PREDICTING WHO REOFFENDS: THE NEGLECTED ROLE OF NEIGHBORHOOD CONTEXT IN RECIDIVISM STUDIES*

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Prior studies of recidivism have focused almost exclusively on individual-level characteristics of offenders and their offenses to explore the correlates of reoffending. Notably absent from these studies are measures reflecting the neighborhood contexts in which individuals live. The current research addresses this shortcoming. Using data on a sample of ex-offenders in Multnomah County, Oregon (Portland and surrounding area) in conjunction with 2000 census data, we answer two questions. First, which individual-level factors influence rates of recidivism? Second, to what extent does neighborhood socioeconomic status account for variation in the reoffending behavior of ex-prisoners that is not explained by their individual-level characteristics? We find that those who return to disadvantaged neighborhoods recidivate at a greater rate while those who return to resource rich or affluent communities recidivate at a lesser rate, controlling for individual-level factors.

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Rising incarceration rates over the past quarter century do not just mean that more people are being locked up. The trend also means that a growing number of inmates are being released from prison back to their communities. With roughly 600,000 prisoners returning to society each year, ex-offenders and the communities to which they return must cope with the challenges of reentry on a much greater scale than ever before. As a result, the issue of prisoner reentry—or the process of leaving the adult prison system and returning to society—is at the forefront of domestic public policy. Prisoner reentry raises questions about public safety, about how corrections systems should manage the volume of releases, and about how communities can absorb and reintegrate returning prisoners (Lynch and Sabol, 2001). The most pressing question, perhaps, has to do with offenders’ likelihood of recidivating. How many of these ex-prisoners will reoffend and which factors influence recidivism the most?

Prior studies have focused almost exclusively on individual-level characteristics of offenders and their offenses to determine the correlates of recidivism. These studies document that those who have committed serious crimes, have prior offenses, drug problems, little education, and those with higher rates of supervision during probation or parole are more likely to recidivate, controlling for other factors (Benedict and Huff-Corzine, 1997; Clarke, Lin, and Wallace, 1988; Irish, 1989; Listwan et al., 2003; MacKenzie et al., 1999; Ulmer, 2001). Men, minorities, and younger offenders also recidivate more (Benedict, Huff-Corzine, and Corzine, 1998; Clarke et al., 1988; Gainey, Payne, and O’Toole, 2000; Gendreau, Little, and Goggin, 1996; Hepburn and Albonetti, 1994; Listwan et al., 2003; Schwaner, 1998; Spohn and Holleran, 2002; Ulmer, 2001).

Notably absent from recidivism studies are measures reflecting the neighborhood contexts in which former prisoners live. These studies fail to document the types of communities ex-offenders are released into and treat neighborhood context as constant, and therefore irrelevant, for understanding recidivism. Yet neighborhoods vary drastically along a number of dimensions. Some have low poverty and unemployment levels, ample and quality housing supply, relatively little residential turnover, little crime, and offer an abundance of resources, services, and amenities. Others are crime ridden with poverty, joblessness, and residential instability, and offer residents few, if any, resources, services, and amenities.

The lack of attention to neighborhood context is due, in part, to the belief that the risk for reoffending is individually determined. Although individual-level factors do play an important role in predicting who will reoffend and who will not, one’s immediate environment is also likely to influence recidivism. Given an extensive body of research that highlights significant neighborhood effects on victimization, delinquency, and rates
of violence for other populations such as juveniles (Elliott et al., 1996; Simcha-Fagan and Schwartz, 1986; Wikstrom and Loeber, 2000) and the mentally ill (Silver, 2000), limiting the analysis of recidivism rates among ex-offenders to individual-level characteristics is problematic.

Neighborhood context is fundamental to our understanding of why individuals offend, and potentially even more important for understanding why former offenders offend again, yet we know very little about how the ecological characteristics of communities influence the recidivism rates of this population. Using recent data on a sample of ex-prisoners in Multnomah County, Oregon (Portland and surrounding area) in conjunction with 2000 census data, this study begins to address these issues. The questions that motivate this research are, first, which individual-level factors influence rates of recidivism? and, second, to what extent does a critical community characteristic—neighborhood socioeconomic status—account for variation in the reoffending behavior of former inmates that is not explained by their individual-level characteristics?

BARRIERS TO SUCCESSFUL EX-OFFENDER REINTEGRATION

When released inmates leave prison and return home, they face a number of pressing challenges including finding housing, securing employment, receiving treatment, and complying with the terms of supervision. Not surprisingly, ex-offenders rely on neighborhood resources, services, and amenities to successfully reintegrate. Without access to these assets, they are at a greater risk to recidivate. Today more than ever, they rely on their neighborhoods, in large part because they leave prison with serious social and medical problems and face substantial reintegration barriers. For example, a study of prisoner reentry in Chicago, Illinois determined that substance abuse was prevalent among a sample of 400 male prisoners. A self-report survey of these soon-to-be-released inmates discovered that 66 percent reported some drug use and 48 percent reported having drunk to the point of intoxication in the 6 months prior to their current prison term. Of the drug users, 22 percent reported using heroin, 15 percent reported using cocaine, and 25 percent reported using marijuana on a daily basis. Despite this extensive abuse, only 2 percent participated in a drug or alcohol treatment program, 8 percent attended Alcoholics or Narcotics Anonymous meetings, and 10 percent participated in both. Even more troubling, 17 percent reported it likely they would use drugs after release if they knew they wouldn't get caught and 12 percent said they would do so even if they would be arrested (Visher, LaVigne, and Farrell, 2003). Undoubtedly, many of these prisoners will return to their communities with unresolved substance abuse problems.
Another barrier to reintegration is the challenge of securing employment, as Mauer (2005: 609) notes:

Once a prison term is completed, the transition back to the community is almost always laden with difficulty. What in many cases is a situation of limited connections with the world of work becomes even more problematic with the stigma of imprisonment attached to former offenders. And particularly in an economy increasingly diverging into a high skills/high technology sector and a broad low skill service economy, few offenders have promising prospects for advancing out of the bottom rungs of the job ladder.

Coupled with this, fewer inmates today have marketable skills or are sufficiently literate to become gainfully employed once released. Among a cohort of soon-to-be-released offenders in 1997, it was determined that about one-third were unemployed prior to entering prison and about two-thirds had not completed high school—yet most of these inmates did not receive employment training in prison (Lynch and Sabol, 2001: 17). Indeed, the percentage of inmates getting any kind of training has been steadily declining. In 1997, 27 percent of the soon-to-be-released inmates reported that they participated in vocational programs and 35 percent stated that they participated in educational programs; these figures are down from 31 and 43 percent in 1991, respectively (Lynch and Sabol, 2001: 11). The Chicago study mentioned above also notes employment deficits in the sample of returning prisoners. Although almost two-thirds of respondents worked for money prior to incarceration, 60 percent reported that at least some of their income came from illegal activity (and 29 percent indicated that most or all of their income was illegal). Moreover, once incarcerated, less than half of the sample (44 percent) held an in-prison job. Notably, however, almost all respondents (96 percent) believed that finding a job after release was important and 87 percent believed that securing a job was necessary to remain out of prison. Unfortunately, only 14 percent of the sample had any kind of job lined up upon release (Visher et al., 2003).

Baltimore ex-offender project manager Felix Mata noted that the average prisoner returning to the city received $40 on release but owed $8,000 in child support, had no means of transportation, no place to live, and could not find a job (Elsner, 2005). In short, inmates reentering society today are more likely to have failed at parole previously, not to have participated in educational and vocational programs while in prison, and to have served longer sentences (Lynch and Sabol, 2001)—conditions ripe for reoffending.

The figures highlighted illustrate how critical neighborhood resources are for ex-offenders. Many need jobs, housing, and a variety of social services to curb recidivism. Equally important, they rely on these
resources to help them successfully comply with the terms of their probation, parole, or community supervision. Frequently ex-offenders are required to hold a job, receive counseling, pay restitution, find housing, and the like as part of their probation or parole.\footnote{For offenders granted probation, for example, the court decides what conditions will be included in the probation contract between the offender and the court. It is the judge’s responsibility to enumerate the conditions the probationer must abide by in order to remain in the community. The conditions are usually recommended by probation officers. In legal terms, the probation conditions form a contract between the offender and the court. The court requires that the probation officer provide the defendant with a written statement setting forth all the conditions to which the sentence is subject. The offender signs the contract, and the probation officer is the contract’s “enforcer” responsible for notifying the court when the contract has been violated (Petersilia, 1997: 164-165).} This is certainly true in Multnomah County, Oregon where the list of supervision conditions is quite extensive (see Appendix 1). And, over the years, the proportion of probationers subject to special conditions such as residential placement, alcohol and drug abuse treatment, drug testing, mental health counseling, house arrest, day programs, and community service has risen (Clear, 1994). Given this, a critical question today is to what extent neighborhood characteristics affect recidivism levels among ex-offenders. And, more important, which characteristics matter the most?

NEIGHBORHOOD SOCIOECONOMIC CONTEXT AND RECIDIVISM

Studies of neighborhood factors and recidivism among ex-offenders are extremely scarce, making it a challenge to answer the questions raised above. However, research on contextual or “neighborhood effects” for related outcomes (for example, victimization) and other populations (for example, juveniles) underscores the possibility that neighborhood context is critical for ex-offenders. Neighborhood effects broadly construed “are the effects imposed on individuals as a result of living in a specific neighborhood that the same individual (or household) would not experience if living in a different neighborhood” (National Research Council, 1999: 54). Criminal behavior is one area that neighborhoods influence; a number of contextual studies find that crime-related dynamics operate at the neighborhood level that are not reducible to the individual characteristics of residents. A major premise of these studies is that individuals’ rates of offending are determined, to some extent, by social forces in their wider environment. Neighborhood characteristics, therefore, are believed to directly affect individuals’ rates of offending, even after controlling for individual-level factors. It is also the case that
neighborhood characteristics may interact with individual-level factors to influence offending.

Since the mid-1990s, there has been a significant increase in the number of empirical studies of neighborhood effects (Sampson, Morenoff, and Gannon-Rowley, 2002: 443). Studies have examined how community characteristics influence a variety of individual-level outcomes including victimization (Miethe and McDowall, 1993; Rountree, Land, and Miethe, 1994; Velez, 2001), adolescent development (Elliott et al., 1996), delinquency (Simcha-Fagan and Schwartz, 1986; Wikstrom and Loeber, 2000), and violence (Sampson, Raudenbush, and Earls, 1997; Silver, 2000). The growing attention to neighborhood effects in the literature reflects in part a major methodological advance—the application of multilevel modeling to assess both the direct impact of neighborhood characteristics (controlling for individual-level factors) and the interactions between neighborhood and individual-level factors (Elliott et al., 1996; Rountree et al., 1994; Sampson et al., 1997).

Concurrent with this methodological advance is the use of more refined neighborhood measures such as concentrated disadvantage to capture the socioeconomic characteristics of community context (Kubrin and Weitzer, 2003: 392). This development reflects the belief that concentration effects contribute to social disorganization, a precursor of crime and other problem behaviors (Wilson, 1987, 1996). In many inner-city communities, it is the combined effect of poverty, joblessness, and family disruption that defines the neighborhood context for residents. As such, researchers have begun to measure the multiple disadvantages that characterize communities by incorporating several measures into an overarching “concentrated disadvantage” index.

Whether or not the study uses multilevel modeling or a concentrated disadvantage index, a sizeable literature underscores the importance of assessing contextual effects, particularly neighborhood socioeconomic status, which consistently emerges as an influential factor. As Sampson et al. (2002: 446) note, “the range of child and adolescent outcomes associated with concentrated disadvantage is quite wide and includes infant mortality, low birthweight, teenage childbearing, dropping out of high school, child maltreatment, and adolescent delinquency.” They further note that “the weight of evidence thus suggests that there are geographic ‘hot spots’ for crime and problem-related behaviors and that such hot spots are characterized by the concentration of multiple forms of disadvantage” (446). In short, empirical research on social-ecological differentiation has established a strong connection between community
socioeconomic resources and a number of outcomes for a variety of populations.\(^2\)

Unfortunately, however, almost no studies have measured contextual effects and, in particular, the effect of neighborhood socioeconomic status on a group of people most likely to be influenced by neighborhood structure—ex-offenders.\(^3\) Poverty, joblessness, welfare assistance, and the like represent conditions that make readjustment into society and one’s community more difficult, and thus contribute to a greater likelihood of offending after release. Given that most offenders return home with little or no money, without a job, with strained family ties, and in need of drug, alcohol or mental health treatment (Lynch and Sabol, 2001; Visher et al., 2003), these neighborhood services are vital to comply with supervision conditions and curb recidivism. In short, given their situation and needs, ex-offenders’ vulnerability to neighborhood concentrated disadvantage is heightened.

How might neighborhood socioeconomic status affect recidivism among ex-offenders? And what intervening social processes may bear on the well-being of this population? A growing literature theorizes the institutional and social-interactional dimensions that explain how neighborhood effects are transmitted. One obvious dimension has to do with neighborhood institutional resources that refer to the quality, quantity, and diversity of institutions in the community addressing the needs of former inmates, such as job placement centers, medical facilities, treatment clinics, and family support centers (Sampson et al., 2002: 458). Communities differ greatly in their ties to external decision makers and hence in their capacity to lobby city government and businesses to keep or create jobs, invest in the community and provide a variety of social services. Poor neighborhoods typically lack such ties and resources (Guest, 2000); even when the resources are there, critical social networks that provide information about social services tend to be absent (Wilson, 1987).

Yet research now recognizes the importance of community networks and ties for building and maintaining social capital. Social capital, or the

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\(^2\) Sampson et al. (2002: 465–473) caution that despite recent progress, significant and complex methodological issues (for example, differential selection of individuals into communities, indirect pathways of neighborhood effects, measurement error, and simultaneity bias) represent obstacles to drawing definitive conclusions on the causal role of neighborhood social context.

\(^3\) Some preliminary work was initiated in the early 1980s. In a study of the impact of neighborhood characteristics on recidivism among parolees released between 1978 and 1980, small but significant interaction effects of environmental and offender characteristics were noted (Gottfredson and Taylor, 1985) although direct neighborhood effects were nonsignificant (Gottfredson and Taylor, 1988). Concerning the latter finding, the authors noted that the results may have been due to data-quality issues.
intangible resources produced in “relations among persons that facilitate action” for mutual benefit (Coleman, 1988: 100), is critical because it provides residents with access to others in the community with economic and cultural capital, others who can serve as an indispensable resource when seeking a job, finding housing, or searching for social services such as child care. Communities with high social capital generate supporting networks and reciprocity, with individual and organizational cooperation to support needs and an expectation that help is available if necessary (Forrest and Kearns, 2001). Neighborhoods, and the residents within them, therefore, are the focal point for satisfying daily needs through informal support networks (Rose and Clear, 1998: 456). Nowhere is this more likely to be true than for ex-offenders, particularly when they first return home from prison.4

Essentially, where ex-offenders live greatly affects their ability to reintegrate into society. By providing an environment either rich or deficient in resources, place of residence tangibly affects the quality of day-to-day living and influences the range of opportunities available through the quality and extent of institutional resources (Elliott et al., 1996) and personal networks (Rose and Clear, 1998: 455–456). When ex-offenders return to resource-poor communities they face much greater challenges. Unfortunately, the barriers to successful reintegration are more formidable than ever because “the ecological concentration of poverty appears to have increased significantly during recent decades, as has the concentration of affluence at the upper end of the income scale” (Sampson et al., 2002: 447).

It is not surprising, therefore, that many who leave prison end up returning shortly after release—usually within a year. Studies report recidivism levels around 30 to 35 percent (Benedict and Huff-Corzine, 1997; Clarke et al., 1998; Irish, 1989), although some note percentages as high as 43 percent (Langan and Cunnif, 1992). And these percentages rise for studies that measure longer release times (for example, more than one year). A 2002 Bureau of Justice Statistics study of 272,111 prisoners released from prisons in 1994 found that 68 percent were rearrested for a new crime (felony or serious misdemeanor) within three years following release (Langan and Levin, 2002). Recidivism rates were highest for property offenders (74 percent) and drug offenders (67 percent), and lowest for those released from private prisons (Lanza-Kaduce, Parker, and

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4. We should point out that although studies find that social and institutional processes mediate the effect of neighborhood socioeconomic status on crime and related behaviors, these processes do not fully account for such effects. In other words, factors such as concentrated disadvantage and affluence remain direct predictors of neighborhood crime (Sampson et al., 2002: 465), implying other causal mechanisms may be at work.
Thomas, 1999: 28). Offenders, especially drug offenders, sentenced to prison have higher recidivism rates and recidivate more quickly than those placed on probation (Spohn and Holleran, 2002: 329; see also Clear and Braga, 1995 and Petersilia, Turner, and Peterson, 1986).

Among probationers, however, recidivism is still quite common. MacKenzie and Li (2002: 243) note that probationers and parolees account for a large proportion of the criminal activities in large, urban areas, and many of them are rearrested within 3 years of starting supervision. Consider that during 1998, 170,253 parole violators were reported nationwide, representing more than 23 percent of new prison admissions (Beck and Mumola, 1999). Of interest is the fact that 76.9 percent of these parole violations were technical, having nothing to do with the commission of a new felony (Camp and Camp, 1998). And, according to the Bureau of Justice Statistics, the percentage of offenders successfully completing probation is falling nationwide. In 1986, 74 percent did so, whereas in 1992 only 67 percent had, and by 1994 only 60 percent (Langan and Levin, 2002). Current estimates are that between 30 and 50 percent of all new prison admissions are probation and parole failures, but in some states—such as Oregon, the focus of this study—the figure is over 80 percent (Parent et al., 1994). Most of these ex-offenders are returning to problematic, resource deficient neighborhoods. It is reasonable, therefore, to conclude that individuals living in these areas are more likely to reoffend once released, controlling for individual-level factors.

Understanding how neighborhood context influences the reoffending behavior of ex-prisoners is essential to developing a method to reduce recidivism. Indeed, there is growing recognition that researchers identify “the increasing barriers to reintegration facing people with a criminal conviction” (Mauer, 2005: 609). In an era when states are beginning to reduce their prison populations and focus more squarely on neighborhood reentry, researchers must consider how and to what extent individuals’ behaviors are shaped by their surrounding communities. To date, however, few studies have considered how community context influences recidivism above and beyond the individual-level characteristics of former prisoners (Gottfredson and Taylor, 1988). This study is a critical step in that direction. We use recent data on ex-offenders in Multnomah County, Oregon and 2000 census data to examine whether a critical neighborhood characteristic—neighborhood socioeconomic status—influences recidivism rates beyond individual-level factors. Because the changes described (for example, greater challenges facing returning prisoners, an increase in supervision conditions, and so forth) have been occurring in Multnomah County, we believe it an appropriate site to study these issues.
DATA AND METHODS

SAMPLE

The study uses 2000 data from the U.S. census and from individuals on community supervision in Multnomah County (Portland and surrounding areas), Oregon. To obtain data on former prisoners, we requested a list of offenders admitted to community supervision between January 1 and June 30, 2000 from the Oregon Department of Corrections, the state’s repository for all community supervision data. An admission was defined as an offender admitted to supervision (1) due to a new crime for which a sentence of probation was given, (2) after serving a prison sentence with additional time to serve on parole or postprison supervision, (3) on returning to active supervision after previously absconding, or (4) on moving into Multnomah County from active supervision in another jurisdiction. These conditions, in combination, capture the population of offenders newly exposed to community supervision during the 6-month period in 2000 (n=5,002).

Once the sample was identified, a variety of data on the individuals were obtained from several criminal justice agencies. The Multnomah County Department of Community Justice provided data on offender characteristics (for example, sex, age, race) offense characteristics (for example, current offense, number of prior arrests), and risk-supervision level (for example, low, medium, high) while on probation. Data on the use of sanctions were extracted from the Department of Correction’s Sanctions Tracking Database, which contains information on whether or not each former inmate committed a sanctionable defense during the study period. Finally, information on arrests made during the supervision period was obtained from the data warehouse, Decision Support System-Justice, which contains integrated, individual-level data from law enforcement agencies (Portland police departments and the Multnomah County sheriff), the district attorney, and the courts. The Decision Support System-Justice provided arrest data for each offender in the sample 1-year post admission date.

Post-charge addresses were identified for ex-offenders in the sample. This address captures the first known housing location after release.5 We

5. A possible concern has to do with whether ex-offenders change residences after release. Unfortunately, the data provide only first known address information for each ex-offender. As such, we are not able to ascertain how frequently ex-offenders in the sample have relocated within the year or to model movements in housing location among these individuals. However, we believe that although ex-offenders may relocate, they are not likely to move frequently. In their study of prisoner reentry and residential mobility in Chicago, LaVigne and Parthasarathy (2005: 2)
used ArcView GIS to match home address information with 2000 census data to determine the Multnomah County census tract in which each individual was located. In this study, census tracts serve as proxies for neighborhoods. There are 170 census tracts in Multnomah County, but fourteen either had no releases or were not residential tracts (for example, parks) and thus were excluded from the analyses. Our final sample size includes 4,630 former inmates living in 156 neighborhoods.

RECIDIVISM

Recidivism has been defined in a number of ways and measured with a variety of indicators. The focus of this study is on recidivism among persons released from prison, on probation, parole, or other forms of correctional supervision. In this case, recidivism typically refers to persons who are rearrested, reconvicted, or reimprisoned during a specified time. In this study, we measure recidivism as a new arrest within a 12-month period. We chose arrest as the indicator because it bypasses problems associated with prosecutorial, court and correctional data, which are not as complete or reliable as law enforcement arrest data. Although arrest data do not capture crimes that did not result in an arrest, the overall effect of this limitation is that the rearrest measure is conservative; that is, any errors or omissions in the data almost surely underestimate the true amount of recidivism in the sample. From a data validity standpoint, it is arguably better to underestimate this critical variable than to overestimate it (Ulmer, 2001: 172). Moreover, Maltz (1984) examined more than ninety different recidivism studies and derived nine measurement categories: arrest, reconviction, incarceration, parole violation, parole suspension,

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6. A long-debated issue is whether census tracts constitute neighborhoods. Tracts generally have stable boundaries and are designed to be relatively homogenous with respect to population characteristics, economic status, and living conditions. Although imperfect, tracts as proxies have been used in most neighborhood effects studies (Sampson et al., 2002: 445).

7. The final N for the analyses is 4,630 because 137 ex-offenders had no reported address information, 130 had reported address information outside of Multnomah County, and the remaining 105 had missing information on one of the variables: supervision level (n=75), type of offending (n=19), sex (n=7), legal status (n=3), and race-ethnicity (n=1).
 parole revocation, offense, absconding, and probation. Maltz (1984: 66) concluded that “the recidivism definition of choice appears to be...arrest recidivism” (see also Blumstein and Cohen, 1979). For these reasons, we use arrest as our measure, in line with much of the research (Benedict and Huff-Corzine, 1997; Jones and Sims, 1997; Lanza-Kaduce et al., 1999; Listwan et al., 2003; Shinnar and Shinnar, 1975; Ulmer, 2001; Visher, Lattimore, and Linster, 1991). Arrest is measured as a binary variable that discerns between those who were and were not rearrested within a 12-month follow-up period (1 = rearrested, 0 = not rearrested). Twenty-eight percent of the sample was rearrested within the study period, a figure consistent with other studies (Benedict and Huff-Corzine, 1997; Clarke et al., 1998; Irish, 1989).

PREDICTORS OF RECIDIVISM

INDIVIDUAL-LEVEL

As noted, a number of individual-level characteristics are related to recidivism. Although all of these predictors are not measured in the current study, we account for many of the most frequently examined individual-level attributes and incorporate some (for example, new sanctions) that have been excluded in prior research. Probation is measured as a dichotomous variable where the reference group is all other forms of supervision (for example, parole, release from prison with supervision). High supervision is a dichotomous variable where the reference group is individuals on low or medium supervision. We also include three dichotomous variables for type of offense (here offense refers to the most serious prior offense): property offending, drug offending, and other offending, with violent offending as the reference category. Prior arrest measures the number of times an individual was ever arrested. New sanction captures whether an individual received a new sanction within the 12 months (the reference category is no new sanction). We also control for gender, race-ethnicity, and age because these demographic factors have been shown to be associated with recidivism. Female is a dichotomous variable with males as the comparison group. Race-ethnicity is measured by a set of dichotomous variables with 1 = black, 1 = Asian, 1 = Hispanic, and 1 = Native American (in each category, white is the reference group). Age is measured in years for each respondent. We also include a quadratic term for age in the model because the relationship between age and recidivism may be curvilinear.8

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8. An important omission from this list of variables is a measure that reflects ex-offenders’ social class, such as socioeconomic status, employment history, or
NEIGHBORHOOD-LEVEL

Four census tract variables were used to form the neighborhood disadvantage construct: proportion of persons on public assistance, proportion of persons below the poverty level, proportion of persons unemployed, and median family income. Previous studies have used some combination of these variables to assess community socioeconomic status (Sampson et al., 1997). Factor analysis indicated that these variables load strongly on a single factor (eigenvalue of 2.49; all loadings were above .70) across census tracts. This construct explains 62 percent of the variance.

The neighborhoods showed substantial variability with regard to indicators of disadvantage. For example, given a range of 0-62 percent, in the least disadvantaged neighborhoods (n=75), the average poverty rate was 8 percent whereas in the most extremely disadvantaged neighborhoods (n=19), it was 30 percent. Like poverty, there were differences in each socioeconomic indicator between the more and less disadvantaged neighborhoods.

Although we control for concentrated disadvantage because it is associated with a variety of negative outcomes (Sampson, Morenoff, and Gannon-Rowley, 2002), focusing solely on disadvantage neglects the phenomenon of concentrated affluence, which may generate a separate set of protective mechanisms, thereby reducing negative outcomes (Brooks-Gunn et al., 1993; Massey, 2001; Morenoff, Sampson, and Raudenbush, 2001; Sampson, Morenoff, and Earls, 1999). Massey (2001) points out that researchers spend too much time focusing on the consequences of disadvantage and little time focusing on affluence, and Sampson et al. (2002: 446) further note that “the common tactic of focusing on concentrated disadvantage may...obscure the potential protective effects of affluent neighborhoods.” We therefore extend our focus to include a measure that captures both the concentration of affluence and poverty.

To measure concentrated affluence and poverty, we used Massey’s (2001: 44) Index of Concentration at the Extremes (ICE) measure. The ICE measure captures the degree of concentrated affluence relative to the concentration of poverty in a neighborhood. As such, it reflects relative inequality in a community, rather than the absolute level of disadvantage.

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education level. Unfortunately, we were unable to obtain this information from the case files. A number of studies, however, find no significant effect for any of these measures on recidivism (for example, Benedict and Huff-Corzine, 1997; Spohn and Holleran, 2002; Ulmer, 2001). Indeed in their meta-analysis, Gendreau et al. (1996) report that across the 131 studies sampled, a relationship between SES and recidivism was reported on only twenty-three occasions, and the associated mean Pearson r for SES with recidivism was only .06 (SD = .11). We therefore believe this omission does not affect the results of the paper.
The ICE index provides insights that go beyond those generated by the standard concentrated disadvantage measure. Whereas the concentrated disadvantage measure assesses the degree to which certain conditions (for example, poverty, public assistance, unemployment) coexist in a neighborhood, the ICE measure reflects the degree to which persons with various levels of those conditions coexist. For a given community, the ICE index is computed using the following formula: \[
\frac{(\text{number of affluent families} - \text{number of poor families})}{\text{total number of families}},
\]
where “affluent” is defined as families with incomes two standard deviations above the mean (\( \bar{x} = $43,645, \sigma = $12,057 \)), which equates to $67,759, and “poor” is defined as families below the officially designated poverty line.

ICE provides a measure of the proportional imbalance of affluence versus poverty in a neighborhood on a scale that ranges from +1 to -1: a value of +1 indicates all families are affluent; a value of -1 indicates all families are poor; and a value of 0 indicates an equal balance of affluent and poor families (for a review see Massey, 2001; Morenoff et al., 2001).

ANALYTIC STRATEGY

We used multilevel modeling techniques to examine the effects of individual- and neighborhood-level factors on recidivism. Multilevel modeling has become customary for estimating contextual effects when individuals are clustered within neighborhoods (Raudenbush and Bryk, 2002). These models explicitly recognize that individuals within a particular neighborhood may be more similar to one another than to individuals in another neighborhood and, therefore, may not constitute independent observations. Consequently, failure to account for nonindependence of observations can result in standard errors that are biased downward, increasing the chances of reaching incorrect conclusions (Kreft and De Leeuw, 1999; Raudenbush and Bryk, 2002). Furthermore, multilevel modeling allows for simultaneous investigations of individual- and neighborhood-level variance components on the outcome variable of interest (for example, rearrested), while maintaining the appropriate level of analysis for the independent variables. We are also able to estimate the amount of variance in rearrest that exists across neighborhoods.

9. The models do not include measures of systems operations in the neighborhoods (for example, arrest rates, calls for service rates, number of police officers and the like). These data are not available at the census tract level. Although we cannot directly measure these characteristics, we believe that we indirectly capture their effects through several variables that reflect contact with law enforcement officials, including whether ex-offenders are on probation, parole, or some other form of supervision, actual supervision level of ex-offenders, and any new sanctions within the 12-month period. All three measures reflect varying degrees of contact with law enforcement officials and so indirectly assess neighborhood systems operations.
The most basic multilevel model estimates the level-1 equation separately for each group. The level-1 model takes the form of a regression-based equation; the level-2 analysis uses the intercept from the level-1 analysis as a dependent variable (Raudenbush and Bryk, 2002). In these analyses, we estimated a random intercept, fixed-slope model because our substantive interest is in whether variation in rearrest is explained by neighborhood context above and beyond individual-level predictors. Because our rearrest measure has a binary coding scheme, we estimated a series of two-level, hierarchical logistic regressions (Guo and Zhao, 2000).

Our analyses proceed in the following manner. First, we generated correlations and descriptive statistics for all variables. Second, we estimated an unconditional multilevel regression model that describes the variation in the dependent variable (rearrested) across neighborhoods. Third, we estimated an individual-level characteristics multilevel regression model. And, fourth, we estimated two neighborhood contextual multilevel models to further account for variation in rearrest.

RESULTS

DESCRIPTIVE STATISTICS AND CORRELATIONS

Table 1 presents the descriptive statistics and correlations for the variables included in our analyses. The descriptive statistics indicate that 28 percent of the sample was rearrested within a year. Eighty-one percent of the sample were on probation and 20 percent were on high-level supervision. The sample is 25 percent female and the average age is 36.10 Whites make up 68 percent of the sample, followed by African Americans (25 percent), Hispanics (4 percent), Asians (2 percent), and Native Americans (1 percent).

The correlations show support for several hypotheses. In particular, neighborhood disadvantage, the ICE measure, being on nonprobation supervision, prior property, drug, “other” offending, prior arrests, and receiving a new sanction are significantly associated with recidivism. Males and blacks are also more likely to recidivate. To investigate these relationships more closely, we turn to the multivariate results.

10. The mean age in our sample is a bit high compared to other offender samples. In most studies, the mean offender age is 30 or 31 (MacKenzie and Li, 2002: 52; Spohn and Holleran, 2002: 342; Ulmer, 2001: 174). This difference, however, is unlikely to affect the overall findings of the study.
### Table 1. Correlations, Means, and Standard Deviations among Study Variables

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**Note:** N = 4630 within neighborhood; N = 156 between neighborhoods. *p<.05. *neighborhood disadvantage.
UNCONDITIONAL MODEL

We began by assessing the degree to which recidivism risk varies across neighborhoods. To do this, we estimated an unconditional, random analysis of variance model (that is, a model with no predictors or control variables) that includes the intercept parameter describing the mean log odds for recidivism. Also included is a variance component that describes whether the dependent variable varies significantly across neighborhoods. The results are presented in Model 1 of Table 2.

The significance of the grand mean intercept (-.96) corresponds to the mean level (.28) of recidivism risk across neighborhoods (.28 = exp (-.96) / 1 + exp (-.96)). Also important is the significant random effects variance component of .053 ($X^2_{(155)} = 479$, $p < .01$), which indicates that recidivism varies significantly across neighborhoods and therefore can be modeled. Figure 1 provides a graphical distribution of the degree of variation in recidivism risk across neighborhoods. The figure shows that risk varies from less than 5 percent to greater than 40 percent.

Figure 1. Distribution of Recidivism Levels

11. It is important to note that the intraclass correlation is less informative in the case of the nonlinear link functions because the level-1 variance is heteroscedastic. Instead, Raudenbush and Bryk (2002) suggest that a useful way to assess the between-neighborhood variation is to estimate a confidence interval of the probabilities across neighborhoods (see 291–335 for a detailed discussion).
Figure 1 raises the question of what predictors account for the differences in levels of recidivism across neighborhoods. One possibility is that these differences reflect individual-level characteristics of residents. For example, it is possible that neighborhoods in which recidivism levels are high simply reflect the fact that these neighborhoods are home to more ex-offenders with attributes predictive of recidivism (for example, high levels of supervision, prior arrests, and the like). On the other hand, recidivism risk may be greater in some neighborhoods because former inmates residing there are exposed to higher levels of concentrated disadvantage and inequality. In Models 2 through 4 of Table 2, we assess these possibilities.

**LEVEL 1 (INDIVIDUAL-LEVEL)**

We estimated a level-1 model that included fourteen individual-level characteristics related to recidivism. These results are presented in Model 2 of Table 2. The individual-level covariates are grand mean centered. Each effect is adjusted for all other effects in the model.

All of the individual-level covariates, except for Hispanic, are significantly related to recidivism. Recidivism is higher among males, blacks, Native Americans, those on nonprobation supervision, those with high supervision levels, property, drug, and “other crime” (relative to violent) offenders, those with a history of prior arrests, as well as those who received new criminal sanctions. The findings also show that risk of recidivism increases with age but that this rate eventually slows. These results are consistent with an extensive body of research on recidivism (Gendreau et al., 1996).

Particularly noteworthy is the finding that probationers are less likely to recidivate than parolees or individuals who served their full sentence before being released with community supervision. Those individuals sentenced to probation are not incarcerated and typically do not leave their neighborhoods for any extended period. As such, there is no true “reintegration process” that must occur. On the other hand, parolees and those who have served a full sentence spend (often extended) time in prison and do face the challenges of reintegration as they return home. It is therefore not at all surprising that, controlling for other factors, probationers recidivate less.

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12. Because we have relatively low cell size counts for the Hispanic, Asian, and Native American ethnic categories, we reestimated models excluding all racial-ethnic groups except for blacks and whites to determine if the results changed. The findings were consistent with the larger models that included all racial-ethnic groups. We therefore present the full models to move beyond the black-white dichotomy.
Table 2. Multilevel Regressions of Variables on Recidivism (Rearrested)

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*p < .05, **p < .01. N = 4630 within neighborhood; N = 156 between neighborhood
A comparison of the variance components for Models 1 and 2 indicates that individual-level characteristics account for roughly 51 percent of the variance in recidivism within neighborhoods (.51 = .053 - .026 / .053). Thus, part of the explanation for why some neighborhoods exhibit higher recidivism levels is that some of the respondents have individual-level risk factors that increase recidivism. Despite this, the variance component in Model 2 indicates that a significant amount of variation in recidivism still remains, suggesting that other factors also contribute to recidivism levels.

LEVEL 2 (NEIGHBORHOOD-LEVEL)

The neighborhood effects literature described emphasizes that living in a community characterized by poverty, inequality, and socioeconomic disadvantage can increase the risk of a number of negative outcomes, including recidivism. On the other hand, living in a neighborhood with ample resources, services, and amenities could mitigate negative outcomes. Models 3 and 4 of Table 2 present results that assess these possibilities while accounting for individual-level characteristics. In Model 3, we added neighborhood disadvantage to the predictive equation of recidivism. As shown, neighborhood disadvantage is significant and positive. Consistent with our predictions, living in a disadvantaged neighborhood is a risk factor that increases the odds of recidivism above and beyond individual-level attributes. In particular, a one unit increase in the disadvantage index results in a 12-percent increase in the odds of recidivism (.12 = 1 – exp(.11)).

In Model 4, we included the Index of Concentrated Extremes (ICE) measure. Recall that ICE is an inequality measure ranging from -1 to +1 and tapping both ends of a neighborhood’s economic structure. The regression coefficient for this measure is significantly and negatively related to recidivism, indicating that an individual living in a neighborhood that has more affluent relative to poor families is less likely to recidivate, controlling for individual-level factors. In fact, a one unit increase in the ICE index results in a 62-percent reduction in the odds of recidivism (.62 = 1 - exp(-.97)). This finding suggests that neighborhoods with large concentrations of affluent families (relative to poor families), or resource-rich neighborhoods, serve a critical protective function in reducing recidivism.

It is worth noting that neighborhood disadvantage accounted for roughly 13 percent of the variance in recidivism across neighborhoods, whereas the ICE measure accounted for roughly 9 percent. Overall, the

13. To determine this, we took the difference between the one individual-level model and the two contextual models. For example, in Model 3 (neighborhood
individual- and neighborhood-level variables accounted for more than half of the variance in recidivism (ND = .64 = .053 - .019 / .053 and ICE = .60 = .053 - .021 / .053). 14

Although individual-level characteristics account for a large portion of the variance in recidivism, neighborhood disadvantage and the ICE measure also explain significant variation in recidivism. Table 3 displays the predicted probabilities of recidivism for individuals who reside in neighborhoods that differ on levels of disadvantage and inequality. The predicted probabilities were computed using the coefficients from Models 3 and 4 of Table 2 and assume mean values for all other variables (Hosmer and Lemeshow, 2000). The predicted probabilities associated with the estimated neighborhood disadvantage effect suggest that recidivism risk ranges from about 42 percent in neighborhoods with less disadvantage (-2$\sigma$) to about 60 percent in those with more disadvantage (+2$\sigma$), assuming mean values for all other variables. This translates into a 43-percent increase in risk going from a low disadvantage to a high disadvantage tract. The ICE measure shows a similar pattern where extreme inequality (-2$\sigma$) is associated with moderate recidivism (54 percent), whereas less (+2$\sigma$) is associated with lower rates (33 percent), translating into a 39 percent reduction in risk. Collectively, the results for neighborhood disadvantage and the ICE measure indicate that community context is an important predictor of recidivism and that recidivism levels do vary depending on neighborhood characteristics. 15

disadvantage), the total amount of variance explained by individual and neighborhood disadvantage variables was 64 percent. Recall that individual-level characteristics accounted for 51 percent of the variance in recidivism. The difference between Model 3 and Model 2 is 13 percent (13 = 64 – 51). Further, the difference between Model 4 (ICE) and Model 2 is roughly nine percent (9 = 60 – 51).

14. To simultaneously assess the joint effects of neighborhood disadvantage and the ICE measure on recidivism, we estimated a single model that included both measures. However, multicollinearity between the two variables was a problem. As such, we estimated the neighborhood variables in separate models (see also Morenoff et al., 2001: 539). We also explored cross-level interactions and found none. Thus, we focus on the main effects of individual and neighborhood effects on recidivism.

15. It is important to consider the issue of spatial dependence in the models given that our level-2 units are neighborhoods (Anselin, 1988). Spatial analyses are somewhat of a challenge in our study because it is multilevel and incorporating spatial effects may produce identification problems in that our neighborhoods of interest are affected by, as well as influence, other neighborhoods creating non-normal residuals. Furthermore, spatial autocorrelation techniques are not currently available in HLM (Morenoff, 2003; Morenoff et al., 2001). However, we believe it necessary to assess whether our findings are influenced by spatial dependency. To determine this we took the proportion of recidivism across neighborhoods and used it to create a spatial lag. We then replicated the main results introducing a spatial
Table 3. Predicted Probabilities of Recidivism (Rearrested) in Different Social Contexts

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CONCLUSION

Previous studies examining recidivism have explored a host of individual-level correlates and generated important findings, yet a consideration of the role of neighborhood context in influencing recidivism is absent. This lack of attention to contextual factors is surprising given that community context has been shown to be an important predictor in shaping a variety of individual-level outcomes (Sampson et al., 2002). In this study, we expanded on earlier work by examining the impact of neighborhood socioeconomic status on recidivism. Drawing on insights from a sizable “contextual effects” literature, we hypothesized that ex-offenders who live in areas with high levels of disadvantage and inequality increase their chances of recidivism, and that those who live in affluent or resource rich communities reduce their chances. We expected neighborhood effects to persist net of individual factors associated with rearrest, and the results supported this expectation—those who return to disadvantaged communities recidivate more, while those who return to relatively affluent communities recidivate less, controlling for individual-level factors.

An important question has to do with the generalizability of the findings. Are the findings for Multnomah County (Portland and surrounding area) applicable to other U.S. counties and cities? We believe so. First, as noted earlier, recidivism rates for our sample of ex-offenders returning to (mostly) Portland neighborhoods mirror rates reported in lag term in our HLM regressions. The results are presented in Appendix 2. Overall, the substantive results did not change, although our models did show some sign of spatial dependency where high recidivism levels of neighborhoods appear to influence recidivism levels in adjacent neighborhoods. These results suggest, therefore, that in addition to neighborhood effects on recidivism, there may also be spatial diffusion or spillover effects of recidivism from one neighborhood to another. We note, however, that our incorporation of the spatial lag term is a crude test at best of the spatial dependency process. To verify our results, we followed the procedure used by Morenoff (2003) to build a hierarchical spatial model. We constructed a neighborhood-level recidivism measure adjusted for the HLM individual-level covariates and then regressed the recidivism measure on the neighborhood-level covariates and the spatial lag term. This procedure produced nearly identical results.
other recidivism studies (Clark, 1988; Irish, 1989; Lanza-Kaduce et al., 1999), including studies that use national data (Benedict and Huff-Corzine, 1997). And second, the socioeconomic and demographic profile of Portland (and Multnomah County) does not differ greatly from the United States as a whole. For example, U.S. racial breakdowns—75 percent white, 12.3 percent black, 3.6 percent Asian, .9 percent Native American, 12.5 percent Hispanic—are not drastically different from racial breakdowns in Portland—77.9 percent white, 6.6 percent black, 6.3 percent Asian, 1.1 percent Native American, and 6.8 percent Hispanic. Economic indicators are equivalent as well. The U.S. median household income is $40,146 and 12.4 percent of the U.S. population lives in poverty. Likewise, in Portland, the median household income is $41,994 and 13.1 percent of the residents live in poverty. Educational levels are also quite similar, with 24.4 percent of U.S. residents holding a bachelor’s degree or higher, compared to 25.1 percent in Portland. Finally, homeownership rates are comparable with 55.8 percent of U.S. residents owning their own homes compared to 66.2 percent in Portland. In short, we do not believe that the findings of this study are unique. Still, a necessary next step for future research is to replicate this study in other cities to corroborate that neighborhood context matters for recidivism.

Another useful direction for future research is to more broadly account for community context in recidivism studies. Given its central role in the neighborhood effects literature, we chose to focus on community socioeconomic status but there are several other characteristics that likely matter for returning prisoners. For example, social disorganization theory highlights neighborhood-level factors such as residential instability, racial-ethnic heterogeneity and family disruption, among others, which inhibit residents’ ability to establish or maintain effective social controls (Bursik, 1988: 521; Kornhauser, 1978: 120; Sampson and Groves, 1989). In racially heterogeneous or residentially unstable neighborhoods, it is more difficult for residents to form strong social bonds around common values, such as crime prevention. This weakens the community’s capacity for social control and leads to elevated crime levels, with consequences for the ability of former inmates to establish and reestablish prosocial bonds (Maruna, 2001). The extent that returning ex-offenders create or maintain ties with criminal “colleagues” in the neighborhood is bound to affect their likelihood of recidivating. In short, highly disorganized neighborhoods can constrain the ability of ex-offenders to successfully reintegrate and pursue conventional lifestyles, encouraging reoffending. Future research should incorporate additional neighborhood characteristics to determine the extent to which this is the case.

Along these lines, future research should also focus on the interactions between offender and environmental characteristics. Although the current
study did not document interaction effects between neighborhood socioeconomic status and individual-level factors, there is still reason to believe that the effects of concentrated disadvantage or affluence along with racial heterogeneity, residential instability, and other community factors on recidivism may depend, to some extent, on the personal characteristics of ex-offenders. Gottfredson and Taylor (1985: 147) note, “We believe that the person, his/her environment, and his/her behavior interact in a process of mutual and reciprocal influence. A first indication that this approach has validity would be the finding that different types of offenders perform differently in different types of environments.”

A final direction for future research is to examine precisely how neighborhoods influence recidivism rates, to more fully capture the community-level processes that matter most. Beyond socioeconomic status, other features of neighborhoods—more proximate features—such as the social services they provide and the personal networks that operate within, are critical for comprehensively understanding the neighborhood structure-recidivism relationship (Sampson et al., 2002). Indeed, Gottfredson and Taylor (1985: 138) noted long ago that “three classes of contextual variables (nature and extent of local social ties, attachment to the locale, and potentially supportive or criminogenic facilities)... should be related to recidivism.” Future efforts to examine these mediating factors will require moving beyond census data to measure neighborhood effects. Ethnographic or survey data on the number and quality of social services or the nature of neighbor networks will go a long way in this effort. We are only beginning to understand how neighborhoods facilitate and impede post-prison reentry and there is much more to explore.

Apart from future directions, the findings of this study have significant public policy implications. Most importantly, they direct attention toward focusing on neighborhoods in efforts to reduce recidivism. Unfortunately, approaches to reducing crime that do not involve additional investments within the criminal justice system have received little attention in the research community and are rarely a subject of sustained analysis in political debate (Mauer, 2005: 608). Nowhere is this more evident than in the policy recommendations on prisoner reentry currently being proposed. Some researchers offer policy recommendations that focus on prison programs to “prepare inmates for what they will face on release and return to the communities” (Seiter and Kadela, 2003: 367), and others argue that special courts should be developed as mechanisms for managing the transition back to the community (Travis, 2000). Others propose a mixed strategy of selective reentry that would increase supervision for the small number of high-risk inmates and sharply reduce the supervision periods for the majority of offenders who pose minimal risk (Austin, 2001). Still others call for a major overhaul of the probation system. In her review of
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probation. Petersilia (1997) offers suggestions for reforming the probation system including providing adequate financial resources to programs shown to work, combining both treatment and surveillance toward appropriate offenders, considering intermediate sanction programs and even seriously reconsidering probation’s underlying mission, administrative structure and funding base. Finally, a prominent former corrections official urges that expectations about corrections’ responsibilities for reentry be scaled back and that the major responsibility be placed on individual ex-prisoners (Horn, 2000).

In this long list of recommendations, one arena of change is completely left out of the equation: changing communities. None of these suggestions focus on fixing the (disadvantaged) communities to which released inmates disproportionately return. Given the challenges of prisoner reentry, particularly in a “get tough on crime” era, former prisoners are more reliant than ever on community services and personal networks not just to comply with the terms of their supervision but also to curb recidivism. They even recognize this. A recent study of prisoner reentry that involved interviews with just released ex-offenders reported that “focus group participants believed that the community should play a role in addressing the needs of ex-prisoners” (Visher et al., 2004: 2). Although providing inmates with an education or vocational training or preparing them for a life outside prison are all steps in the right direction, skills matter little if the communities to which ex-offenders return offer few jobs or opportunities. In short, by ignoring community context, we are likely setting up ex-inmates for failure. It’s not surprising, therefore, that recidivism levels are as high as they are today. As Rose and Clear (2003) note, “individualistic public policies that focus solely on offenders overlook the importance of neighborhoods. Local areas must be considered when we think about the impact of incarceration and reentry because they provide the environments that contextualize the lives of offenders and nonoffenders alike. Local areas afford opportunities and constraints for both normative and nonnormative behavior” (318). Indeed, this is exactly what our study finds.

REFERENCES


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Appendix 1. Standard Conditions of Adult Probation/Parole/Post-Prison Supervision in Multnomah County, Oregon

Although the specific conditions of supervision may vary from case to case, there is a group of standard conditions which apply to almost every offender. What follows are the standard conditions of supervision typically used by the criminal courts in Multnomah County.

- Pay supervision fees, fines, restitution or other fees ordered by the Court.
- Do not use or possess controlled substances except pursuant to a medical prescription.
- Submit to testing of breath or urine for controlled substances or alcohol use if the probationer has a history of substance abuse or if there is a reasonable suspicion that the probationer has illegally used controlled substances.
- Participate in a substance abuse evaluation as directed by the supervising officer and follow the recommendations of the evaluator if there are reasonable grounds to believe there is a history of substance abuse.
- Remain in the state of Oregon until written permission to leave is granted by Adult Community Justice or a county community corrections agency.
- If physically able, find and maintain gainful full-time employment, approved schooling, or a full-time combination of both. Any waiver of this requirement must be based on a finding by the Court stating the reasons for the waiver.
- Change neither employment nor residence without promptly informing Adult Community Justice or a county community corrections agency.
- Permit the probation officer to visit the probationer or the probationer’s residence or worksite, and report as required and abide by the direction of the supervising officer.
- Consent to the search of person, vehicle or premises upon the request of a representative of the supervising officer if the supervising officer has reasonable grounds to believe that evidence of a violation will be found, and submit to fingerprinting or photographing, or both, when requested by the Department of Corrections or a county community corrections agency for supervision purposes.
• Obey all laws, municipal, county, state and federal.

• Promptly and truthfully answer all reasonable inquiries by the Department of Corrections or a county community corrections agency.

• Do not possess weapons, firearms or dangerous animals.

• If under supervision for, or previously convicted of, a sex offense under ORS 163.305 to 163.465, and if recommended by the supervising officer, successfully complete a sex offender treatment program approved by the supervising officer and submit to polygraph examinations at the direction of the supervising officer.

• Participate in a mental health evaluation as directed by the supervising officer and follow the recommendation of the evaluator.

Source: http://www.co.multnomah.or.us/dcj/vision.shtml.

Appendix 2. Multilevel Spatial Regressions of Individual- and Neighborhood-Level Variables on Recidivism (Rearrested)

<table>
<thead>
<tr>
<th></th>
<th>Model 1: Contextual: ND</th>
<th>Model 2: Contextual: ICE</th>
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<tr>
<td>Intercept, $\gamma_{00}$</td>
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<td>S.E.</td>
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<td>Individual-Level</td>
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<tr>
<td>Female</td>
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<tr>
<td>Black</td>
<td>.47**</td>
<td>.08</td>
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<tr>
<td>Native American</td>
<td>.92**</td>
<td>.30</td>
</tr>
<tr>
<td>Age</td>
<td>.09**</td>
<td>.03</td>
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<tr>
<td>Age²</td>
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<td>.0003</td>
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<td>High Supervision</td>
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<td>.10</td>
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<tr>
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<td>.14</td>
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<td>Other Offending</td>
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<tr>
<td>Prior Arrests</td>
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<td>.03</td>
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<tr>
<td>New Sanction</td>
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<tr>
<td>Neighborhood-Level</td>
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<tr>
<td>Disadvantage (ND)</td>
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<td>ICE Measure</td>
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<tr>
<td>Spatial Lag</td>
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<tr>
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<td>$\sigma^2$</td>
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<td>$\chi^2$</td>
<td>366**</td>
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*p < .05, **p < .01. N = 4630 within neighborhood; N = 156 between neighborhoods.