood-level variables. The final model had two significant neighborhood-level variables, percent in poverty and density of all offenders.

Finally, a comparison of the predictive power of individual-level and neighborhood-level variables showed that individual-level variables have more predicative power than neighborhood-level variables. For example, a one year increase in the criminal career of an offender (crimespan) increases his or her odds of being a recidivist by 66.96%, while a 10% increase in the percent in poverty of a census tract results in a 4.4% increase in the odds of an offender being a recidivist. This value by itself does not equal the power of an individual-level variable, like length of criminal career, but combine this with the effects of dozens of other neighborhood-level variables and the total impact would be substantial.

Individual-level behavior is, by definition, shaped by the offender himself/herself. Their life experiences, personality, and morals combine with criminal opportunities in the environment to create specific behaviors and it makes perfect sense that the personal actions and decisions of an individual would have a much greater effect than the characteristics of ones neighborhood.

One's environment, while very important in shaping personality and actions, does not in itself determine specific behavior and actions. Research has shown that moral people placed in extreme situations will commit immoral acts (Milgram, 1963; Haney et al., 1973), so the characteristics of ones environment can directly lead to criminal behavior. However, these extreme situations are rare and must be extreme for the individual placed in the situation. For individuals born and raised in a poor, minority, inner-city neighborhood, the effects of this poverty has accumulated over years in many aspects of their life and the life of their community: broken homes, poor educational opportunities, exposure to delinquent peers, fewer positive role models, etc. These combined environmental influences shape personality but, once shaped, the personality takes over as the primary driving force behind

actions. The fact that environment can have any influence at all in a primarily individual-level model is amazing and it should be seen as recognition of the importance of environment in the development of delinquent behavior and recidivism.

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[19] Since density of offenders (den_all_offenders) is actually the "square root of the average density of offenders per square foot" it cannot be translated into a useful odds number.

CHAPTER 6

Discussion

Summary

Between 1980 and 2000 the correctional population in the United States grew from 1.84 million people to 6.47 million people, a 250% increase (Beck and Glaze, 2001). This huge increase in the number of incarcerated people in the United States has led to an unprecedented number of offenders returning home after long periods of incarceration. For example, 585,000 prisoners were released and returned to their neighborhoods in the year 2000 (Travis et al., 2001). These ex-offenders return home to a small number of disadvantaged inner-city neighborhoods with health problems, alcohol and drug addiction, mental illness, HIV or AIDS, illiteracy, few skills, and little support from the justice system. High recidivism rates ensure that about two-thirds of these ex-offenders will be rearrested within a few years of release and almost half will be returned to prison or jail within three years only to be released once again with more social and psychological problems and fewer ties to their community. This cycle of *reentry* → *recidivism* → *incarceration* will continue unless researchers can better understand recidivism and criminal justice agencies can better prepare offenders for reentry.

Most of the previous research on recidivism focuses on the significant characteristics of recidivists such as their criminal history, age, gender, and race. While important, research on such static variables does not provide enough useful information for those planning programs intended to reduce recidivism. While high-risk ex-offenders can be identified using these variables, this information does not do enough to explain the specific causes and triggers of recidivism since many high-risk ex-offenders will not reoffend. In an effort to improve upon our understanding of recidivism, this research study analyzed the relationship

between the residential neighborhood of the offender and recidivism. This topic has been touched upon by some researchers (e.g., Kubrin and Stewart, 2006; Kirk, 2009) but a thorough study of the identification and characteristics of recidivism hot spots using many census variables and an analysis of the complex relationship between neighborhood characteristics and recidivism has not yet been conducted.

This research study used data on one million admissions to jail and two million discharges from jail in New York City over a 17½ year period from 1986 to 2003. This data set easily represents the single most impressive and comprehensive criminal justice data set ever used for an analysis of the neighborhood impact on recidivism. In order to make the data processing and manipulation manageable, Brooklyn was chosen as the target location and census tracts were used as the unit of analysis due to their common use in many spatial analysis studies as well as the fact that they are spatially small and, as a result, will capture the depth of socio-economic and demographic variations within Brooklyn neighborhoods. The operational definition of recidivism for this analysis was a felony conviction. After (a) removing addresses outside of Brooklyn, (b) removing non-felony convictions, and (c) geocoding the data to a Brooklyn street map with a 92.68% hit rate, the final data set contained 38,411 felony convictions.

Several additional data sets were used to better understand the neighborhood environment, such as social service data from the department of city planning and from the NYC Nonprofit Project, locations of religions institutions from a digital phone book file, location of public housing units from NYCHA, HUD, and HPD, and crime data from the NYPD (see table 9 for more information). These data provided valuable information about

the characteristics of recidivism hot spots and was also used as neighborhood-level indicators in the multi-level model.

The first research question examined in this study was *do recidivism hot spots exist?* This is an important question that is necessary to establish the fact that recidivism hot spots are real and better understand the number and size of hot spots in Brooklyn. Hot spots were calculated using several steps. First, density maps of recidivists and nonrecidivists were created using a technique called kernel smoothing. Second, the density of nonrecidivists was subtracted from the density of recidivists to create a density map of the difference between the two densities. Third, these density values were converted into z-scores and any density values greater than 5 standard deviations above the mean were classified as a hot spot. This very conservative definition let to the identification of 6 recidivism hot spots in Brooklyn. Therefore, the answer to the first research question in yes, recidivism hot spots do exist.

The second research question was *what are the characteristics of recidivism hot spots?* After establishing the existence of hot spots, the next logical step is to examine the characteristics of these hot spots using multiple regression analysis. The dependent variable for the analysis was the average density difference value per census tract using the data in the final map used to answer question one. The initial Pearson Correlations indicated that density of public housing ($r = .486$), density of all offenders ($r = .478$), and percent foreign born ($r = -.458$) had the highest correlations with the dependent variable.

Due to the high correlations among the independent variables and to the overall difficulty of developing complex statistical models using a large number of real-world data variables, this analysis was conducted in four stages. The first stage included only the control variables, the second stage included characteristics of the built environment, the third stage

included characteristics of the social environment, and the fourth stage created an overall model using the control variables and the most promising variables from stages two and three. Results of the final stage four model indicated that the model itself was significant at the .00001 level and accounted for 46.2% of the variability in tract-level recidivism. The model results showed that, after controlling for density of all offenders and percent in poverty, increased recidivism was significantly related to areas with fewer churches, fewer foreign born residents, fewer single parent households, fewer working mothers, and increased residential mobility.

The third and final research question was *how important is the effect of local environment on recidivism when compared to traditional individual-level characteristics?* Since we have already identified the existence of recidivism hot spots and described their characteristics, the next logical step was to compare the predictive power of environment to the predictive power of individual characteristics. This last, and perhaps most important analysis, involved the development of a multi-level model that combined both individual-level and neighborhood-level predictors of recidivism. The individual-level variables used in the analysis were gender (binary), black (binary), Hispanic (binary), age at first conviction, length of criminal career, number of misdemeanor convictions, number of non-conviction admissions, and the count of felony convictions that took place outside of Brooklyn. The neighborhood-level variables used were the most promising and important ones from the previous question.

Two distinct series of multi-level models were created. The first series (Step A) included all individual-level variables and one neighborhood-level variable to see if any neighborhood-level variables have a significant relationship with recidivism after controlling

for all available individual-level characteristics. Results of Step A indicate that several neighborhood-level variables had a significant relationship with individual-level recidivism including percent in poverty, density of public housing, percent foreign born, density of all offenders, density of violent crime, percent Hispanic, median household income, percent one parent households, and percent working mothers.

Next, the Step B analyses involved a series of nine multi-level models that included the most promising neighborhood-level and individual-level variables. The goal was to develop a more complex multi-model of recidivism than the Step A models. The final model contained six significant individual-level variables and two significant neighborhood-level variables, percent in poverty and density of all offenders, indicating that more than one neighborhood-level variables in the same model can have a significant affect on recidivism. Finally, the predictive power of a significant individual-level variable (length of criminal career) was compared with that of a significant neighborhood-level variable (poverty) and results indicated that a one year increase in the criminal career of an offender increases his or her odds of having a recidivism event by 66.96% while a 10% increase in percent in poverty of a tract increases his or her odds of having a recidivism event by 4.4%. These results clearly indicate that environment has a significant and measureable effect on recidivism.

The Recidivism Feedback Model Revisited

The positive feedback model of recidivism hot spots (Figure 2 at the end of Chapter 1) provides a model for understanding the impact of local environment on recidivism. The feedback model indicates that the individual causes of delinquent behavior, such as poor parenting and strain, are part of a much larger system that involves many neighborhood-level

factors, such as social disorganization, incivilities, neighborhood poverty, and the availability of delinquent peer groups or gangs, the neighborhood crime rate, the concentration of offenders, and the lack of social services. These individual and neighborhood characteristics combine to generate more offenders and more criminal behavior in specific neighborhoods.

According to this model, higher levels of neighborhood poverty and unemployment increases individual-level poor parenting and stress. This, combined with a sufficient number of delinquent peer groups, leads to the development of criminal behavior. The criminal behavior leads to incarceration, then to reentry back to the neighborhood with a criminal record, and fewer legitimate opportunities than before. In addition, the neighborhood now has a higher concentration of offenders and more delinquent peers which increased the neighborhood crime rate, poverty, and social disorganization. Now the cycle starts again, but this time a bit stronger because of increased poverty and more offenders.

This is not a simple model but the real world is not simple either. This model accounts for the constant interplay between the individual characteristics and neighborhood environment and for the fact that high offender, poor, minority communities seem stuck in a negative spiral that is very difficult to alter. Add in public housing projects and high rates of residential mobility and it is easy to see how environment can shape residents and vice versa.

Policy Implications

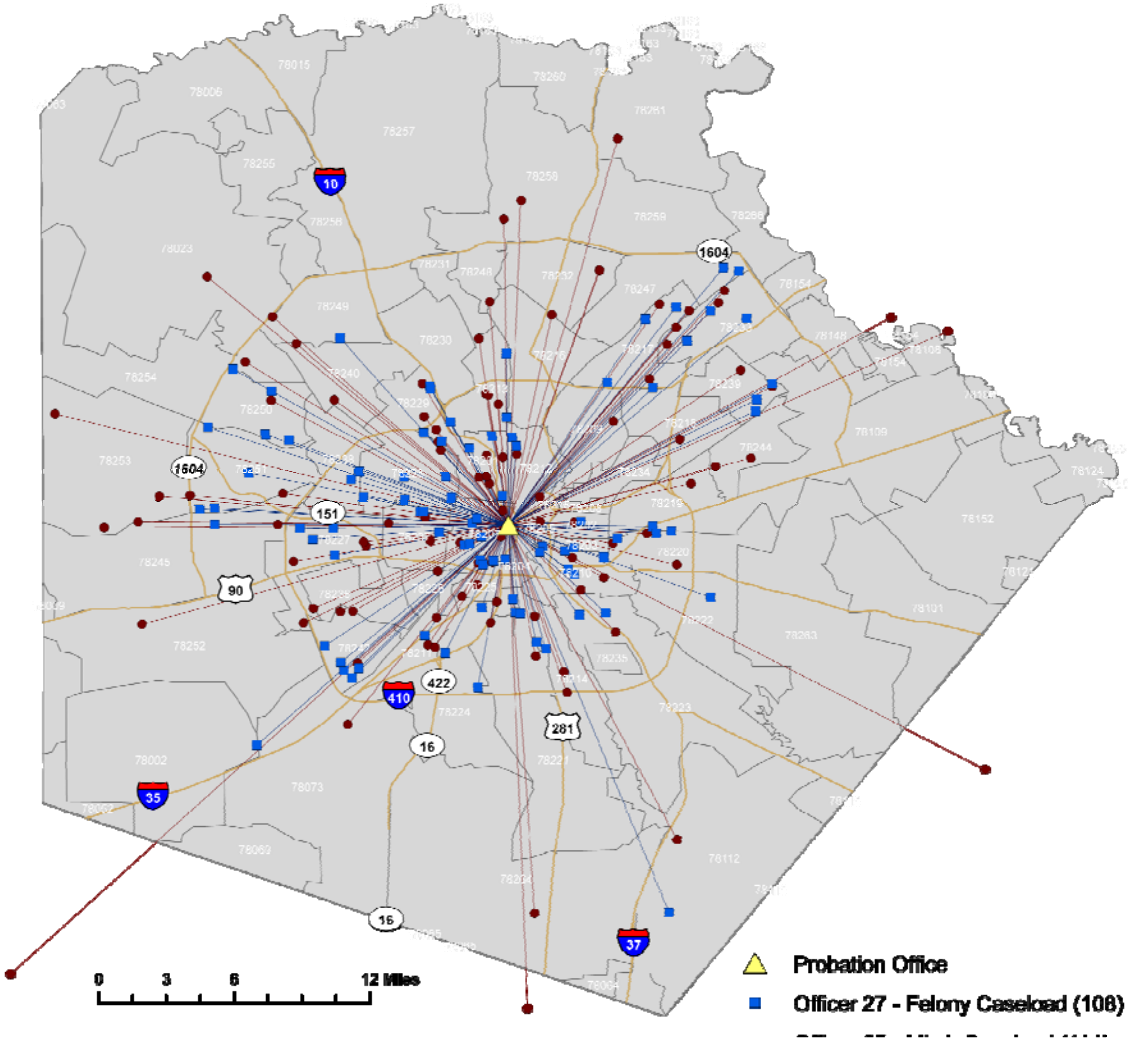
The results of this research study can be used to change how governments and criminal justice agencies view the relationship between offenders and neighborhoods. Currently, the focus of the criminal justice system is on individual offenders. Neighborhoods are ignored and the decision to reoffend is viewed as a personal decision. As discussed in the

first chapter, the *reentry → recidivism → incarceration* cycle can be viewed as a mass migration of people from poor, minority, inner-city neighborhoods to prison and then back to these same neighborhoods. The continued focus on individual offenders means that many of the core causes of the development of delinquency and recidivism will not be addressed in any way. Criminal activity is a social act that takes place in the context of a neighborhood and, in order to reduce recidivism, society must address neighborhood issues.

Starting with the "easier to implement" side of the spectrum, these results can be used to educate prison officials and departments of probation about the increased risk of recidivism associated with specific locations. Prisoners returning to these areas could receive additional assistance and attention before leaving prison. After leaving prison their parole officers could be given smaller caseloads and more resources to help find legitimate opportunities for their parolees. Interventions could be designed specifically to deal with the influences of certain neighborhood-level factors. Also, some returning prisoners might want to move to a new neighborhood in an effort to escape old habits and triggers, and financial or planning assistance could be given to these individuals.

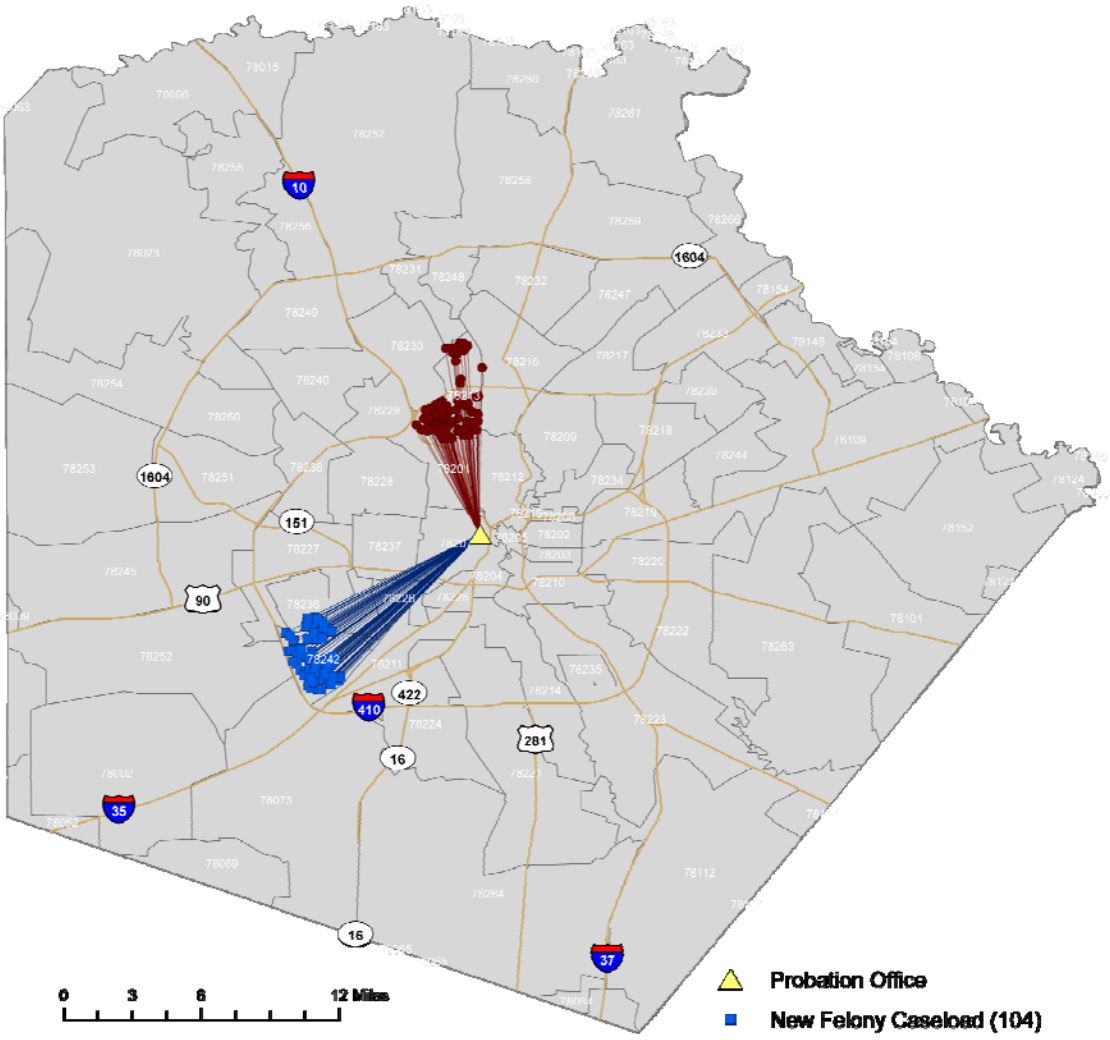
Another approach would be to focus on existing or missing social services in these areas in order to improve upon current ex-offender services. The identification of recidivism hot spots means that any existing social services that work with returning prisoners from these areas could receive additional funding to work more intensively with higher risk offenders such as those with a longer criminal history and more prior offenses. Social services could be designed and implemented in partnership with prisons and parole offices that specifically address the needs of returning offenders such as the development of job skills, new affordable housing options, or expanded drug treatment services.

Map 10: Current Probation Caseload Distribution, San Antonio, TX



These results also have important implications for departments of parole and probation. Even though these agencies supervise offenders who live in the community, the agencies themselves still focus on the individual and ignore neighborhood environments. An excellent illustration of this can be seen in analyses of parole caseload distributions conducted by the author. Map 10 above is a spider map of two different probation office caseloads in San Antonio, Texas. This map is typical of many probation and parole caseloads in cities across the country and it shows that caseloads are assigned randomly to probation officers without regard for the residential address or local environment of the probationer.

Map 11: Proposed Probation Caseload Distribution, San Antonio, TX



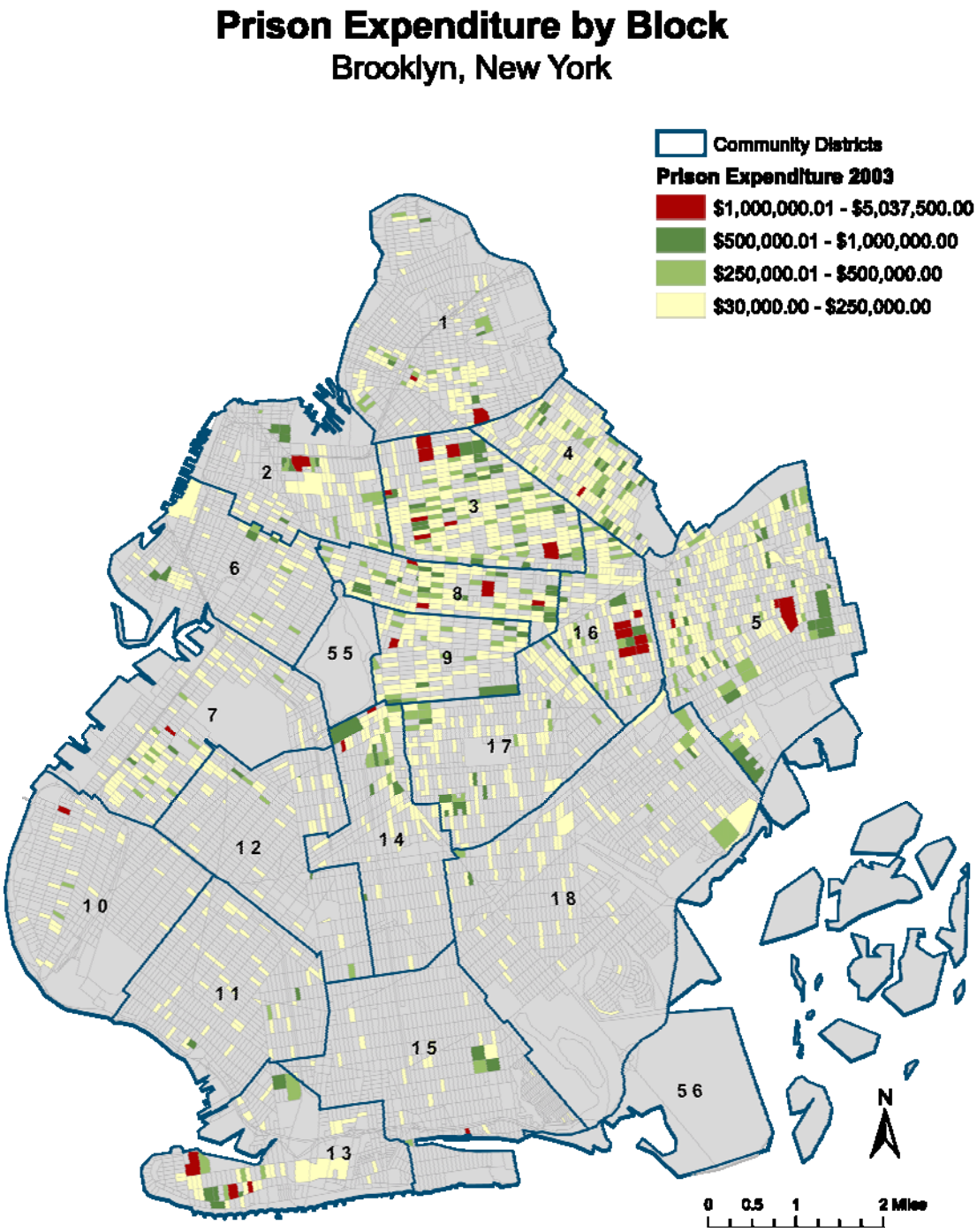
An alternative approach would be to integrate neighborhood into the very fabric of these agencies. Instead of housing all officers in a central office, officers should have satellite officers within the neighborhood that they serve. Officers would then be assigned to residents from that neighborhood and only from that neighborhood. As a result, probation and parole officers would become experts in the positive and negative aspects of their neighborhoods. They would get to know the local businesses, social services, and schools. They would know where the high crime areas are located and where people buy drugs. They would understand the daily struggles of the residents and be in a much better position to help each of the people

whom they serve. This approach would not be possible in less populated areas but is a very viable option in most cities. Map 11 above shows an example of this second approach.

These policy recommendations beg the question *how will we pay for all of these policy ideas?* This is an extremely important question that must be answered if there is to be any change in the current individual centered approach of the justice system. The answer is a new and exciting concept called Justice Reinvestment (Tucker and Cadora, 2003; Cadora, 2007). Justice reinvestment is the process of taking "unproductive spending in corrections budgets", putting aside a portion of this money, and then reinvesting a portion of this money back into high incarceration neighborhoods (Tucker and Cadora, 2003, p. 3).

Justice reinvestment, developed by Susan Tucker and Eric Cadora, was originally inspired by the concept of the "Million Dollar Block" (Tucker and Cadora, 2003). The author, along with Eric Cadora of the Justice Mapping Center, mapped the residential addresses of residents admitted to prison in New York State in 2003. Then, using the sentence length of each offender, the total expenditure per person was calculated and this value associated with a city block and any blocks with values over $1 million were identified. Map 12 shows the resulting map. Each of the red blocks on this map are million dollar blocks – over $1 million dollars are spent to incarcerate the residents of the block in a single year, and one block in Brooklyn had an expenditure value of over $5 million. This amount is spent year after year with no improvement on these blocks and no resources being spent to halt the cycle of incarceration. The natural next step was to think about ways to reinvest this money.

Map 12: Million Dollar Blocks, Brooklyn, NY



Justice reinvestment is a data driven approach that first uses sophisticated Geographic Information System technology and detailed address-level data on incarcerated individuals to map the spending of criminal justice dollars back to neighborhoods. Then, taking into

account the unique characteristics of the study area, experts develop options for the reallocation of justice dollars back into the community. These options include, but are not limited to, reducing parole revocations, reducing sentence lengths for non-violent criminals, and giving local governments more control over how criminal justice dollars are spent. Next, the amount of savings is calculated and reallocated towards neighborhood-level initiatives in high offender areas. "For example, officials can reinvest the savings and deploy existing resources in a high-stakes neighborhood to redevelop abandoned housing and better coordinate such services as substance abuse and mental health treatment, job training, and education" (The Council of State Governments, 2009). Finally, performance measures and desired outcomes are outlined and reports on the effectiveness of the new programs shared with policymakers (The Council of State Governments, 2009).

Justice reinvestment received a huge boost on November 16th, 2009 when Senators Whitehouse, Cornyn, and Leahy and Representatives Schiff and Lungren introduced the Criminal Justice Reinvestment Act of 2009 (S.2772/HR.4080). The goal of the Act is "To establish a criminal justice reinvestment grant program to help States and local jurisdictions reduce spending on corrections, control growth in the prison and jail populations, and increase public safety….In this Act, the term 'criminal justice reinvestment' refers to a data-driven program that (1) analyzes criminal justice trends to understand what factors are driving the growth in prison and jail populations, (2) develops and implements policy options to manage the growth in corrections populations and increase the effectiveness of current spending and investment to increase public safety and improve individual and system accountability; and (3) measures the impact of the policy changes and reinvestment resources

and holds policymakers accountable for projected results" (HR.4080, available online at http://www.opencongress.org/bill/111-h4080/show).

Future Research

The results of this study make it clear that more research is needed on the relationship between recidivism and neighborhood environments. But, one of the biggest hurdles to future research is the availability of multi-year, address-level prison or jail admissions data. Most agencies make it almost impossible to obtain address-level data due to the sensitivity of the data and convincing them to provide several years worth would be extremely difficult. This means that the first step is for criminal justice agencies to understand the importance of research on recidivism and understand the potential benefits they could gain from high quality research on the subject.

Assuming that the data can be obtained, additional research in other cities on the existence and characteristics of recidivism hot spots is needed to confirm the findings of this study. While the results of this research study can be applied to large, ethnically diverse urban centers, similar research must be conducted in smaller, less diverse cities to see if the results still apply.

Also, more research must be conducted on the complex interactions between individual-level characteristics and neighborhood environments. The goal of this study was to assess the relative importance of neighborhood-level variables as compared with individual-level variables. It was not intended to be a comprehensive analysis and so more research is needed to flesh out the specific individual and neighborhood level variables that best predict recidivism.

In addition, it would be interesting to attempt a study similar to Kirk (2009), where the focus of the analysis was on parolees displaced by hurricane Katrina. Given the size and time span of the data set used in this analysis, it would be possible to identify and isolate offenders who have lived in more than one census tract or ZIP Code and analyze the impact of this residential relocation on recidivism. Focusing on individuals who have changed their residential environment could make it easier to identify the specific characteristics of the environment that most effect recidivism.

Finally, quantitative research should not be the only tool used to understand this relationship. It is important that both quantitative and qualitative studies are conducted in order to develop a richer picture of the relationship between neighborhood environment and recidivism. Qualitative research could include interviews with returning prisoners, interviews with serial recidivists, interviews with offenders who did not reoffend, or focus groups composed of ex-prisoners discussing how their neighborhoods contribute to or inhibit criminal behavior. This type of qualitative research is difficult and time consuming but it would provide a very rich and fascinating look at the personal motivations behind recidivism.

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