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EXAMINING PAROLEES IN THEIR COMMUNITIES:

POVERTY, RURALITY, AND CRIMINAL JUSTICE RESOURCES

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ABSTRACT

Over the past thirty years, the number of people incarcerated in the United States has increased dramatically and since 93 percent of offenders are eventually released, recent years have witnessed a corresponding dramatic increase in the number of ex-prisoners returning to communities. Among these released offenders, two out of three parolees are returned to prison within three years of release. This study examines community-level risk factors for parolees in order to learn how different communities affect parolee recidivism. Specifically, the parolee population in Georgia was used to investigate how parolee recidivism is affected by three community characteristics – poverty, rurality, and the presence of criminal justice resources.

Using Geographical Information Systems, a multilevel dataset was created that included individual-level parolee data, socio-structural measures and crime data of communities, and the location of parole offices in Georgia. Using Hierarchical Linear Modeling, parolees were followed over a two-year period in order to learn which community characteristics contributed to their return to prison. Each community characteristic was examined independently in order to avoid issues of multicollinearity between the socio-structural variables measuring poverty, rurality, and criminal justice resources. From these analyses, six important findings emerged.

First, parolees who lived in urban communities with high levels of concentrated disadvantage, high population density, and high crime rates had significantly lower odds of being returned to prison. Because parolees increasingly reside in these impoverished urban communities, these areas are precisely the type of communities where parolees are

safest from being returned to prison. This finding might be explained in part by the presence of informal social control and criminal justice resources, which could affect the level of parolee recidivism across communities. Although this study attempted to evaluate whether this finding could be explained by local criminal justice resources, these effects were not statistically significant. Additional analyses should be conducted using finer measures of criminal justice resources.

The second and third findings showed that community effects were not uniform across parolee subopulations. Specifically, parolee race and risk scores each significantly interacted with community poverty. While all parolees had similar odds of recidivism in communities marked by extreme poverty, this recidivism gap widened in wealthier communities with white parolees recidivating significantly more than minority parolees. Further, a significant interaction was found between risk scores and racial inequality, with minority parolees more likely to be returned to prison in high racial inequality communities that favored African Americans. These findings suggest that some populations can benefit from residing in certain types of communities, while other populations reintegrate successfully regardless of where they live.

This study also sought to better understand how five different theoretical and empirical poverty measures affected recidivism. The fourth finding established that only concentrated disadvantage significantly affected individual parolees' odds of being returned to prison. The fifth finding showed that only extreme poverty significantly affected community rates of recidivism. Poverty measures of relative deprivation, racial inequality, and spatial proximity to poverty did not significantly impact parolees' odds of being retuned to prison. These latter two findings suggest that poverty measures examining the magnitude of poverty are more important predictors of recidivism than relativistic measures of poverty (i.e., relative deprivation, racial inequality) or spatial measures of poverty (i.e., neighboring poverty levels). It is important to note that the geographic level at which this data was analyzed may affect the significance level of certain poverty measures, meaning that smaller community measures may result in different poverty outcomes.

Finally, individual characteristics of parolees were found to be signficant across every model in this study. The magnitude of the effects of these parolee characteristics, both static (e.g., race, gender) and dynamic (e.g., drug and alcohol use, risk scores), suggest that while understanding community effects is important, one should still consider the impact of individual parolee characteristics on recidivism.

Several limitations to this study are noted. First, this study provided a thorough examination of socio-structural variables, yet was unable to measure important mediating variables (e.g., neighborhood attachment). Second, the lack of randomness of parolees' reintegration into residential communities is an inherent limitation in all community-level research, including the present study. Although there are a few examples of random assignment of communities, these examples are usually extremely expensive as well as politically unpopular. Finally, given that the poverty findings from this study are inconsistent with previous parolee research, the results from this study showing that the community effects affect parolees differently across geographical areas may not be generalizable to the entire parolee population of the United States.

The community effects findings from this study indicate that communities can be important to the reintegration efforts of parolees. This study, in conjunction with other studies, found that various geographic areas can affect parolees differently. Additionally, community effects are not constant across different racial and ethnic groups. Given the differential effects communities have upon parolees across states and among different racial and ethnic groups, implications from this study suggest that a "one size fits all" approach to parole policy will be ineffective. Indeed, these results indicate that parole policy should be crafted locally with an understanding as to how communities operate in different jurisdictions in order to be successful.

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CHAPTER 1:
INTRODUCTION

Almost 70 percent of parolees are arrested for a new offense within three years of their initial release (Langan and Levine, 2002). Parolees have such high recidivism rates because they have risk factors that predispose them to crimes (e.g., youth, broken family, uneven employment history), and their incarceration weakened such protective factors as health and family relations. This study focuses on a third risk factor for parolees -- the communities to which they are released. Research indicates that certain communities are linked to negative outcomes, such as lower educational achievement and higher crime rates. These "risky" communities are often precisely those places to which parolees return.

Using the entire parolee population in Georgia, this study examines how community contextual factors are related to parolees' recidivism. Unlike most of the urban sociology literature, which focuses attention on cities, and sometimes only the slums within these cities, this study compares extremes, including poor to affluent areas, rural to urban areas, and areas with greater criminal justice resources to those with fewer resources. This study addresses three questions. First, this study examines how community poverty (measured in different ways to tap into selected theories of poverty) affects individual parolees. Secondly, this study analyzes recidivism rates and whether they vary across urban and rural areas. Finally, this study looks at how the presence of parole offices affects recidivism among parolees.

With regard to the first component, this study examines five theoretical perspectives on how poverty might be related to recidivism: concentrated disadvantage, extreme poverty, relative deprivation, racial inequality, and proximity to poverty. Concentrated disadvantage assesses the level of structural poverty in communities and is one of three variables from social disorganization theory. Social disorganization studies generally measure concentrated disadvantage as a composite of structural characteristics, such as female-headed households, rates of welfare recipients, unemployment rates, and percentages of the population living below the poverty line. Generally, concentrated disadvantage has consistently predicted crime rates (Sampson and Lauritsen, 1994) and in two studies concentrated disadvantage has been shown to increase parolee recidivism (Kubrin and Stewart, 2006; Mears et al., 2008).

William Julius Wilson (1987, 1996) suggested that it was not poverty that affects crime rates and other social problems, but the extreme poverty faced by many inner-cities. Communities with extreme poverty are indeed so poor that there are few or no employment opportunities and often no positive middleclass influences (Wilson, 1987, 1996). It is also likely that extreme poverty communities have negative effects on a parolee's likelihood of staying out of prison, as these communities have few positive influences (e.g., employment opportunities, positive social bonds) and multitudinous negative influences (e.g., high crime rate, unreliable public transportation).

Aside from concentrated disadvantage and extreme poverty, crime rates are driven by economic inequalities and the "relative deprivation" that individuals feel as they compare their lot in life with others. According to this theory, individuals commit crime either to supplement their needs (Merton, 1938) or to vent their frustration (Blau and Blau, 1982). Consistent with this theory, studies have found that relative deprivation is generally linked to crime rates (Land et al., 1990; Blau and Blau, 1982; Loftin and Hill, 1974), and one study in particular found a positive relationship between relative deprivation and recidivism (Kubrin and Stewart, 2006).

While relative deprivation measures the economic deprivation one faces, racial inequality attempts to measure the deprivation one race faces compared to members of another race. A recent article linked community racial inequality to higher recidivism rates for African American parolees (Reisig et al., 2007). This finding is in line with other racial inequality research that links high rates of racial inequality with black interracial homicide (Parker & McCall, 1999), the number of African Americans killed by police, and the number police officers killed (Jacobs, 1998). Therefore, one would predict that high levels of racial inequality would also predict higher rates of recidivism in Georgia, particularly for minority parolees.

Finally, proximity to poverty is also linked to crime rates. From this diffusion perspective, crimes are committed in and around areas where poverty rates are high. Generally, crimes cannot be explained by the presence of structural factors alone (Baller et al., 2001); rather, they cluster in space (Sherman et al., 1989). Recently, studies have suggested that community poverty clusters also predict certain types of crimes (Stretesky et al., 2004; Mears and Bhati, 2006). These studies suggest that impoverished communities have a stronger negative effect upon residents when these residents are surrounded by other impoverished communities (Krivo and Peterson, 1996). This study examines the effects clusters of poverty and their effects upon parolee recidivism.

This study uses these five theoretical perspectives on the role of poverty in predicting parolees' recidivism. Each of these theories has a different prediction. Concentrated disadvantage and the extreme poverty perspectives suggest that poor communities have high recidivism rates, although each theory may identify different poor communities. Relative deprivation suggests that wealthy areas situated near poor areas have high recidivism rates, due to people from poor areas traveling to an attractive crime opportunity. Racial inequality indicates that counties with large differences in economic achievements between African American and Caucasian residents have high rates of recidivism, whereas counties in which African Americans and Caucasians are economically similar have low levels of recidivism. Finally, the proximity perspective suggests that communities, whether poor or wealthy, have higher crime rates if situated near a poor community.

The second component of this study examines how rurality affects recidivism. Almost all research on criminals has been conducted in urban areas (e.g., Shaw and McKay, 1942), despite the fact that 59.6 percent of the population in the United States lives in rural and suburban areas (Census, 2000). The issue is theoretically important because evidence suggests that crime rates and the correlates of crime (e.g., poverty and informal social control) differ greatly between urban, rural, and suburban areas. Thus, it may be incorrect to assume that the causes of crime are invariant across the spectrum of rural and urban areas.

Finally, the third component of this study explores the relationship between the presence of parole offices in counties and the recidivism rates for those counties. The ability of a parole officer to monitor parolees is likely to be affected by both the officer's caseload (i.e., the number of parolees he or she needs to supervise) and the characteristics of the officer's domain (e.g., long distances between parolees might translate into less supervision). By examining the 53 parole offices across Georgia, this study attempts to understand how criminal justice agencies and their geographical distribution affect recidivism rates among parolees.

Georgia is an excellent study area for this current investigation as it has one of the largest per capita incarceration rates nationally (Hughes et al., 2001). Additionally, Georgia offers a diverse range of structural characteristics including urban areas (e.g., Atlanta), several counties that are exclusively rural, a sizeable minority population, and severe pockets of both rural and urban poverty. Moreover, Georgia has invested heavily in data collection and these computerized records are accessible to researchers.

In sum, this study addresses three broad questions: (1) Of the five theoretical perspectives on poverty (concentrated disadvantage, extreme poverty, relative deprivation, racial inequality, and proximity to poverty), which is the best predictor of recidivism?; (2) Is a parolee's successful reintegration into society affected by living in a rural area?; and (3) Is there a relationship between presence of criminal justice resources and higher recidivism rates?

The next chapter summarizes the literature on parolees and the three components of the current study. First, individual-level risk factors for parolees and their communities are examined. Then, community-level theories on poverty, rural areas, and the distribution of criminal justice resources in Georgia are discussed. This literature review is followed by Chapter 3, which describes the seven hypotheses underlying this research. Chapter 4 describes the methodology and data. The results are described in Chapter 5 (Descriptive Results) and Chapter 6 (Multivariate Results). Chapter 7 contains the discussion and conclusions.

CHAPTER 2:
LITERATURE REVIEW

Parolee recidivism rates have risen dramatically over the past three decades (Petersilia, 2003; Lurigio, 2001), and there is also evidence that offenders are recidivating more quickly and for more serious crimes (Petersilia, 2003). Overall, about 30 percent of parolees are rearrested within the first six months, 44 percent of parolees are rearrested within their first year out of prison, and 68 percent are rearrested during their first three years out of prison (Langan and Levin, 2002). These high rates of recidivism reflect the high risks that parolees face.

This chapter examines the literature on how recidivism has been defined and the individual-level risk factors of parolees. Attention is paid to the field of community research, some of the more important criticisms of this area of research, and the current research on communities in which parolees live. As this study is particularly interested in examining how parolees are affected by their community poverty, rurality, and criminal justice resources, this section of the study focuses on the current state of research knowledge in these three areas.

Defining Recidivism:

Recidivism occurs when offenders, who have been released from community supervision or prison after serving their sentence, commit new crimes. One problem with measuring recidivism is that researchers must rely on official records (Travis and Visher, 2005). Self-report data from parolees on their criminal activities would be a superior measure of recidivism, yet the high costs of this form of data collection makes this option unlikely. Therefore, most recidivism studies measure recidivism using official records of parolee rearrest, reconviction, probation or parole revocation, and reimprisonment (Claggion, 2008). This study measures recidivism using return to prison, which is the most conservative measure but which also contains the least measurement error (Langan and Levin, 2002).

Parolees today face a number of individual and community factors that impede their successful reintegration into society. The next section discusses research on individual-level factors that make parolees more likely to recidivate during parole.

***Individual-Level Risk Factors*:**

Generally, parolees' likelihood of returning to prison can be estimated by calculating a risk score based on such factors as criminal history, demographic characteristics (e.g., gender and race), criminogenic need (e.g., drug or alcohol addiction), social bonds (e.g., family ties), and the effects of having served time in prison (e.g., lower employment opportunities). The following section summarizes research on risk factors that have been shown to increase recidivism.

Criminal Record: The length of an offender's criminal record and the type of conviction offense are strong predictors of recidivism (Gottfredson and Gottfredson, 1994). Specifically, parolees with longer criminal records are more likely to recidivate than parolees with shorter criminal records (Langan and Levine, 2002; Gendreau et al., 1996), although length of time served in prison is not related to recidivism (Langan and Levine, 2002). The type of crime parolees initially commit also affects their later probability of recidivism. In the most recent large-scale study, conducted by the Bureau of Justice Statistics (BJS), 73.8 percent of all property offenders were rearrested within three years, compared to 61.7 percent of violent offenders and 62.2 percent of public order offenders. Drug offenders were also rearrested at high rates; within three years, 66.7 percent of drug offenders were rearrested (Langan and Levine, 2002).

Demographic Variables: There are differences in the recidivism rates of parolees by gender, race, and age. Specifically, in the BJS study, men (53 percent) were returned to prison at higher rates than women (39.4 percent), and African Americans (54.2 percent) were reimprisoned at higher rates than whites (49.9 percent) (Langan and Levine, 2002). However, it is important to note that in predictive modeling, demographic variables, particularly race and gender, are not always consistent statistical predictors of recidivism (Gottfredson and Gottfredson, 1994).

In the BJS study, younger parolees were reimprisoned at higher rates than older parolees (Langan and Levine, 2002; Beck and Shipley, 1989). However, in predictive modeling, the effect of age is lessened and sometimes even nullified with the addition of other variables (Gottfredson and Gottfredson, 1994). On the other hand, the age at first official involvement in delinquency is a strong and consistent predictor of recidivism (Ashford and LeCroy, 1990). This finding suggests that while younger parolees offend more often than older parolees, their youth is not necessarily the reason for continued criminal activity.

Criminogenic Need: There are two types of risk factors, those that are static (e.g., demographic factors) and those that are mutable (e.g., criminogenic need). Researchers have suggested that criminogenic needs should be targeted so as to decrease recidivism (Andrews and Bonta, 1994). Gendreau's meta-analysis (1996) found that criminogenic needs, particularly substance abuse history, are important in predicting recidivism. Moreover, the study found that criminogenic needs, rather than static characteristics (e.g., age, gender, race), were much stronger predictors of recidivism among parolees. Several studies have also supported the important role that substance abuse can play in determining success or failure in reintegrating into society (Sampson and Laub, 1993; Gottfredson and Gottfredson, 1994).

It is also important to note that drug and alcohol dependency issues are widespread among prison populations. In one study of inmates, 52 percent of the inmates surveyed reported that they were under the influence of drugs or alcohol at the time they committed the crimes for which they were incarcerated (Mumola, 1999). Additionally, among first-time offenders, 40 percent reported a substance abuse problem, but among high rate repeat offenders (5 or more prior convictions), 80 percent reported a substance abuse problem (Petersilia, 2003). This finding suggests that substance abuse is not only widespread among the offender population, but that it poses a continued risk factor in determining future recidivism throughout parolees' lifetimes.

Social Bonds: Former criminals who establish social bonds, such as marriage, are less likely than those who do not to reoffend (Fagan, 1989; Laub and Sampson, 2001). But, fewer than half of all prisoners are married. Across the general prison population, just 17 percent of state prisoners and 30 percent of federal prisoners are married (Petersilia, 2003). Marriage can also provide parolees with a place to live upon their release from prison and these supportive social bonds can also help parolees find work (Solomon et al., 2001).

Because of their criminal history, former inmates are often disadvantaged in their attempts to forge social bonds (Laub et al., 1998). Having served time in prison makes ex-offenders less able to form future social bonds through marriage or cohabitation (Western and McLanahan, 2000), and repeat offenders are at high risk for separation and divorce (Laub et al., 1998).

Effects of Prison: Having served time in prison increases parolees' risk for future offending by further increasing their risk factors. For instance, studies show that serving time in prison worsens employment opportunities (Pager, 2003), chances for steady employment (Crutchfield and Pitchfork, 1997; Western and Beckett, 1999), and prospects for higher lifetime earnings (Needles, 1996).

In addition, prison aggravates health and mental illness problems (Hammett et al., 2001; Lurigio, 2001), and has been linked with early death (Binswanger et al., 2007). Prison is also problematic for family relations, which suffer when a loved one is imprisoned (Clear et al., 2001), and is especially difficult when the loved one is the primary caregiver (Hagan and Coleman, 2001).

The next section examines community-level factors and how they relate to parolees. This discussion begins with the historical background of community studies and how community studies are defined and then proceeds to examine some of the strengths and weaknesses of these studies. Finally, this section concludes with a discussion on where parolees live upon release from prison.

Community-Level Studies:

Social scientists have long been interested in understanding the ways in which society affects individuals and in the last century, many social scientists have focused on smaller units of society, or neighborhoods (Sampson, 1987a). At the turn of the twentieth century, American cities were becoming more industrialized and urbanized and inside these cities, communities were becoming more spatially segregated by nationality, economic status, and the physical condition of neighborhood structures.

The School of Human Ecology at the University of Chicago was at the forefront of community-level research (Park et al., 1925; Shaw and McKay, 1942; Wirth, 1938). Human ecology conceptualized cities as ecosystems, with people interacting with other people in their environment in much the same way animals and plants interact in their natural habitats. These human ecosystems were referred to as "natural areas" (e.g., Little Italy, downtown), or communities in which every individual plays a role in the social processes of "invasion, dominance, and secession." More specifically, new groups of people "invade" a city area, come to "dominate" that area in numbers and cultural influence, and the old group moves out of that area, or "secedes." These social processes of invasion, dominance, and secession tended to occur in radiating concentric zones, originating from the city center (Park et al., 1925). Neighborhood structural characteristics between these concentric zones varied considerably, especially in poverty, population heterogeneity, residential instability (Shaw and McKay, 1942), and density (Wirth, 1938).

By its nature, ecological research measures the effect that a geographical place has upon individuals, but the measurement of ecology can vary substantially. Neighborhood studies tend to be place-based, meaning that these studies measure the impact that a geographically bounded area has upon an individual. Communities, which can include neighborhoods, also include social boundaries. Thus, communities imply connections or a combination of shared beliefs, circumstances, priorities, relationships, and concerns (Chaskin, 1994). This study assesses the influence that communities, or counties, have upon parolees. Counties were chosen as the geographical unit of analysis because counties represent political, social, and governmental entities that can influence their residents. Additionally, counties were chosen because they are the unit of geography best suited to rural analysis (Osgood & Chambers, 2000). Although the current study examines parolees and their communities at the county-level, many of the neighborhood-level studies cited here are appropriate as they contribute greatly to our understanding of how place affects individuals.

In the past twenty-five years, there has been a resurgence of community studies, most searching for elusive "neighborhood effects." Neighborhood effects studies attempt to quantify the effect that living in a particular community has over individuals. Often, neighborhood effects are referred to as contextual effects, or direct causal relationships that communities have on their residents, although many neighborhood effects studies are also interested in social effects (e.g., social ties, collective efficacy) that mediate the relationship between communities and their residents. Statistically, neighborhood effects can be assessed by measuring the proportion of total variance between the communities, a measure commonly referred to as the Intraclass Correlation Coefficient (ICC) (Leventhal and Brooks-Gunn, 2000). The ICC measures the amount of variance that is explained by communities and an ICC greater than zero signifies the existence of neighborhood effects and justifies the use of multilevel models (Kreft and De Leeuw, 1998).

Neighborhood effects studies are important because communities continue to play an important role in people's lives. Neighborhood structural characteristics are created by the unequal distribution of resources across geographic areas, such as socioeconomic status, education, and employment (Leventhal and Brooks-Gunn, 2000). Growing evidence indicates that these neighborhood structural characteristics, especially socioeconomic inequality, continue to operate at the community level and influence individuals throughout their lifetimes (Massey, 1998; Sampson et al., 2002). Both positive resources (e.g., libraries, food stores) and negative resources (e.g., drug markets, liquor stores) are distributed across communities, differentially exposing residents to positive and negative community-level influences. Many social processes (e.g., socializing with neighbors and families) and institutional participation (e.g., schooling, voting, parole officer appointments) are based upon the communities in which people live. With these structural, resource, social, and institutional processes all occurring at the community-level, it is little wonder that so many studies have documented the important role communities play in their residents' lives (Sampson et al., 2002; Leventhal and Brooks-Gunn, 2000).

However, neighborhood effects research does face some serious criticisms. The next section discusses the five most serious criticisms of neighborhood effects research:

(1) definitions of neighborhoods (e.g., census tracts, metropolitan statistical areas), (2) selection bias (e.g., people select the communities in which they want to live), (3) omitted variable bias (e.g., other variables such as families and policing operate simultaneously as neighborhood effects), (4) neighborhood effects affect subpopulations differently and these effects can change over time, and (5) neighborhood effects are mostly small in size.

Criticisms of Neighborhood Effects Studies:

One criticism of neighborhood effects studies is that they examine community structural processes at different aggregation units, including metropolitan statistical areas (MSAs) (Blau and Blau, 1982; St. John, 2002), counties (Baller et al., 2001; Osgood and Chambers, 2000), political wards (Sampson and Groves, 1989; Flint, 1998), census tracts (Peterson et al., 2000; Miethe and McDowall, 1993), and block groups (Smith et al., 2000; Roncek, 2000). The choice of aggregational unit is often driven more by the convenience and availability of community-level data at these aggregation levels (Tienda, 1991) than by the actual social and physical boundaries of these communities (Sampson et al., 2002; Grannis, 1998).[1] Evidence suggests that these statistical communities are reasonably consistent with the communities they attempt to measure (Sampson et al., 2002; Tienda, 1991). However, one recent study found that neighborhood structural variables assumed

[1] Recently, definitions of communities have improved by considering social and/or ecological aspects of communities. For example, the Project on Human Development in Chicago Neighborhoods (PHDCN) is a residential survey that was administered across 847 census tracts in Chicago. Sampson et al. (1997) then aggregated these census tracts into 343 neighborhood clusters based on knowledge of the communities, ecological factors from the census tracts and salient physical features (e.g., highways, bodies of water). Additionally, Grannis (1998) studied residential segregation by dividing larger communities into "tertiary communities," or those communities that are bounded by ecological boundaries such as railroads, highways, and parks.

different significant relationships to a common outcome variable when measured with block groups and census tracts (Hipp, 2007).

Secondly, researchers have suggested that a selection bias is likely when individuals are examined in their communities. Specifically, people are not randomly distributed across communities. Certain people choose to live in certain communities, making it difficult to separate out true neighborhood effects from those effects of similar people congregating together in chosen communities that appeal to specific segments of the population (Sampson et al, 2002; Leventhal and Brooks-Gunn, 2000; Blalock, 1984). Although selection bias is a potentially serious problem, it is one that can be partially mitigated by using models (e.g., hierarchical linear models) that control for both individual-level and community-level effects simultaneously (Sampson et al., 2002). Even with HLM models however, community-level effects may be underestimated when individual-level effects are strong.

A third serious limitation of neighborhood effect studies is the search for the direct effect of communities upon individuals, without controlling for all of the other processes operating at the community-level (Leventhal and Brooks-Gunn, 2000). For instance, institutional resources (e.g., presence of police and parole officers) vary by community. If a model does not consider these additional institutional resources, then it may overestimate the effects that communities have upon individuals. Another way of describing this condition is to say that there is an omitted variable bias in community-level research unless a series of overlapping institutions that operate at the community-level are considered simultaneously (e.g., families, schools, community resources).

A fourth limitation is that neighborhood effects may vary in nature and intensity at different stages of the lifecycle (Massey, 1998; Leventhal and Brooks-Gunn, 2000) and for different populations (Haynie and Payne, 2006; Crane, 1991). Although this limitation is potentially a serious one, it is shared by other areas of study, including family research (Leventhal and Brooks, 2000). The varying nature and intensity of neighborhood effects on individuals by age and race can be tested using cross-level interactions in hierarchical linear models (HLM) between neighborhood structural variables and the individuals present in the study sample.

The final drawback of neighborhood effects research is that neighborhood effects are often small in nature (Jencks and Mayer, 1990; Mayer and Jencks, 1989). Typically, neighborhood effects explain between 4 and 6 percent of the variation between communities (Leventhal and Brooks-Gunn, 2000). While this criticism does not invalidate the neighborhood effects research, it does suggest that neighborhood effects are not very meaningful, as they only explain a small part of the variation in individual outcomes. [2] On the other hand, neighborhood effects may be small because the natural community-level variation is low. Duncan and Raudenbush (1999) illustrated this point by examining neighborhood structural variables across different cities. Although the means of these structural variables varied, the standard deviations were all very similar. Another way of thinking of neighborhood effects is to translate them into effect sizes, which measure the strength of a relationship. Duncan and Raudenbush (1999) illustrated that even small levels of explained variation between communities (e.g., ICCs) corresponded with medium effect sizes (e.g., Cohen's d).

[2] Additionally, Guest (2006) illustrated the important role control variables play in community-level analyses. Significant relationships between community-level variables typically became weaker and mostly insignificant with the addition of certain control variables.

Relatively little is known about how communities help or hinder a parolee's reintegration into society. The present study understands the limitations involved in community-level research and where possible, takes proper precautions necessary for examining individuals in their communities. Although communities are understudied as a potential risk factor for parolees, research has examined where parolees return upon their release from prison. The next section discusses this research on the types of communities to which parolees return.

Parolees' Communities:

Although approximately 93 percent of all prisoners are eventually released from prison (Petersilia, 2003), little is known about the communities to which they are released. This lacuna is unfortunate, because evidence suggests that crime rates vary across communities. In fact, these different crime rates can cause large percentages of a community's residents to be removed to prison. For example, in some communities in Washington, DC approximately 25 percent of adult males are arrested in any given year (Lynch and Sabol, 1992).

Though there is limited information on how communities affect individuals' recidivism, a number of studies examine how high rates of imprisonment can jeopardize the health and well being of a community. For instance, Rose and Clear (1998) suggested that when more than 2 percent of a population is removed each year, the community suffers more social disorganization and, as a result, experiences more crime. This hypothesis was later supported empirically (Clear et al., 2003).

Generally, there are three factors that cause parolees to return to the communities where they lived before they were incarcerated. The first is that parolees often want to be near their families and friends, and these individuals usually still live in their old communities. Secondly, living in a community with social supports may be a condition of parolees' release from prison. Finally, because of limited budgets for parole officers, many states force parolees to return to the county where they were living prior to their arrest (Petersilia, 2000).

Interestingly, "home" for parolees is increasingly geographically concentrated in impoverished and high crime communities of metropolitan areas (Lynch and Sabol, 2001; Visher and Farrell, 2005; LaVigne et al., 2003). In one study, the percentage of parolees who returned to counties that contained a central city grew by more than 16 percent between 1984 and 1996 (Lynch and Sabol, 2001). In addition, the study found that, compared with first time offenders, parolees who are repeat offenders are even more drawn to cities (Lynch and Sabol, 2001). This city bias corresponds with descriptive and ethnographic research suggesting that parolees return to urban, economically hollowed out, and socially disorganized communities (Anderson, 1990; Bourgois, 1995; Newman, 1999).

Research on urban communities with high levels of concentrated disadvantage indicates that these communities can negatively impact individuals and their life chances. But this effect may not be limited to urban areas, in that rural areas also have concentrations of extreme poverty (Rural Sociological Society Task Force on Persistent Rural Poverty, 1993). Because important resources such as the availability and cost of housing, access and proximity to jobs, and health and substance abuse treatment facilities are distributed by communities, it is important to understand the structural characteristics of these communities to which parolees are increasingly returning.

Several studies have linked individuals' life outcomes to their communities. These studies assume that opportunities are not equally distributed throughout society, and, indeed, certain physical areas are harmful for their residents. These harmful, or "risky" neighborhoods share certain common structural characteristics, such as elevated poverty, high population density, and dilapidated housing. The next section discusses general findings on the effects of community poverty on individual residents.

***Research on Poverty*:**

Neighborhood studies have found that high levels of poverty lead to nine negative outcomes: (1) higher rates of infant mortality (Coulton and Pandey, 1992), (2) lower birth weight (Morenoff, 2003), (3) higher rates of teen pregnancy (Crane, 1991; Harding, 2003), (4) higher rates of dropping out of high school (Crane, 1991; Crowder and South, 2003; Harding; 2003), (5) lower educational attainment (Dachter, 1982), (6) higher rates of adolescent delinquency and crime (Sampson and Groves, 1989), (7) poorer mental health (Wheaton and Clarke, 2003; Silver, 2000; Leventhal and Brooks-Gunn, 2003), (8) higher rates of victimization (Sampson and Lauritsen, 1990), and (9) higher rates of domestic violence (Van Wyck et al, 2003).

Even though poverty has been shown to be a direct and positive predictor in many neighborhood studies (Sampson et al., 2002; Leventhal and Brooks-Gunn, 2000), there is disagreement about how to best measure the concept of poverty. While measures of poverty are grounded in different theoretical approaches, some measures of poverty have been shown to be empirically similar (Morenoff et al., 2001; Kovandzic et al., 1998). One of the goals of this study is to discover which of five theoretical measures of poverty – concentrated disadvantage, extreme poverty, relative deprivation, racial inequality, and proximity – best predicts recidivism. The following sections discuss each of the five measures of poverty and then describe research on how poverty moderates the relationship between demographic factors and recidivism.

One important measure of the structural poverty in a community is concentrated disadvantage. This study tests whether higher levels of concentrated disadvantage predict higher recidivism rates among parolees.

Concentrated Disadvantage:

Shaw and McKay (1942, 1969) found that crimes appeared to cluster in physically dilapidated communities (or "zones in transition") near the central business district. Structurally, these communities were impoverished, composed of different racial and ethnic populations, and possessed high levels of residential instability. Over time, new populations moved into the zone in transition and the old population (who had assimilated into American society) moved to the slightly wealthier districts a little farther out from the central business district. This finding led Shaw and McKay to conclude that crime was an outcome of place rather than types of people. Specifically, different types of people were not inherently criminal, but rather, certain types of places were more criminal than other places.

In their research, Shaw and McKay (1942, 1969) posited that three neighborhood structural characteristics – poverty, racial and ethnic heterogeneity, and residential mobility – led to higher crime rates. These three structural characteristics disrupted a community's ability to organize, which in turn led to higher rates of crime and delinquency, a condition referred to as social disorganization. Shaw and McKay never posited a direct, causal relationship between the neighborhood structural characteristics and the outcomes of delinquency and crime. Instead, the relationship between these three structural characteristics and crime was mediated by social organization, a concept that Shaw and McKay never actually measured. Later studies corrected this lacuna in the social disorganization literature by measuring and testing the mediating social organizational processes with indicators of social ties (Kasarda and Janowitz, 1974), informal social control (Bursik and Grasmick, 1993), and collective efficacy (Sampson et al., 1997).

Four historical and structural changes eventually led to the incorporation within Social Disorganization Theory of a direct relationship between poverty and crime. First, African Americans who moved from the South in search of jobs in the city were not assimilated. Indeed, residential segregation restricted them to the inner-cities and racist unions segregated them to low skilled work (Farley and Frey, 1994; Massey and Denton, 1993). Second, the ecological stability of communities was assumed constant, until Bursik (1986) showed how Chicago had changed between 1940 and 1980. Third, in post-World War II America, cars and FHA home loans allowed people to live in the suburbs and commute into cities for work, changes that contributed to the decline of urban areas (Keister, 2000). Finally, the structure of the economy shifted from a manufacturing base to a service-based economy, which meant that only low skilled, lower wage jobs were left in the inner-cities and higher skilled, higher wage jobs moved to the suburbs (Kasarda, 1995).

These historic social and economic shifts transformed the character of inner-cities by increasing the concentration of the most disadvantaged segments of society – the poor, minorities, female-headed households, and the unemployed. These disadvantaged populations have become even more concentrated, as upper and middle class families relocated outside the inner-city (Wilson, 1987, 1996). Wilson (1987, 1996) noted that the concentration of poverty served not only to isolate residents economically, but socially as well – which in turn encouraged the transmission of deviant values (Anderson, 1990).

Generally, concentrated disadvantage is determined by neighborhood structural variables, indicators of which are available from the U.S. Census. In recent years, one particular measure of concentrated disadvantage has become the standard – an index of five census variables: (1) poverty levels, (2) public assistance, (3) unemployment, (4) female-headed families, and (5) percentage black (Sampson et al., 1999; Lauritsen and White, 2001; Morenoff et al., 2001). Some researchers have added additional variables, such as the percentage of those under the age of 18 years in the community (Sampson et al., 1997).

Within the past decade, there has been a great deal of empirical studies examining how concentrated disadvantage affects individuals. Communities with high levels of concentrated disadvantage have been linked to six negative outcomes: (1) high school drop out rates (Crowder and South, 2003), (2) early adolescent initiation into sexual relationships (Browning et al., 2005), (3) adolescent violent behavior (McNulty and Bellair, 2003), (4) intimate assaults (Wooldredge, 2003), (5) poor mental health

(Wheaton and Clarke, 2003), and (6) homicides (Sampson et al., 1997; Lee and Bartowski, 2004).

Two studies found a positive relationship between communities with high levels of concentrated disadvantage and resource deprivation and probationers' and parolees' recidivism (Kubrin and Stewart, 2006; Mears et al., 2008). The first of these studies was limited to the census tracts in one city (Kubrin and Stewart, 2006). The current study also examines the relationship between concentrated disadvantage and recidivism, but with the entire state of Georgia, county-by-county. Further, the current study focuses on the relationship between concentrated disadvantage and parolee recidivism, rather than probationer recidivism. Since parolees are a more vulnerable population compared to probationers, they are hypothesized to be more affected by their communities. Therefore, it is likely that parolees will have an even stronger relationship with their communities when examined in the absence of probationers.

The second study examined parolees in counties across the state of Florida, finding that parolees in communities with high levels of resource deprivation were significantly more likely to be reconvicted for violent felonies (Mears et al., 2008).[3] This current study examined the effect of concentrated disadvantage on parolees at the county-level using the theoretical approach of social disorganization, which also accounts for concentrated immigration and residential instability. Additionally, the Mears et al. (2008) study examined a censored population of male parolees who were reconvicted for

[3] This study also found that parolees in communities with higher levels of resource deprivation were significantly less likely to be reconvicted for drug felonies than parolees in wealthier communities. While this is an important finding, it is important to note that with the addition of statistical interactions, the main effect of resource deprivation became positive and was no longer statistically significant. This suggests that the relationship between community resource deprivation and drug felony reconvictions is tempered by the following three statistically insignificant interactions: (1) young men in resource deprived communitiess, (2) non-white men in resource deprived communities, and (3) young, non-white men in resource deprived disadvantaged communities.

a felony, while this current study examines all of the criminal activities that result in both male and female parolees being returned to prison, including felonies, misdemeanors, and technical violations. Thus, this current study has findings that are more applicable to policymakers seeking to lower the percentage of parolees returning to prison.

Concentrated disadvantage has also been shown to interact with individual characteristics, such that communities affect some residents more strongly than others. Individual characteristics that have been studied in the context of communities include the following: age, gender, race, marital status, and socioeconomic status (Sampson and Lauritsen, 1994). The present study examined two individual-level characteristics – race and age.

Parolees' racial and ethnic backgrounds were thought to affect recidivism in two important ways. First, African Americans commit serious crimes at a higher rate than whites (Walker et al., 1996), and African American parolees have significantly higher recidivism levels than whites (Langan and Levin, 2002). Secondly, previous studies have shown that the effects of concentrated disadvantage on individuals are not constant across communities. Specifically, concentrated disadvantage is a stronger predictor of criminal outcomes for whites than for African Americans (Ousey, 1999; Velez et al., 2003). Thus, whether or not an African American parolee commits a crime while on parole is determined more by that parolee's individual characteristics and experiences, and less by that parolee's community characteristics. This finding suggested that concentrated disadvantage would have a differential impact on parolees by race.

Secondly, the age crime curve suggests that as offenders age, on average, they become less likely to commit crime (Gottfredson and Hirschi, 1990). Based on the age crime curve, one would expect to find younger parolees recidivate at higher rates than older parolees. But this effect may vary across communities. For instance, compared to older residents, younger residents have been shown to be more susceptible to the negative effects of their communities (Massey, 1998), and in particular, high concentrated disadvantage communities (Sampson et al., 2002).

In sum, although there are fairly consistent findings regarding the link between concentrated disadvantage and criminal outcomes (Krivo and Petersen, 2000; Lee, 2000), there has been disagreement over whether concentrated disadvantage truly taps into the extremity of poverty concentrated in the inner cities (Jargowsky, 1994). The next section discusses a poverty variable that measures only those communities faced with extreme poverty rates.

Extreme Poverty:

Jargowsky et al. (1991) suggested that the geographic concentration of poverty occurred not because of the out-migration of the middle class, as suggested by Wilson (1987), but instead because the poverty level of people in these areas worsened. Thus, many of the same people who were "poor" in the 1960s became "very poor" by the 1980s. Jargowsky (1994, 1997) later compared census tracts across census years, finding that the number of extreme poverty census tracts increased by 132 percent between 1970 and 1990 (Jargowsky, 1997). In addition, these extremely poor communities expanded in three ways: geographic size, number of both overall residents and impoverished residents, and percentage of metropolitan populations living within them (Jargowsky, 1997).

Although Jargowsky's initial research found extreme poverty among African American communities (Jargowsky, 1994), other studies linked extreme poverty to Hispanic (Massey and Eggers, 1990) and Caucasian communities (Jargowsky, 1997). Jargowsky operationally defined extreme poverty as those neighborhoods having 40 percent or more of residents living below the poverty line. This definition was based on Jargowsky's fieldwork and substantiated by city planners and local census officials (Jargowsky and Bane, 1991). Additionally, one study provided empirical support for the 40 percent poverty definition (Stretesky et al., 2004).[4]

The extreme poverty concept is empirically related to criminal offending. Specifically, extreme poverty predicts violent crime, property crime (Krivo and Peterson, 1996), and homicides (Stretesky et al., 2004). Although extreme poverty is theorized to be racially invariant, at least one study has found that extreme poverty affected white homicides, while having no effect on black homicides (Parker and Pruitt, 2000).

Previous research on extreme poverty suggests its relevance as a predictor of recidivism. It is important to note that previous studies incorporating measures of extreme poverty have examined only aggregate-level criminal outcomes (Krivo and Peterson, 1996; Stretesky et al., 2004; Parker and Pruitt, 2000). No studies have examined the effect of extreme poverty on individuals. Therefore, this study is the first to examine whether community-level extreme poverty affects the individual-level criminal outcomes of recidivism.

[4] In this study Stretesky et al. compared the predictive power of extreme poverty defined in two ways – with 30 percent of the population falling below the poverty line and with 40 percent of the population falling beneath the poverty line. Jargowsky's 40 percent cut off point proved to be the better measure of extreme poverty.

While both concentrated disadvantage and extreme poverty measure only the absolute poverty in a community, some studies have moved beyond this single indicator of poverty to include factors of affluence and the effects of an increasing divide between the very wealthy and the middle class (Massey, 1996; Sampson et al., 1999; Brooks-Gunn et al., 1997; Velez et al., 2003). These studies have found that the presence of affluence, professionals, and high-income families is a strong protective factor against crime. Sometimes the affluence measures are even more powerful than the poverty measures (Sampson et al., 1997; Velez et al., 2003). Using both concentrated disadvantage and concentrated affluence assesses the absolute poverty and wealth of a community, and in addition, taps into the concept of relative deprivation.

Relative Deprivation:

Relative deprivation is defined as the level of self-perceived poverty felt by individuals when they compare themselves to others. Thus, it is a relative rather than absolute measure of deprivation. In recent years, researchers have suggested that the ideal measure of poverty should be relative rather than absolute (Brady, 2003). The present study tests whether higher rates of relative deprivation within a community (regardless of absolute poverty) result in higher rates of recidivism.

Merton (1949) offered one of the first theories of relative deprivation, when he suggested that levels of deviance were correlated with society's opportunity structure. Since opportunities are not distributed equally throughout society, certain classes of people are de facto excluded from achieving societal goals – especially the accumulation of wealth. Indeed, communities will have varying crime rates because they differ in the extent to which they retain or create residents who experience relative deprivation (Agnew, 1999).

The most likely outcome of relative deprivation should be instrumental crimes (e.g., property crimes) that help alleviate the deprivation individuals feel. Despite this reasonable link to property crimes, criminologists have focused almost exclusively on violent outcomes, such as homicide rates, when examining relative deprivation (Blau and Blau, 1982; Loftin and Hill, 1974; Velez et al., 2003). For example, socioeconomic inequality between whites and minorities fully explained the relationship between poverty and higher levels of violence (Blau and Blau, 1982; Hipp, 2007). Relative deprivation has also been shown to increase recidivism among probationers and parolees (Kubrin and Stewart, 2006), although this finding has yet to be replicated with more serious offenders.[5]

Two measures tap into the theoretical concept of relative deprivation. The first is the Gini coefficient, which became the standard measure of relative deprivation after Blau and Blau's 1982 paper. Although the Gini coefficient has been used in recent research (Maume and Lee, 2003; Pratt and Godsey, 2003), it has been shown to be biased, especially for communities that vary in geographic size (Robinson, 1998).[6] The second measure of relative deprivation is an index of concentration at the extremes (ICE), which examines the difference between affluent families and poor families within a community (Massey, 2001). Because it is less biased than the Gini coefficient, this study

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[5] See the Concentrated Disadvantage section above for a fuller discussion of the Kubrin and Stewart (2006) paper.
[6] The Gini index is a measure of inequality. However, the index may be biased by the size of the areal unit (e.g. counties, census tracts). In general, smaller areal units tend to have larger Gini index values than larger areal units (Robinson, 1998). This study relies on counties in Georgia, which have considerable variance in their geographic size.

uses the ICE index to measure the severity of relative deprivation present within a community.

One notable characteristic of all three of these theoretical poverty variables – concentrated disadvantage, extreme poverty, and relative deprivation – is that they assume racial invariance. In other words, compared to whites, people of color commit crimes at higher rates not because of their race but because more people of color live in high concentrated disadvantage, extreme poverty, and relative deprivation communities that promote crime (Peterson and Krivo, 2003; McNulty, 2001). This current study evaluates the racial invariance hypothesis by examining concentrated disadvantage, extreme poverty, relative deprivation and how these community characteristics interact with parolees' race to predict parolee recidivism. However, another way of examining how poverty affects individuals of different races is to measure the community level of racial inequality, which is discussed in the following section.

Racial Inequality:

In almost every urban setting, African American communities have a larger share of concentrated disadvantage and extreme poverty than their white counterparts (Sampson and Wilson, 1995; Jargowsky, 1997). Reasons for this concentration of poverty among African Americans have been linked to residential segregation (Charles et al., 2004; Massey and Denton, 1993) and middle class out-migration from cities (Wilson, 1987). Regardless of the social structural process, the resulting racial inequality promotes gaps between the rates of violence of African Americans and those of whites (Krivo and Peterson, 2000; McNulty, 2001).

The racial invariance hypothesis suggests that community-level causes of crime are the same for both African Americans and whites, although the degree to which members of different races experience crime-producing social conditions varies widely (Sampson and Wilson, 1995; McNulty, 2001). Some studies have found support for the racial invariance hypothesis (Sampson, 1987b; Sampson et al., 2005), while other studies have shown that community structural characteristics do in fact have differential impacts on crimes for blacks and whites (Harer and Steffensmeier, 1992; Ousey, 1999).

Interestingly, studies have shown that white violence is more strongly predicted by explanatory variables than is African American violence (Ousey, 1999; Parker and Pruitt, 2000; Parker, 2001). McNulty (2001) demonstrated that blacks live in communities that are structurally so much more disadvantaged than white communities, that their communities have entirely different statistical distributions. He suggested that these disparate communities explained why researchers found conflicting evidence for the racial invariance hypothesis.

Research into neighborhood effects on racial inequality has focused almost exclusively on homicide outcomes (Wadsworth and Kubrin, 2004; Velez et al., 2003; Kovandzic et al., 1998), with the exception of two studies. The first study found that racial inequality increased parolee recidivism among African Americans (Reisig et al., 2007) and the second study found that counties with high racial segregation increased parolee felony reconvictions among young minorities for drug crimes (Mears et al., 2008).

The research designs from both the Reisig et al. (2007) and the Mears et al. (2008) studies are similar to the current study in that both studies examined statewide parolee populations at the county-level. However, this study extends the current research on racial inequality and race in an important direction. Research suggests that minorities are more “at risk” for recidivism than white parolees (Petersilia, 2003), which results in higher recidivism rates among minorities. Both African Americans (54.2 percent) and Hispanics (51.9 percent) are returned to prison at higher rates than Whites (49.9 percent) (Langan and Levin, 2002). This study extends the racial inequality research by examining whether there is a significant interaction among minorities who are “at risk” and live in communities with high racial inequality. It is likely that parolees who are “at risk” will be more impacted by the racial inequality in their community than other parolees, an effect that may help to further explain why minorities are differentially impacted by community racial inequality (Reisig et al., 2007).

Generally, racial inequality is measured as the ratio of African American to white poverty rates, median family incomes, unemployment rates, poverty rates, and graduation rates. Sometimes these variables are factored (Wadsworth & Kubrin, 2004; Reisig et al., 2007), although some studies have used the ratios of these variables independently (Ousey, 1999; Velez et al., 2001). This study measures racial inequality using the factor analytic method in order to be able to compare one measure of racial inequality directly to other theoretical measures of poverty (instead of four ratios).

Concentrated disadvantage, extreme poverty, relative deprivation, and racial inequality all assume that community characteristics are the only type of relevant contextual factor. One drawback of this assumption is that neighborhoods are often artificially constructed, not following ecological boundaries of a community (Smith et al., 2000). It is very possible that individuals who live on the edge of one community compare themselves with neighbors who live in an adjacent community. However, standard methodological techniques do not take this possibility into consideration. Indeed, one needs to employ spatial analysis in order to overcome some of these problems.

Proximity to Poverty:

Diffusion theory posits that community characteristics (e.g., crime, poverty) spread from one community to nearby communities.[7] Therefore, given that poverty predicts crime rates, diffusion theory would suggest that, independent of an area's own poverty (however defined), the poverty of its surrounding communities will affect its crime rate. Many of the aggregation units used by researchers to represent neighborhoods are arbitrary, guided more by the availability of data from the U.S. Census Bureau, than by the ecological units of neighborhoods. For example, rarely are statistical measures of neighborhoods consistent with ecological boundaries (Grannis, 1998) or residents' perceptions of their communities (Lee and Campbell, 1997).

Research shows that areas sharing spatial proximity generally share the same structural factors (Bailey and Gattrell, 1995) and crime rates (Roncek and Montgomery, 1993). Yet, these shared community characteristics do not fully explain crime rates and

[7] Cohen and Tita (1999) suggested that there are two types of diffusion – contagion and hierarchical diffusion. Contagion diffusion acts like the spread of disease, where people come in direct contact with one another, spreading crime. For example, in gang warfare any assault against one gang member usually sparks retaliatory crimes. Hierarchical diffusion suggests that a spontaneous innovation enables the spread of neighborhood outcomes (e.g., a new device to disable electronic car locks is created, thus increasing car thefts throughout cities). Although these developments in diffusion theory are important, they do not apply to this study, which concentrates on structural characteristics of a neighborhood. That is, this study does not examine diffusion in the dependent variable of recidivism, and instead focuses on the diffusion in predictor variables measuring poverty. Diffusion in this context suggests that an area that experiences high poverty will be at an elevated risk for criminal outcomes when surrounded by communities with high poverty levels. This study does not examine the diffusion of recidivism because there are no theoretical reasons for believing that recidivism would spread in either of the diffusion patterns (contagion and hierarchical) noted by Cohen and Tita (1999).

their tendency to cluster in space (Baller et al., 2001). Spatial models overcome these limitations introduced by contrived communities by recognizing the dependence between communities. Even though spatial analysis offers the opportunity to examine communities and their interdependence, only a handful of studies have employed these new techniques. These studies find support for the diffusion of burglaries (Bernasco and Luyxx, 2003), robberies (Smith et al., 2000), violent crime (Fagan and Davies, 2000), homicides (Morenoff et al., 2001), and even crime control benefits (Lawton et al., 2005; Weisburd et al., 2006).

While there is a great deal of evidence suggesting criminal outcomes are clustered in space (Messner et al., 1999; Morenoff et al., 2001), not many studies have examined the effects of clusters of poverty on criminal outcomes. Evidence from two studies suggests that poverty clusters predict homicides and robberies (Stretesky et al., 2004; Mears and Bhati, 2006). In addition, high poverty communities have even more negative effects on residents when these communities are surrounded by other poor communities (Krivo and Peterson, 1996). This finding corresponds with ethnographic research showing that residents are affected not just by their community, but also by other communities in their vicinity (Patillo-McCoy, 1999).

These findings on spatial diffusion have led some to suggest that spatial dynamics outside a community may be more important than the dynamics within a community for predicting community outcomes (Sampson and Bean, 2006). Following that suggestion, this study examines the effects of diffusion of poverty, or proximity to poverty, on individual recidivism. Because this study attempts to better understand different measures of concentrated disadvantage, extreme poverty, relative deprivation, and racial inequality, this study created measures of the diffusion of these four poverty variables from adjacent communities, and examined their interactions with the main poverty variable.

Conclusions from the Poverty Discussions:

Research indicates that all five measures of poverty – concentrated disadvantage, extreme poverty, relative deprivation, racial inequality, and proximity – are related to overall crime rates. By extension, it is expected that all five poverty measures will each be related to recidivism rates of parolees living across Georgia. Conceptually, these theories have distinct perspectives about the role poverty plays in predicting parolees' recidivism and each of these poverty theories has a different prediction. Both concentrated disadvantage and extreme poverty predict that poor communities will have higher recidivism rates than more wealthy communities, although each theoretical measure would identify different communities. Specifically, extreme poverty would identify communities in which poverty is endemic, while concentrated disadvantage, which measures a wider number of characteristics related to poverty (e.g., unemployment, female headed households), would identify communities in which structural characteristics related to poverty are widespread.[8] Relative deprivation predicts that communities that have the greatest differential between poor and wealthy residents would have the highest levels of recidivism. Racial inequality suggests that communities with the greatest levels of differences in economic achievements by white and minority residents would have the highest levels of recidivism, especially for certain

[8] Empirically, these concentrated disadvantage and extreme poverty were not strongly related ($r = .26$; $p < .001$).

subpopulations (e.g., African Americans). Finally, proximity to poverty suggests that communities that are situated near high poverty communities would have higher recidivism rates than communities surrounded by more wealthy communities.

Although each of these measures of poverty may be theoretically distinct, they are not necessarily empirically distinct. Previous studies that examined different measures of poverty found that both measures of poverty were statistically significant in their predictions of community-level outcomes (Kubrin and Stewart, 2006; Morenoff et al., 2001). These findings occur because many of these poverty concepts are interrelated. For example, communities with high levels of relative deprivation may also have high levels of racial inequality, which would indicate that not only is there a divide between the “haves” and the “have nots” in communities, but that this divide tends to fall along racial lines. Said another way, several of these poverty variables are strongly correlated with one another, which necessitates that these poverty variables be treated carefully in the later statistical analyses. Specifically, it was necessary to examine these theoretical measures of poverty individually, in order to avoid the statistical problem of multicollinearity. However, each result provides more information on how the underlying poverty concept operates and insights on which aspects of each theory apply to the study of recidivism in communities.

Most studies examining poverty have focused exclusively on urban areas, including Chicago (Shaw and McKay, 1942; Sampson et al., 1997), Baltimore (Taylor, 1997), and Seattle (Miethe and McDowell, 1993). The underlying implication of these studies is that structural characteristics of communities have a constant effect on crime and delinquency rates across geographical areas, including rural and urban areas.

Urban/ Rural Continuum:

In their classic work, *Juvenile Delinquency and Urban Areas*, Shaw and McKay (1942, 1969) suggested that the combination of three structural factors – poverty, racial and ethnic heterogeneity, and residential mobility – lead to the disruption of community social organization. Communities that are not able to organize and influence their residents' behaviors are likely to experience crime and delinquency. In the past twenty years, research has gone beyond these three structural factors to examine other variables that increase the level of social disorganization of a community, including single-parent families, density, and urbanization (Bursik and Grasmick, 1993; Sampson, 1985; Sampson and Groves, 1989).

The Social Disorganization School began by analyzing patterns of social disruption arising out of the Industrial Revolution and affecting both rural and urban areas. Although rural and urban areas undoubtedly faced the broader social changes caused by high levels of immigration, industrialization, and urbanization, there were and continue to be two important differences between rural and urban areas: their different structural characteristics and their divergent crime rates. These differences are important considerations because they both likely affect recidivism rates of parolees. The next section describes how three structural factors (poverty, mobility, density) and rural culture operate in rural areas to produce different crime rates.

In the only test of the effect of structural factors on crime in rural areas, Osgood and Chambers (2000) found that residential mobility, ethnic heterogeneity, and single-parent families predicted juvenile crime in rural areas, but that poverty was unrelated to juvenile crime. This lack of a link between rural crime and poverty may be due to the different character of poverty in rural areas, which is sometimes more severe than poverty in inner-cities (The Rural Sociological Society Task Force, 1993). There is also evidence that poverty is more widespread in rural areas. For example, in 1979 one report found that of the 159 U.S. counties with the highest rates of poverty, only six contained a city of 25,000 or more (Weisheit et al., 1994). Secondly, mobility is more limited in rural areas. Whereas in urban areas poverty is associated with higher levels of mobility, in rural areas residents often stay in the same county and even the same house for generations (Weisheit et al., 1994).

The third structural variable, population density, also varies greatly between rural and urban areas. Wirth (1938) was one of the first scholars to note that as population density increased, social relationships began to break down. However, density is usually overlooked in the examination of rural areas. This oversight is important, as some rural areas experience dramatic surges in population following the opening of new businesses and/or suburban growth. In 21 of 23 studies, communities with rapid population growth experienced explosions in crime rates, often at three to four times the pace of the population growth (Weisheit et al., 1994).[9] In addition, density can help differentiate suburbs from the urban/rural continuum. This distinction is important, as research shows that suburbs typically have lower crime rates (Farley, 1987) and lower poverty levels (Fuggitt et al., 1989; Massey, 1996) than urban areas.

Rural culture differs from urban culture in several important ways. In urban communities, variables such as informal social control and collective efficacy mediate the

[9] Between the 1990 and 2000 census, Atlanta added eight counties to its metropolitan area. Growth such as Atlanta experienced suggests that wisdom of examining population density and suburban measures.

relationship between social disorganization and community crime rates (Sampson and Groves, 1989; Sampson et al., 1997). Because rural areas foster even stronger social ties and higher levels of informal social control (Wilkinson, 1984b; Weisheit et al., 1994), this mediation is likely even stronger.

In addition, people who live in rural communities are often less tolerant of most types of deviance, and more suspicious of outsiders and the government (Wilson, 1991; Weisheit, 1993; Wilkinson, 1984a). Rural residents are also more traditional and conservative in many of their political views (Hansen, 1987). Rural areas have a higher density of acquaintanceships than urban areas, resulting in official crime rates that are typically lower, because individuals are less likely to commit crimes against people who recognize them and disapprove of their transgressions (Freudenburg, 1986). Accordingly, one would expect that parolees are less likely to recidivate in communities with a strong rural culture.

The final major difference between urban and rural areas is that urban areas have higher official crime rates than do rural areas (Laub, 1983; Weisheit et al., 1994). However, other data sources, such as surveys and agency data (e.g., rape crisis centers), suggest that certain crimes may actually be higher in rural areas. For instance, studies using non-UCR data indicate that people living in rural areas are more likely than those who live in urban areas to be the victims of sexual crimes (Ruback and Menard, 2001), minor thefts (Mustaine and Tewksbury, 1998), household larceny (Thompson and Fisher, 1996), and theft of farming equipment (Weisheit et al., 1994). Because of these differences between official crime rates and other data sources, it is important to account for criminal justice resource distribution differences between urban and rural areas, which may also impact crime rates.

Criminal Justice Resources:

Three criminal justice factors are probable determinants of parolee recidivism rates: the number of law enforcement and parole officers in an area, parole officer caseload size, and type of community. Higher levels of police supervision often lead to increased crime rates (Martin and Sherman, 1986; O'Brien, 1985), probably because a greater number of police officers can document a higher number of crimes. Similarly, higher levels of parolee supervision result in more parolees being returned to prison, especially for violations of their parole terms, or technical violations (Petersilia and Turner, 1993).

Technical violations can occur for many reasons: failing drug or alcohol tests, failing to report to the parole officer, not notifying the parole officer of an address or employment change, failing to follow a treatment plan, consorting with known felons, or committing a new crime (Hughes et al., 2001). Today, technical violations are being used to return parolees to prison more often than in the past. Between 1985 and 2001, the number of parolees returned to prison for technical violations increased from 32 to 49 percent of recommitments (Blumstein and Beck, 2005). Although technical violations may appear to be less serious than the new criminal activity, evidence suggests parole officers may be using technical violations as a shortcut to return parolees to prison for more serious violations. In one survey, for 70 percent of those inmates returned to prison for technical violations, the cause of their technical violation was actually a new crime or conviction (Hughes et al., 2001).

The caseloads of parole officers have grown substantially in the past 30 years and this growth has limited the amount of time parole officers are able to devote to individual parolees. One consequence of this increased work burden is that parole officers rely more on technology to monitor their caseloads (e.g., drug and alcohol tests and electronic monitoring), and this reliance, in turn, has generated more technical violations (Petersilia, 2003; Petersilia, 1998; Petersilia and Turner, 1993). Yet, parole officers still have considerable discretion in returning parolees to prison (Piehl and LoBuglio, 2005), and individual differences in parole officers can significantly affect recidivism (Wilson and Davis, 2006).

The third factor affecting parole supervision is the type of community in which parole officers operate. Evidence suggests that community characteristics such as residential instability and fear of crime can affect both crime rates (Warner and Pierce, 1993; Bursik and Grasmick, 1993) and the amount of reported crimes (Klinger and Bridges, 1997). Specifically, Warner and Pierce (1993) found that community-level residential mobility had different relationships with different types of crimes (e.g., robbery, assault, and burglary). Klinger and Bridges (1997) found that residents underreported crimes to police in communities in which residents were most afraid of crime and more cynical about police response time in their communities. Additionally, the behavior of officers varies across different community types, such that police officers in urban areas are much more likely to take a professional, or legalistic, approach to processing crimes (Wilson, 1968). Indeed, recent research has shown that police have a growing reliance upon formal social control in urban areas (Parker et al., 2005).

Although research on parole supervision is limited, in smaller and more rural settings officers generally rely on more informal means of social control (Wilson, 1968; Weisheit et al., 1996). Therefore, it is expected that, compared to parole supervision in urban areas, rural parole supervision will rely less on technical violations, because rural areas have higher levels of informal social control.

In summary, this study examines how different measures of poverty (concentrated disadvantage, extreme poverty, relative deprivation, racial inequality, and proximity), rurality, and criminal justice resources affect recidivism rates of parolees. The next chapter presents hypotheses and research questions derived from this literature review.

CHAPTER 3:
RESEARCH GOALS AND HYPOTHESES

Although there is research on individual-level predictors of recidivism among parolees, comparatively little is known about how community-level factors influence recidivism. This study addresses this gap in knowledge by addressing the following seven hypotheses:

1. ***<u>Concentrated Disadvantage and Recidivism</u>***

    a. ***Counties with higher levels of concentrated disadvantage will have higher levels of parolee recidivism.***

    b. ***Concentrated disadvantage will be a stronger predictor of parolee recidivism in urban settings than in rural areas.***

    c. ***Younger parolees will recidivate more than older parolees in counties of high concentrated disadvantage.***

    d. ***White parolees will be more susceptible to the effects of concentrated disadvantage, causing them to recidivate significantly more than minority parolees in high concentrated disadvantage communities.***

Concentrated disadvantage is a strong and positive predictor of delinquency (Sampson and Groves, 1989) and victimization (Sampson and Lauritsen, 1990). Additionally, one study found that concentrated disadvantage positively predicted the recidivism of probationers and parolees (Kubrin and Stewart, 2006).[10] This current study examines whether concentrated disadvantage's effect on recidivism is generalizable across an entire state. In addition, it is also likely that concentrated disadvantage interacts with three variables: urban areas, younger parolees, and parolees of color.

[10] In the Kubrin and Stewart (2006) study, 81 percent of the sample were probationers and only 19 percent were on parole.

Most of the studies examining concentrated disadvantage have been located in urban settings (e.g., Chicago). However, there is some evidence suggesting that concentrated disadvantage does not predict juvenile delinquency in rural settings (Osgood and Chambers, 2000). Therefore, concentrated disadvantage in rural areas may not predict recidivism of individual parolees, although it is likely that concentrated disadvantage will predict recidivism in urban areas (Kubrin and Stewart, 2006).

It is likely that concentrated disadvantage will affect segments of the parolee population in at least two different ways. First, Massey (1998) suggested that neighborhood effects arising out of concentrated disadvantage may not have a constant effect, and in particular, children and late adolescents are more susceptible than adults to these negative effects. Therefore, one would expect that younger parolees would be more affected than older parolees by their community's level of concentrated disadvantage.

Secondly, Ousey (1999) found that African Americans in communities with high levels of concentrated disadvantage were less likely to engage in violence than whites in similar communities.[11] Given this finding of differential outcomes by racial groups, one can assume that, compared to minority parolees, white parolees will be more likely to recidivate in communities with high levels of concentrated disadvantage.

2. ***<u>Extreme Poverty and Recidivism</u>***

a. ***Counties with higher percentages of extreme poverty will have higher levels of recidivism than counties with lower percentages of extreme poverty.***

[11] Ousey (1999) examined several structural neighborhood characteristics across 125 U.S. cities in order to determine whether these structural characteristics were racially invariant or whether blacks and whites were affected by their communities in different ways.

b. ***Counties with higher percentages of extreme poverty will have higher levels of aggregate recidivism than counties with lower percentages of extreme poverty*.**

c. ***Compared to minority parolees, white parolees will be more affected by their community-level of extreme poverty.***

Extreme poverty is a strong predictor of crimes (Krivo and Peterson, 1996; Stretesky et al., 2004); therefore, it also likely predicts individual recidivism among parolees. To date, extreme poverty has not been used to study individual-level criminal offending. Indeed, extreme poverty studies have relied mostly on aggregate data predicting aggregate outcomes. In order to compare individual-level and aggregate-level outcomes, this study examines whether extreme poverty predicts community-level recidivism rates.

Parker and Pruitt (2000) found that extreme poverty significantly increased white homicides but did not predict black homicides. This finding suggests that extreme poverty works differently for blacks and whites. Therefore, this study tests whether communities with extreme poverty significantly interact with parolee race. White parolees are expected to be returned to prison at much higher rates than minority parolees in high extreme poverty communities.

3. ***Relative Deprivation and Recidivism***

a. ***As compared to counties with more homogeneous levels of wealth, counties that have higher levels of relative deprivation will have higher levels of recidivism*.**

b. ***High levels of relative deprivation will predict higher recidivism among white parolees, although not among minority parolees*.**

Relative deprivation predicts increases in violent crimes (Blau and Blau, 1982; Velez et al., 2003), and more recidivism among probationers and parolees (Kubrin and Stewart, 2006). Therefore, this study expects to find a positive and significant relationship between counties with high levels of relative deprivation and parolee recidivism.

Ousey (1999) found that higher levels of relative deprivation significantly predicted higher levels of violence only of whites (and not African Americans). Therefore, this study expects that in areas with high levels of relative deprivation, white parolees will be more likely to recidivate than minority parolees. This finding of an interaction between relative deprivation and parolee race would suggest that relative deprivation has a different impact on not only violent outcomes but also on parolee recidivism, thus providing additional evidence against the racial invariance hypothesis.

4. ***Racial Inequality and Recidivism***

   a. ***Substantial levels of racial inequality will result in counties with higher levels of recidivism compared to counties with close racial parity.***

   b. ***Minority parolees will be more affected by their community racial inequality than white parolees, resulting in higher rates of recidivism among minority parolees living in high racial inequality communities.***

   c. ***Minority parolees will be returned to prison at higher rates when they reside in communities with high racial inequality that favors whites (i.e., whites are more affluent than African Americans).***

   d. ***When minority parolees are examined separately, community racial inequality will affect minority parolees who are more "at risk" than minority parolees who are less "at risk."***

Racial inequality positively predicts parolee recidivism (Reisig et al., 2007). This component of the current study replicates and extends the Reisig et al. study. Therefore, it is expected that Georgia state parolees will recidivate at higher rates in counties with high levels of racial inequality. Additionally, Reisig et al. (2007) found that racial inequality significantly increased black parolees' likelihood of recidivating, while white parolees were not significantly impacted by the racial inequality in their communities. Hence, this study expects to find that throughout Georgia, minority parolees will be significantly more likely to recidivate in communities with high levels of racial inequality.

The racial inequality variable used in this study represents racial inequality in which whites are more affluent than African Americans and racial inequality in which African Americans are more affluent than whites. This study expects that minority parolees will recidivate at high rates when they reside in communities with high racial inequality favoring whites than when they reside in communities with high racial inequality favoring African Americans.

Recidivism rates are highest among African Americans (Langan and Levine, 2002; Petersilia, 2003). One explanation for this effect is that African American parolees are more affected by their community's racial inequality (Reisig et al., 2007). Another possible explanation is that African Americans are more affected by their community racial inequality because they are more "at risk" than other parolees. This study extends the racial inequality research by examining minority parolees separately in order to determine whether "at risk" minority parolees are significantly more likely to recidivate than minority parolees who are less "at risk".

5. ***Proximity to Poverty and Recidivism***

   a. ***Counties with high levels of concentrated disadvantage, extreme poverty, relative deprivation, and racial inequality will have higher levels of recidivism when they are adjacent to other impoverished counties.***

Diffusion suggests that crime rates are affected by the poverty of neighboring areas, independent of the area's own poverty (e.g., concentrated disadvantage, relative deprivation). Diffusion of poverty, or clustering of high poverty communities, has been shown to increase community rates of homicide and robbery (Stretesky et al., 2004; Mears and Bhati, 2006). Therefore, this study expects to find that communities with larger poverty clusters (defined by concentrated disadvantage, extreme poverty, relative deprivation, and racial inequality) will have higher recidivism rates than communities where poverty is more isolated.

6. ***Rurality and Recidivism***

   a. ***Rural counties will have lower levels of parolee recidivism than urban counties.***

   b. ***Suburban counties will have levels of parolee recidivism that are lower than both urban and rural areas.***

Official data sources describe urban areas as having higher overall crime rates than rural areas (Laub, 1983). Yet, other studies have found that certain crimes are comparable, if not higher, in rural areas than urban areas (Thompson and Fischer, 1996; Ruback and Menard, 2001). In addition, crime correlates, such as structural characteristics (e.g., poverty, density, and mobility) and culture, operate differently in rural areas (Weisheit et al., 1996). If crime operates similarly to recidivism, there is reason to expect parolee recidivism will also be lower in rural areas due to these rural structural and cultural differences.

Suburban areas add another layer of complexity when looking at criminal outcomes. Generally, suburbs have lower crime rates (Farley, 1987) and lower poverty levels than urban areas (Massey, 1996). These lower levels of crime and poverty suggest that parolees will have lower exposure to negative structural characteristics of their communities (e.g., poverty or crime) that might influence parolees' likelihood of recidivating. Therefore, this study expects to find that suburban areas have significantly lower levels of recidivism than either rural or urban communities.

7. ***<u>Criminal Justice Resources and Recidivism</u>***

   a. ***The presence of parole offices in counties will result in counties experiencing higher rates of parolee recidivism compared to counties whose jurisdictions are covered by parole offices located in nearby counties.***

   b. ***Counties with nearby parole offices will also result in higher rates of parolee recidivism than counties that are not near parole offices.***

   c. ***Parole offices in urban areas will detect higher levels of recidivism than parole offices in rural areas.***

   d. ***Counties with higher crime rates will result in higher rates of recidivism than counties with lower crime rates.***

Criminal justice resources may also explain recidivism rates. More offenders are apprehended when parole resources are focused on overseeing parolees (Petersilia and Turner, 1993). This study uses parolee proximity to parole offices as a proxy for increased levels of supervision under the assumption that parole officers will be better able to monitor parolees in their immediate vicinity than parolees who are farther away and require increased travel time.

Therefore, this study expects that the presence of a parole office inside a county will result in higher recidivism rates because parole officers will come in more frequent contact with parolees in their counties, thus uncovering nearby parole violations and crimes more frequently than violations and crimes in more distant counties. This study also expects to find second order distance effects, meaning that parolees who live in counties with parole offices in neighboring counties will have higher rates of recidivism than parolees who live in counties that have no parole offices and whose nearest parole office is not immediately contiguous to their county of residence.

There are two reasons why parole officers in urban areas, compared to officers in rural areas, will likely uncover more parolee violations and crimes. First, because parole officers in urban areas are probably less acquainted with the parolees in their caseloads, the officers may take a more legalistic approach, revoking parole for any violation of parolees' terms of parole, commonly referred to as technical violations. In contrast, parole officers in rural areas may be better acquainted with the parolees they supervise, and as a result, issue a warning for a parolee's first technical violation instead of arresting the parolee. Secondly, rural parole agents may trust in the informal social control that encourages their parolees to refrain from technical violations or crimes. Hence, this study expects that parole offices in urban areas will uncover significantly more parole and criminal violations than parole offices in rural areas, resulting in higher recidivism rates in urban areas with parole offices.

Communities with high crime rates are expected to have higher rates of recidivism. Crime rates are a function of both criminal activity and criminal justice response. Therefore, parolees residing in communities with high crime rates may be drawn into committing new crimes because of the attractive crime opportunities or criminal networks present in their communities. It is also possible that counties with higher crime rates signify increased police presence and greater scrutiny of community activities. Therefore, parolees living in high crime communities would likely suffer from this increased access to criminal opportunities and stronger criminal justice presence, resulting in higher recidivism rates.

This section has discussed the seven hypotheses examined in this study. The next chapter presents the information on the study area, the data preparation techniques, and the variables used in the statistical analyses.

CHAPTER 4:
METHODLOGY AND DATA

This chapter outlines in three sections the data and methodology used for this research study. The first section discusses the study area of Georgia. Secondly, this study examines the data preparation in terms of how Geographical Information Systems (GIS) was used and how the unit of analysis was chosen for this study. The third section examines the variables, their preparation, and measurement.

***The Study Site*:**

This study relies on data from the Georgia Board of Pardons and Paroles (GBPP), which followed the entire parole population of 18,285 men and women under parole supervision on January 1, 2000 through January 1, 2002. This dataset includes parolees' demographic information, residence, employment history, arrest information, prior convictions, and assigned risk level. Of this population of parolees, approximately 25 percent were reincarcerated over the course of two years. For the most part, the characteristics of these parolees mirror the characteristics of parolees across the United States, although there were fewer white parolees among the population of Georgia parolees (see Table 1).[12]

[12] The Glaze (2004) report examined parolees across the entire United States, which is why it was chosen to compare to the parolee population in this study. Other reports, such as the Langan and Levine (2002) study examined only a subpopulation of the United States (i.e.., fifteen states -- AZ, CA, DE, FL, IL, MD, MI, MN, NJ, NY, NC, OH, OR, TX, VA).

Table 1: Comparing Parolees in Georgia to Parolees across the United States		
Demographic Characteristics	**U.S. Parolees – 2000[13]**	**Georgia State Parolees – 2000**
White	**40%**	**31%**
Black, Hispanic & Other	**61%**	**69%**
Male	**88%**	**89%**
Female	**12%**	**11%**
Parole Revoked[14]	**39%**	**25%**

There are three reasons for using the state of Georgia as our study area. First, Georgia offers an interesting range of structural characteristics, including urban areas, several counties that are exclusively rural, a sizeable minority population, and severe pockets of both rural and urban poverty. Second, Georgia has excellent data in computerized files. Parole officers collect data on recidivism (e.g., rearrest, type of crime, drug test results), demographic information (e.g., age, gender), and ties to the community (e.g., employment). Recently, the GBPP has instituted a new risk assessment tool that provides dynamic risk assessments of parolees based on changes in their circumstances (e.g., change of residence, drug failure) throughout the length of their parole (Meredith et al., 2007). Third, the population of parolees in Georgia is larger than parolee populations in most other states (Georgia Board of Pardons and Paroles, 1999). At the same time, Georgia's incarceration and release rates have mirrored national trends (LaVigne and Mamalian, 2004), which suggests that findings about Georgia parolees would be representative of parolees nationally.

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[13] Glaze, Lauren E. (2004). "Probation and Parole in the United States, 2003." (NCJ 205336). Washington DC: Bureau of Justice Statistics.

[14] The differences in the percentages of revoked parole between the U.S. population of parolees and Georgia state parolees is due mostly to the different lengths of time during which parolees were supervised. The Georgia dataset spans 2 years, while the United States (BJS) dataset covers 4 years.

***Data Preparation and Measurement*:**

Geographical Information Systems (GIS) has the ability to process spatial data about some segment of the world (DeMers, 1997). It is a useful tool for examining data, merging data files, and performing introductory exploratory analyses that identify pockets of spatially correlated data. During the data preparation and measurement phase, GIS was used in two important ways. First, GIS was used to link parolee addresses to their county of residence. Secondly, GIS was used to combine separate spatially referenced datasets.

In the first step, the dataset of parolee addresses was linked to their county of residence. Under normal address matching procedures, ArcGIS would match addresses by matching two spatially referenced fields – the address field (e.g., 123 Maple Street) and the zip code. Unfortunately, the address data provided by the GBPP did not contain zipcodes, which necessitated an extremely labor intensive process of locating parolees based on their city of residence.[15] In order to accomplish this task, a two-step procedure was employed. First, a map of places and cities in Georgia was imported, which provided boundaries for all cities and places in Georgia. Parolees were then sorted into different datasets based on their city of residence. In cases where cities were located entirely within a county, ten percent of the addresses from a city dataset were selected and matched to their county using an interactive method called "address matching."[16] If

[15] It is not possible to match only on an address field for such a large geographic area, as it is likely that different cities may have the same address. For example, two cities might easily both have a "150 Main Street" address.
[16] Some places and cities were home to fewer than 100 parolees. For these places/ cities, I address mapped 10 addresses instead of 10 percent of the addresses.

all these addresses were located within the same county, that county was assigned to all residential records for that city. In cases where parolees lived in a city whose boundaries were either between two or more counties or on the edge of a county, then all parolees were address matched for that city to ensure parolees were assigned to the correct county. In total, the final rate of address matching was 98.5 percent and a final sample size of 18,013 parolees.[17]

GIS was also used to combine spatially referenced data, in this case, the parolee addresses and county-level data. Using Geographical Information Systems (GIS), this study created a dataset composed of several different types of information, including the individual-level data from the Georgia Board of Pardons and Paroles, county-level Census data (e.g., concentrated poverty, relative deprivation), county-level crime data from the FBI's Uniform Crime Reports, and locations of parole offices. Table 2 summarizes the different types of data used in this research project, their sources and years.

Table 2: Description of Variables

Type of Factor	**Variables**	**Source**	**Year**
Dependent Variable			
Recidivism	Returned to Prison (yes/no)	Georgia Board of Pardons and Paroles	2000-2002
Individual-Level Variables			
Demographic Variables	(1) Alcohol & Drug Use (2) Risk Scores (3) WRAT Reading Score (4) Number of Priors (5) Number of Jobs (6) Race (7) Gender (8) Age	Georgia Board of Pardons and Paroles	2000-2002
Community-Level			

[17] I was unable to match 1.5 percent of addresses because there were either too many errors in the address or else the city was missing.

Variables			
Poverty Variables			
Structural Poverty	Concentrated Disadvantage	U.S. Census Bureau	2000
Extreme Poverty	40+ % Residents in Poverty	U.S. Census Bureau	2000
Relative Deprivation	The ICE Index	U.S. Census Bureau	2000
Racial Inequality	Racial Inequality Factor	U.S. Census Bureau	2000
Diffusion of Poverty (1)	Spatial Lag of Concentrated Disadvantage	U.S. Census Bureau	2000
Diffusion of Poverty (2)	Spatial Lag of Extreme Poverty	U.S. Census Bureau	2000
Diffusion of Poverty (3)	Spatial Lag of the ICE Index	U.S. Census Bureau	2000
Diffusion of Poverty (4)	Spatial Lag of the Racial Inequality Factor	U.S. Census Bureau	2000
Urban/ Rural Measures			
Rural	Percent rural	U.S. Census Bureau	2000
Population Density	Number of people per square kilometer	U.S. Census Bureau	2000
Commuting Time	The average commuting time of county residents	U.S. Census Bureau	2000
Criminal Justice Resources			
Parole Offices (1)	Location of parole offices	Georgia Board of Pardons and Paroles	2004
Parole Offices (2)	Spatial lag of parole office locations	Georgia Board of Pardons and Paroles	2004
UCR	County-level indexed crime rates	Uniform Crime Reports (FBI))	1999-2001

This multi-level dataset was then used to examine the effect of community characteristics on parolees in Georgia over a two-year period. In particular, this study focuses on whether certain communities serve to increase parolees' likelihood of recidivism, and, if so, discover which of these community characteristics make some communities "risky" for parolees.

County-Level Data: Units of Analysis

There are several strong reasons to use county-level data as the unit of analysis. First, several studies have used counties as the level of aggregation for investigations of crime (Reisig et al., 2007; Baller et al., 2001; Osgood, 2000; Messner et al., 1999; Kposowa and Breault, 1993). Indeed, some have suggested that there are no strong theoretical reasons to expect different outcomes from different units of analysis (Land et al., 1990; Tienda, 1991; Sampson et al., 2002). However, one recent study found that across different aggregation units (i.e., census tracts and block groups), structural variables had different means, standard deviations, and statistical outcomes (Hipp, 2007). The findings from the Hipp (2007) study illustrate the modifiable areal unit problem (MAUP) which can occur when geographical data are aggregated into arbitrary units of geography such as census tracts or block groups (Tienda, 1991; Unwin, 1996). Using counties, which are not arbitrary units of geography, will help to avoid some of the problems associated with census tracts and block groups in analyses.

The second reason for using counties as the unit of analyses is that county-level data links to other data sources, including the U.S. Census, the Uniform Crime Reports and other federal and state data collection agencies. Finally, counties are preferable to cities or MSAs, as counties offer a complete social landscape, ranging from sparsely populated rural areas to dense urban cities (Nielsen and Alderson, 1997). Additionally, smaller aggregational units typically have a rural bias, as it is difficult to map many rural addresses that contain rural routes (Harries, 1999). Using counties as the aggregational unit enables researchers to assess a more complete geographical landscape that includes rural and urban areas, while avoiding some of the biases introduced with smaller aggregational units.

There is one important drawback to using county-level data. Due to the relatively large size of counties compared to other aggregational units (e.g., census tracts), counties can sometimes mask the regional variation of structural characteristics. One recent study found that the ecological concept of residential segregation operated differently at both smaller and larger aggregational units (Lee et al., 2008). Therefore, it is important to note that some of the community-level measures employed in this study may operate at lower aggregational levels, even if they do not to have a significant relationship with recidivism at the county-level. While this is an important drawback, this study does benefit the field of criminology by examining how community-level characteristics affect recidivism at the county-level.

***Measurement of Variables*:**

In order to investigate the research questions proposed in this study, it was necessary to construct a multilevel dataset. The different variables from this multilevel dataset are discussed in greater depth below.

Dependent Variable: Recidivism

Official records underestimate the amount of actual criminal offending committed by offenders (Blumstein et al., 1986), mostly because official records do not include either unreported crimes or crimes that do not result in an arrest. Ideally, official records would be supplemented by survey data. However administering a broad scale survey is expensive and time intensive (Travis and Visher, 2005).

Criminal justice actors and researchers have long debated the best way to measure recidivism (Ritter, 1997). There are three commonly used measures of recidivism: rearrest, reconviction, and return to prison. Generally, parolee arrest rates are highest, followed by reconviction rates, followed by return to prison rates (Langan and Levine, 2002). The differences between these three outcomes can be seen in two studies which found that within three years of release from prison, 62 to 67.5 percent of parolees were rearrested, 47 to 49 percent were reconvicted, and 25 to 41 percent were returned to prison for new sentences (Beck and Shipley, 1989; Langan and Levine, 2002, respectively).

Evidence suggests that rearrest and reconviction overestimate recidivism (Langan and Levine, 2002). Specifically, arrest records include arrests in which the offender's charges were later dropped and court records include cases in which the defendant was given probation. On the other hand, the return to prison measure underestimates the amount of criminal activity in which parolees are actually engaged and includes vagaries of the criminal justice system (Travis and Visher, 2005). For example, sentencing may not reflect the actual crime of the defendant and return to prison may reflect policy choices of certain states (e.g., certain states rely more heavily on technical violations than other states).

The present study uses the conservative return to prison measure of recidivism. Because this study examines only one state, the local criminal justice policy on return to prison is more consistent than in studies examining return to prison measures across the United States. Additionally, one problem with using arrest data in recidivism studies is that parolees are often known by the criminal justice agents in their community, and as a result may be arrested more frequently than individuals who have yet to be apprehended and processed by the criminal justice community (Travis and Visher, 2005). In Georgia, approximately 25 percent of the parolees were returned to prison during the two-year study period either for a new offense or a violation of their parole agreement.

Independent Variables: Poverty Variables

The next section examines the measurement of the independent variables – poverty, rurality, and criminal justice resources – used in this study.

Concentrated Disadvantage:

In recent years, one measure of concentrated disadvantage has become the standard indicator of the level of absolute structural poverty within a community. This measure of concentrated disadvantage is an index of five community variables from the U.S. Census: (1) poverty levels, (2) public assistance, (3) unemployment, (4) female-headed families, and (5) percentage black. Following research precedents, an index based on weighted z-scores, divided by the number of items, was created (Morenoff et al., 2001).[18] These variables were highly interrelated and loaded on a single factor using principal components analysis, making this index consistent with other research methodologies that also found high loadings on their factors (Sampson et al., 1997; Morenoff and Sampson, 1997; Sampson et al., 1999; Morenoff et al., 2001).

Because concentrated disadvantage is only one of three variables that constitute social disorganization, residential stability and concentrated immigration are also included as controls in this study. Residential stability is an index based on census

[18] Several studies have used a similar concentrated disadvantage variable created by indexing the factor loadings of the same five variables (Sampson and Raudenbush, 1999; Sampson et al., 1997).

variables measuring the percentage of those who lived in the same house for more than five years and the percentage of owner-occupied housing. Concentrated immigration is an index of the percentage of foreign-born residents and the percentage of Hispanic residents. Both of these indexes are based on z-scores, divided by the number of items.

In order to ensure that the variables composing the three social disorganization indices are highly associated with one another, the factor loadings and reliabilities for these three constructs were created and examined to ensure the stability of the concepts. As can be seen in Table 3, every factor loaded onto the same construct, with all factor loadings higher than .7, which is well above the recommended .41 necessary for these factors given the size of our dataset (Norman and Streiner, 1994). In addition, all three of the reliabilities (Cronbach Alphas) were above .6, which is the social science standard.

Table 3: Reliabilities and Factor Loadings on Social Disorganization Constructs using Principal Components Analysis with Varimax Rotation[19]

Variable	Factor Loadings	Reliabilities
Concentrated Disadvantage		**.642**
(1) Below the poverty line	**.876**	
(2) On public assistance	**.884**	
(3) Female-headed families	**.912**	
(4) Unemployed	**.746**	
(5) Percent African American	**.888**	
Concentrated Immigration		**.933**
(1) Percent Hispanic/ Latino	**.971**	
(2) Foreign Born	**.906**	
Residential Stability		**.712**
(1) Same House as in 1995	**.853**	
(2) Owner-occupied Home	**.802**	

[19] These data were also examined using oblique rotation. The third eigenvalue was just under the standard 1.0 (.958), which prompted concentrated immigration to load with residential stability. However, when these variables were run separately, they loaded in the same patterns as with principal components factor analysis.

Extreme Poverty:

While concentrated disadvantage assesses the different dimensions of poverty, other measures address the extremity of poverty. Jargowsky (1997) measured extreme poverty as a dummy variable with a "1" reflecting those census tracts where at least 40 percent of residents are living below the poverty line. Because the present study is at the county-level, many of the extreme pockets of poverty, which were found to be so influential at lower aggregation levels (Jargowsky, 1997; Stretesky et al., 2004), did not exist at the county-level.[20] Therefore, extreme poverty was first measured at the census tract level and then aggregated to the county-level. Specifically, the number of census tracts in extreme poverty in each county was divided by the total number of census tracts in each county to create a county-level measure of extreme poverty.

Relative Deprivation:

Relative deprivation is measured by Massey's Index of Concentration at the Extremes (ICE). The ICE index subtracts the number of families below the poverty line from the number of wealthy families.[21] Then this difference is weighted by the total number of families in the county (Massey, 2001). The ICE index may range from -1 (extreme poverty) to 1 (extreme wealth). Any value near 0 indicates an equal level of

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[20] Indeed, the county with the highest percentage of residents below the poverty line (28 percent) was still below Jargowsky's 40 percent threshold. This would have resulted in none of this study's counties being classified as having extreme poverty. Therefore, this study examined extreme poverty at the census tract level and aggregated extreme poverty to the county-level, so that extreme poverty reflected the percentage of census tracts in extreme poverty for each county.

[21] Family income in Georgia had a mean of \$50,680.18 and a standard deviation of \$10,754. 'Wealthy' was defined as those families with incomes greater than three standard deviations above the mean; in this case, \$82,942.18. However, the next highest range of family income available from the census was \$100,000 per year. Therefore, \$100,000 was used to define wealthy families in Georgia.

poverty to affluence. Thus, the ICE index measures the proportional imbalance of poverty to affluence within a community.

Racial Inequality:

The racial inequality variable taps into the economic differences between white and black residents of Georgia, in order to understand whether areas with higher racial inequality have a different impact on recidivism than other communities. Racial inequality is a factor composed of the following four ratios: (1) ratio of African American to white recipients of high school diplomas or GEDs (age 25 and older),[22] (2) ratio of African American to white poverty rates, (3) ratio of African American to white unemployment rates, and (4) ratio of white to African American median family incomes.[23]

Principal components factor analysis confirmed that the four variables loaded onto a single racial inequality factor with the following factor loadings: (1) ratio of education (.627), (2) ratio of poverty rates (.754), (3) ratio of unemployment rates (.506), and (4) ratio of family income (.787).[24] The eigenvalue was 1.84, and all of the factor loadings were higher than the recommended .41 (Norman and Streiner, 1994).

Spatial Poverty:

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[22] This educational measure of high school graduates did not include any respondents who went onto pursue post high school education.
[23] The final ratio of median family incomes was reversed, changing it from comparing African Americans to whites, to comparing whites to African Americans. This was done to facilitate interpretation of the factor as the original ratio was negatively related to the other three variables, making interpretation difficult.
[24] Following previous research, this factor used the default Kaiser-Guttman criterion (eigenvalue >1.0) (Reisig et al., 2007). No other factors emerged with eigenvalues that were greater than 1.0.

The proximity to poverty variables also measure poverty, but the focus of these variables shifts from the characteristics of a particular location to the characteristics of the location's surrounding localities. In order to measure diffusion of poverty, spatial lag variables were created to quantify each community's surrounding communities' poverty levels as indicated by each of the following four variables: (1) concentrated disadvantage, (2) extreme poverty, (3) the ICE index, and (4) the racial inequality factor.

Spatial lags for each of the four variables were created by multiplying the poverty variable by its spatial weights matrix. Using GeoDA 0.9.5-I (Beta), which is a free computer program that enables researchers to examine spatial data, a spatial weights matrix was created (Anselin, 2004). This spatial weights matrix was based on the queens criteria, meaning that any counties that share a common border or corner to the county of interest were included in the spatial weights matrix. This matrix is a dummy variable, with "1"s representing the community's spatial neighbors, and "0"s representing the county of interest (i.e., no county can be a neighbor to itself). The matrix is standardized by dividing each row element by its row sum, thus creating the weights. When this resulting spatial weights matrix is multiplied by one of the poverty variables, the new variable represents the average poverty level of counties surrounding the county of interest, or a spatial lag.

In order to measure the spatial poverty variable, it is then necessary to multiply the poverty variable with its spatial lag. This interaction represents poor counties that are clustered together (Stretesky et al., 2004).

Rural/ Urban Measures:

This study examines the following three measures of the urban/ rural continuum: (1) percent rural, (2) population density, and (3) average commuting time to work of county residents. The first measure of percent rural was taken from the U.S. Census Bureau, which tracks the percentage of urban, rural, and rural farmland in each state. The population density variable represents the number of residents in each county divided by each county's square kilometers.

According to the U.S. Census Bureau, a place is deemed rural if it contains a population of less than 2,500 and is not contiguous to an urbanized area, meaning that suburban areas may be classified as rural if they are not immediately contiguous to central cities. In order to control for suburban counties, an additional variables was created based upon the work of Burgess (1925), who noted that as people became wealthy, they moved to the suburbs and commuted into the city for work. Therefore a variable was created to measure the average commuting time of residents in each county, using the assumption that residents of suburban locales would have longer commutes to nearby cities for work than residents of rural or urban areas.[25] Commuting pattern network analysis revealed that suburban centers tended to be less connected than urban areas (Hughes, 1993) and according to one recent study, residents of suburban areas spend more time in their cars than residents of either urban or rural areas (Hu & Reuscher, 2004).

[25] More recently, some have noted that epicenters and business corridors are based in suburban locales (White, 1987). This may mean that this variable is not an effective representation of "suburbaness".

Criminal Justice Resources:

This section on criminal justice resources examines the following three criminal justice variables: (1) presence of parole offices, (2) spatial measure of nearby parole offices, and (3) crime rates.

Parole Offices and Spatial Measures:

In order to control for county parole resources, addresses for the 53 parole offices across Georgia were mapped.[26] Many offices oversaw several counties, and in order to control for the added distance parole officers needed to travel to oversee their parolees, two variables were created to measure: (1) the presence of a parole office in a particular county and (2) a spatially lagged measure of parole offices. The first variable assesses the nearness, and theoretical increased supervision, of a parole office to parolees in that county. The second variable captured the attenuated presence of nearby parole offices located in other counties. As it proved impossible to obtain data on the number of parole officers or caseloads per parole office, the spatially lagged parole office variable accounts for the attenuated oversight provided by nearby parole offices in next-door counties.[27]

UCR Crime Data:

In order to control for communities with exceptionally high crime rates and better understand the relationship between crime rates and parolee recidivism, a crime rate variable was constructed from the Uniform Crime Reports (UCR, 1999, 2000, 2001). Three years of UCR data were averaged into a single crime rate that yields more stable

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[26] The parole office addresses were accessed from records from the GBPP in 2004.
[27] Attempts were made to call individual parole offices to ascertain the number of employees per office. However, many departments do not have answering services or regular hours and others did not return repeated phone messages.

crime rates across the counties, which is important as some counties have very small populations (Wilkinson, 1984a; Lobmayer and Wilkinson, 2002).

This crime rate represents the indexed crime rate per 100,000 persons (Biderman and Lynch, 1991; O'Brien 1985). Maltz and Targonski (2002) pointed out that the county population estimates in the UCR contain serious discrepancies; therefore the county population from the U.S. Census Bureau was used in its place (Park, 2007).[28] In total, there are eight indexed crime types: (1) murder, (2) rape, (3) robbery, (4) aggravated assault, (5) burglary, (6) larceny, and (7) motor vehicle theft, and (8) arson. However, for the purposes of this study, only the first seven types of indexed crimes were used, as is recommended by Gove et al. (1985).[29] Although arson crimes became indexed crimes in 1979, it is a difficult crime to measure reliably because arson does not fall wholly under police jurisdiction (i.e., fire departments also have jurisdiction) and at least one study found that arson reporting varied considerably by region across the United States (Jackson, 1990).

Individual Parolee Demographics:

A great deal of research focuses on the individual-level predictors of recidivism. Generally, parolees' likelihood of recidivism can be estimated by calculating their risk

[28] Maltz and Targonski (2002) outlined three discrepancies in UCR population differences: (1) double counting of agency population, (2) different estimates of agency populations, and (3) agencies with overlapping jurisdictions.

[29] Gove et al. (1985) assessed the validity of the seven UCR crime measures. Although the National Crime Survey (NCS) was found to uncover more crimes, Gove found that the UCR was an excellent representation of "relatively serious crimes" and suggested that the UCR crimes are a good measure of "what the citizens and police perceive as violations of the law which pose a significant threat to social order (Gove et al., 1985: 490)." In particular, Gove et al. (1985) reviewed studies that found rates of murder, motor vehicle theft, robbery, burglary corresponded (e.g., bivariate correlations) consistently with the rates in the NCS. Aggravated assault, rape, and larceny also corresponded with the rates in the NCS, but there are higher levels of underreporting for all three of these crimes in the NCS. Gove et al. (1985) maintained that if the UCR is seen as a measure of society's most serious crimes, then this underreporting is acceptable.

factors (e.g., criminal history), criminogenic need (e.g., drug or alcohol addiction), demographic characteristics (e.g., race and gender), and the effects of having served time in prison (e.g., lowered or unstable employment opportunities).

Three variables measure parolees' risk factors. The first variable is a risk score assigned by the Georgia Department of Corrections (DOC) that relies on a point scale to assess minimum, medium, and maximum risk offenders.[30] The second variable measures the number of prior incarcerations a parolee had in his/ her criminal career according to Georgia DOC's records. Finally, the Wide Range Achievement Test (WRAT) reading score, reflecting the approximate level of reading attainment by grade, was included (Jastak, 1993).

To measure criminogenic need, a drug and alcohol usage variable was created from the drug and alcohol tests given to parolees as a condition of their parole over a two-year period. The variable is coded to reflect the number of times a parolee failed his or her drug and alcohol test.

Although race and gender are not always consistent predictors of recidivism (Gottfredson and Gottfredson, 1994), they were included as control variables. Unfortunately, the GBPP records only whether the parolee is white or non-white, which is a blunter measure than this study would have wished. Race was dummy coded to reflect white parolees and gender was coded to reflect men. In addition, parolees' ages were also included.

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[30] The risk score was calculated using the LSI-R tool which is compoised of 54 items spanning the following ten areas believed to be related to future criminal behavior: (1) criminal behavior, (2) education and employment, (3) financial, (4) family and marital, (5) accommodations, (6) leisure and recreation, (7) companions, (8) alcohol and drugs, (9) emotional and personal, and (10) attitude and orientation. Although these 54 items from the LSI-R are similar to other independent variables used in this study (e.g., any prior convictions, an alcohol problem ever), there is not a perfect correspondence between the independent variables in this study and any of the LSI-R items.

The final measure is designed to tap into the effects of having served in prison. It is known that having been incarcerated decreases one's employment opportunities (Pager, 2003) and chances for steady employment (Western and Beckett, 1999). Therefore, a count variable was created to measure the number of jobs parolees held during the course of this study.

The next chapter examines the study variables in further detail, using descriptive statistics, bivariate correlations, and illustrative maps of key variables. This is followed by a short description of missing data and the analytic techniques used in this study.

CHAPTER 5:
DESCRIPTIVE RESULTS

In the next five sections, this chapter examines the descriptive statistics and preliminary analytic techniques used in the current study. First, this study examines the descriptive statistics for individual-level and community-level variables included in the final models. Secondly, using GIS to create maps of the geographic area, this study examines the dependent variable of recidivism and how it relates spatially to the counties in which parolees cluster after release from prison. Thirdly, this study examines bivariate correlations for individual-level and community-level variables. Fourthly, because there were missing data, a short discussion on the missing data techniques employed in this study is included. Finally, this chapter concludes with a discussion of the analytical techniques and models used in this study to estimate the final models.

***Descriptive Statistics*:**

Table 4 presents descriptive statistics for the individual and community-level variables. These variables were examined for normality using histograms.[31] Among the individual-level variables, all of the variables were positively skewed. This study followed the recommended approach of not transforming variables in conditions where the variables share the same approximate distribution (Tabachnick and Fidell, 1996). If all the variables for analysis have the same degree of skewness and in the same direction,

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[31] When sample sizes are smaller (i.e., fewer than 100 cases), one can assess the z-scores of the distributions to determine whether the extent of skewness is significant. This study examined the z-scores for the grouped data of parolees by county and found that all of the variables had significant skewness. However, since the number of grouped cases (N=159) exceeded the guideline of 100 cases, visual inspection of skewness is more appropriate than formal inference testing (Tabachnick and Fidell, 1996).

transformation at best provides only minimal improvements of analysis.[32] Additionally, given the large sample size in this study (N=18,013), the central limit theorem (CLT) suggests that skewness is not a significant problem as the data will begin to approximate a normal curve.

The dependent variable of recidivism had a mean of 25 percent, meaning that within two years of release from prison approximately 25 percent of the parolees were returned to prison. It is important to note that recidivism varied greatly across counties; in eight counties no parolees were returned to prison while in one county 67 percent of parolees were returned to prison.

When examining the individual-level predictor variables, one sees that many of the parolees varied in their risk level for being returned to prison. On average, parolees in Georgia had committed 2.25 previous crimes, although 3 percent of parolees had never committed any previous crimes and one parolee committed 14 previous crimes. The average parolee in Georgia had also failed more than one drug and alcohol test (mean=1.22), and one parolee failed 42 drug and alcohol tests.

The average risk score for parolees was 201.31, which is in the "minimum" range for this variable.[33] The average WRAT reading score was 7.50, meaning that most parolees were between a 7^{th} and 8^{th} grade reading level. In addition, one can see that parolees were not a stable population in terms of employment. On average, parolees held approximately four jobs, and one parolee held as many as 46 jobs over two years.

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[32] Additionally, transforming variables often makes it difficult to interpret statistical results (Tabachnick and Fidell, 1996). For example, if parolee risk scores were positively skewed and a researcher transformed the risk score variable, then the resulting relationship between risk scores and the outcome of recidivism would no longer adhere to the number of risk points created by the Georgia Board of Pardons and Paroles, thereby rendering interpretation difficult.

[33] According to the GBPP, the Risk Scores point system is as follows: (1) Minimum Risk Scores are lower than 362, (2) Medium Risk Scores are between 362 and 579, and (3) Maximum Risk Scores are 579 and higher.

Finally, across the parolee population, 31 percent of parolees in Georgia were white and 89 percent of parolees were men. The average age of parolees was 37 years.

The community-level variables could be examined at either the county-level or at the individual-level (i.e., merging the community-level data with the parolee dataset). This latter approach was chosen because more information about the types of communities in which parolees reside would be provided. For instance, because concentrated disadvantage was created from an index of z-scores, the mean of concentrated disadvantage across the community-level data was zero. However, the mean of concentrated disadvantage across the community-level data merged with the parolee data was .09, which means that parolees were not evenly distributed across communities (or else the mean would be zero), and in fact, parolees tended to live in communities with slightly higher concentrated disadvantage.

Table 4: Descriptive Statistics

Variable Name	N	Min.	Max.	Mean	Std. Dev.
Dependent Variable					
(1) Recidivism	**18,013**	**0.00**	**1.00**	**0.25**	**0.44**
Individual-Level Variables					
(1) Alcohol & Drug Use	**18,013**	**0.00**	**42.00**	**1.22**	**2.36**
(2) Risk Scores	**17,845**	**35.00**	**651.00**	**201.31**	**74.69**
(3) WRAT Reading Score	**16,039**	**0.00**	**80.20**	**7.50**	**3.99**
(4) Number of Priors	**18,006**	**0.00**	**14.00**	**2.25**	**1.59**
(5) Number of Jobs	**18,012**	**1.00**	**46.00**	**4.04**	**3.10**
(6) Race	**17,845**	**0.00**	**1.00**	**0.31**	**0.46**
(7) Gender	**17,845**	**0.00**	**1.00**	**0.89**	**0.31**
(8) Age	**17,844**	**20.00**	**92.00**	**37.15**	**9.49**
Community-Level Variables N=159					
(1) Concentrated Disadvantage	**18,013**	**-1.66**	**2.43**	**0.09**	**0.80**
(2) Concentrated Immigration	**18,013**	**-.86**	**4.73**	**0.57**	**1.24**
(3) Residential Stability	**18,013**	**-5.21**	**1.42**	**-0.76**	**0.88**
(4) Extreme Poverty (40%)	**18,013**	**0.00**	**0.28**	**0.06**	**0.08**
(5) Relative Deprivation (ICE)	**18,013**	**-0.23**	**0.31**	**0.01**	**0.11**
(6) Racial Inequality	**18,013**	**-4.01**	**3.98**	**0.09**	**1.10**

(7) Con. Dis. Spatial Lag	**18,013**	**-1.24**	**1.73**	**-0.21**	**0.62**
(8) Extreme Poverty Spatial Lag	**18,013**	**0.00**	**0.10**	**0.02**	**0.02**
(9) ICE Index Spatial Lag	**18,013**	**-0.19**	**0.14**	**0.00**	**0.09**
(10) Racial Inequality Spatial Lag	**18,013**	**-1.27**	**0.94**	**0.05**	**0.45**
(11) Percent Rural	**18,013**	**0.00**	**1.00**	**0.33**	**0.30**
(12) Population Density	**18,013**	**3.28**	**958.56**	**239.43**	**282.23**
(13) Average Commuting Time	**18,013**	**15.10**	**41.48**	**27.04**	**5.03**
(14) Parole Office	**18,013**	**0.00**	**4.00**	**0.97**	**0.99**
(15) Parole Office Spatial Lag	**18,013**	**0.00**	**1.50**	**0.46**	**0.47**
(16) Crime Rate	**18,013**	**0.00**	**0.09**	**0.05**	**0.02**

The community-level variables varied considerably across counties. Concentrated disadvantage ranged from -1.66 to 2.43, with an average of .09, suggesting that on average parolees lived in communities with slightly higher levels of concentrated disadvantage. Extreme poverty ranged from 0 to 28 percent, with a mean of 6 percent. Thus, on average, parolees lived in counties in which 6 percent of the census tracts had 40 percent or more of residents living below the poverty line.

The ICE index ranged from -.23 (poverty) to .31 (wealth). The ICE index's mean was .01, which indicates that the average parolee lived in a community with approximately equal amounts of poverty and wealth. Finally, the racial inequality variable's mean was .09, with a standard deviation of 1.10, meaning that any county with racial inequality measuring below -1.01 and above 1.19, was more than one standard deviation away from the mean. With the racial inequality's range varying from -4.36 to 4.05, it was apparent that a number of counties had high levels of racial inequality.

The final four poverty variables are spatial lags. With a mean of -.21, the concentrated disadvantage spatial lag indicated that counties were typically surrounded by counties with lower levels of concentrated disadvantage than the original county of interest. The extreme poverty spatial lag indicated that counties bordered counties with an average rate of two percent of extreme poverty. The ICE index spatial lag (mean =

0.0) revealed that counties were generally surrounded by counties that have low levels of relative deprivation (i.e., counties with comparable levels of wealth and poverty). Finally, the racial inequality spatial lag had a mean of .05 and a range of between -1.27 and .94, which suggests that on average, counties were surrounded by other counties that were within one standard deviation of the racial inequality variable's mean.

In total, 33 percent of counties in Georgia were defined by the U.S. Census Bureau as "rural," with some counties entirely rural and others entirely urban. Population density per square kilometer ranged from 3 to 958 people, with an average density of 234 people. Residents of Georgia spent an average of 27 minutes commuting to work, although in some counties people averaged as little as 15 minutes, while in other counties people averaged 42 minutes of commuting.

There were a total of 53 parole offices distributed across Georgia. In the Atlanta area alone, there were four parole offices, while many counties had no parole offices and were covered by parole offices from nearby counties. The spatial lag for parole offices ranged from 0 to 1.5, which means that some counties did not neighbor a parole office, while other counties had one or more parole offices as neighbors. It is important to note that a county with no neighboring parole offices may in fact contain a parole office itself. This is one reason why when examining spatial lags, one should also include the original variable of parole office presence, its spatial lag, and their interaction. Finally, crime rates varied from 0 to 9 percent (Atlanta), with the average county crime rate of 5 percent.

The next section addresses the spatial aspects of recidivism by presenting maps of the cities in Georgia, the locations of parolees and the locations of where parolees committed crimes that caused their return to prison. Appendix A provides additional maps of several of the independent variables used in this study.

Maps of Parolees and Recidivism in Georgia:

Figure 1 depicts the major cities (populations > 10,000 residents) in Georgia. As can be seen, most of the larger cities are located in the northern part of the state, with the exception of a few large coastal cities (e.g., Savannah, Brunswick) in the southern coastal region. Atlanta is the largest city in Georgia, with a population of 416,474 residents in 2000.

Figure 2 illustrates the number of parolees throughout Georgia standardized by the total population in each county. Counties in eastern and southwestern Georgia appeared to have had the highest concentrations of parolees. However, in examining the map illustrating recidivism rates of parolees (Figure 3), the largest rates of recidivism did not correspond with the areas that had the highest percentages of resident parolees. Indeed, most counties appear to have had an average parolee recidivism rate of between 15 and 30 percent, with several pockets of severe recidivism distributed across the state. When bivariate correlations were calculated for parolee recidivism rates and the percentage of resident parolees, the correlation was low but significant ($r = .18$; $p < .05$).

Figure 1: Major Cities in the State of Georgia

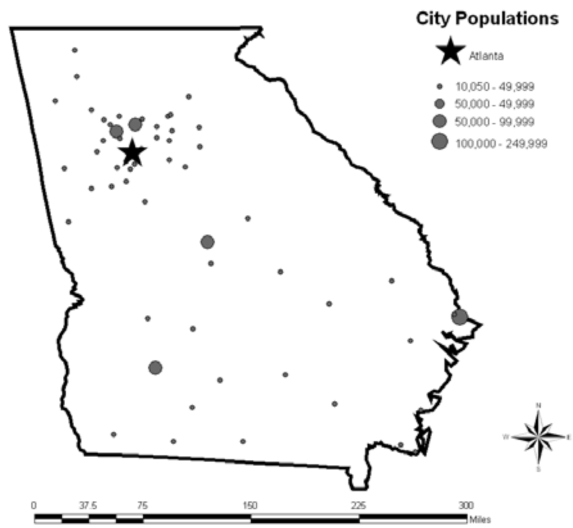


Figure 2: Percentage of Parolees in the Population

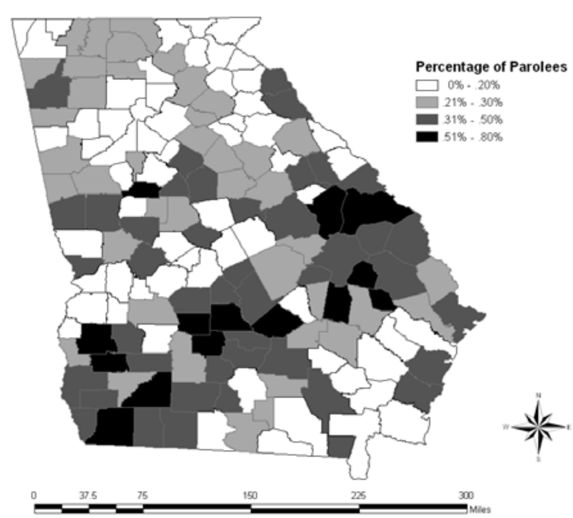
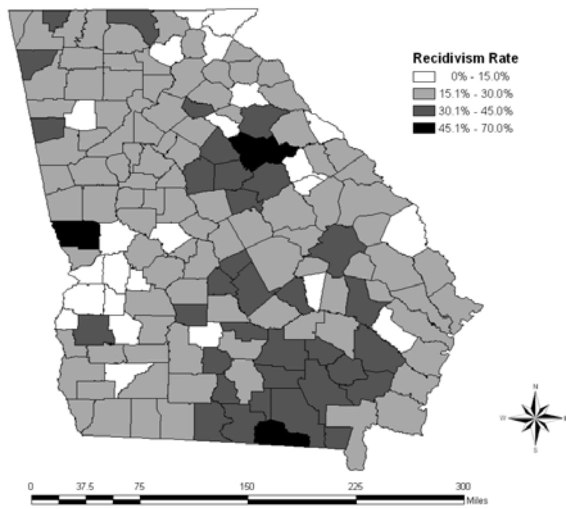


Figure 3: Recidivism Rates of Parolees in Georgia



The next section presents bivariate correlations of parolee and community characteristics, which is an important precursor to developing the final models for analysis.

***Bivariate Correlations*:**

Table 5 presents the bivariate correlations for the individual-level independent and dependent variables in this study (a key appears below the table). The dependent variable of recidivism was moderately correlated with only two variables – risk score (r = .45) and number of priors (r = .40). The remaining independent variables were not highly correlated with recidivism.[34]

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[34] There was also a high correlation between parolee risk scores and the number of priors (r = .55). This high correlation was further examined with Variance Inflation Factors (VIFs), which found that neither risk scores (VIF = 2.48) nor number of priors (VIF = 2.35) were too high to be included in the same model.

Table 5: Correlation Matrix of Dependent and Individual-Level Independent Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	1.00								
(2)	.09 ***	1.00							
(3)	.45 ***	.11 ***	1.00						
(4)	.00	-.02 *	-.02 *	1.00					
(5)	.40 ***	.08 ***	.55 ***	-.07 ***	1.00				
(6)	-.01	.22 ***	.12 ***	.04 ***	-.02 *	1.00			
(7)	-.07 ***	-.09 ***	-.06 ***	.24 ***	-.05 ***	.02 *	1.00		
(8)	.05 ***	.03 ***	.05 ***	-.09 ***	.07 ***	.03 ***	-.04 ***	1.00	
(9)	-.10 ***	-.06 ***	-.30 ***	-.13 ***	.18 ***	-.20 ***	.07 ***	-.05 ***	1.00

*** p<.05; ** p<.01; *** p<.001**

(1) Recidivism	(4) WRAT Reading Score	(7) Race
(2) Alcohol & Drug Usage	(5) Number of Priors	(8) Gender
(3) Risk Score	(6) Number of Jobs	(9) Age

Table 6 presents the community-level correlations among the independent variables representing poverty, rurality, and criminal justice resources (a key appears below the table). These community correlations are presented separately from the individual-level correlations, in order to examine the correlations between the variables at their true aggregation level (i.e., community).

Cohen (1988) suggested that correlations higher than .50 (or lower than -.50) are large, although he cautioned that this categorization was somewhat arbitrary and one should always consider the nature of the relationships examined. Among the poverty variables, concentrated disadvantage was highly correlated with relative deprivation (r = -.72), racial inequality (r = .55), concentrated disadvantage spatial lag (r = .70), and relative deprivation spatial lag (r = -.58). This pattern suggests that although many of the theories concerning poverty are theoretically distinct, empirically, these community-level variables have high correlations.[35]

Additionally, several variables had strong levels of correlation between different theoretical variables. For example, extreme poverty was highly correlated with crime rates (r = .52); relative deprivation was highly correlated with population density (r = .52); and population density was highly correlated with parole offices (r = .50).

Table 6: Correlation Matrix of Community-Level Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	1.00											
(2)	-.20 *	1.00										
(3)	-.01	-.46 ***	1.00									
(4)	.26 ***	.02	-.43 ***	1.00								
(5)	-.72 ***	.26 ***	-.24 **	-.00	1.00							
(6)	.55 ***	-.20 *	.03	.17 *	-.24 **	1.00						
(7)	.70 ***	-.25 ***	.15	.02	-.54 ***	.49 ***	1.00					
(8)	.04	.04	.05	-.05	.01	.00	.26 ***	1.00				
(9)	-.58 ***	.25 ***	-.24 **	-.01	.76 ***	-.33 ***	-.74 ***	-.06	1.00			
(10)	.02	-.03	-.07	-.02	.02	-.10	.04	-.09	-.02	1.00		
(11)	.00	-.37 ***	.68 ***	-.42 ***	-.44 ***	.01	.16 *	-.02	-.34 ***	-.11	1.00	
(12)	-.11	.46 ***	-.48 ***	.27 ***	.52 ***	-.08	-.28 ***	.05	.58 ***	.06	-.63 ***	1.00
(13)	-.35 ***	-.09	.34 ***	-.30 ***	.35 ***	-.20 *	-.28 ***	.08	.53 ***	-.05	.27 ***	.16 *
(14)	.04	.29 ***	-.48 ***	.41 ***	.26 ***	.06	-.18 *	-.08	.27 ***	-.06	-.55 ***	.50 ***
(15)	-.27 ***	.16 *	-.04	-.07	.45 ***	-.12	-.20 *	.25 **	.49 ***	-.13	-.16 *	.44 ***
(16)	.18	.18	-.49	.52	.15	.11	-.11	-.06	.21	-.01	-.64	.43

[35] There are also other strong correlations within rurality variables, with rurality highly correlated with density (r = -.63).

	*	*	***	***					**		***	***

	(13)	(14)	(15)	(16)
(13)	1.00			
(14)	-.15	1.00		
(15)	.40 ***	.03	1.00	
(16)	-.33 ***	.55 ***	-.01	1.00

*** p<.05; ** p<.01; *** p<.001**

(1) Concentrated Disadvantage	(7) Con. Dis. Spatial Lag	(13) Average Commuting Time
(2) Concentrated Immigration	(8) Extreme Poverty Spatial Lag	(14) Parole Offices
(3) Residential Stability	(9) Relative Dep. Spatial Lag	(15) Parole Offices Spatial Lag
(4) Extreme Poverty (40%)	(10) Racial Inequality Spatial Lag	(16) Crime Rate
(5) Relative Deprivation (ICE)	(11) Percent Rural	
(6) Racial Inequality	(12) Population Density	

These high correlations suggest that not only should poverty variables be examined in separate models, but that poverty variables should also be examined independent of rurality and criminal justice resource variables. In order to assess whether these community-level predictors were collinear, variance inflation factors (VIFs) were calculated.

VIFs are a ratio of coefficients that assess the predictability of an independent variable by another independent variable. The generally accepted cutoff point for VIF scores is above 10 (Neter et al., 1996: 387), although some have suggested that a better cutoff point would be above 4 (Fox, 1991). No variable emerged with a VIF score over the threshold of 10, although there were five variables with high VIFs, including: (1) concentrated disadvantage (7.09), (2) relative deprivation (7.27), (3) the concentrated disadvantage spatial lag (5.43), (4) the relative deprivation spatial lag (7.98), and (5) rurality (4.07).

These correlations and VIFs, while not overly worrisome, do suggest the wisdom of testing hypotheses individually using a series of models in order to ensure that moderately correlated variables are examined in separate equations (Land et al., 1990). To minimize this potentiality, this study opted to test each hypothesis separately, with one exception. Of the five spatial lags, two were strongly correlated with the variable from which they were created.[36] Yet, the main poverty variable, its spatial lag, and an interaction between the two variables were necessarily included in the same model because these three variables were necessary to test spatial measures of poverty.

Statistical Methods:

The following two sections address the missing data techniques that were employed and the reasons why hierarchical linear modeling was used in this study.

Missing Data Techniques:

One of the first analytic issues in this study was missing data. Although there was no missing data at the county-level, almost 11 percent of parolee records had missing values. Missing data is a serious issue because it reduces power (Fichman and Cummings, 2003) and it may threaten internal and external validity of statistical inferences (Allison, 2002).

Presently, multiple imputations is the best available missing data technique available for replacing missing data (Allison, 2002), dealing with dichotomous or categorical missing data (Schafer, 1997), and replacing non-normal missing values (Enders, 2001). Simulations of missing data techniques have shown that multiple

[36] Concentrated disadvantage was highly correlated with its spatial lag (r = .70) and relative deprivation was highly correlated with its spatial lag (r = .76).

imputations outperforms other missing data replacement techniques (Chen and Astebro, 2003), even given different patterns of missing data (Fichman and Cummings, 2003).

Rubin (1987) proposed the technique of multiple imputations and listed five steps necessary to conduct them. First, it is necessary to impute missing values with an appropriate model that includes random variation. Second, this multiple imputation process is repeated to create the desired number of datasets. Third, the statistical analyses are performed on each of the multiply imputed datasets. Fourth, the values of the parameter estimates are averaged across the five imputed datasets. Finally, the standard errors and variance are calculated across the five imputed datasets.

For this study, multiply imputed datasets were created in SAS 9.1 and analyzed in HLM 6.0. Five datasets were created in SAS 9.1 with missing values filled in with plausible values for the missing observations based on the multiple imputations algorithm. In recent years, researchers have shown that five imputed datasets are usually more than adequate for multiple imputations, and often two or three imputations are sufficient for correct statistical inferences (Fichman and Cummings, 2003). In HLM, each set of data was analyzed and in the final step, the results were combined across the five datasets for a single set of parameter estimates and standard errors.

Multilevel Analyses:

This study involves a hierarchical dataset, with individuals nested within their counties. Multilevel modeling becomes necessary when the data are of a nested nature. Because one of the goals of this study was to better understand individual parolees' likelihood of recidivism within the county context, hierarchical linear modeling (HLM) was employed to overcome some of the biases that might occur were the data to be examined collectively.

There are at least three potential problems that HLM helps researchers to overcome. First, aggregation bias can sometimes occur when a variable assumes different meanings at the individual and community levels. Secondly, HLM also allows one to model the heterogeneity of regression coefficients, meaning that one is able to see how the relationships between individuals' outcomes and their demographic and social characteristics vary across the aggregate units of their communities. For example, it is possible that the effect of having recently been released from prison may affect the likelihood of moving into some counties, but not into others. Finally, HLM helps to correct for the effect of misestimated standard errors that may occur when individual observations are correlated within the aggregate county-level data. Thus, HLM helps to control for spatial autocorrelation, by controlling for the probability that "like" people live near other "like" people, and may in turn influence their neighbor's actions.

The next chapter examines the type of hierarchical linear model chosen to perform the analyses and the variance estimates of the analyses. Finally, the results from the analyses are presented.

CHAPTER 6:
MULTIVARIATE RESULTS

In this chapter, the models and results are presented in four sections. First, the unique nature of the dependent variable and the hierarchical logistic regression model used to overcome limitations of this dependent variable are discussed. Second, the model equations are examined. The third section considers results from the unconditional model and the individual-level models. Finally, the results from the analyses examining the relationships between recidivism and the three primary theoretical variables – poverty, rural/suburban, and criminal justice resources – are discussed.

Hierarchical Logistic Regression Models:

This study's dependent variable, recidivism, indicated whether or not a parolee was returned to prison within two years of release from prison. Because the dependent variable is dichotomous, all of the parolees were assigned either a zero (i.e., not returned to prison) or a one (i.e., returned to prison). This coding precluded a linear relationship between recidivism and the independent variables (e.g., community poverty, urban areas, parole offices).

Using a standard linear HLM model would have been inappropriate because a linear model allows the predicted values for the dependent variable to assume any real value and assumes a normal distribution, neither of which is possible for a dichotomous outcome variable. To overcome this, HLM 6.0 software allows one to select a nonlinear analysis, or a hierarchical generalized linear model (HGLM), which is appropriate for this study's discrete, bimodal dependent variable (Bryk et al., 2005).

It is important to note that while ordinary linear HLM equations for level 1 variables include an error term, because logistic regression requires one to take the odds of a variable occurring, an error term at level 1 is unnecessary. In standard HLM models, homogeneous level 1 variance is assumed. However, this study's HGLM model had heteroskedastic variation. Hence, there was not a single level 1 variance component in this or other nonlinear models, although there was still an error term in the level 2 equation.

The next section examines the equation models and discusses the strategy for analyzing this study's hypotheses. In total, there were three distinct steps in building these analytical models: (1) estimation of the unconditional model, (2) an examination of the effects of models with parolee variables, designed to control for individual-level effects, and finally, (3) a look at the full models with both individual and the theoretically-driven county-level variables. All of this study's hypotheses were tested in this later section.

Equation Models:

Generally, this study was concerned with examining both the proportion of explained variance and the statistical relationships between variables. The first two steps in these analyses – estimating the unconditional and the parolee level models – were performed with the primary goal of better describing the proportion of explained variance, which is one measure of how important significant findings are in comparison to one another.

First, an unconditional model determined the overall level of county variance before explanatory variables were examined. Second, in order to control for individual parolee characteristics, the following eight individual-level control variables were added to the model: (1) alcohol and drug use, (2) risk score, (3) WRAT reading score, (4) number of prior convictions, (5) number of jobs, (6) race, (7) gender, and (8) age.

The third step involved adding the hypothesized county-level variable measuring poverty, rural areas, or criminal justice resources at level 2. In this step, significant relationships were examined and compared with one another. Because each county-level variable measured a single hypothesis and the multicollinearity between these county-level variables precluded them from being examined together, a series of separate regression models were run in order to test each county variable. Additionally, by examining these models separately, it was possible to identify increases (or decreases) to the proportion of explained variance and then compare these variance measures across models. The following equation illustrates the statistical model used in these analyses.

$$\eta(Recidivism)_{ij} = \beta_{0i} + \beta_{1i}(Alcohol\,/\,Drugs)_{ij} + \beta_{2i}(Risk\ Scores)_{ij} + \beta_{3i}(WRAT\ Scores)_{ij} + \beta_{4i}(No.of\ \ Priors)_{ij} + \beta_{5i}(No.of\ \ Jobs)_{ij} + \beta_{6i}(Race)_{ij} + \beta_{7i}(Gender)_{ij} + \beta_{8i}(Age)_{ij}$$

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(County\ Characteristic)_j + u_{0j}$$

All of the independent variables were grand mean centered, meaning that any county-level coefficient represented the additional average level of recidivism from that variable, controlling for individual-level and county-level differences. Grand mean centering was chosen in order to ease the translation of the log-odds findings into odds ratios when examining statistical interactions (Hox, 2002).[37]

[37] When interpreting statistical interactions, grand mean centering can ease interpretation. Grand mean centering is a technique that centers predictor variables on their respective means, thereby removing effects of individual predictor variables on the outcome variables. Thus, when examining statistical interactions,

Multilevel modeling allowed for the estimation of individual-level and county-level error terms, which allowed independent variables to vary across counties. For example, if an error term was included for a parolee-specific variable, then that parolee variable could vary across counties. Because this study focused on the hypothesized relationships between county-level variables and the dependent variable, this study used a fixed effects model, meaning that no error terms were placed at the individual-level.[38] A random error term was included at the county-level intercept. This random error term ensured that only the intercept would vary across counties, while the individual-level variables were fixed across counties.

There was one exception to the fixed effects models. For this study's examinations of racial inequality, the population of minority parolees was examined separately in Table 12. When these three models were examined with a fixed effects model, the variance components increased, which resulted in negative proportions of explained variance. Several authors have noted that proportions of explained variance can be negative in HLM models and that negative variation does not necessarily signify a misspecified model (Snijders and Bosker, 1994; 1999; Hox, 2002). However, after the random slopes were tested and a suggested diagnostic that also acts as a measure of the proportion of explained error was calculated, it was clear that the models benefited from the addition of random slopes (see Appendix B for the final results of the diagnostic

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grand mean centering enables one to focus solely on the interaction and ignore other explanatory variables in the model.

[38] Although the fixed effects model was chosen for theoretical reasons, full models (i.e., models with random slopes and intercepts) were examined to ensure that these models were properly specified. Only one of the individual-level slopes, parolee age, had significant variation ($p < .05$). Models were examined with and without the constrained slope for parolee age and the resulting models were not significantly impacted by the additional variance term for parolee age. Therefore, the final models excluded this random slope for age on both theoretical and empirical grounds.

measures). Therefore, the minority parolee models included two individual-level variable slopes that were allowed to vary. This was the only exception to the fixed effects model.

The next step in this study assesses the unconditional model of parolee recidivism, which helped determine the amount of variance explained by the county-level.

Unconditional Model:

The first step in any multivariate analysis is to estimate the unconditional model, or null model, in order to determine how much between county-variance exists in the recidivism outcome. In the following equation, γ_{00} represents the average level (log-odds) of recidivism across counties, and τ_{00} represents the variance of recidivism between counties.

$$\text{Logit (recidivism)} = \beta_{0j} = \gamma_{00} + u_{0j}, \text{ where } u_{0j} \sim N(0, \tau_{00})$$

The results of the unconditional model indicated that the average level of recidivism was -1.085, meaning that parolees started out with a low log-odds of recidivating. Additionally, the null model indicated there was significant between-county variation in recidivism (u_{0j}=.048; p=.001). The significant error term suggested that it was necessary to control the between-county variation in recidivism, meaning that some counties had significantly different levels of variance in the dependent variable of parolee recidivism than other counties.

The intraclass correlation (ICC) is the preferred tool for assessing how much of the variance in the dependent variable was due to the county in which parolees live. Usually, it is necessary to have both the county-level and the individual-level variance components to compute the ICC. However, as noted earlier, the individual-level variance in a logistic model is assumed under the odds function. By assuming that the level 1 equation has a standard logistic distribution with a mean of 0 and a variance of $\pi^2/3$, it is possible to calculate the ICC (Long, 1997; Reisig et al., 2007; Becker et al., 2006; Snijders and Bosker, 1994).

The ICC for the unconditional model was 1.5 percent, which means that only 1.5 percent of the total variation in recidivism was between counties. Although this percentage may seem small, researchers have found that neighborhood effects are often small in magnitude (Elliott et al., 1996; Leventhal & Brooks-Gunn, 2000). Additionally, some researchers have shown that medium effect sizes can translate into small neighborhood effects, or proportion of variance that explained by county of residence (Duncan and Raudenbush, 1999).[39]

In the next section, parolee-level variables were added to the previous model to investigate the relationships between parolee characteristics and recidivism. The variance components from this model also helped to clarify the amount of between-county variation explained by the types of parolees who live in different counties.

Individual-Level Model: Parolees' Backgrounds and Characteristics

In Table 7, all eight parolee characteristics were found to be significantly related to recidivism, although some variables were related to recidivism in unexpected directions. Because the logit coefficients for this model were log odds, which are

[39] Effect sizes are used to measure the strength of a relationship between two variables. Once one has determined that a statistical relationship is significant, it is useful to also know whether this relationship is sizeable, that is, whether it matters in a practical sense. According to Cohen (1992), an effect size of .2 would be a small effect size, .5 would be a medium effect size, and .8 would be a large effect size. Even though Cohen cautioned against such simplistic cut off points, they are widely used today.

difficult to interpret, the analyses in this study focused on the more understandable odds ratios.

Recidivism was significantly higher among parolees who had higher risk scores and more priors. Indeed, for every standard deviation increase in parolee risk scores, parolees increased their odds of being returned to prison by 111 percent, and for every standard deviation increase in the number of prior crimes, parolees increased their odds of being returned to prison by 105 percent. These results are consistent with previous research indicating the importance of parolees' criminal history in understanding future offending (Gottfredson and Gottfredson, 1994; Gendreau et al., 1996).

The WRAT reading score represents the equivalent number of years of education at which the parolee reads. Therefore, it was surprising to find that for every additional WRAT reading year of education, parolees multiplied their odds of being returned to prison by 1.03 times. However, research has shown that the WRAT reading score is a poor predictor of recidivism (Benda, 2001). Further, the mean difference between the parolees who recidivated (mean=7.52) and those who did not recidivate (mean=7.51) was small, and the Cohen's d effect size was zero.

On average, an increase of one standard deviation in the number of drug and alcohol tests failed by parolees increased parolees' odds of returning to prison by 14 percent, while a standard deviation increase in the number of jobs a parolee held over two years decreased parolees' odds of being returned to prison by 17 percent. As sobriety and employment are often conditions of parole, this finding was consistent with parole terms (Piehl and LoBugilo, 2005). Additionally, substance abuse history has been shown to be one of the most important predictors of recidivism (Gendreau et al., 1996), and former criminals who establish employment post-release are less likely to reoffend (Laub and Sampson, 2001).

Finally, white and older parolees were less likely to recidivate, while male parolees were more likely to recidivate. These findings were also consistent with other recidivism studies (Kubrin and Stewart, 2006; Reisig et al., 2007).

Table 7: Hierarchical Logistic Regression Models Predicting Parolee Recidivism (Standard Errors in Parentheses)

	Model 1: Level 1 Individual Parolee Characteristics		
	B	S.E.	Exp(b)
Individual-Level Controls			
Alcohol & Drug Usage	.055***	(.008)	1.06
Risk Scores	.010***	(.000)	1.01
WRAT Reading Score	.025***	(.005)	1.03
Number of Priors	.451***	(.017)	1.57
Number of Jobs	-.061***	(.007)	.94
Race	-.269***	(.051)	.76
Gender	.157*	(.072)	1.17
Age	-.037***	(.003)	.96
Intercept	-1.352***	(.032)	
Level 2 Error Term	.043		

*p<.05; **p<.01; ***p<.001

The results of the individual-level model indicated that there was significant variation in between-county recidivism, meaning that individual-level parolee characteristics helped to explain a notable proportion of the variance in recidivism. Comparison of the variance components for the null model and model 1 indicated that 10.4 percent of recidivism was explained by parolee characteristics varying between counties.[40] Although a significant amount of variation in recidivism was explained by individual parolee characteristics, there remained a sizeable amount of variation that may be explained by county-level variables.

Community-Level Models:

The next section examined the seven hypotheses that this study outlined in Chapter 3. Specifically, this section analyzed the relationship between recidivism and county-level contextual measures of poverty, rural areas, and criminal justice resources, having controlled for individual parolee characteristics. Among the poverty models, this study examined five different theoretical approaches to measuring poverty: (1) concentrated disadvantage, (2) extreme poverty, (3) relative deprivation, (4) racial inequality, and (5) spatial proximity to poverty.

Poverty Models: Concentrated Disadvantage

Table 8 presents results from the final models which tested the main effect of concentrated disadvantage and its three interactions with urban areas, parolee age, and parolee race. In order to represent the theory of Social Disorganization, concentrated immigration and residential stability were also included as contextual variables.

Model 2a examined the main effects of concentrated disadvantage, concentrated immigration, and residential stability on individual parolee recidivism. Of these three variables, only concentrated disadvantage had a significant and negative relationship with individual parolee recidivism, meaning that parolees who lived in counties with high

[40] One calculates the Proportion of Variance Explained (PEV) by taking the difference between the variance components of the null model and the full model and then dividing this difference by the null model's variance component.

Table 8: Concentrated Disadvantage Hierarchical Logistic Regression Models Predicting Parolee Recidivism (Standard Errors in Parentheses)

	Model 2a: Concentrated Disadvantage			Model 2b: Interaction with Urban Areas			Model 2c: Interaction with Parolees' Age			Model 2d: Interaction with Parolees' Race		
	b	S.E.	Exp(b)	b	S.E.	Exp(b)	b	S.E.	Exp(b)	b	S.E.	Exp(b)
Community Variables												
Concentrated Disadvantage	-.091*	(.041)	.91	-.175*	(.078)	.84	-.093*	(.041)	.91	-.093*	(.041)	.91
Concentrated Immigration	-.053	(.033)	.95	-.031	(.035)	.97	-.053	(.033)	.95	-.052	(.033)	.95
Residential Stability	.015	(.042)	1.02	-.001	(.065)	1.00	.015	(.042)	1.02	.019	(.042)	1.02
Urban	----	----	----	-.165	(.171)	0.85	----	----	----	----	----	----
Individual-Level Controls												
Alcohol & Drug Usage	.056***	(.008)	1.06	.056***	(.008)	1.06	.056***	(.008)	1.06	.056***	(.008)	1.06
Risk Scores	.010***	(.000)	1.01	.010***	(.000)	1.01	.010***	(.000)	1.01	.010***	(.000)	1.01
WRAT Reading Score	.025***	(.005)	1.03	.026***	(.005)	1.03	.025***	(.005)	1.03	.025***	(.005)	1.03
Number of Priors	.451***	(.017)	1.57	.451***	(.017)	1.57	.452***	(.017)	1.57	.452***	(.017)	1.57
Number of Jobs	-.062***	(.007)	.94	-.062***	(.007)	.94	-.062***	(.007)	.94	-.062***	(.007)	0.94
Race	-.300***	(.054)	.74	-.306***	(.054)	.74	-.300***	(.054)	.74	-.288***	(.054)	0.75
Gender	.155*	(.072)	1.17	.155*	(.072)	1.17	.155*	(.072)	1.17	.155*	(.072)	1.17
Age	-.037***	(.003)	.96	-.037***	(.003)	.96	-.037***	(.003)	.96	-.037***	(.003)	0.96
Intercept	-1.332***	(.034)		-1.319***	(.036)		-1.333***	(.034)		-1.316***	(.035)	
Interactions												
Con. Dis. * Urban	----	----	----	.172	(.142)	1.19	----	----	----	----	----	----
Con. Dis. * Parolee Age	----	----	----	----	----	----	-.001	(.003)	1.00	----	----	----
Con. Dis. * Parolee Race	----	----	----	----	----	----	----	----	----	.101t	(.061)	1.11
Level 2 Error Term	.038			.038			.038			.038		

*p<.05; **p<.01; ***p<.001

levels of concentrated disadvantage were less likely to recidivate than parolees who lived in counties with lower levels of concentrated disadvantage. Specifically, having controlled for individual parolee characteristics and backgrounds, living in a community with an additional unit of concentrated disadvantage significantly lowered the odds of being returned to prison by 9 percent. This finding was contrary to research suggesting that as concentrated disadvantage increases, so do parolees' odds of recidivism (Kubrin and Stewart, 2006), and is discussed further in the next chapter.

Concentrated disadvantage maintained its significant negative relationship to parolee recidivism throughout the interaction models 2b, 2c, and 2d, but neither the interaction between urban areas and concentrated disadvantage (model 2b), nor the interaction between young parolees and concentrated disadvantage (model 2c) proved to be significant predictors of recidivism. However, the interaction between Caucasian parolees and their concentrated disadvantaged counties approached a significant relationship to recidivism ($p < .10$).

Figure 4: The Effects of Concentrated Disadvantage by Race of Parolees on Recidivism.

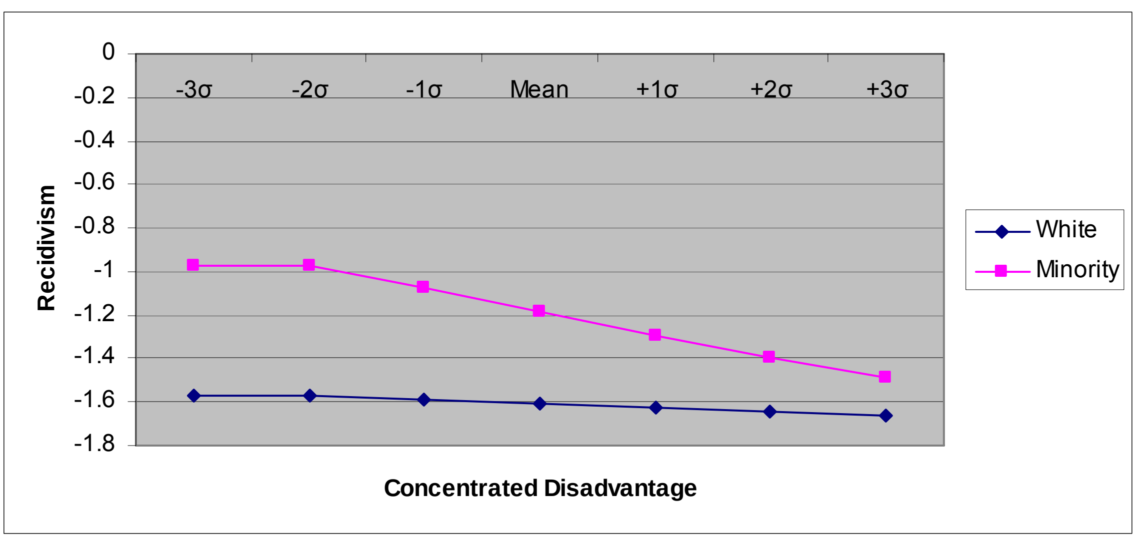


Figure 3 presents the interaction between race and concentrated disadvantage on recidivism.[41] Compared to minority parolees, white parolees were considerably less likely to recidivate in counties with low levels of concentrated disadvantage (e.g., -3σ). In counties with high levels of concentrated disadvantage (e.g., +3σ), both white and minority parolees' likelihood of recidivism decreased to similar levels of recidivism, although minority parolees were still slightly more likely to recidivate than white parolees.

By comparing the variance components of two different models, one can determine which variables explained a greater proportion of the between-county variance in recidivism. The concentrated disadvantage model (model 2a) accounted for 20.8 percent of the explained variance between counties, while the individual-level model (model 1) accounted for only 10.4 percent of the explained variance in recidivism between counties. This means that concentrated disadvantage, concentrated immigration, and residential stability explained as much between-county variance in recidivism as the combination of all eight individual-level parolee variables.

Poverty Models: Extreme Poverty

In Table 9, the results of the HGLM analyses predicting the effects of extreme poverty on parolee recidivism are presented. Models 3a and 3b examined whether extreme poverty predicted individual recidivism and community recidivism, respectively. Because model 3b had a non-normal distribution, a Poisson model was used to examine

[41] In Figures 3 and 4, the concentrated disadvantage and extreme poverty values were determined by adding standard deviations to the mean value. In cases where the standard deviations exceeded the minimum and maximum range, the score was censored to reflect these minimum and maximum scores.

model 3b (see Appendix C for more information). Finally, model 3c presents the results of the interaction between extreme poverty and parolee race.

Model 3a found that the percentage of community extreme poverty was not significantly related to individual parolee recidivism. However, in model 3b, the percentage of extreme poverty significantly predicted higher county-level recidivism rates. That is, controlling for individual parolee characteristics and backgrounds, counties with a standard deviation increase of extreme poverty significantly increased their recidivism rates by 7.4 percent. Additionally, none of the individual-level predictors retained their significant relationships with the aggregated outcome of recidivism. These aggregate-level findings were explored further in Appendix C.

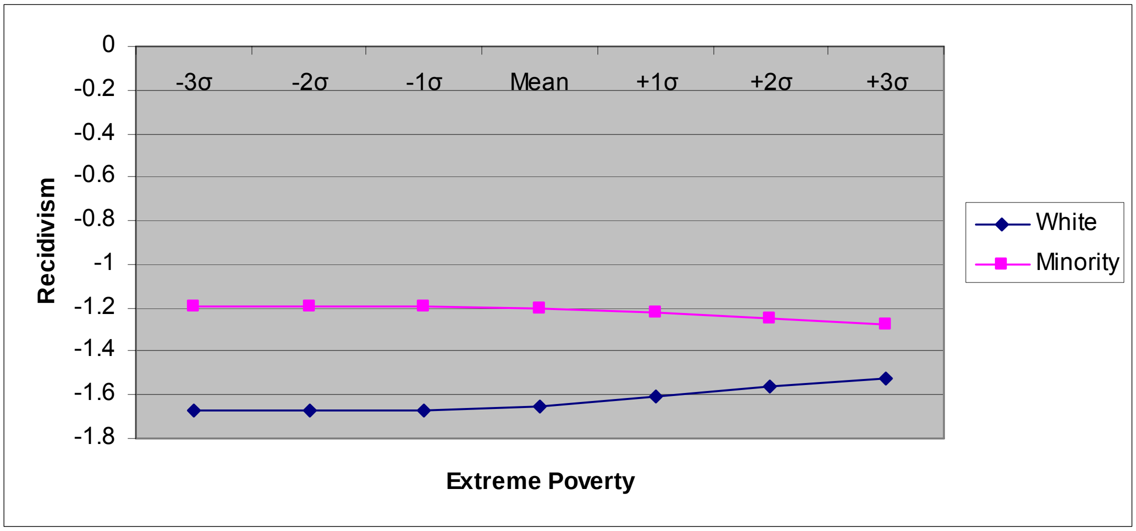
Finally, model 3c revealed a significant interaction between parolee race and community extreme poverty. Specifically, whites who live in high extreme poverty counties had significantly increased odds of being returned to prison (odds ratio = 3.93) compared to minority parolees. In order to further understand the nature of this statistical interaction, Figure 4 was created to illustrate the relationship between parolee race and extreme poverty in their counties. White parolees who lived in counties with low levels of extreme poverty (e.g., -3σ) were much less likely to recidivate than were minority parolees who lived in similar counties. Similarly, white parolees who lived in counties with high levels of extreme poverty (e.g., +3σ) were still less likely to recidivate than minority parolees, although the gap between whites' and minorities' likelihood of recidivism had narrowed considerably.

Table 9: Extreme Poverty Hierarchical Logistic Regression Models Predicting Parolee Recidivism (Standard Errors in Parentheses)

	Model 3a: Extreme Poverty			Model 3b: Aggregated Recidivism Outcome			Model 3c: Interaction with Parolees' Race		
	B	S.E.	Exp(b)	b	S.E.	Exp(b)	B	S.E.	Exp(b)
Community Variables									
Extreme Poverty	-.241	(.428)	.79	.894**	(.280)	2.445	-.072	(.436)	.93
Individual-Level Controls									
Alcohol & Drug Usage	.055***	(.008)	1.06	.000	(.000)	1.00	.055***	(.008)	1.06
Risk Scores	.010***	(.000)	1.01	.000	(.000)	1.00	.010***	(.000)	1.01
WRAT Reading Score	.025***	(.005)	1.03	-.000	(.000)	1.00	.025***	(.005)	1.03
Number of Priors	.452***	(.017)	1.57	.000	(.000)	1.00	.452***	(.017)	1.57
Number of Jobs	-.061***	(.007)	.94	.000	(.000)	1.00	-.061***	(.007)	.94
Race	-.273***	(.052)	.76	-.000	(.000)	1.00	-.309***	(.054)	.73
Gender	.157*	(.072)	1.17	-.000	(.000)	1.00	.156*	(.072)	1.17
Age	-.037***	(.003)	.96	-.000	(.000)	1.00	-.037***	(.003)	.96
Intercept	-1.347***	(.034)		-1.442	(.028)		-1.341***	(.034)	
Interactions									
Extreme Pov*Parolee Race	----	----	----	----	----	----	1.369*	(.624)	3.93
Level 2 Error Term	.044						.045		

*p<.05; **p<.01; ***p<.001

Figure 5: The Effects of Extreme Poverty by Race of Parolees on Recidivism.



The proportion of explained between-county variance was calculated for each of the following models: (3a) the main effect of extreme poverty on individual recidivism (8.3 percent), (3b) the main effect of extreme poverty on aggregated recidivism (3.4 percent), and (3c) the interaction between extreme poverty and parolee race (6.3 percent). Considering that the individual-level parolee model (model 1) explained 10.4 percent of the between-county variance, models 3a and 3c actually declined in the proportion of explained variance.[42] Model 3b was the only model that maintained the same proportion of explained between-county variance between the null model and model 3b.[43]

[42] It is not surprising that models 3a and 3c had such low levels explained proportions of variance. Model 3a did not have any significant county-level predictors, which is one possible explanation for the low proportion of between-county variance explained. Model 3c also decreased in the percentage of between-county variance of recidivism. However, this reduction was due to the introduction of the significant interaction between parolee race and extreme poverty, which lowered the proportion of explained between-county variance by 4.1 percent. This reduction in variance often happens when the between-group variance is much smaller than the within-group variance divided by the group size (Snijders and Bosker, 1994).

[43] Because model 3b is a Poisson model, it had a different error structure than the logistic models. Therefore, the proportion of explained variance was first calculated between the null and the individual-level Poisson models (i.e., including all eight parolee-level variables) with the aggregate-level recidivism outcome (5.9 percent). Thus, the addition of the community-level measure of extreme poverty increased the proportion of explained variance by 11.7 percent.

Poverty Models: Relative Deprivation

Table 10 presents the results from the HGLM analyses predicting the effects of relative deprivation (the ICE index) and its interaction with parolee race on recidivism. Model 4a found that community relative deprivation was not significantly related to recidivism. This finding is contrary to other studies that found a significant relationship between relative deprivation and recidivism (Kubrin and Stewart, 2006). One possible explanation for the difference in findings may be the different measurements of neighborhoods used – this study employed counties, while the other study used census tracts in one county. Therefore, it is possible that relative deprivation affects parolees when communities are measured in smaller aggregational units (i.e., census tracts) rather than larger aggregational units (i.e., counties).

In addition, model 4b showed that relative deprivation did not significantly interact with parolee race. These findings suggested that on the whole, relative deprivation not only did not significantly affect parolees, but it also did not disproportionately affect subpopulations of parolees by race. Neither the addition of relative deprivation (model 4a) nor the addition of the interaction between relative deprivation and parolee race (model 4b) increased the proportion of explained between-county variance from the individual-level model (model 1). As neither of these models added significant predictors, it is not surprising that the proportion of explained variance did not change (Kreft and De Leeuw, 1998).

Table 10: Relative Deprivation Hierarchical Logistic Regression Models Predicting Parolee Recidivism (Standard Errors in Parentheses)

	Model 4a: Relative Deprivation			Model 4b: Interaction with Parolees' Race		
	b	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**
Community Variables						
Relative Deprivation	**-.184**	**(.309)**	**.83**	**-.182**	**(.310)**	**.83**
Individual-Level Controls						
Alcohol & Drug Usage	**.055*****	**(.008)**	**1.06**	**.055*****	**(.008)**	**1.06**
Risk Scores	**.010*****	**(.000)**	**1.01**	**.010*****	**(.000)**	**1.01**
WRAT Reading Score	**.025*****	**(.005)**	**1.03**	**.025*****	**(.005)**	**1.03**
Number of Priors	**.452*****	**(.017)**	**1.57**	**.452*****	**(.017)**	**1.57**
Number of Jobs	**-.061*****	**(.007)**	**.94**	**-.061*****	**(.007)**	**.94**
Race (White)	**-.266*****	**(.052)**	**.77**	**-.244*****	**(.058)**	**.78**
Gender	**.157***	**(.072)**	**1.17**	**.157***	**(.072)**	**1.17**
Age	**-.037*****	**(.003)**	**.96**	**-.037*****	**(.003)**	**.96**
Intercept	**-1.347*****	**(.033)**		**-1.344*****	**(.033)**	
Interactions						
Relative Dep * Parolee Race	**----**	**----**	**----**	**-.371**	**(.451)**	**.69**
Level 2 Error Term	**.043**			**.043**		

*p<.05; **p<.01; ***p<.001

Poverty Models: Racial Inequality

In Table 11, the results from the HGLM analyses predicting the effects of racial inequality and its interaction with parolees' race on recidivism are presented. In model 5a community racial inequality did not significantly predict parolee recidivism. In addition, minority parolees were not disproportionably affected by their county-level of racial inequality compared to white parolees (model 5b). This finding is contrary to another study concerning racial inequality and recidivism (Reisig et al., 2007). The addition of relative deprivation and its interaction with parolee race in models 5a and 5b decreased the proportion of explained variance by 2.1 percent from the individual-level model (model 1).

Table 11: Racial Inequality Hierarchical Logistic Regression Models Predicting Parolee Recidivism (Standard Errors in Parentheses)

	Model 5a: Racial Inequality			Model 5b: Inequality with Parolees' Race		
	B	**S.E.**	**Exp(b)**	**B**	**S.E.**	**Exp(b)**
Community Variables						
Racial Inequality	**-.014**	**(.033)**	**.99**	**-.018**	**(.034)**	**.98**
Individual-Level Controls						
Alcohol & Drug Usage	**.056*****	**(.008)**	**1.06**	**.056*****	**(.008)**	**1.06**
Risk Scores	**.010*****	**(.000)**	**1.01**	**.010*****	**(.000)**	**1.01**
WRAT Reading Score	**.025*****	**(.005)**	**1.03**	**.025*****	**(.005)**	**1.03**
Number of Priors	**.451*****	**(.017)**	**1.57**	**.452*****	**(.017)**	**1.57**
Number of Jobs	**-.061*****	**(.007)**	**.94**	**-.061*****	**(.007)**	**.94**
Race (White)	----	----	----	----	----	
Race (Minority)	**.271*****	**(.052)**	**1.31**	**.264*****	**(.052)**	**1.30**
Gender	**.157***	**(.072)**	**1.17**	**.158***	**(.072)**	**1.17**
Age	**-.037*****	**(.003)**	**.96**	**-.037*****	**(.003)**	**.96**
Intercept	**-1.352*****	**(.032)**		**-1.345*****	**(.033)**	
Interactions						
Racial Ineq * Parolee Race	----	----	----	**-.058**	**(.047)**	**.94**
Level 2 Error Term	**.044**			**.044**		

*p<.05; **p<.01; ***p<.001

This study also examined minority parolees to determine whether "at risk" parolees were more affected by their community racial inequality than parolees who were not "at risk." In order to make this comparison, only minority parolees (N=12,370) were selected for the following analyses which examined statistical interactions between community racial inequality and two parolee "at risk" measures – risk scores and number of priors.[44]

In Table 12, minority parolees were first examined separately with only the main effects of their risk scores, number of priors, community racial inequality, and other parolee-level characteristics (model 5c). Both parolee risk scores and the number of

[44] White "at risk" parolees were also examined and their results are presented in Appendix D.

priors maintained significant positive relationships to parolee recidivism, although community racial inequality was not significant. This last finding was expected as model 5b did not find a significant interaction between race and community racial inequality. Additionally, the other individual-level variables did not change their direction or significance levels from the model 1 findings examining only parolee-level variables. Thus, all eight parolee-level characteristics were stable for the subpopulation of minority parolees.

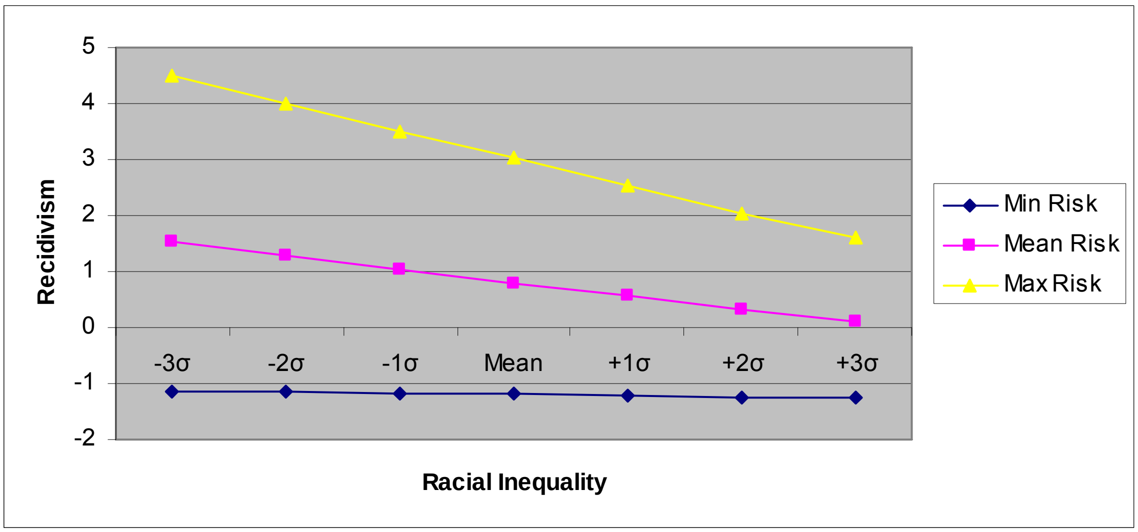
Next, this study examined the statistical interactions between community racial inequality and parolee risk scores (model 5d) and number of priors (model 5e), of which only the former was statistically significant. Racial inequality is lowest when it is zero and highest when at the extreme values of three standard deviations below zero (racial inequality favoring blacks) and at three standard deviations above zero (racial inequality favoring whites).

In model 5d, minority parolees who had higher risk scores were significantly more likely to recidivate (odds ratio = -.001) in counties with high levels of racial inequality favoring blacks. This significant statistical interaction is graphed in Figure 5 in order to illustrate how parolees' log odds of recidivism varied across high and low racial inequality counties according to the parolee's level of risk.[45] Both maximum risk and mean risk parolees were significantly more likely to be returned to prison when they lived in counties with racial inequality favoring blacks (e.g., -3σ) compared to counties with high racial inequality favoring whites (e.g., +3σ). Minimum risk parolees had the

[45] The minimum and maximum risk scores were identified by adding and subtracting standard deviations from the mean risk score. Since it is impossible to have a negative risk score, the score was censored to reflect the minimum score. The risk scores were not defined in accordance with the Georgia DOC's definitions because too few parolees were classified as maximum risk parolees.

lowest log odds of recidivism and were only slightly more likely to be returned to prison in high racial inequality counties favoring blacks than in high racial inequality counties favoring whites. This suggests that minority parolees, especially parolees with high risk scores, are most at risk for being returned to prison when they reside in communities where African Americans are more affluent that whites.

Figure 6: The Effects of Racial Inequality by Risk Scores of Minority Parolees on Recidivism.



The variance components for the minority parolee outcomes in models 5c, 5d, and 5e were different from the other models in this study because the slopes of two parolee-level characteristics – age and number of priors – were allowed to vary.[46] One consequence of these additional random slopes was that each model resulted in three variance components.

[46] This study followed the recommendations of Snijders and Bosker (1999) in examining the model specifications for the minority parolee models in Table 12. Using backward regression and forward regression, this study examined how each variable affected the other variables' effects and the overall variance of the models. Additionally, the descriptive statistics, bivariate correlations, and variance inflation factors were examined and compared with the total parolee population and found to be similar and non-threatening to the final models.

Table 12: Racial Inequality Hierarchical Logistic Regression Models Predicting Minority Parolee Recidivism (Standard Errors in Parentheses)

	Model 5c: Racial Inequality with Minority Parolees Only			Model 5d: Interaction with Minority Parolees' Risk Scores			Model 5e: Interaction with Minority Parolees' No. of Priors		
	b	S.E.	Exp(b)	b	S.E.	Exp(b)	B	S.E.	Exp(b)
Community Variables									
Racial Inequality	-.010	(.034)	.99	-.009	(.034)	.99	-.007	(.038)	.99
Individual-Level Controls									
Alcohol & Drug Usage	.053***	(.009)	1.05	.053***	(.009)	1.05	.053***	(.009)	1.05
Risk Scores	.010***	(.000)	1.01	.010***	(.000)	1.01	.010***	(.000)	1.01
WRAT Reading Score	.024***	(.006)	1.02	.024***	(.006)	1.02	.024***	(.006)	1.02
Number of Priors	.518***	(.030)	1.68	.513***	(.030)	1.67	.518***	(.030)	1.68
Number of Jobs	-.074***	(.009)	.93	-.075***	(.009)	.93	-.074***	(.009)	.93
Gender	.214*	(.089)	1.24	.216*	(.089)	1.24	.214*	(.089)	1.24
Age	-.041***	(.005)	.96	-.041***	(.005)	.96	-.041***	(.005)	.96
Intercept	-1.205***	(.036)		-1.205***	(.036)		-1.204***	(.036)	
Interactions									
Racial Ineq * Risk Score	----	----	----	-.001**	(.000)	1.00	----	----	----
Racial Ineq * No of Priors	----	----	----	----	----	----	.005	(.030)	1.01
Level 2 Error Term	.040			.041			.040		
Age Slope Error Term	.001			.001			.001		
No. Priors Error Term	.032			.032			.033		

*p<.05; **p<.01; ***p<.001

The proportion of explained between-county variance was calculated for each of the following models: (5c) the main effect of racial inequality on minority parolees' recidivism (4.8 percent), (5d) the interaction between racial inequality and risk scores (2.4 percent), and (3c) the interaction between racial inequality and number of priors (4.8 percent). These proportions of explained variance were positive but small in nature, which may in part be due to the additional random variation in these models.

Two additional variance components in these models were considered (Hox, 2002). Two parolee-level variables were allowed to assume different values across counties by the inclusion of a random error term at each variable's intercept. For instance, allowing the variable measuring parolee age to vary meant that in some counties parolees' ages had a stronger relationship to recidivism than in other counties. In all three of the models, both parolee age and number of priors significantly varied across counties ($p < .001$). As neither of the error terms for parolee age and number of prior offenses changed significantly across these three models, there was no way to quantify the amount of variance explained by these two random slopes.[47]

Poverty Models: Spatial Proximity to Poverty

In Table 13, models 6a through 6d incorporated the spatial measures of the four poverty variables – concentrated disadvantage, extreme poverty, relative deprivation, and racial inequality – into models that examined whether spatial measures of poverty were effective in predicting recidivism. Each of the four models included the following three variables: (1) the main effect of the type of poverty examined, (2) the spatial lag of that

[47] One might examine the difference in the proportion of variance explained between a random slope and that random slope with an interaction term, however there was no theoretical justification for examining how age and number of priors interacted with county-level variables.

poverty variable (e.g., a poverty cluster measure), and (3) the interaction between the type of poverty and its corresponding spatial lag.

Across the four spatial models, none of the interactions were statistically significant, meaning that counties with high poverty that were near other counties with high poverty did not significantly increase recidivism among parolees. This pattern held true regardless of the type of poverty examined.

In model 6c, with the addition of its spatial lag, relative deprivation approached statistical significance ($p < .10$). Specifically, every standard deviation increase in a community's relative deprivation resulted in a 2 percent increase in parolees' odds of recidivism. Additionally, parolees living in counties surrounded by high relative deprivation counties were significantly less likely to recidivate ($p < .01$). Thus, when a parolee lived in a community that bordered a high relative deprivation community (i.e., a standard deviation increase in relative deprivation), a parolee decreased his or her odds of being returned to prison by 2 percent.[48] The combination of these two findings suggested that a parolee was less likely to be returned to prison if he or she lived in a county near a high relative deprivation county and more likely to be returned to prison if the parolee lived in a county with high relative deprivation.

The proportion of explained between-county variance for the spatial relative deprivation model was 25 percent. A comparison of the proportion of explained variance between the individual-level model (model 1) and the spatial model of relative

[48] Relative deprivation shared a high zero-order correlation with its spatial lag (r=.76). Therefore, these analyses paid particular attention to multicollinearity, although the VIFs calculated in Chapter 5 indicated that multicollinearity was not a serious problem with this data. Each variable – relative deprivation and its spatial lag – was examined individually before both variables were examined together, and their standard errors were found to be similar across the models. This final step confirmed that multicollinearity was not a serious problem for this data.

Table 13: Spatial Measures of Proximity to Poverty Hierarchical Logistic Regression Models Predicting Parolee Recidivism

	Model 6a: Spatial Concentrated Disadvantage			Model 6b: Spatial Extreme Poverty			Model 6c: Spatial Relative Deprivation			Model 6d: Spatial Racial Inequality		
	b	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**
Community Variables												
Concentrated Disadvantage	-.126*	(.051)	.88	----	----	----	----	----	----	----	----	----
Con Dis. Spatial Lag	.101	(.065)	1.11	----	----	----	----	----	----	----	----	----
Extreme Poverty	----	----	----	-.219	(.551)	.80	----	----	----	----	----	----
Extreme Poverty Spatial Lag	----	----	----	-1.312	(1.571)	.27	----	----	----	----	----	----
Relative Deprivation	----	----	----	----	----	----	.787t	(.478)	2.20	----	----	----
Relative Dep. Spatial Lag	----	----	----	----	----	----	-1.561**	(.591)	.21	----	----	----
Racial Inequality	----	----	----	----	----	----	----	----	----	-.013	(.034)	.99
Racial Ineq. Spatial Lag	----	----	----	----	----	----	----	----	----	-.029	(.076)	.97
Individual-Level Controls												
Alcohol & Drug Usage	.056***	(.008)	1.06	.056***	(.008)	1.06	.055***	(.008)	1.06	.056***	(.008)	1.06
Risk Scores	.010***	(.000)	1.01	.010***	(.000)	1.01	.010***	(.000)	1.01	.010***	(.000)	1.01
WRAT Reading Score	.025***	(.005)	1.03	.025***	(.005)	1.03	.025***	(.005)	1.03	.025***	(.005)	1.03
Number of Priors	.452***	(.017)	1.57	.452***	(.017)	1.57	.452***	(.017)	1.57	.451***	(.017)	1.57
Number of Jobs	-.061***	(.007)	.94	-.061***	(.007)	.94	-.061***	(.007)	.94	-.061***	(.007)	.94
Race	-.285***	(.054)	.75	-.275***	(.052)	.76	-.261***	(.052)	.77	-.275***	(.053)	.76
Gender	.158*	(.072)	1.17	.157*	(.072)	1.17	.156*	(.072)	1.17	.157*	(.072)	1.17
Age	-.037***	(.003)	.96	-.037***	(.003)	.96	-.037***	(.003)	.96	-.037***	(.003)	.96
Intercept	-1.341***	(.033)		-1.346***	(.034)		-1.341***	(.032)		-1.351***	(.033)	
Interactions												
Con Disadv * Spatial Lag	-.059	(.056)	.94	----	----	----	----	----	----	----	----	----
Extreme Pov * Spatial Lag	----	----	----	-3.602	(22.689)	.03	----	----	----	----	----	----
Relative Dep * Spatial Lag	----	----	----	----	----	----	-3.459	(3.440)	0.03	----	----	----
Racial Ineq * Spatial Lag	----	----	----	----	----	----	----	----	----	.039	(.090)	1.04
Level 2 Error Term	.040			.045			.036			.045		

*p<.05; **p<.01; ***p<.001

deprivation revealed that relative deprivation and its spatial lag increased the proportion of explained variance between counties by 14.6 percent.

Rural Models: The Effects of Rural and Suburban Communities

In Table 14, models 7a through 7c examined the effects of rural and suburban counties on parolee recidivism. In model 7a, rural areas were shown to have significantly increased parolee recidivism. Specifically, for every standard deviation increase in the percent of rural areas in their counties, parolees increased their odds of being returned to prison by 7 percent. In model 7b, population density was shown to have significantly reduced recidivism among parolees. Indeed, for every standard deviation increase in population density, parolees decreased their odds of being returned to prison by 11 percent. As rural areas typically have a lower population density than either urban or suburban areas, these two findings are consistent with one another.

The average commuting time to work measure of suburbaness approached statistical significance ($p < .10$). Specifically, parolees who lived in counties in which residents had longer commute times to work (i.e. one standard deviation), lowered their odds of being returned to prison by 6 percent.

The proportion of explained between-county variance was calculated for each of the following models: (7a) the rural model (20.8 percent), (7b) the population density model (27.1 percent) and (7c) the average commuting time model (18.8 percent). All three models showed an increase in the amount of explained variance from the individual-level model (model 1). Specifically, the addition of the rurality measure to the

Table 14: Rural Hierarchical Logistic Regression Models Predicting Parolee Recidivism (Standard Errors in Parentheses)

	Model 7a: Rural			Model 7b: Population Density			Model 7c: Average Commuting Time		
	B	S.E.	Exp(b)	b	S.E.	Exp(b)	b	S.E.	Exp(b)
Community Variables									
Percent Rural	.221*	(.105)	1.25	----	----	----	----	----	----
Population Density	----	----	----	-.0004**	(.000)	1.00	----	----	----
Avg. Commuting Time	----	----	----	----	----	----	-.012t	(.006)	.99
Logged Road Segments	----	----	----	----	----	----	----	----	----
Individual-Level Controls									
Alcohol & Drug Usage	.055***	(.008)	1.06	.055***	(.008)	1.06	.055***	(.008)	1.06
Risk Scores	.010***	(.000)	1.01	.010***	(.000)	1.01	.010***	(.000)	1.01
WRAT Reading Score	.026***	(.005)	1.03	.026***	(.005)	1.03	.025***	(.005)	1.03
Number of Priors	.452***	(.017)	1.57	.452***	(.017)	1.57	.452***	(.017)	1.57
Number of Jobs	-.061***	(.007)	.94	-.061***	(.007)	.94	-.061***	(.007)	.94
Race	-.277***	(.052)	.76	-.274***	(.051)	.76	-.254***	(.052)	.78
Gender	.156*	(.072)	1.17	.155*	(.072)	1.17	.158*	(.072)	1.17
Age	-.037***	(.003)	.96	-.037***	(.003)	.96	-.037***	(.003)	.96
Intercept	-1.316***	(.036)		-1.328***	(.032)		-1.360***	(.032)	
Level 2 Error Term	.038			.035			.039		

*p<.05; **p<.01; ***p<.001

individual-level model increased the proportion of explained variance by 10.4 percent, while the addition of population density added 16.7 percent to the amount of explained variance. Finally, the addition of commuting time added 8.4 percent to the amount of explained variance.

Criminal Justice Resource Models: Parole Offices and Crime Rates

In Table 15, models 8a and 8b indicated that neither the presence of parole offices in a community, nor the presence of parole offices in nearby counties, significantly impacted the likelihood of parolees being returned to prison. Additionally, model 8c showed that there was not a significant interaction between urban areas and parole offices on recidivism outcomes.

The final model (model 8d) examined whether high crime counties impacted individual parolees' likelihood of recidivism. The results from this model indicated that parolees who lived in counties with less crime were significantly more likely to be returned to prison. Specifically, an increase of one standard deviation in crime rates decreased parolees' odds of being returned to prison by 6 percent. The addition of county-level crime rates also increased the proportion of explained variance by 8.4 percent from the individual-level model (model 1), for a total of 18.8 percent of explained between-county variance in model 8d.

Table 15: Criminal Justice Resources Hierarchical Logistic Regression Models Predicting Parolee Recidivism (Standard Errors in Parentheses)

	Model 8a: Parole Offices			**Model 8b: Spatial Measure of Parole Offices**			**Model 8c: Parole Offices Interaction with Urban Areas**			**Model 8d: Crime Rates**		
	b	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**
Community Variables												
Parole Offices	**-.042**	**(.043)**	**.96**	**.002**	**(.078)**	**1.00**	**-.009**	**(.129)**	**.99**	----	----	----
Parole Offices Spatial Lag	----	----	----	**-.033**	**(.128)**	**097**	----	----	----	----	----	----
Percent Urban	----	----	----	----	----	----	**-.245t**	**(.143)**	**.78**	----	----	----
UCR Crime Rate	----	----	----	----	----	----	----	----	----	**-2.706***	**(1.369)**	**.067**
Individual-Level Controls												
Alcohol & Drug Usage	**.055*** **	**(.008)**	**1.06**	**.055*** **	**(.008)**	**1.06**	**.055*** **	**(.008)**	**1.06**	**.055*** **	**(.008)**	**1.057**
Risk Scores	**.010*** **	**(.000)**	**1.01**	**.010*** **	**(.000)**	**1.01**	**.010*** **	**(.000)**	**1.01**	**.010*** **	**(.000)**	**1.010**
WRAT Reading Score	**.025*** **	**(.005)**	**1.03**	**.025*** **	**(.005)**	**1.03**	**.026*** **	**(.005)**	**1.03**	**.025*** **	**(.007)**	**1.025**
Number of Priors	**.452*** **	**(.017)**	**1.57**	**.452*** **	**(.017)**	**1.57**	**.452*** **	**(.017)**	**1.57**	**.452*** **	**(.021)**	**1.571**
Number of Jobs	**-.061*** **	**(.007)**	**.94**	**-.061*** **	**(.007)**	**.94**	**-.061*** **	**(.007)**	**.94**	**-.061*** **	**(.008)**	**.941**
Race	**-.273*** **	**(.052)**	**.76**	**-.270*** **	**(.052)**	**.76**	**-.276*** **	**(.052)**	**.76**	**-.281*** **	**(.049)**	**.755**
Gender	**.156***	**(.072)**	**1.17**	**.155***	**(.072)**	**1.17**	**.156***	**(.072)**	**1.17**	**.155***	**(.069)**	**1.168**
Age	**-.037*** **	**(.003)**	**.96**	**-.037*** **	**(.003)**	**.96**	**-.037*** **	**(.003)**	**.96**	**-.037*** **	**(.004)**	**.964**
Intercept	**-1.340*** **	**(.034)**		**-1.342*** **	**(.035)**		**-1.316*** **	**(.037)**		**-1.326*** **	**(.034)**	**.266**
Interactions												
Parole Offices * Spatial Lag	----	----	----	**-.068**	**(.109)**	**.93**	----	----	----	----	----	----
Parole Offices * Urban	----	----	----	----	----	----	**.025**	**(.157)**	**1.03**	----	----	----
Level 2 Error Term	**.044**			**.043**			**.040**			**.039**		
Error Term Interaction Term												

*p<.05; **p<.01; ***p<.001

Summary of Main Findings:

Based on the research questions and hypotheses, this study resulted in the following main findings:

1. Of the five poverty measures (concentrated disadvantage, extreme poverty, relative deprivation, racial inequality, and proximity to poverty), only concentrated disadvantage significantly impacted individual parolee recidivism.

    a. Concentrated disadvantage significantly decreased recidivism, which is an effect in the opposite direction of the hypothesized relationship.

2. Although extreme poverty did not significantly affect individual parolee outcomes, extreme poverty was the only poverty variable to significantly increase the aggregate community rate of parolee recidivism (see Appendix C).

    a. A significant interaction emerged between parolee race and extreme poverty. White parolees who lived in counties with low levels of extreme poverty were considerably less likely to recidivate than minority parolees. However, this gap between white and minority parolees' recidivism narrowed appreciably in counties with high levels extreme poverty.

3. Contrary to previous research, this study did not find a significant link between either relative deprivation or racial inequality and parolee recidivism.

    a. Among minority parolees, there was a significant interaction between community racial inequality and parolees' risk scores. Specifically, higher risk minority parolees were significantly more likely to be returned to prison in high racial inequality counties favoring blacks compared to high racial inequality counties favoring whites. Minimum risk parolees followed the same pattern of recidivism, but to a lesser degree.

4. None of the spatial measures of clustered poverty (e.g., the interaction between poverty and the poverty cluster) significantly affected parolee recidivism.

    a. The relative deprivation spatial cluster (e.g., high relative deprivation in counties adjacent to parolees) significantly affected parolees' likelihood of recidivism. At the same time, relative deprivation increased parolees' likelihood of being returned to prisons ($p < .10$).

b. The interaction between relative deprivation and its spatial lag was not significant even though parolees were affected by both relative deprivation and the spatial diffusion of relative deprivation in their counties. These two findings together suggested that parolees have a spatial relationship with relative deprivation that is additive (i.e., relative deprivation and its spatial measure) and not multiplicative (i.e., the interaction between relative deprivation and its spatial lag).

5. Parolees who lived in rural areas were significantly more likely to recidivate than parolees who lived in urban areas.

6. Similarly, parolees who lived in more densely populated areas were significantly less likely to recidivate than parolees who lived in more sparsely populated counties.

7. Parolee recidivism was not affected by either the presence of a parole office or the presence of a nearby parole office in adjacent counties.

8. Parolees who lived in high crime counties were significantly less likely to recidivate than parolees who lived in low crime areas.

CHAPTER 7:
DISCUSSION AND CONCLUSIONS

Although there has been a great deal of research examining how parolees' individual characteristics and backgrounds affect recidivism, relatively little attention has been paid to understanding the effects of communities on parolees. This study sought to add to the parolee research by clarifying how poverty, rurality, and criminal justice resources affect a parolee's likelihood of being returned to prison. This chapter discusses the six main findings from this study and the practical and theoretical implications these findings have for the field. Finally, this study examines its limitations and the conclusions this study has for public policy.

Findings:

The next section examines the following six main findings from this study: (1) the types of communities in which parolees recidivate; (2) the differential effects of poverty on parolees of different racial and ethnic backgrounds; (3) the significant interaction among minority parolees, their "at risk" status, and racial inequality; (4) the poverty measures that were most influential in predicting recidivism; (5) the difference between aggregate-level and individual-level outcomes; and (6) the relative strength of individual-level predictors compared to community-level predictors.

Communities and Recidivism:

Prisoners today are increasingly being released into a small number of "core counties" that have high poverty rates (Lynch and Sabol, 2001). This geographic concentration of parolees is assumed to increase the level of recidivism among parolees, many of whom are "churners," or parolees who routinely cycle through the criminal justice system (Petersilia, 2003). However, this study found that these core counties are precisely the types of communities in which parolees will be less likely to recidivate. Specifically, parolees are more likely to recidivate in communities that are wealthier, rural, have a lower population density, and lower crime rates.

These findings are in the opposite direction of this study's hypotheses that suggested high poverty, urban, densely populated, and high crime communities would increase individual parolees' odds of recidivism. Additionally, the findings from this study are contrary to previous research that found parolees were more likely to recidivate in communities with high levels of concentrated disadvantage, relative deprivation, and racial inequality (Kubrin and Stewart, 2006; Mears et al., 2008; Reisig et al., 2007).

When an urban community has high rates of poverty (i.e., concentrated disadvantage), crime, and population density, it is often described as socially disorganized (Shaw and McKay, 1942; Sampson et al., 1997). Several ethnographies have focused on urban, socially disorganized communities in which the norms and social cohesion of communities have devolved, only to be replaced by a street culture in which young men rule their communities with guns (Anderson, 1990, 1997; Bourgois, 1995). Law-abiding members of these socially disorganized communities became socially isolated as they withdraw from their community and stay inside their homes (Anderson, 1990; Wilson, 1987). Some ethnographic studies have shown that these disadvantaged communities are precisely the areas in which former prisoners live (Bourgois, 1995).

Several possible explanations might account for the lower rates of reimprisonment of parolees in socially disorganized communities for parolees. First, socially disorganized communities are known to be less able to "realize the common values of residents and maintain effective social controls" (Sampson et al., 1997). Indeed, evidence has shown that socially disorganized communities are less able to inhibit crime (Sampson et al., 1997). Thus, residents of these socially disorganized communities may be more tolerant of parolees' misbehaviors. Several ethnographers have noted that people in certain communities are encouraged to "mind their business" (Anderson, 1990). Some studies have suggested that certain socially disorganized communities may in fact be more tolerant of crime and delinquency (Wolfgang and Ferracuti, 1967), although these contextual beliefs may not extend to individual residents (Sampson and Bartusch, 1998). Therefore, parolees who inhabit these socially disorganized communities may be returned to prison at lower rates than parolees in more socially organized communities because socially disorganized communities are either more tolerant of deviance and criminal activity or else, less capable of inhibiting crime through collective action.[49]

Secondly, parolees in more socially organized communities (i.e., wealthier, rural, less population density, and lower crime rates) may be returned to prison at higher rates because these communities are less tolerant of crime and more capable of inhibiting

[49] Individually, parolees may also be motivated to desist from crime in high crime, socially disorganized communities because they wish to avoid personal victimization. Research indicates that offenders have higher rates of victimization than non-offenders (Sampson & Lauritsen, 1990) and that this victim-offender relationship is often reciprocal (Shaffer, 2000). Therefore, parolees may estimate the likelihood of their victimization as increasing in more dangerous neighborhoods, which in turn, would lead parolees to desist from future crimes.

criminal and delinquent behaviors. Evidence suggests that affluent areas tend to be more socially organized than less prosperous communities (Sampson et al., 1999). Therefore, members of affluent communities would be more likely to identify and report any parole failures (e.g., drunkenness, witnessed fights) or criminal behavior (e.g., credit card theft) than members of other communities. Additionally, rural and more sparsely populated communities tend to have deeper friendship networks (Weisheit et al., 1994) and be less tolerant of deviance (Wilson, 1991). Thus, parolees who returned to rural, less populated areas would find that the community they left not only remembered their past crimes, but also would be quick to report any current involvements in deviant or criminal behavior.

Thirdly, there is evidence that criminal justice officers respond to crime and delinquency differently depending on the type of community (Stark, 1987; Klinger and Bridges, 1997). Parolees can be returned to prison for a wide array of offenses ranging from the serious (e.g., committing a new burglary) to the more trivial, such as violations of their parole conditions (e.g., drinking alcohol). Given that parolees may be apprehended for a wider array of offenses than an average individual, the type of policing style practiced in parolees' communities may have serious consequences for parolees and their reintegration efforts.

Police officers have long been known to adapt their policing strategies to the character of the communities they patrol (Wilson, 1968), although there is some disagreement over the resulting policing style. Some researchers have suggested that police over-patrol socially disorganized communities (Wilson, 1968), while others have suggested that police make fewer arrests in socially disorganized communities, and then only for serious crimes (Stark, 1987). The results from this study could suggest that police tend to under-patrol socially disorganized communities and/or over-patrol socially organized communities, resulting in higher rates of recidivism among parolees who live in more socially organized communities seen in this study.

Although this study attempted to measure criminal justice responses by examining the presence of parole offices in communities across Georgia, the parole office results were not statistically significant. This study was able to measure only the location of parole offices, and not more meaningful criminal justice variables such as manpower and workload (Klinger, 1997). Therefore, it is likely that better measures of criminal justice officers – both parole and police – in communities may yet yield insight into the relationship between supervision and recidivism.

In sum, there are three potential explanations for the finding in this study that parolees were more likely to recidivate in wealthier, rural, less populated, and lower crime communities. It is possible that one, two, or all three of these scenarios explain the findings from this study. Although attempts were made to measure the criminal justice response (i.e., parole offices), it is apparent that more work is necessary to untangle the community-level processes which resulted in these findings. Specifically, more information on the social organization of these communities and the level of criminal justice oversight would lead to a more complete picture of how and why parolees recidivate.

Race and Recidivism:

This study confirmed that re-imprisonment rates vary by race, with minority parolees returned to prison at higher rates than white parolees. Additionally, this study found a significant interaction between race and extreme poverty. Specifically, white parolees who lived in communities with low levels of extreme poverty were less likely to recidivate than minority parolees. However, this gap between white and minority parolees' recidivism narrowed considerably in communities with higher levels of extreme poverty.[50]

According to the racial invariance hypothesis, the community-level causes of crime are the same across racial and ethnic groups, but the degree to which members of different racial and ethnic groups are exposed to these criminogenic conditions varies (Sampson and Wilson, 1995). Some studies have supported the racial invariance hypothesis, finding no difference in rates of violence between blacks and whites once community and individual-level factors are controlled (Sampson et al., 2005; McNulty and Bellair, 2003). Conversely, other studies have found that community-levels of extreme poverty affect individuals differently by race on criminal outcomes (Krivo and Peterson, 1996; Parker and Pruitt, 2000). The findings from this study are consistent with this latter group of studies. Specifically, this study found that as community extreme poverty increases, white parolees have increased odds of being returned to prison.

The differential effect of extreme poverty on parolees may be explained in part by the nature of communities that are high in extreme poverty. Wilson (1987, 1996) suggested that African American communities in extreme poverty were uniquely disadvantaged and their poverty was more extreme than similar communities with other racial majorities, in part due to the isolation of African American communities. Although this study lacks a measure of the predominant racial groups living in each community, it

[50] A similar interaction was found between race and concentrated disadvantage, although this effect was not statistically significant ($p < .10$).

is likely that extreme poverty communities were also predominantly African American communities in the current study. If this assumption is true, then the interaction between parolee race and extreme poverty might be explained by fact that the white parolees are more visible in predominantly African American community and any mistakes by white parolees would therefore be noticed by more people.

When considering this finding, one must take into account the limited nature of the race variable used in this study. The Georgia Board of Pardons and Paroles delineates only white parolees and categorizes all other parolees as minority parolees. While the majority of parolees in Georgia are African American, there are community pockets of members of races other than white and black. This is a limitation of the current study, and future research should reexamine these findings using a finer definition of parolee race.

***Race, Risk Scores, and Recidivism*:**

This study examined community-levels of racial inequality and its effect on parolee recidivism. Previous research found that racial inequality exerted a significant negative impact on African American parolees (Reisig et al., 2007). This study does not support this finding. Indeed, the racial inequality did not significantly affect total parolee recidivism, minority parolee recidivism, or white parolee recidivism.

This study also examined whether among minority parolees, there was a significant interaction between “at risk” parolees and their community racial inequality. This study hypothesized that parolees who were at a higher risk for recidivism would be more likely to recidivate in higher racial inequality communities. The racial inequality measure is one in which the lowest levels of racial inequality occur at zero, and the highest levels of racial inequality are at the extreme values of three standard deviations below zero (racial inequality favoring blacks) and three standard deviations above zero (racial inequality favoring whites). When racial inequality favors one racial group, this means that one racial group is scoring higher than the other on the four variables composing this measure (poverty, unemployment, receiving a high school diploma, and mean income).

Among minority parolees, there was a significant interaction between parolee risk scores and neighborhood racial inequality. Specifically, higher risk minority parolees were more likely to be returned to prison in high racial inequality communities that favored African Americans. In high racial inequality communities favoring whites, all minority parolees, regardless of their risk scores, faced similar low odds of being returned to prison. There are two possible explanations for this finding, although both require certain assumptions.

First, it is possible that high racial inequality communities favoring African Americans have higher levels of social control than high racial inequality communities favoring whites. Patillo-McCoy (1999) discusses a middle class community, composed predominantly of African Americans, in which there is racial inequality favoring African Americans.[51] This community, Groveland, self-consciously regulated the behaviors of its residents and the (often unstated) rules of the community. Parolees released into communities like the one Patillo-McCoy described would face high levels of community informal social control. Patillo-McCoy wrote of elder community members who

[51] Patillo-McCoy (1999) noted that the residents of Groveland were members of two different groups – whites who were struggling financially and African Americans who were solidly middleclass. Thus, Groveland is an example of a community higher in racial inequality that favored African Americans.

regularly chastised residents who were misbehaving. These elders appeared to be impervious to intimidation and might be effective in policing parolees, even the higher risk parolees. The result of this increased informal social control would be higher rates of parolees being returned to prison.[52]

Second, high racial inequality communities favoring whites may be concerned primarily with crimes that are violent in nature and not the relatively minor crimes that return even high risk parolees to prison (e.g., not maintaining employment, drinking). Empirical research has shown strong links between racial inequality and violent outcomes, including violent crimes and interracial homicides (Parker and McCall, 1999; Blau and Blau, 1982). It is possible that communities with high racial inequality favoring whites may be more concerned with violent crimes and less so with relatively minor crimes and technical violations that may result in a large number of parolees being returned to prison.

While it is possible that these two explanations may partially explain this study's statistically significant interaction between racial inequality and risk scores, more in depth research is needed before this significant interaction between racial inequality and risk scores can be better understood.

Community Poverty Measures:

Of the five theoretical poverty measures and their different approaches to understanding parolee recidivism, only two measures significantly predicted recidivism.

[52] Patillo-McCoy also described reluctance on the part of Groveland residents to use formal social control (i.e., the police) because of the deep, multi-generational social ties of community residents. Any police intervention would harm the extended family and close friends of the wrong doer. While reduced reliance on formal social control may reduce parolee recidivism, Groveland may be unique in terms of its deeply rooted community ties, which may not exist across Georgia.

First, concentrated disadvantage significantly and directly affected individual parolee recidivism, and second, extreme poverty resulted in significantly higher rates of community-level recidivism. Both concentrated disadvantage and extreme poverty are measures that were hypothesized to predict recidivism only inside their communities. Other poverty measures in this study – spatial proximity to poverty variables – were hypothesized to predict that the poverty measures of one community would impact the level of recidivism in other nearby communities.

The findings from this study suggest that poverty measures do not operate in a diffused or spatial manner in predicting recidivism. Indeed, poverty measures are strongest when predicting the individual and aggregate-level outcomes of their communities. It is possible that the spatial processes of poverty may affect recidivism only at smaller aggregational levels, such as census tracts and community clusters (Stretesky, 2004; Mears and Bhati, 2006). Indeed, recent research has shown that community measures can have different relationships at different levels of aggregation (Hipp, 2007; Lee et al., 2008). Therefore, the spatial poverty findings from this study should be qualified when suggesting that the proximity to poverty measures were not predictive of parolee recidivism at the county-level. Future research should examine these relationships more thoroughly using lower aggregational levels.

Aggregate-Level Recidivism:

While individual parolees are not significantly affected by the level of extreme poverty in their communities, extreme poverty does significantly affect the aggregate rate of recidivism in communities. Until this study, extreme poverty had been examined only on aggregate crime outcomes. Therefore, this finding is not unexpected (Krivo and Peterson, 1996; Stretesky et al., 2004). As community effects are rare, this study also examined whether the other poverty measures were more effective at predicting community recidivism rates (i.e., community-level predictors may more easily predict community-level outcomes). Extreme poverty was the only poverty measure that significantly affected parolee recidivism at the community-level (see Appendix C). This finding suggests that extreme poverty is an explanatory variable that operates at the community-level, which is consistent with its theoretical basis.

It is interesting to note that communities high in extreme poverty resulted in higher recidivism rates, while individually, parolees who lived in high concentrated disadvantage communities were significantly less likely to recidivate. One must remember that extreme poverty and concentrated disadvantage shared a low but significant correlation ($r = .26$; $p < .01$), which suggests that these findings are operating independently across most communities in this study.

The Relative Strength of Individual-level Predictors:

The eight individual-level predictors of parolees were consistently significant across every model in this study examining individual recidivism outcomes. In addition, these individual-level variables were generally stronger predictors of parolees' recidivism with a greater level of magnitude (as measured by odds ratios) than the community-level variables. Thus, while this study has shown the importance of community-level factors in predicting recidivism, it is also important to consider the relative importance of community-level factors when compared to individual-level factors. While some of the individual-level predictors were static (e.g., race, gender), others were dynamic (e.g., drug and alcohol failures). Thus, when crafting parole public policy, it is important to consider the magnitude of these individual-level effects and to understand the potential interactions between the communities and parolees' personal characteristics instead of narrowing one's focus to only communities.

The next section examines the limitations of this study and its implications for public policy. Specifically, the next section examines this study's generalizability, the limitations of the study variables, and one important drawback of community-level research.

Limitations:

There are several important limitations of this study that, while not unique to the current study, nevertheless should be considered. This section examines the three most important limitations of this study. First, given that the findings from this study are inconsistent with other parolee studies, the results from these studies should not be generalized to the entire parolee population across the United States. Secondly, this study provided a strong examination of socio-structural variables, yet was unable to measure important mediating variables (e.g., community attachment). Finally, the last limitation of this study is the selection issue inherent in most community-level research. That is, the lack of randomness of parolees' reintegration into residential communities is a limitation that must be considered in all community-level research on parolees.

One of the biggest limitations of this study is that it examines a single geographic area – the State of Georgia. Indeed, it would be unwise to generalize the findings from this study to other parolee populations in the United States given some of the contrary findings. This study, in conjunction with other studies, has found that measures of poverty affect parolees differently in various study sites across the country. Specifically, high levels of concentrated disadvantage caused individual parolees to recidivate more often in Portland, Oregon, and less often in Georgia (Kubrin and Stewart, 2006). Additionally, while measures of community relative deprivation in Portland, Oregon and measures of racial inequality in Florida State significantly increased parolees' odds of being returned to prison, neither of these measures significantly impacted parolees in Georgia (Kubrin and Stewart, 2006; Reisig et al., 2007).

The findings from these studies suggest that the experience of parole operates differently across geographic areas. Unfortunately, this study was not able to discover whether these different parole experiences are grounded in the socio-structural community variables (i.e., concentrated disadvantage, relative deprivation, racial inequality) or the reactions of individuals to these communities (e.g., parole officers, police officers, parolees). This leads to the next point that considers other potential measures that might have helped in further understanding the relationship between parolees and their communities.

The second limitation is that this study did not have access to mediating variables that would have helped the research community understand the process that led parolees to be returned to prison. Many studies face similar difficulties, and in general there are few empirical studies that are able to measure the processes that mediate individuals' relationships to their communities (Sampson, 1987a). However, the lack of access to mediating variables means that while certain communities can be identified as "risky" communities for parolees, no information on how these community characteristics affect parolees is available. For instance, parolees tend to change residences at high rates (Ruback and Burden, 2009), which could not be explored in the context of this study. Parolees' length of residence is likely a key indicator of the magnitude of impact a community can have upon parolees.

One of the most important mediating variables missing from these analyses was a measure of parolees' attachment to the community. Research indicates that parolees are likely to return to the same communities they were living in upon their last arrest, usually because their families are living in these same communities or because it is a condition of their parole (Petersilia, 2000). Kasarda and Janowitz (1974) found that as individuals' length of residence increases, their attachment to their community and their informal social networks become stronger. Thus, this study would have benefited from understanding the process by which parolees chose to live in certain communities. It is likely that attachment to community may help to explain why parolees were less likely to be returned to prison when they lived in more socially disorganized communities.

The final limitation of this research is a problem inherent to almost all community-based research, the problem of selection. Parolees generally choose their community of residence, bound by the limitations of the terms of their parole, and by generic limitations of affordability, the proximity of their family, friends, and place of employment. It is possible that the processes by which individuals decide where to live may cause neighborhood effects to be significantly underestimated or overestimated

(Leventhal and Brooks-Gunn, 2000).[53] For example, if parolees chose to live in a socially disorganized community, there may be an underlying reason that led parolees to make their community choices (e.g., low self-efficacy). If the other parolees who move into this community have similar low levels of self-efficacy and if self-efficacy is related to recidivism, then neighborhood effects may be underestimated.

The only way to solve this selection problem would be to randomly assign parolees to different communities – a process that would undoubtedly be extremely unpopular with the public. There is precedence for this random assignment with the Moving to Opportunity (MTO) program. However, it is extremely difficult to randomly assign individuals to contextual influences, especially residential neighborhoods (Duncan and Raudenbush, 1999).

Although the three limitations outlined in this section are important, this study presented interesting new insights into how parolees are affected by their communities. The next and final section concludes with a brief overview of the major findings from this study and suggests possible linkages to public policy.

Conclusions:

In recent years, several studies have begun examining the ways in which communities impact parolees as they are returned to society (Kubrin and Stewart, 2006; Reisig et al., 2007; Mears et al., 2008). This study attempted to add to this growing body

[53] It is also possible to overestimate neighborhood effects through this selection process. For instance, a parolee may choose a community because this community is within walking distance of his or her place of employment. If this parolee is the only employee at this place of employment, then this choice of community may lead to an overstatement of neighborhood effects.

of research by assessing the ecological impacts community poverty, rurality, and criminal justice resources have upon parolees and their odds of being returned to prison. The most important finding from this study is that communities did indeed affect parolees, although not consistently across geographic regions. That is, in Georgia, parolees were more likely to return to prison when they lived in socially organized communities, or rural communities with low rates of concentrated disadvantage, population density, and crime. A second key finding of this current study is that communities affect parolees differentially by race. These racial differences have also been found in other studies, and may indicate the existence of unexamined mediating variables that explain this gap, such as criminal justice response (Reisig et al., 2007; Mears et al., 2008).

This study's findings of geographical variation and racial differentials make it difficult to successfully apply a "one size fits all" criminal justice policy to communities to help parolees avoid prison in the future. Unfortunately, this approach has been suggested as the logical conclusion of several community-level recidivism studies (Kubrin and Stewart, 2006; Mears et al., 2008). Considering the variability in effects communities can have upon parolees across different geographies and across different races, this would be an unwise extension at this point. Instead, further studies are necessary to clarify the relationship between communities and parolees.

More research is needed to understand how parolees are shaped by and in turn shape their communities. Specifically, research is needed to address the following three questions: (1) How are parolees' community choices formed? (2) Do mediating variables such as community attachment and social networks influence whether parolees are returned to prison? (3) How can communities support parolees to successfully reintegrate into society (e.g., work programs, housing)? In order to achieve these goals, research on communities and parolees extending beyond socio-structural variables is necessary. That is, more research is needed by ethnographers and through stratified samples of parolees that uncovers some of the possible mediating variables that explain the findings from current community-level studies.

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Appendix A:
Maps of the Independent Variables

This study examined the effects of three socio-structural measures – poverty, rurality, and criminal justice resources – on recidivism. To better understand these three predictors in their geographical contexts, Appendix A presents the maps of these measures across Georgia. In total, this appendix examined the following five geographic measures: (1) residents on public assistance, (2) residents below the poverty line, (3) rurality, (4) parole offices, and (5) crime rates.

Figures 7 and 8 depict the distribution of two measures of poverty, percentage of residents who receive public assistance (Figure 7) and who are below the poverty line (Figure 8). Both figures indicate that the geographic areas with the lowest levels of poverty are located in the northern part of the state, while the Southern areas appear to have large percentages of residents below the poverty line and receiving public assistance.

Figure 7: Percentage of County Residents Who Receive Public Assistance

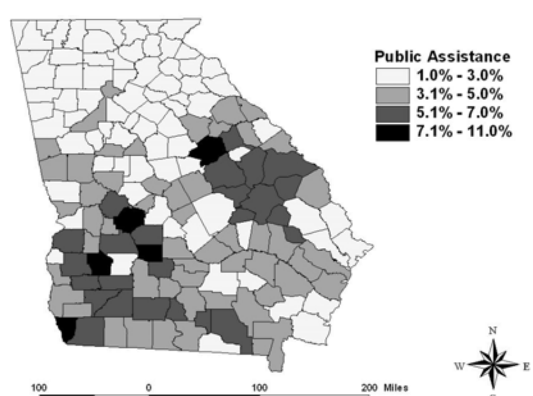


Figure 8: Percentage of Residents Who Live Below the Poverty Line

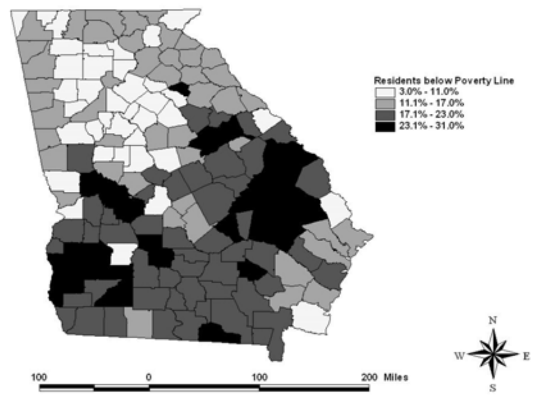


Figure 9 presents the rurality of counties in Georgia. Nine counties are almost exclusively urban (i.e., below 10 percent rural), while 38 counties are almost exclusively rural (i.e., above 90 percent rural). Many of the predominantly urban counties are located in the Atlanta metropolitan area, although there are several pockets of urban counties throughout the southern sections of Georgia and along the eastern coast.

Figure 9: Percentage of Rural Counties in Georgia

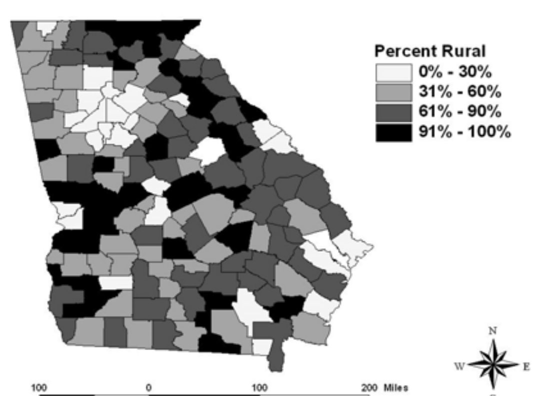
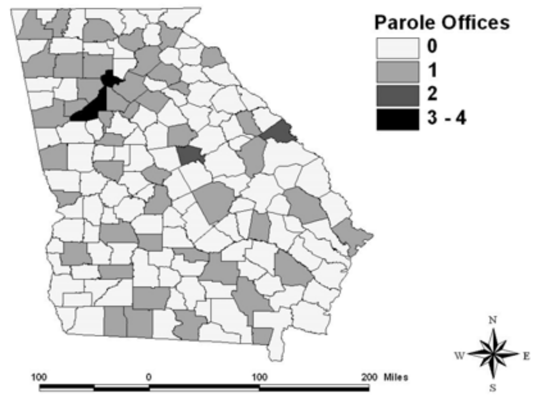


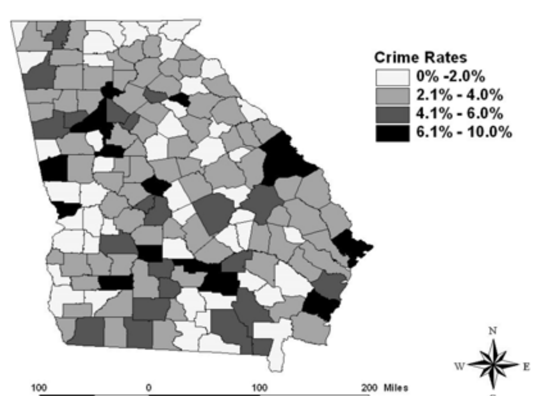
Figure 10 depicts the number of parolee offices distributed across Georgia. For the most part, parole offices are distributed evenly throughout the state with the exception of Fulton county (Atlanta), which contains four parole offices.

Figure 10: Number of Parole Offices in Georgia



Finally, Figure 11 examines the county-level crime rates in Georgia. Higher crime rate counties appear to generally correspond with more urban counties, a pattern which is confirmed by the significant bivariate correlation between rurality and crime rates (r = -.64).

Figure 11: County Crime Rates in Georgia



Appendix B:
Additional Variance Components Analyses

In multilevel modeling, variance is divided between levels of analyses. Most multilevel studies examine the variance components using a simple computation that divides the difference between variance components of the null and full models by the variance component of the null model (Raudenbush and Bryk, 2002 ; Kreft and De Leeuw, 1998). One unfortunate consequence of this computation of the proportion of explained variance (PEV) is that this measure can sometimes decrease with the addition of variables and sometimes even return a negative PEV (Snijders and Bosker, 1994; 1999; Hox, 2002). A negative PEV does not necessarily signify that a model is misspecified. For instance, one possible explanation for a negative PEV is that adding a variable at one level may serve to explain more of the variation at a different level (Snijders and Bokser, 1994; 1999). Additionally, negative variation in logistic models is more common because the variation at level one is fixed (Snidjers and Bosker, 1999).[54]

Snijders and Bosker (1994; 1999) suggest a different computation for multilevel PEVs, or as they suggest, R squared for between-groups. The equation for Snijders and Bosker's computation is as follows:

$$R_2^2 = 1 - [(\frac{\sigma_N^2}{n} + \tau_N)/(\frac{\sigma_F^2}{n} + \tau_F)],$$

where,

[54] Logistic HGLM models constrain the variance at level one. Therefore, the addition of any variable that explains a large amount of level one variation will cause the variance components to increase (Snijders and Bosker, 1999).

n is the harmonic mean of the average number of parolees in each county[55]
σ_N^2 is the level-1 variance component for the null model[56]
τ_N is the level-2 variance component for the null model
σ_F^2 is the level-1 variance component for the full model
τ_F is the level-2 variance component for the full model

Snijders and Bosker (1994, 1999) suggest that their PEV measure could not only act as a measure of variance, but could also act as a tool for diagnosing models that are misspecified. Therefore, this study reexamined the PEVs of the logistic models using the suggested diagnostic PEV by Snijders and Bosker (1994; 1999). The results of the new PEV calculations are presented in Table 16.[57]

None of the PEVs were negative, which is one indication that the models in this study were properly specified (Snijders and Bosker, 1994; 1999). Models 5c, 5d, and 5e had the lowest PEVs (.5-1.0%), which can be explained in part by the two random slopes in these models. Typically, the addition of random slopes to models affects the between-group PEVs, which makes it more difficult to assess the relative importance of the between-group PEVs (Hox, 2002).

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[55] The harmonic mean is calculated with the following formula: $N(\frac{1}{a_1}+\frac{1}{a_2}+...+\frac{1}{a_n})$. In this formula, N represents the number of counties and a_n represents the number of parolees in county n. The harmonic mean is suggested for use when the number of individuals in a group varies (i.e., are unbalanced) as was the parolee data in this study. When groups are equivalent the harmonic mean can be substituted with the number of individuals in each group.
[56] Because these models are logistic, variance components for level 1 (i.e., σ^2) were not calculated as they are assumed under the odds function. Therefore, these calculations substituted $\pi^2/3$ for the level 1 variance components for logistic models (Raudenbush and Bryk, 2002).
[57] Several of the models in this study were examined with Poisson models (Table 9, model3b; Table 17, models 9a-9d). Because Poisson models do not provide a level one variance component, it was not possible to examine the PEVs of these models.

Table 16: Re-examining the Proportions of Explained Variance

Table No.	Description of Model	Proportion of Variance Explained
7	Model 1: Level 1 Individual Parolee Characteristics	**2.5%**
8	Model 2a: Concentrated Disadvantage	**5.1%**
8	Model 2b: Interaction with Urban Areas	**5.1%**
8	Model 2c: Interaction with Parolees' Age	**5.1%**
8	Model 2d: Interaction with Parolees' Race	**5.1%**
9	Model 3a: Extreme Poverty	**2.0%**
9	Model 3c: Interaction with Parolees' Race	**1.5%**
10	Model 4a: Relative Deprivation	**2.5%**
10	Model 4b: Interaction with Parolees' Race	**2.5%**
11	Model 5a: Racial Inequality	**2.0%**
11	Model 5b: Inequality with Parolees' Race	**2.0%**
12	Model 5c: Racial Inequality with Minority Parolees Only	**1.0%**
12	Model 5d: Interaction with Minority Parolees' Risk Scores	**0.5%**
12	Model 5e: Interaction with Minority Parolees' No. of Priors	**1.0%**
13	Model 6a: Spatial Concentrated Disadvantage	**4.0%**
13	Model 6b: Spatial Extreme Poverty	**1.5%**
13	Model 6c: Spatial Relative Deprivation	**6.1%**
13	Model 6d: Spatial Racial Inequality	**1.5%**
14	Model 7a: Rural	**5.1%**
14	Model 7b: Population Density	**6.6%**
14	Model 7c: Average Commuting Time	**4.5%**
14	Model 7d: Road Segments	**2.5%**
15	Model 8a: Parole Offices	**2.0%**
15	Model 8b: Spatial Measures of Parole Offices	**2.5%**
15	Model 8c: Parole Offices Interaction with Urban Areas	**4.0%**
15	Model 8d: Crime Rates	**4.5%**
18	Model 10a: Racial Inequality with White Parolees Only	**11.5%**
18	Model 10b: Interaction with White Parolees' Risk Scores	**11.0%**
18	Model 10c: Interaction with White Parolees' No. of Priors	**11.5%**

Appendix C:
Examining the Effects of Four Types of Poverty upon Aggregate-Level Recidivism

Community-level studies examine either individual-level outcomes (Kubrin and Stewart, 2006; Reisig et al., 2007; Browning et al., 2005) or community-level outcomes (Morenoff et al., 2001; Sampson et al., 1997; Sampson and Groves, 1989). Studies generally choose the aggregation-level of their outcome variables based on two factors – the nature of the theories being tested (e.g., social disorganization versus self control theory) and the limitations of certain dependent variables. In some studies, it would be almost impossible to examine certain dependent variables at the individual-level (e.g., homicides), while in other studies it is both possible and logical to examine individual outcomes (e.g., recidivism).[58]

After discovering that community levels of extreme poverty significantly increased community-level recidivism among the parolees, this study decided to further examine whether the other three types of poverty – concentrated disadvantage, relative deprivation, and racial inequality[59] – also had significant relationships to community-level recidivism.[60] It was possible that the extreme poverty finding may in part have been a result of examining aggregate-level predictors with aggregate-level outcomes as

[58] Homicides are rare criminal occurrences and it would be difficult for a study to sample a large enough population in which there was enough variation (e.g., murdered or not murdered) to understand which ecological variables influenced an individual's murder. Other dependent variables, such as parolee recidivism occur with enough frequency that the outcome might be measured at either the community or individual level.

[59] Although this study presented the results from the Poisson model examining the effect of extreme poverty on county-level recidivism (model 3b), these results are presented again in model 9b, in order to ease the comparisons between the four poverty models.

[60] The four measures of spatial proximity to poverty were also examined; however, none of these four models found a significant relationship between spatial poverty and county-level recidivism. In order to preserve space, these four models were not presented.

opposed to the rarer neighborhood effects models examining aggregate-level predictors with individual-level outcomes.

The dependent variable of aggregate-level recidivism approximated a Poisson distribution with many communities having had low proportions of parolees returned to prison and only a few communities having had large percentages of parolees returned to prison. Therefore, these analyses were performed using hierarchical generalized linear models (HGLM) in which the outcome is modeled as a Poisson process. Poisson model coefficients are interpreted as the increase (or decrease) in the log odds of the outcome with every unit increase in the predictor.

In Table 17, model 9a, concentrated disadvantage was not significantly related to community recidivism. This is an interesting finding because concentrated disadvantage was found to significantly impact individual parolee recidivism, meaning that concentrated disadvantage affects individual parolees' likelihood of recidivism, but not the overall level of community recidivism. In models 9c and 9d, neither the relationship between relative deprivation and community recidivism nor the relationship between racial inequality and community recidivism were statistically significant. The proportion of explained between-county variance (3.4 percent) was consistent across all four models.

The results from the model 9b in Table 17 and model 2a in Table 8 (i.e., concentrated disadvantage) indicate that only one aggregate-level outcome was significant (i.e., extreme poverty) and only one individual-level outcome was significant (i.e., concentrated disadvantage). This suggests that community-level outcomes do not necessarily improve statistical results.

Table 17: Poverty Measures Hierarchical Poisson Regression Models Predicting Aggregate Parolee Recidivism (Standard Errors in Parentheses)

	Model 9a: Concentrated Disadv. Aggregated Recidivism Outcome			Model 9b/3b: Extreme Poverty Aggregated Recidivism Outcome			Model 9c: Relative Deprivation Aggregated Recidivism Outcome			Model 9d: Racial Inequality Aggregated Recidivism Outcome		
	b	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**	**b**	**S.E.**	**Exp(b)**
NeighborhoodCommunity Variables												
Concentrated Disadvantage	**.004**	**(.035)**	**1.004**	----	----	----	----	----	----	----	----	----
Concentrated Immigration	**-.034**	**(.030)**	**.967**	----	----	----	----	----	----	----	----	----
Residential Stability	**-.056**	**(.038)**	**.946**	----	----	----	----	----	-----	----	----	----
Extreme Poverty	----	----	----	**.894****	**(.280)**	**2.445**	----	----	----	----	----	----
Relative Deprivation	----	----	----	----	----	----	**-.072**	**(.292)**	**.931**	----	----	----
Racial Inequality	----	----	----	----	----	----	----	----	----	**.035**	**(.028)**	**1.036**
Individual-Level Controls												
Alcohol & Drug Usage	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**
Risk Scores	**.000***	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000***	**(.000)**	**1.00**
WRAT Reading Score	**-.000**	**(.000)**	**1.00**	**-.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**
Number of Priors	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000**	**(.001)**	**1.00**	**.000**	**(.000)**	**1.00**
Number of Jobs	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**	**.000**	**(.000)**	**1.00**
Race	**-.000**	**(.000)**	**1.00**	**-.000**	**(.000)**	**1.00**	**-.000**	**(.002)**	**1.00**	**-.000**	**(.000)**	**1.00**
Gender	**-.000**	**(.000)**	**1.00**	**-.000**	**(.000)**	**1.00**	**-.000**	**(.002)**	**1.00**	**-.000**	**(.000)**	**1.00**
Age	**-.000**	**(.000)**	**1.00**	**-.000**	**(.000)**	**1.00**	**-.000**	**(.000)**	**1.00**	**-.000**	**(.000)**	**1.00**
Intercept	**-1.443*****	**(.028)**					**-1.441*****	**(.028)**		**-1.440*****	**(.028)**	
Level 2 Error Term	**.117**			**.115**			**.117**			**.115**		

*p<.05; **p<.01; ***p<.001

Appendix D:
Examining the Effects of Racial Inequality on White Parolees

This study found evidence that minority parolees with high risk scores were less likely to recidivate in communities with high levels of racial inequality than parolees with lower risk scores who lived in similar communities. In order to take a balanced approach to race in these analyses, Table 18 examines whether there was also a significant interaction between community racial inequality and "at risk" measures for white parolees.

In Table 18, model 10a indicates that there was not a significant relationship between community racial inequality and the propensity to be returned to prison among white parolees. This finding is consistent with previous research that found that white parolees were not significantly more likely to recidivate in communities with higher rates of racial inequality (Reisig et al., 2007). Additionally, models 10b and 10c indicate that there were no significant interactions between community racial inequality and either parolee risk score or number of priors. This finding suggests that white parolees are less susceptible to the effects of racial inequality in their communities than minority parolees.

Table 18: Racial Inequality Hierarchical Logistic Regression Models Predicting White Parolee Recidivism (Standard Errors in Parentheses)

	Model 10a: Racial Inequality with White Parolees Only			Model 10b: Interaction with White Parolees' Risk Scores			Model 10c: Interaction with White Parolees' No. of Priors		
	B	S.E.	Exp(b)	b	S.E.	Exp(b)	B	S.E.	Exp(b)
Community Variables									
Racial Inequality	.017	(.041)	1.02	-.006	(.045)	.99	.008	(.043)	1.01
Individual-Level Controls									
Alcohol & Drug Usage	.071 ***	(.019)	1.07	.070 ***	(.019)	1.07	.071 ***	(.019)	1.07
Risk Scores	.009 ***	(.001)	1.01	.009 ***	(.001)	1.01	.009 ***	(.001)	1.01
WRAT Reading Score	.027 **	(.010)	1.03	.028 **	(.010)	1.03	.027 **	(.010)	1.03
Number of Priors	.467 ***	(.030)	1.60	.465 ***	(.030)	1.59	.473 ***	(.032)	1.60
Number of Jobs	-.037 **	(.012)	.96	-.037 **	(.012)	.96	-.037 **	(.012)	.96
Gender	.036	(.122)	1.04	.034	(.122)	1.03	.035	(.122)	1.04
Age	-.044 ***	(.006)	.96	-.043 ***	(.006)	.96	-.044 ***	(.006)	.96
Intercept	-1.696 ***	(.050)	.18	-1.703 ***	(.051)	.18	-1.698 ***	(.051)	.18
Interactions									
Racial Ineq * Risk Score	----	----	----	.001	(.001)	1.00	----	----	----
Racial Ineq * No of Priors	----	----	----	----	----	----	.018	(.024)	1.02
Level 2 Error Term	.019			.020			.019		

*p<.05; **p<.01; ***p<.001

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ICPSR Tuition Award and Stipend, Bureau of Justice Statistics	2005
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SELECTED PUBLICATIONS AND WORK IN PROGRESS

Ruback, R. Barry & Frances F. Burden. (in progress). Parolee Recidivism: Individual Risk, Neighborhood Risk and Criminal Justice Response.

Taylor, Bruce, Nan Stein, & Frances Burden. (under review). The Effects of Gender Violence/ Harassment Prevention Programming in Middle Schools. *Violence and Victims*.

Nastasi, Bonnie K., John Hitchcock, Kristen Varjas, Asoka Jayasena, Sreeroopa Sarkar, Rachel B. Moore, Frances Burden, & Lauren Albrecht. (under review). "School-Based Stress and Coping Program for Adolescents in Sri Lanka: Mixed Methods Approach to Testing Effectiveness." In K.M.T. Collins, A.J. Onwuegbuzie, & Q.G. Jiao (Eds.), *Toward a Broader Understanding of Stress and Coping: Mixed Methods Approaches*. (Invited chapter for publication 2008).

St. Pierre, Tena. L., D. Wayne Osgood, Sonja E. Siennick, Tina J. Kauh, & Frances F. Burden. (2007). Project ALERT with Outside Leaders: What Leader Characteristics Are Important for Success? *Prevention Sciences* 8(1): 51-64.

INVITED PRESENTATIONS

Clawson, Heather & Frances F. Burden. (2008). GIS and Its Potential Uses for Anti-Trafficking Task Forces. *BJA and OVFC Federal Working Group on Training and Technical Assistance for Anti-Trafficking Task Forces*. Washington, D.C.

Burden, Frances F. & R. Barry Ruback. (2007). Reexamining Social Disorganization: An Analysis of Recidivism Patterns of Parolees. *Crime Mapping Research Conference*. Pittsburgh, PA.

Burden, Frances F. & R. Barry Ruback. (2004). Neighborhood Structural Determinants of Recidivism: A Multilevel Study of Parolees in their Neighborhoods. *Crime Mapping Research Conference*. Boston, MA.

Burden, Frances, Tina Kauh, & Tena St. Pierre. (2005). Implementation Quality of Project ALERT Delivered in Schools by Cooperative Extension. *Society for Prevention Research*, Washington, DC.