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PREDICTING RECIDIVISM FOR RELEASED STATE PRISON OFFENDERS:

Examining the Influence of Individual and Neighborhood Characteristics and Spatial Contagion on the Likelihood of Reincarceration

Gerald J. Stahler,
Temple University

Jeremy Mennis,
Temple University

Steven Belenko,
Temple University

Wayne N. Welsh,
Temple University

Matthew L. Hiller, and
Temple University

Gary Zajac
Pennsylvania State University

Abstract

We examined the influence of individual and neighborhood characteristics and spatial contagion in predicting reincarceration on a sample of 5,354 released Pennsylvania state prisoners. Independent variables included demographic characteristics, offense type, drug involvement, various neighborhood variables (e.g., concentrated disadvantage, residential mobility), and spatial contagion (i.e., proximity to others who become reincarcerated). Using geographic information systems (GIS) and logistic regression modeling, our results showed that the likelihood of reincarceration was increased with male gender, drug involvement, offense type, and living in areas with high rates of recidivism. Older offenders and those convicted of violent or drug offenses were less likely to be reincarcerated. For violent offenders, drug involvement, age, and spatial contagion were particular risk factors for reincarceration. None of the neighborhood environment variables were associated with increased risk of reincarceration. Reentry programs need to particularly address substance abuse issues of ex-offenders as well as take into consideration their residential locations.

Keywords

reincarceration; recidivism; reentry; spatial contagion; neighborhood effects

There are currently more than 7 million adults in the United States under some form of criminal justice supervision, including more than 2 million offenders who are incarcerated

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Correspondence concerning this article should be addressed to Gerald J. Stahler, PhD, Department of Geography and Urban Studies, 309 Gladfelter Hall, Temple University (025-27), Philadelphia, PA 19122; jstahler@temple.edu.

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and 5 million who are on probation or parole (Bureau of Justice Statistics, 2011). Virtually all of those currently incarcerated will eventually return to their communities, with about 85% returning within 3 years of admission (West, Sabol, & Greenman, 2010). In recent years, releases from state and federal prisons have been totaling more than 700,000 annually (West et al., 2010).

The difficulties of prisoners returning home are well-documented in the literature. Released prisoners typically face obstacles in obtaining employment and stable housing often due to lack of work skills, stigma, and low levels of educational attainment (Petersilia, 2003). Many also experience difficulties in returning to a problematic family and social environment, unresolved substance abuse and mental health problems, and numerous other challenges in establishing a conventional prosocial lifestyle (Mallik-Kane & Visher, 2008; National Research Council, 2007; Petersilia, 2003; Visher & Travis, 2003). A typical situation for released offenders is arriving home "with very little money, resources, or social capital, and because of their felony record they are unable to obtain employment or find housing. Petersilia [2003] argues that because of these deficits, successful reentry for many prison inmates is both difficult and unlikely" (Makarios, Steiner, & Travis, 2010, p. 1377).

Research has shown that offenders who are released from prison reenter their communities with a considerable likelihood of reoffending and eventual reincarceration. The most recent large-scale national study on recidivism found that two thirds of prisoners released in 1994 were rearrested within 3 years and about one quarter were reincarcerated within that period (Langan & Levin, 2002). More recent studies at the state level suggest that recidivism rates are still high, including one study reporting that 22% of a sample of released offenders were reincarcerated within a year of release (Visher, Yahner, & La Vigne, 2010) and other studies showing rates as high as 80% (The Sentencing Project, 2011). On the other hand, for those who do not reoffend within 3 years of release, the likelihood of reincarceration at a later time is greatly diminished (Greenfeld, 1985). Within 3 years, about 95% of released state inmates with drug use histories return to drug use (W. L. White, 1998, as cited in Martin, Butzin, Saum, & Inciardi, 1999), 67% of drug offenders are rearrested (41% for a new drug offense), 47% are reconvicted, and 25% are sentenced to prison for a new crime (Langan & Levin, 2002). The time to recidivism is shorter for drug-involved offenders than other types of offenders (Spohn & Holleran, 2002).

Some have argued and demonstrated that criminal behavior is influenced not only by individual characteristics but also by the neighborhood characteristics (e.g., concentrated disadvantage, lack of collective efficacy) in which individuals live (Sampson, Morenoff, & Gannon-Rowley, 2002). The neighborhood environmental context has been found to influence behavior above and beyond individual explanatory variables and may provide an important additional independent level of explanation for examining the likelihood of reincarceration for offenders released back to the community (Kirk, 2009; Kubrin & Stewart, 2006; Wehrman, 2010). Perhaps one of the more important community influences on criminal behavior is the offender's social networks in the neighborhood. Interactions with criminally involved peer networks in the community may increase the likelihood of reoffending (Andrews, Bonta, & Wormith, 2006, 2011; Gendreau, Little, & Coggin, 1996; Hagan, 1993; Visher & Travis, 2003), and these networks have a spatial expression. That is, one would expect to see a "spatial contagion" effect—living in proximity to others who are reoffending will increase the likelihood of an individual also reoffending (Mennis & Harris, 2011).

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INDIVIDUAL-LEVEL PREDICTORS OF RECIDIVISM

Given the high rates of persistent criminal activity and reincarceration among released prisoners and the resulting economic and human toll on communities, victims, offenders, and their families, it is understandable that there is such a substantial body of research and much theoretical discussion on how best to predict recidivism, as well as how to design strategies, interventions, and programs to reduce the likelihood of reoffending (e.g., Andrews & Bonta, 2010a; Andrews & Dowden, 2007; Makarios et al., 2010; Siddiqi, 2010; Singh & Fazel, 2010). Andrews et al. developed the Risk-Needs-Responsivity (R-N-R) model (Andrews et al., 1990; Andrews et al., 2006), which “has had considerable impact within justice and corrections in Canada, the United Kingdom, Australia, New Zealand, and parts of the United States” (Andrews & Bonta, 2010b, p. 49). The risk factors described in this model were identified from a meta-analysis of prior research and include criminogenic factors that appear to increase the likelihood for reoffending: antisocial personality, procriminal attitudes, association with antisocial peers, social support for crime, substance abuse, poor family/marital relationships, school/work problems, lack of prosocial recreational activities, and past criminal history (Andrews et al., 2006; Bonta & Andrews, 2007; Taxman & Marlowe, 2006; Taxman, Thanner, & Weisburd, 2006). This R-N-R model has been widely used in assessing offender treatment needs and in planning individual programmatic interventions based on the principles of “risk” (i.e., providing the most intensive treatment for those at highest levels of risk), “need” (i.e., matching services to specific criminogenic needs), and “responsivity” (i.e., matching the mode of services to the individual learning styles and abilities of the offender).

Aside from criminal history, these risk factors are all “dynamic” in the sense that they can change over time, and therefore, interventions can be developed to address these criminogenic domains of need (Andrews & Bonta, 1994). “Static” factors such as criminal history, age, gender, and race may also be predictive of recidivism, but these are not amenable to change and therefore cannot be targeted for interventions on an individual level. There has been extensive research examining the relationship between both kinds of these factors and recidivism. Indeed, Singh and Fazel (2010) identified 40 review articles and meta-analyses that examined the findings from 2,232 studies investigating various predictors of recidivism. Among the static factors that have been identified as predictors of recidivism are recent release, with the risk for reoffending declining over time (Huebner & Berg, 2011; Kurlychek, Bushway, & Brame, 2006; Langan & Levin, 2002), prior arrests and prison sentences (Gendreau et al., 1996; Langan & Levin, 2002), being African American (Gendreau et al., 1996; Steen & Opsal, 2007; Wehrman, 2010), male gender (Langan & Levin, 2002), and younger age (Huebner & Berg, 2011; Langan & Levin, 2002). Although statistically African Americans may have a greater likelihood of recidivism, this may reflect other factors that differentially affect blacks compared to other racial groups (e.g., poverty, unemployment, or racial bias). There is some evidence to suggest that predictors of recidivism are similar for both men and women (Makarios et al., 2010). Finally, type of offense appears to be related to recidivism, with property and drug offenses associated with greater risk (Langan & Levin, 2002).

Research on dynamic risk factors can potentially lead to the development of prison or community-based programs and interventions that can address offender needs and potentially lower the probability of reincarceration after release (Andrews & Bonta, 2010a, 2010b). The stigma of a prison record, low educational attainment, and lack of job skills among released offenders can create substantial barriers for finding employment and stable housing after release (Petersilia, 2003; Rosenfeld, Petersilia, & Visher, 2008; Travis, Solomon, & Waul, 2001; Visher & Travis, 2003). For example, lack of stable housing upon release (Huebner & Berg, 2011; Makarios et al., 2010) and low educational attainment

(National Research Council, 2007) have been shown to increase the risk of recidivism. Stable employment reduces reoffending (Laub & Sampson, 2003; Uggen, 2000; Western, Kling, & Weiman, 2001), although Bucklen and Zajac (2009) did not find that job acquisition predicted successful parole.

Marriage and reconnecting with the family can act as buffers to increase the likelihood of successful reentry because family members often provide a considerable amount of the tangible as well as emotional support for offenders initially after release (Huebner & Berg, 2011; Mallik-Kane & Visher, 2008; Sampson & Laub, 1993; Sullivan, Mino, Nelson, & Pope, 2002; Visher & Travis, 2003; Visher, Knight, Chalfin, & Roman, 2009). However, some research suggests that returning home can also increase the likelihood of recidivism (Huebner & Berg, 2011; Yahner & Visher, 2008), possibly because they may return to the same criminogenic social networks.

One of the strongest dynamic predictors of recidivism is drug involvement and continued drug use (Belenko, 2006; Bonta, Law, & Hanson, 1998; Dowden & Brown, 2002; Mallik-Kane & Visher, 2008), and the connections between the abuse of illegal drugs and crime have been well-documented (Belenko & Peugh, 2005; Chandler, Fletcher, & Volkow, 2009). Histories of illegal drug use are common among inmates and other offenders, and more than 80% have indications of serious drug or alcohol involvement (Belenko & Peugh, 2005). National surveys of state prison inmates indicate that 82% of state prison inmates reported a lifetime use of an illegal drug and more than two thirds (68%) report having ever used illegal drugs regularly (Mumola & Karberg, 2006). In addition, 32% were under the influence of drugs at the time of the offense, and 16.5% reported committing their crime to get money to buy drugs. Based on *Diagnostic and Statistical Manual of Mental Disorders* (4th ed.; American Psychiatric Association, 1994) criteria, 53.4% of state prisoners, including 53% of male and 60% of female inmates, meet criteria for substance abuse or dependence (Mumola & Karberg, 2006), compared with an estimated 12.5% of males and 5.7% of females in the general population aged 18 or older (Substance Abuse and Mental Health Services Administration, 2008). Drug abuse or dependence ranges from 47% of those incarcerated for violent crimes to 63% for those convicted of drug or property offenses (Mumola & Karberg, 2006).

Substance abuse may affect the likelihood of reoffending in multiple ways: by increasing financial needs at the same time as reducing the likelihood of obtaining and maintaining employment and family support, increasing the likelihood of reconnecting with negative peer social networks, committing other offenses while under the influence, and increasing the possibility of parole violation detection (Belenko, 2006; Huebner & Berg, 2011; Taxman, Byrne, & Young, 2003; H. R. White & Gorman, 2000). Indeed, Bucklen and Zajac (2009) found that substance use distinguished parole successes from failures in a large sample of Pennsylvania parolees.

NEIGHBORHOOD CONTEXT AND RECIDIVISM

Most of the prior empirical and theoretical literature focuses on individual and social factors associated with recidivism. Only recently have empirical studies begun to investigate the role of the neighborhood environment on reentry outcomes. The focus on individual characteristics has occurred because the risk of reoffending has traditionally been viewed as individually determined (Kubrin & Stewart, 2006). This perspective, however, ignores the body of evidence concerning the strong independent influence of neighborhood contextual factors that have been found to affect various other behavioral and health risk factors and outcomes, in such diverse domains as coronary heart disease and adult physical health (Diez-Roux, 2001; Galea, Rudenstine, & Vlahov, 2005; Pickett & Pearl, 2001; Ross &

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Mirowsky, 2001), mental health disorders (Boardman, Finch, Ellison, Williams, & Jackson, 2001; Mair, Diez-Roux, & Galea, 2008; Sampson et al., 2002; Silver, Mulvey, & Swanson, 2002; Stahler et al., 2007; Stahler, Mennis, Cotlar, & Baron, 2009), as well as criminal behavior (Bursik & Grasmick, 1993; Sampson, Raudenbush, & Earls, 1997; Sampson et al., 2002). As Sampson et al. (2002) conclude in their review of the "neighborhood effects" research that investigates the relationship between crime and the neighborhood context, "the weight of evidence … 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" (p. 446).

If there is a relationship between neighborhood characteristics and crime, then it seems logical that there should also be a relationship between neighborhood context and recidivism for released inmates. Where ex-offenders live greatly affects their accessibility to both opportunities for institutional resources as well as personal networks that affect reentry outcomes (Kubrin & Stewart, 2006; Rose & Clear, 1998). As Kubrin and Stewart (2006) conclude, the "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" (p. 167).

Only a few studies have actually examined the influence of the neighborhood context on recidivism empirically, and the findings have been mixed. One of the earliest studies to examine the effect of neighborhood context on parolee recidivism found some small interaction effects between offender characteristics and neighborhood environmental context but no direct neighborhood influences (Gottfredson & Taylor, 1988). In contrast, Kubrin and Stewart (2006) found strong neighborhood effects on rates of recidivism. Using data from the Portland, Oregon area, they found that, controlling for individual characteristics, offenders returning to neighborhoods with higher levels of concentrated disadvantage were far more likely to be rearrested within 1 year than those returning to more affluent and resource-rich neighborhoods. The natural experiment that occurred as a result of Hurricane Katrina found evidence that parolees who relocated from devastated portions of New Orleans had reduced rates of recidivism compared to other parolees who could return to their old neighborhoods, suggesting some benefit deriving from a change in venue (Kirk, 2009). However, other recent studies did not find a similar relationship between neighborhood disadvantage and either timing of reconviction (Huebner, Varano, & Bynum, 2007) or risk of felony reconviction (Wehrman, 2010).

Recent research on the relationship between neighborhood context and recidivism among juvenile offenders is also informative. Grunwald, Lockwood, Harris, and Mennis (2010) suggest that concentrated disadvantage and social capital influence drug offense recidivism, but not other types of offenses. Mennis and Harris (2011) found that not only did certain individual factors such as ethnicity, parental criminality, and juvenile justice history predict recidivism but also a variable they termed *spatial contagion*. The concept of spatial contagion is derived from the notion of "peer contagion" in the youth criminal justice literature that posits that the likelihood of deviant behavior is increased through association with other deviant youth (Andrews et al., 2006, 2011; Andrews & Bonta, 2010a; Dodge, Lansford, & Dishion, 2006).

Theoretical support for this concept comes from the mechanism of differential association theory and differential reinforcement theories (Akers, 1985; Burgess & Akers, 1966; Sutherland, Cressey, & Luckenbill, 1992). Mennis and Harris (2011) found that the spatial manifestation of peer contagion strongly influenced the likelihood of recidivism among delinquent youth. The likelihood of recidivism was enhanced by proximity to others who

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reoffended. Although the relationship between spatial contagion and recidivism has not yet been examined among adult offender populations, it is conceivable that the same mechanisms may also occur with adult ex-offenders. That is, living in proximity to ex-offenders who become reincarcerated may increase the likelihood of recidivism, consistent with differential association theory (Akers, 1985). This may reflect the influence of negative peer associations within the neighborhood; more generally, association with deviant peers has been cited as a key risk factor for criminal behavior within the R-N-R framework (Andrews & Bonta, 2010a).

PRESENT STUDY

Despite the important policy implications for identifying factors that predict poor reentry outcomes and despite the large amount of research that has examined various types of predictors of recidivism, most studies of released inmates have focused on individual predictors rather than including both individual and neighborhood predictors of reincarceration (Gottfredson & Taylor, 1988; Kubrin & Stewart, 2006). Data on prior drug involvement have also been frequently lacking in prior research. The current study addresses this gap by including not only such individual factors as demographic variables, offense type, and drug involvement, but also neighborhood contextual factors and spatial contagion. Using a large sample of Pennsylvania state prison inmates released back home to Philadelphia between July 1, 2002 and June 30, 2006, we examine the effects of these multilevel and multidimensional factors on reincarceration within 3 years of release.

METHOD

SAMPLE

Our initial sample consisted of a deidentified retrospective dataset of all Pennsylvania state prisoners sentenced in Philadelphia County and released to Philadelphia between July 1, 2002, and June 30, 2006, a total of 9,441 individuals. Excluded were offenders whose address prior to incarceration was not a home address, such as any kind of institutional facility including county jail, homeless shelters, and so forth. We exclude these individuals from the analysis because our interest is in the influence of the neighborhood environment on reincarceration, and these institutional facilities typically represent temporary living arrangements. This reduced the sample to a total of 6,465 cases.

Of the 6,465 cases in the sample, the 5,354 cases that could be geocoded using geographic information systems (GIS) software and street centerline data acquired from the Philadelphia Department of Planning form the basis of this analysis. This represents about 83% of the sample, or 57% of the original total number of cases in the database. The cases that could not be geocoded represented individuals with either missing addresses or addresses that lacked a street name and/or number (e.g., address listed as “brother’s house”). We note that given that the database of prisoners was never intended for geocoding or analysis but rather for administrative purposes for the prison population, our 83% geocoding success rate compares favorably with other large prisoner population datasets that involve geocoding (cf., Wehrman, 2010).

The descriptive characteristics of our sample are shown in Table 1. The sample is primarily African American, male, and unmarried, with a mean age at release from prison of 35 years. The vast majority of ex-prisoners have a verified drug problem, defined as having either a TCU (Texas Christian University) Drug Screen II (Broome, Knight, Joe, & Simpson, 1996; Peters et al., 2000) score of 3 or greater, or otherwise classified by the Pennsylvania Department of Corrections as having a verified drug problem using their standard

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assessment procedures. Approximately one third of the sample was reincarcerated within 3 years of release from prison.

We conducted an analysis comparing the 83% of cases that were geocoded to the 17% of the cases that could not be geocoded using Chi-square and *t* tests. The results suggest that the two groups are largely similar, though there were some statistically significant differences between them, which is to be expected given the large number of cases in each group. The geocoded sample, compared to the nongeocoded group, was not statistically different in terms of the proportion of males (96%) and married individuals (14.5% vs. 13.3%) in the two groups. However, the geocoded sample had a slightly higher rate of reincarceration (35% vs. 32%, $\chi^2 = 3.93$, $p < .05$). It also was slightly younger (35.2 vs. 36.6, $t = 4.54$, $p < .005$), had a higher proportion of African Americans (76% vs.73%, $\chi^2 = 5.29$, $p < .05$), and had a greater percentage of individuals with drug involvement (84% vs. 70%, $\chi^2 = 128.59$, $p < .005$), which may suggest that this sample could be at a higher risk for recidivism.

VARIABLES

Dependent variable—Our measure of recidivism in the analysis was reincarceration in the Pennsylvania state prison system within 3 years of release whether due to a new crime or a technical parole violation. For our sample of released inmates, we chose to use the most conservative estimate of recidivism, which has been commonly used in prior research on recidivism of released inmates (e.g., Huebner & Berg, 2011; Visher et al., 2010; Wehrman, 2010).

Independent variables—The individual-level explanatory variables in the analysis included such demographic variables as age (mean age at release), race (African American, Hispanic, and White/other), and gender. Other individual variables used in the analysis were drug involvement (assessed by prison staff at intake using the TCU Drug Screen, intake interview, or other instruments) and offense type, defined as the primary category of offense for which the ex-prisoner was most recently incarcerated—violent (murder, manslaughter, rape, assault, robbery), drug (most commonly manufacture, sale, delivery, or possession with intent to distribute), or other offense (i.e., all other nonviolent/nondrug offenses, such as burglary, theft, receiving stolen property). The demographic variables were intended as controls to test for the influence of drug involvement and offense type on reincarceration.

A final individual-level explanatory variable was “spatial contagion,” defined as the percentage of ex-offenders recidivating within 3 years who live within 1 mile of each other where the preincarceration address serves as the proxy for residence location. We derived this variable using a similar method reported by Mennis and Harris (2011). Consider, for example, Figure 1, which shows the spatial distribution of ex-prisoners, and where each point represents the preincarceration residence location of an ex-prisoner. Now consider a single ex-prisoner who resided at the gray, bolded point location at the center of the figure. To calculate the spatial contagion variable value for this case, a search is conducted for all the ex-prisoners whose preincarceration address was within a 1 mile radius, illustrated by the surrounding circle. Approximate locations of ex-prisoners within this circle are color-coded to indicate that they either were reincarcerated within 3 years of release (red) or they were not (blue). The spatial contagion variable is calculated as simply the number of ex-prisoners who were reincarcerated over the total number of ex-prisoners within the search radius, expressed as a percentage (e.g., 185 reincarcerated ex-prisoners / 546 ex-prisoners = 34%) and assigned as an attribute of that particular ex-prisoner who resided at the center of the circle. The spatial contagion value is calculated in this manner for every ex-prisoner in turn.

Regarding the neighborhood-level environment variables, we collected a variety of U.S. Bureau of the Census and other publicly available survey variables indicating concentrated disadvantage, residential mobility, and social capital at the Census tract level (*N* = 381). These variables included the percentage of the population receiving public assistance income, percentage of the population 25 years of age and older with a high school diploma, percentage of housing units that are vacant, and percentage of housing units occupied by renters, as well as variables derived from the Philadelphia Health Management Corporation's (PHMC, 2008) health survey relating to perceptions of trust among neighbors and a sense of belonging to a neighborhood. These variables were found to be related to recidivism among juveniles and adults in past research (Grunwald et al., 2010; Kubrin & Stewart, 2006; Kubrin, Squires, & Stewart, 2007; Mears, Wang, Hay, & Bales, 2008; Mennis et al., 2011).

ANALYSIS

We began our analysis by investigating the character of spatial clustering of reincarceration across Philadelphia. For this purpose, we employ the G_i* statistic (Getis & Ord, 1992; Ord & Getis, 1995), which measures the degree to which the observations within a distance *d* of observation *i* have values distinctly similar to, or different from, the global mean. The G_i* yields a map of local spatial clustering that can be used to visualize the statistical significance of spatial clustering of reincarceration. Consider the spatial weights matrix $\{w_{ij(d)}\}$ such that $w_{ij(d)} = 1$ if location *i* is within distance *d* of location *j*, and $w_{ij(d)} = 0$ if it is not. In this study, *d* = 1 mile, chosen as a compromise between minimizing the distance over which we hypothesize peer contagion to occur while also allowing for a sufficient number of observations to be collected for calculation of G_i*. If $w_i^*=\Sigma_j w_{ij}(d) \text{ and } S_{1i}^*=\Sigma_j w_{ij}^2(d)$, and if $\bar{z}$ and s^2 denote the sample mean and variance, respectively, then:

$$G^*{}_i(d)=\frac{\sum_j w_{ij}(d)\, z_j - W_i^*\bar{\mathrm{z}}}{s\left\{\left[(nS_{1i}^*) - W_i^{*2}\right]/(n-1)\right\}^{1/2}}$$

As noted above, because our outcome variable is dichotomous, we employ logistic regression to estimate the likelihood of an ex-prisoner being reincarcerated within 3 years of release. Modeling proceeded in four stages. In Stage 1, only the demographic variables were entered. In Stage 2, the drug offense type variable was added. In Stage 3, the drug involvement variable was entered, followed by the spatial contagion variable in Stage 4. We then investigated whether explanations of reincarceration differed among offense types—in other words, are certain types of offenders affected by various explanatory variables more than others? In addition to other research that has identified the importance of the relationship between offense type and recidivism (e.g., Langan & Levin, 2002), our prior research on juvenile offenders has also underscored the prominence of this relationship, especially with regard to spatial contagion (Mennis & Harris, 2011). We thus calibrated a separate regression equation for each type of offender (violent, drug, and other). Each model used the same set of predictors; however, because nearly all drug offenders in our sample were also found to be drug-involved (99%), this variable was excluded from that model.

We employed the area under the receiver operating characteristic (ROC) curve (AUC) statistic to indicate the overall efficacy of the models. To aid in the interpretation of the results, the age and spatial contagion variables were transformed such that odds ratios for these variables reflect the change in the likelihood of reincarceration for each additional decade of age and an increase of 10% in the spatial contagion variable.

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When data are spatially nested, as in the present analysis where individuals are nested within neighborhoods, multilevel modeling is typically used to infer causal relationships between explanatory and outcome variables. Multilevel models allow the intercept and slope of a regression model to vary over spatial units, such that an individual-level outcome may be estimated by the effect of individual-level explanatory variables as well as neighborhood-level effects (Raudenbush & Bryk, 2002). The first step in such an analysis is to ascertain whether variation in the outcome can be ascribed to neighborhood-level variation. If so, multilevel modeling is justified and neighborhood-level explanatory variables may be entered to explain the neighborhood-level variation in the outcome.

The intraclass correlation coefficient (*ICC*) is typically used to indicate the fraction of the total variance that can be ascribed to between-group variation and thus whether multilevel modeling is warranted. In conventional multilevel models with a continuous outcome variable $ICC = V_N/(V_N + V_I)$, where V_N is the neighborhood-level variance and V_I is the individual-level variance. In the present study we employed the linear threshold model for calculating the ICC for dichotomous outcome data (Snijders & Bosker, 1999), where V_I follows a logistic distribution with a mean of zero and a variance of $\pi^2/3 \approx 3.29$. Therefore, $ICC = V_N/(V_N + 3.29)$, an approach used by several other studies employing multilevel ordinal or logistic models (Chen, Chang, & Yang, 2008; Theall et al., 2011).

RESULTS

The initial step in our analyses was to calculate the *ICC* to determine whether multilevel modeling is appropriate. Using this approach, we calculated that the $ICC = 0.00003$, indicating that multilevel modeling was not appropriate. Thus, no tract-level variable will contribute to the explanation of the outcome at the individual level. Because the *ICC* may be sensitive to the spatial neighborhood boundaries used, we also calculated the *ICC* using a spatial data tessellation of colloquially defined Philadelphia neighborhoods ($N = 45$), for which we have previously found neighborhood-level effects in juvenile delinquency recidivism in Philadelphia using multilevel modeling (Grunwald et al., 2010). However, again the *ICC* statistic indicated that there was effectively no significant variation in reincarceration among neighborhoods that cannot be explained by individual-level variation ($ICC = 0.00038$), and thus, multilevel modeling was not warranted.

To confirm this finding, we calculated the overall reincarceration rate for each of the 45 neighborhoods (i.e., the total number reincarcerated ex-offenders over the total number of ex-prisoners in each neighborhood) and derived the Pearson correlation with several neighborhood-level variables, indicating aspects of concentrated disadvantage, residential mobility, and social capital that we found to be related to juvenile delinquency and recidivism in past research (Grunwald et al., 2010; Mennis & Harris, 2011; Mennis et al., 2011). As mentioned previously, these variables included data on public assistance, education, housing vacancy, home ownership, as well as variables derived from PHMC health survey items relating to collective efficacy (i.e., perceptions of trust among neighbors and a sense of belonging to a neighborhood) (PHMC, 2008). None of these variables were significantly correlated ($p < .05$) with neighborhood reincarceration rate.

We therefore did not incorporate the neighborhood-level collective efficacy variables in any further analyses because they were not related to reincarceration for this sample. Neighborhood socioeconomic characteristics did not predict the likelihood of reincarceration at the individual level with this sample. Instead we concentrated on the demographic, drug involvement, offense type, and spatial contagion variables to examine their influence on reincarceration. We should emphasize that, though calculated over a region, spatial

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contagion is an individual-level variable, not a neighborhood-level variable, in the following analyses.

Figure 2 shows the map of location spatial clustering of reincarceration across Philadelphia, where each dot represents a released prisoner. A red dot indicates an ex-offender living in an area of a statistically significantly high reincarceration rate, and a blue dot indicates a released prisoner living in an area of a significantly low reincarceration rate. Other dots not colored red or blue indicate a location that is neither a significantly high nor low rate of reincarceration. There are clear swaths of high reincarceration rates in Southwest Philadelphia, portions of North Philadelphia stretching towards lower Northeast Philadelphia, and in a portion of the Germantown section of Philadelphia. The value of the spatial contagion variable varies among individuals because the region over which the spatial contagion value is calculated is unique to each individual.

Table 2 reports the results of the standard logistic regression models of reincarceration. Model 1 includes only the demographic variables and indicates that being younger (OR = 0.78, $p < .005$) and male (OR = 1.50, $p < .01$) increased the likelihood of reincarceration, while race and marital status did not. Males were one and a half times more likely to be reincarcerated within 3 years of release compared to females, and every additional decade of age reduced the likelihood of reincarceration by approximately one fifth. The addition of offense type in Model 2 indicates that certain types of offenders were less likely to be reincarcerated than others. Violent offenders, as compared to nonviolent/nondrug offenders, were less likely to be reincarcerated within 3 years of release (OR = 0.73, $p < .005$). Model 3, which adds the drug involvement variable, indicates that drug involvement increased the likelihood of reincarceration (OR = 1.38, $p < .005$). Spatial contagion also influenced reincarceration, as shown in Model 4, where an increase of 10% in the reincarceration rate nearby an ex-offender increased the likelihood of reincarceration by more than 1.5 times (OR = 1.57, $p < .005$). Other explanatory variables that were significant at $p < .10$ in previous models became significant at $p < .05$ in Model 4, including being White/other race (as compared to African American) (OR = 0.80) and being a drug offender (as compared to committing a nonviolent/nondrug offense) (OR = 0.84), both of which decreased the likelihood of reincarceration, even though *drug involvement* still increased the risk of reincarceration (OR = 1.39, $p < .005$). The AUC increased slightly with the addition of explanatory variables from 0.57 (Model 1) to 0.60 (Model 3).

Because we are particularly interested in spatial contagion as a mechanism for reincarceration, we used Cox regression to perform a survival analysis (Cox & Oakes, 1984). Here, we investigate whether particular high versus low values of spatial contagion influence how long an ex-offender is likely to be reincarcerated following release. The model specification is the same as in Model 4, but spatial contagion is encoded not as a continuous variable (as in Model 4) but rather divided into tertiles, where each ex-prisoner is encoded as having low, middle, or high spatial contagion, with an approximately equal number of ex-prisoners in each spatial contagion category. The outcome variable is the number of days between release and reincarceration, where ex-offenders who were not reincarcerated are censored. For brevity, we do not present the coefficient results, which are generally similar to those presented in Model 4, but rather a graph illustrating the cumulative probability of survival over time for each spatial contagion tertile (Figure 3). The graph clearly shows that, after controlling for other explanatory variables, an ex-offender with high spatial contagion is likely to be reincarcerated sooner than an ex-prisoner with low spatial contagion. Notably, the graph appears to distinguish between low spatial contagion and the combination of middle and high spatial contagion categories, suggesting the impact of spatial contagion is particularly pronounced for those ex-offenders who are highly spatially isolated from concentrations of reincarceration.

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To examine more closely the relationship between offense type and reincarceration, a separate series of logistic regression models were run. The results of the logistic regression models of reincarceration for different offense types are reported in Table 3. Models 1, 2, and 3 show the regression results only for those released offenders who were incarcerated for a violent offense, drug offense, and other offense type, respectively. The models indicate that younger age was a highly significant predictor of reincarceration for violent and drug offenders. Thus, being older decreased the likelihood of reincarceration for those imprisoned for violent or drug offenses but not for other types of offenses. Gender, on the other hand, was found to only influence the likelihood of reincarceration of drug offenders, where being male enhanced the likelihood of reincarceration. The influence of drug involvement on reincarceration was limited to violent offenders, increasing the likelihood of recidivism. A high degree of spatial contagion of reincarceration, on the other hand, increased the likelihood of reincarceration for all offense types. The AUC is highest for the model of violent offenders as compared to the other offense types, though only slightly.

DISCUSSION

Identifying factors associated with recidivism represents an important policy-relevant focus in criminal justice research. Although there has been extensive prior empirical research and theoretical discussion in this area, little research has examined both individual and neighborhood contextual factors that relate to reincarceration concurrently (Kubrin & Stewart, 2006), and the results have been inconsistent. One of the most notable findings in our analysis was that, contrary to expectations, neighborhood characteristics relating to the economic health of neighborhoods (including poverty and concentrated disadvantage), residential mobility, and collective efficacy (the tendency for neighbors to trust and cooperate with each other) were not associated with the likelihood of reincarceration. This was somewhat surprising given the documented relationships between neighborhood characteristics and crime (Sampson et al., 2002), and some prior evidence that has shown similar relationships with recidivism (Kubrin & Stewart, 2006). We note that although the model AUC values were all highly significant, they were also relatively modest in magnitude, suggesting a noisy outcome variable and the difficulty of predicting individual-level behavior from contextual factors.

Of particular interest is that variables relating to concentrated disadvantage and residential mobility did not predict reincarceration (cf., Kubrin & Stewart, 2006). Neighborhoods with very similar demographic profiles in terms of race, unemployment, and level of poverty varied in their respective rates of recidivism, and these variables were not significantly associated with recidivism. Collectively, these findings suggest that reincarceration in this instance was not explained by the standard geographic and demographic variables typically shown in other research to be associated with reincarceration and crime (e.g., Kubrin & Stewart, 2006). Our findings may lend further support for the R-N-R framework and the relative importance of individual-level factors (e.g., criminal thinking and decision-making skills) over ecological ones in explaining reentry outcomes (Andrews & Bonta, 1994; Bucklen & Zajac, 2009). This does not mean, however, that there are not community variables that could help explain reincarceration. For example, it is possible that differences in community resources, neighborhood cohesion, or other factors not measured in the present study may help explain differences in neighborhood reincarceration rates. Similarly economically disadvantaged neighborhoods may vary in terms of collective efficacy, social capital, and social services, and it is possible that these differences may help explain our results. Moreover, as noted by numerous researchers, communities also vary in their stage of readiness for implementing services and interventions needed to solve problems like recidivism (Edwards, Jumper-Thurman, Plested, Oetting, & Swanson, 2000; Oetting, Jumper-Thurman, Plested, & Edwards, 2001). It is likely that the communities in the current

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study ranged from the No Awareness (unaware of a problem) through Professionalization stages (services and treatment are available) (Edwards et al., 2000). Future research, therefore, is needed to examine community readiness, especially with respect to services targeted at the specific problems (e.g., employment services, substance abuse treatment, and stable housing) faced by those who are returning from prison. Higher levels of community readiness may act as a buffer to reincarceration.

Other findings of the current study are more consistent with prior research that shows an increased likelihood of reincarceration for those who are younger, male, and African American. Among drug offenders, we found that males were more than twice as likely to be reincarcerated as females. Though females made up only a small number in the sample, we also ran the models presented in Table 2 for males only and did not find any substantial differences from those presented for the entire sample. Consistent with previous research, we find that drug involvement also appears to be a substantial risk factor for reincarceration, and this is particularly true for violent offenders. Notably, we also find that both violent and drug offenders are less likely to be reincarcerated as compared to nonviolent/nondrug offenders, although nearly all drug offenders are drug involved. These results suggest some interaction between offense type and drug involvement. It is likely, for instance, that for drug-involved, nondrug offenders, drug abuse plays a central role in their criminal activities, whether through precipitation of violent acts or motivation to rob or burglarize to support a drug addiction. Incarceration for drug offending implies an economically oriented offense and does not necessarily imply disposition toward violence or burglary/theft. Also of note is that we use the most recent primary offense to categorize the offense type—many ex-prisoners have been incarcerated multiple times for different types of offenses.

Using the principles of the R-N-R model described in our introduction, risk for reincarceration in our study was related to both static risk factors (i.e., age, gender, race/ethnicity) and criminogenic needs (i.e., substance abuse). Although static factors are not directly amenable to change, criminogenic needs are. An application of this finding may be that assessment of risks and needs should continue, as indicated by the R-N-R model, from prison to community (see Hiller, Belenko, Welsh, Zajac, & Peters, 2011). Information from these assessments could be used to adjust reentry plans to emphasize the particular criminogenic needs evident for the individual.

Perhaps one of the most important findings of the current study, and consistent with the results from Mennis and Harris (2011) for juvenile recidivism, relates to spatial contagion. Having an intake address near relatively high concentrations of ex-offenders who recidivate greatly increases one's likelihood of reincarceration within 3 years of release and also decreases the likely length of time from release to reincarceration. This study empirically demonstrates that recidivism is not randomly spatially distributed among the ex-offender population but rather is spatially clustered into high and low recidivism regions of the city, and this has a particularly negative effect on those ex-prisoners from high reincarceration rate regions. Applying the community readiness model discussed above, this finding could help local government and community leaders to specifically plan for the allocation or reallocation of resources and services to address the spatial configuration of reincarceration risk. Much like "hot-spot" policing, where patrol and other resources are specifically allocated to geographic areas with a dense concentration of crime, so too could community resources be placed in those geographic areas where there appears to be the greatest likelihood of reoffending based on evidence of spatial contagion of reincarceration. The larger policy quandary, though, concerns what to do about where ex-offenders can live, or choose to live. Paroling authorities do exercise some control over residence while the ex-offender is under supervision. But once off supervision, there is no opportunity to condition ex-offenders' choice of residence. Moreover, regardless of supervision status, many ex-

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offenders are constrained by factors such as finances and family ties in their residential options. They simply may not have the resources to relocate to less risky (and potentially more expensive) neighborhoods and may feel out of place there in any event. Their old high-risk ("spatially contaminated") neighborhoods may present the most feasible housing option. The challenge for prison reentry programs, then, may be to better prepare soon-to-be-released inmates to manage and minimize the risks that they will be exposed to in such neighborhoods, which is a matter of addressing their thinking and decision-making patterns. There is some evidence that the ability of the individual parolee to manage such risk does play a role in successful reentry (Bucklen & Zajac, 2009).

We acknowledge that there are a number of limitations to the current study. First, the analysis relied on a retrospective dataset that was not created for the purposes of this study. Similar to some prior research (e.g., Wehrman, 2010), the addresses that were used in our analyses were from the time of prison admission. Our analyses assume that these individuals stayed at the same address from admission to follow-up. Obviously, it is possible that the address data used did not necessarily reflect the offender's true address upon return to the community. This concern is attenuated, in part, by prior research that has found that offenders released from prison tend to return to the same neighborhoods that they initially came from or highly similar and proximate disadvantaged neighborhoods (Kirk, 2009; Travis, 2006). Indeed, one study (La Vigne & Parthasarathy, 2005) found that 72% of returning offenders were residing at the same address 2 years after release, with just 10% having moved more than once, with the average distance between first and last known residence being just 2.8 miles. Nevertheless, using the individual's address at release would have added additional precision to the study and analysis.

A second limitation relates to our operationalization of recidivism as reincarceration within 3 years. We acknowledge that this is only one measure of recidivism and that other measures could include rearrests, parole violations, and reconvictions. Reincarceration, however, may be the most conservative metric given that only more serious crimes may result in being returned to prison. Reincarceration may also be the most important and reliable policy-relevant outcome because returning to prison represents arguably the worst and most costly outcome for a released offender, and arrest data inevitably result in some proportion of dismissals and acquittals (Maltz, 1984/2001). Another limitation is that data on relative levels of law enforcement activity in different neighborhoods over the observation period were not available. Differences in police activity or spatial concentration of enforcement activity could affect the probability of arrest and therefore reincarceration. In particular, it might have been useful to map locations of drug sales and drug arrests using police data (Hunt, Sumner, Scholten, & Frabutt, 2008; Rengert, Chakravorty, Bole, & Henderson, 2000). Had the data been available, this would have added depth to our analyses, especially in relation to the finding that drug involvement predicts reincarceration. Finally, there is the possibility of sample bias because institutional addresses were excluded that reduced the sample by about a third, and then approximately 17% of the remaining addresses could not be geocoded. As discussed previously, the geocoded sample was similar in most respects but had a higher rate of substance abuse than those cases that could not be geocoded. Collectively, this suggests that our findings may somewhat underestimate the spatial contagion effect rather than overestimate it.

In conclusion, the current study adds to a limited literature that considers both individual and community factors concurrently. Findings showed that reincarceration was not a random phenomenon; rather, it was predictable knowing to what extent an individual was near an area where reincarceration was happening most frequently. Our findings suggest that furthering our understanding of the individual- and neighborhood-level factors associated with reincarceration of released inmates will require new data that include social network, spatial contagion, and service delivery factors. Achieving the goals of improving public safety, public health, neighborhood stability, and enhanced social capital require a better understanding of the higher level determinants of recidivism that can inform the development of more effective prevention, enforcement, and community support programs. By mapping the residential location of ex-offenders who become reincarcerated, it may be possible to locate services with greater precision that address the specific needs of these individuals, which may in turn reduce recidivism.

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REFERENCES

Akers, RL. Deviant behavior: A social learning approach. Belmont, CA: Wadsworth; 1985.

American Psychiatric Association. Diagnostic and statistical manual of mental disorders. 4th ed.. Washington, DC: Author; 1994.

Andrews, DA.; Bonta, J. The psychology of criminal conduct. Cincinnati, OH: Anderson; 1994.

Andrews, DA.; Bonta, J. The psychology of criminal conduct. 5th ed.. New Providence, NJ: LexisNexis Matthew Bender; 2010a.

Andrews DA, Bonta J. Rehabilitating criminal justice policy and practice. Psychology, Public Policy, and Law. 2010b; 16:39–55.

Andrews DA, Bonta J, Wormith SJ. The recent past and near future of risk and/or need assessment. Crime and Delinquency. 2006; 52:7–27.

Andrews DA, Bonta J, Wormith JS. The risk-need-responsivity (RNR) model: Does adding the good lives model contribute to effective crime prevention? Criminal Justice and Behavior. 2011; 38(7): 735–755.

Andrews DA, Dowden C. The Risk-Need-Responsivity Model of assessment and human service in prevention and corrections: Crime-prevention jurisprudence. Canadian Journal of Criminology and Criminal Justice. 2007; 49:439–464.

Andrews DA, Zinger I, Hoge RD, Bonta J, Gendreau P, Cullen FT. Does correctional treatment work? A clinically relevant and psychologically informed meta-analysis. Criminology. 1990; 28:369–404.

Belenko S. Assessing released inmates for substance-abuse-related service needs. Crime and Delinquency. 2006; 52:94–113.

Belenko S, Peugh J. Estimating drug treatment needs among state prison inmates. Drug and Alcohol Dependence. 2005; 77:269–281. [PubMed: 15734227]

Boardman JD, Finch BK, Ellison CG, Williams DR, Jackson JS. Neighborhood disadvantage, stress, and drug use among adults. Journal of Health and Social Behavior. 2001; 42:151–165. [PubMed: 11467250]

Bonta, J.; Andrews, DA. Risk-Need-Responsivity Model for Offender Assessment and Rehabilitation 2007-06. Ottawa, Ontario, Canada: Public Safety Canada; 2007. (User Report 2007–06).

Bonta J, Law M, Hanson K. The prediction of criminal and violent recidivism among mentally disordered offenders: A meta-analysis. Psychological Bulletin. 1998; 123:123–142. [PubMed: 9522681]

Broome KM, Knight K, Joe GW, Simpson DD. Evaluating the drug-abusing probationer: Clinical interview versus self-administered assessment. Criminal Justice and Behavior. 1996; 23:593–606.

Bucklen B, Zajac G. But some of them don’t come back (to prison!): Resource deprivation and thinking errors as determinants of parole success and failure. The Prison Journal. 2009; 89:239–264.

Bureau of Justice Statistics. [Retrieved September 23, 2011] Bureau of Justice Statistics, U.S. Department of Justice. 2011. from http://bjs.ojp.usdoj.gov/content/glance/tables/corr2tab.cfm

NIH-PA Author Manuscript NIH-PA Author Manuscript NIH-PA Author Manuscript

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Burgess RL, Akers RL. A differential association-reinforcement theory of criminal behavior. Social Forces. 1966; 14:128–147.

Bursik, RJ.; Grasmick, HG. Neighborhoods and crime. Lanham, MD: Lexington; 1993.

Chandler RK, Fletcher BW, Volkow ND. Treating drug abuse and addiction in the criminal justice system: Improving public health and safety. Journal of the American Medical Association. 2009; 301:183–190. [PubMed: 19141766]

Chen DR, Chang LY, Yang ML. Gender-specific responses to social determinants associated with self-perceived health in Taiwan: A multilevel approach. Social Science & Medicine. 2008; 67:1630–1640. [PubMed: 18782648]

Cox, DR.; Oakes, D. Analysis of survival data. London: Chapman and Hall; 1984.

Diez-Roux AV. Investigating neighbourhood and area effects on health. American Journal of Public Health. 2001; 91:1783–1789. [PubMed: 11684601]

Dodge, KA.; Lansford, JE.; Dishion, TJ. The problem of deviant peer influences in intervention programs. In: Dodge, KA.; Dishion, TJ.; Lansford, JE., editors. Deviant peer influences in programs for youth: Problems and solutions. New York: The Guilford Press; 2006. p. 14-43.

Dowden C, Brown SL. The role of substance abuse factors in predicting recidivism: A meta-analysis. Psychology, Crime, & Law. 2002; 8:243–264.

Edwards RW, Jumper-Thurman P, Plested BA, Oetting ER, Swanson L. Community readiness: Research to practice. Journal of Community Psychology. 2000; 28:291–307.

Galea S, Rudenstine S, Vlahov D. Drug use misuse and the urban environment. Drug and Alcohol Review. 2005; 24:127–136. [PubMed: 16076582]

Gendreau P, Little T, Goggin C. A meta-analysis of the predictors of adult offender recidivism: What works! Criminology. 1996; 34:575–607.

Getis A, Ord JK. The analysis of spatial association by use of distance statistics. Geographical Analysis. 1992; 24:189–206.

Gottfredson, SD.; Taylor, RB. Community contexts and criminal offenders. In: Hope, T.; Shaw, M., editors. Communities and crime reduction. London: Her Majesty's Stationery Office; 1988. p. 62-82.

Greenfeld, L. Examining recidivism. Washington, DC: Bureau of Justice Statistics; 1985. (NCJ 96501).

Grunwald H, Lockwood B, Harris P, Mennis J. Influences of neighborhood context, individual prior history and parenting behavior on recidivism among juvenile offenders. Journal of Youth and Adolescence. 2010; 39:1067–1079. [PubMed: 20204686]

Hagan J. The social embeddedness of crime and unemployment. Criminology. 1993; 31:465–492.

Hiller, ML.; Belenko, S.; Welsh, W.; Zajac, G.; Peters, RH. Screening and assessment: An evidence-based process for the management and care of adult drug-involved offenders. In: Leukefeld, CG.; Gregrich, J.; Gullotta, T., editors. Handbook on evidence based substance abuse treatment practice in criminal justice settings. New York: Springer; 2011. p. 45-62.

Huebner MB, Berg MT. Examining the sources of variation in risk for recidivism. Justice Quarterly. 2011; 28:146–173.

Huebner BM, Varano SP, Bynum TS. Gangs, guns, and drugs: Recidivism among serious offenders. Criminology and Public Policy. 2007; 15:437–461.

Hunt, ED.; Sumner, M.; Scholten, TJ.; Frabutt, JM. Using GIS to identify drug markets and reduce drug-related violence: A data-driven strategy to implement a focused deterrence model and understand the elements of drug markets. In: Thomas, YF.; Richardson, D.; Cheung, I., editors. Geography and drug addiction. New York: Springer; 2008. p. 395-413.

Kirk DS. A natural experiment on residential change and recidivism: Lessons from Hurricane Katrina. American Sociological Review. 2009; 74:484–505.

Kubrin CE, Squires GD, Stewart EA. Neighborhoods, race, and recidivism: The community-reoffending nexus and its implications for African-Americans. Race Relations Abstracts. 2007; 32:7–37.

Kubrin CE, Stewart EA. Predicting who reoffends: The neglected role of neighborhood context in recidivism studies. Criminology. 2006; 44:165–197.

NIH-PA Author Manuscript
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Kurlychek M, Bushway S, Brame R. Scarlet letters and recidivism: Does an old criminal record predict future offending? Criminology and Public Policy. 2006; 5:483–504.

Langan, PA.; Levin, DJ. Recidivism of prisoners released in 1994. Washington, DC: Bureau of Justice Statistics; 2002. (Bureau of Justice Statistics Publication No. NCJ 193427).

Laub, J.; Sampson, R. Shared beginnings, divergent lives: Delinquent boys to age 70. Boston: Harvard University Press; 2003.

La Vigne, N.; Parthasarathy, B. Returning home Illinois policy brief: Prisoner reentry and residential mobility. Washington, DC: Urban Institute; 2005.

Mair C, Diez-Roux AV, Galea S. Are neighbourhood characteristics associated with depressive symptoms? A review of evidence. Journal of Epidemiology and Community Health. 2008; 62:940–946. [PubMed: 18775943]

Makarios M, Steiner B, Travis LF III. Examining the predictors of recidivism among men and women released from prison in Ohio. Criminal Justice and Behavior. 2010; 37:1377–1391.

Mallik-Kane, K.; Visher, CA. Health and prisoner reentry: How physical, mental, and substance abuse conditions shape the process of reintegration. Washington, DC: Urban Institute; 2008.

Maltz, MD. Recidivism. Orlando, FL: Academic Press, Inc.; [1984] 2001. Retrieved from http://www.uic.edu/depts/lib/forr/pdf/crimjust/recidivism.pdf

Martin SS, Butzin CA, Saum SA, Inciardi JA. Three-year outcomes of therapeutic community treatment for drug-involved offenders in Delaware. The Prison Journal. 1999; 79:294–320.

Mears DP, Wang X, Hay C, Bales WD. Social ecology and recidivism: Implications for prisoner reentry. Criminology. 2008; 46:301–340.

Mennis J, Harris P. Contagion and repeat offending among urban juvenile delinquents. Journal of Adolescence. 2011; 34:951–963. [PubMed: 21215443]

Mennis J, Harris P, Obradovic Z, Izenman A, Grunwald H, Lockwood B. The effect of neighborhood characteristics and spatial spillover on urban juvenile delinquency and recidivism. The Professional Geographer. 2011; 63:174–192.

Mumola, CJ.; Karberg, JC. Drug use and dependence, state and federal prisoners, 2004. Washington, DC: U.S. Department of Justice, Bureau of Justice Statistics; 2006. (Bureau of Justice Statistics Special Report) (NCJ 213530).

National Research Council. Parole, desistance from crime, and community integration. Washington, DC: Committee on Community Supervision and Desistance from Crime, National Academy of Sciences Press; 2007.

Oetting ER, Jumper-Thurman P, Plested BA, Edwards RW. Community readiness and health services. Substance Use & Misuse. 2001; 36:825–843. [PubMed: 11697613]

Ord JK, Getis A. Local spatial autocorrelation statistics: Distributional issues and an application. Geographical Analysis. 1995; 27:286–306.

Peters RH, Greenbaum PE, Steinberg ML, Carter CR, Ortiz MM, Fry BC, Valle SK. Effectiveness of screening instruments in detecting substance use disorders among prisoners. Journal of Substance Abuse Treatment. 2000; 20:349–358. [PubMed: 10812308]

Petersilia, J. When prisoners return to communities: Political, economic and social consequences. New York: Oxford University Press; 2003.

Pickett KE, Pearl M. Multilevel analyses of neighbourhood socioeconomic context and health outcomes: A critical review. Journal of Epidemiology and Community Health. 2001; 55:111–122. [PubMed: 11154250]

Public Health Management Corporation. Public Health Management Corporation's Community Health Data Base, Southeastern Pennsylvania Household Health Survey. 2008 Available at http://www.chdbdata.org/index.asp.

Raudenbush, SW.; Bryk, AS. Hierarchical linear models: Applications and data analysis methods. 2nd ed.. Newbury Park, CA: Sage; 2002.

Rengert G, Chakravorty S, Bole T, Henderson K. A geographic analysis of illegal drug markets. Crime Prevention Studies. 2000; 11:219–239.

Rose DR, Clear TR. Incarceration, social capital, and crime: Implications for social disorganization theory. Criminology. 1998; 36:441–479.

NIH-PA Author Manuscript NIH-PA Author Manuscript NIH-PA Author Manuscript

Rosenfeld R, Petersilia J, Visher C. The first days after release can make a difference. Corrections Today. 2008; 70:86–87.

Ross C, Mirowsky J. Neighbourhood disadvantage, disorder and health. Journal of Health and Social Behavior. 2001; 42:258–276. [PubMed: 11668773]

Sampson, R.; Laub, J. Crime in the making: Pathways and turning points through life. Cambridge, MA: Harvard University Press; 1993.

Sampson RJ, Morenoff JD, Gannon-Rowley T. Assessing "neighborhood effects": Social processes and new directions in research. Annual Review of Sociology. 2002; 28:443–478.

Sampson RJ, Raudenbush SW, Earls F. Neighborhoods and violent crime: A multilevel study of collective efficacy. Science. 1997; 277:918–924. [PubMed: 9252316]

The Sentencing Project. [Retrieved September 23, 2011] State recidivism studies. 2011. from http://sentencingproject.org/doc/publications/inc_StateRecidivismFinalPaginated.pdf

Siddiqi, Q. Predicting post-sentencing re-arrest. New York: New York City Criminal Justice Agency, Inc.; 2010. (Research Brief Series, No. 24).

Silver E, Mulvey EP, Swanson JW. Neighborhood structural characteristics and mental disorder: Faris and Dunham revisited. Social Science and Medicine. 2002; 55:1457–1470. [PubMed: 12231022]

Singh JP, Fazel S. Forensic risk assessment: A metareview. Criminal Justice and Behavior. 2010; 37:965–988.

Snijders, TAB.; Bosker, RJ. Multilevel analysis: An introduction to basic and advanced multilevel modeling. Thousand Oaks, CA: Sage; 1999.

Spohn C, Holleran D. The effect of imprisonment on recidivism rates of felony offenders: A focus on drug offenders. Criminology. 2002; 40:329–357.

Stahler G, Mazzella S, Mennis J, Chakravorty S, Rengert G, Spiga R. The effect of individual, program, and neighborhood variables on continuity of treatment among dually diagnosed individuals. Drug and Alcohol Dependence. 2007; 87:54–62. [PubMed: 16962255]

Stahler G, Mennis J, Cotlar R, Baron D. The influence of the neighborhood environment on treatment continuity and rehospitalization for dually diagnosed patients discharged from acute inpatient care. The American Journal of Psychiatry. 2009; 166:1258–1268. [PubMed: 19797433]

Steen S, Opsal T. Punishment on the installment plan: Individual-level predictors of parole revocation in four states. The Prison Journal. 2007; 87:344–366.

Substance Abuse and Mental Health Services Administration. Results from the 2007 National Survey on Drug Use and Health: National findings. Rockville, MD: Author; 2008. (Substance Abuse and Mental Health Services Administration, Office of Applied Studies, NSDUH Series H-34, DHHS Publication No. SMA 08-4343).

Sullivan, E.; Mino, M.; Nelson, K.; Pope, J. Families as a resource in recovery from drug abuse: An evaluation of La Bodega de la Familia. New York: Vera Institute of Justice; 2002.

Sutherland, EH.; Cressey, DR.; Luckenbill, DF. Principles of criminology. Dix Hills, NY: General Hall; 1992.

Taxman, FS.; Byrne, JM.; Young, D. Targeting for reentry: Matching needs and services to maximize public safety. Washington, DC: National Institute of Justice; 2003.

Taxman FS, Marlowe DB. Risk, needs, responsitivity: In action or inaction? Crime & Delinquency. 2006; 52:3–6.

Taxman FS, Thanner M, Weisburd D. Risk, Need, and Responsivity (RNR): It all depends. Crime & Delinquency. 2006; 52:28–51. [PubMed: 18542715]

Theall K, Scribner R, Broyles S, Yu Q, Chotalia J, Simonsen N, Schonlau M, Carlin BP. Impact of small group size on neighborhood influences in multilevel models. Journal of Epidemiology and Community Health. 2011; 65:688–695. [PubMed: 20508007]

Travis, J. But they all come back: Facing the challenges of prisoner reentry. Washington, DC: Urban Institute; 2006.

Travis, J.; Solomon, AL.; Waul, M. From prison to home: The dimensions and consequences of prisoner reentry. Washington, DC: Urban Institute; 2001.

Uggen C. Work as a turning point in the life course of criminals: A duration model of age, employment, and recidivism. American Sociological Review. 2000; 67:529–546.

NIH-PA Author Manuscript NIH-PA Author Manuscript NIH-PA Author Manuscript

Visher, CA.; Knight, CR.; Chalfin, A.; Roman, JK. The impact of marital and relationship status on social outcomes for returning prisoners. Washington, DC: Urban Institute; 2009.

Visher CA, Travis J. Transitions from prison to community: Understanding individual pathways. Annual Review of Sociology. 2003; 2:89–113.

Visher, CA.; Yahner, J.; La Vigne, N. Life after prison: Tracking the experiences of prisoners returning to Chicago, Cleveland, and Houston. Washington, DC: Urban Institute; 2010.

Wehrman MM. Race, concentrated disadvantage, and recidivism: A test of interaction effects. Journal of Criminal Justice. 2010; 38:538–544.

West, HC.; Sabol, WJ.; Greenman, SJ. Prisoners in 2009. Washington, DC: Bureau of Justice Statistics, U.S. Department of Justice; 2010. (NCJ 231675).

Western B, Kling JR, Weiman D. The labor market consequences of incarceration. Crime & Delinquency. 2001; 47:410–427.

White, HR.; Gorman, DM. Dynamics of the drug-crime relationship. In: LaFree, G., editor. Criminal justice 2000: The nature of crime: Continuity and change. Washington, DC: U.S. Department of Justice; 2000. p. 151-218.

White, WL. Slaying the dragon: The history of addiction treatment and recovery in America. Bloomington, IL: Chestnut Health Systems; 1998.

Yahner, J.; Visher, C. Illinois prisoners' reentry success three years after release. Washington, DC: Urban Institute; 2008.

Biographies

Gerald J. Stahler, PhD, is a professor in Temple University's Department of Geography and Urban Studies. He is a clinical psychologist whose research interests have focused on developing and evaluating innovative interventions for substance abuse and more recently on the influence of environmental factors on treatment outcomes and recidivism. Recent articles have appeared in the *American Journal of Psychiatry, Drug and Alcohol Dependence*, and the *Annals of the Association of American Geographers*.

Jeremy Mennis is an associate professor in geography and urban studies at Temple University. He received his PhD in geography from Pennsylvania State University in 2001. He is a geographic information scientist with research interests in environmental and social contextual effects on behavior, particularly for health and crime outcomes. He has served as chair of the GIS Specialty Group of the Association of American Geographers and on the Boards of Directors of the University Consortium for Geographic Information Science and the GIS Certification Institute.

Steven Belenko, PhD, is a professor in the Temple University Department of Criminal Justice. He is also an adjunct professor in the Department of Psychiatry at the University of Pennsylvania School of Medicine and is the director of the Methods Core for the Center for Behavioral Health Services and Criminal Justice Research at Rutgers University. His research interests focus on the implementation of evidence-based treatment and other services into the criminal justice system, the impact of substance abuse and other health problems on the adult and juvenile justice systems, and developing and testing organizational change strategies to improve implementation of treatment and other health services for offenders.

Wayne N. Welsh is a professor of criminal justice at Temple University. His research interests include violence, corrections, and substance abuse. He is author of *Counties in Court: Jail Overcrowding and Court-Ordered Reform* (Temple, 1995), *Criminal Justice Policy and Planning* (4th ed.; Elsevier, 2012), and *Criminal Violence: Patterns, Causes and Prevention* (3rd ed., with M. Riedel; Oxford, 2011). Recent articles have appeared in

Criminal Justice and Behavior, *Drug and Alcohol Dependence*, *Substance Abuse*, and *The Prison Journal*.

Matthew L. Hiller, PhD, is an associate professor in the Temple University Department of Criminal Justice. He has authored or co-authored more than 50 articles on addiction and criminal justice. His currently funded research projects include an evaluation of a DUI court and of a drug court that specifically targets heroin users. His research interests include substance abuse treatment and the criminal justice system, implementation science, treatment motivation, HIV in correctional samples, and screening, assessment, and services planning for those in prison.

Gary Zajac, PhD, is the Managing Director of the Justice Center for Research at the Pennsylvania State University, and Senior Research Associate with the College of Liberal Arts and University Outreach. He has published widely in journals such as *Criminal Justice and Behavior, Criminology and Public Policy*, and *The Prison Journal*.

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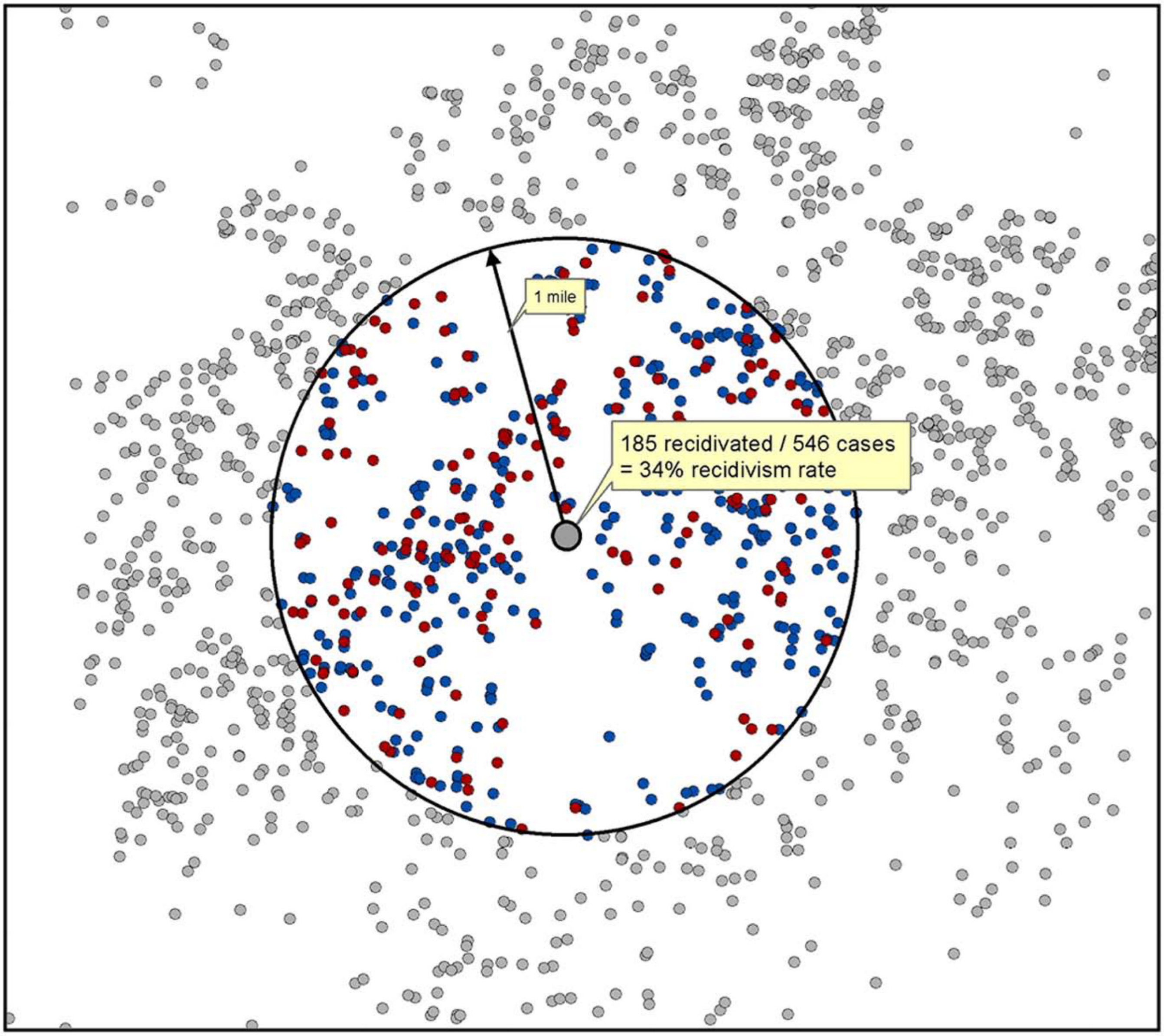

Figure 1.
Construction of the Spatial Contagion Variable (See Text for Explanation)

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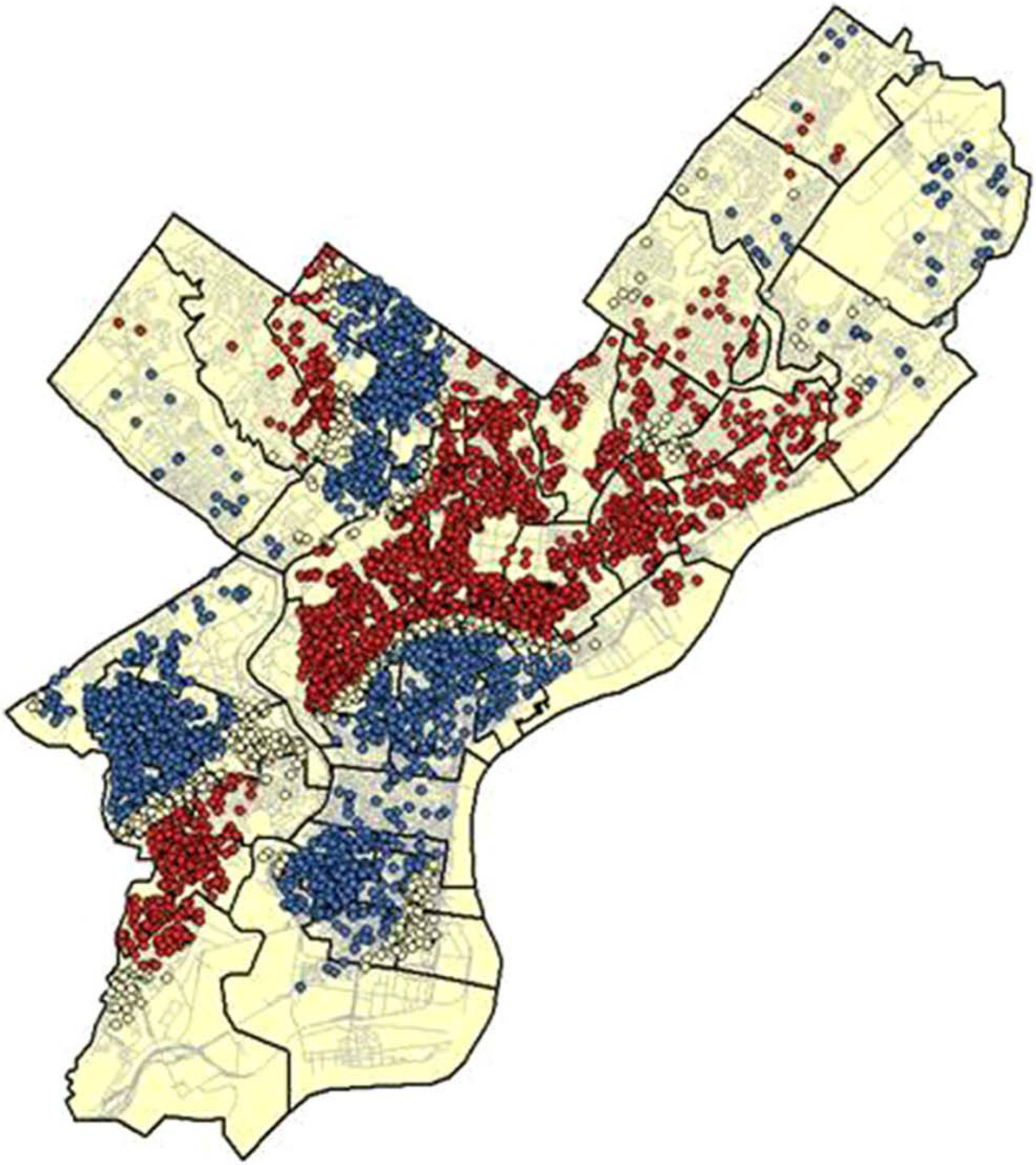

Figure 2.

Map of Spatial Clustering of 3-Year Recidivism in Philadelphia

Note. Red dots = locations with significant spatial cluster of high reincarceration rate compared to Philadelphia's overall rate; blue dots = locations with significant spatial cluster of low reincarceration rate compared to Philadelphia's overall rate.

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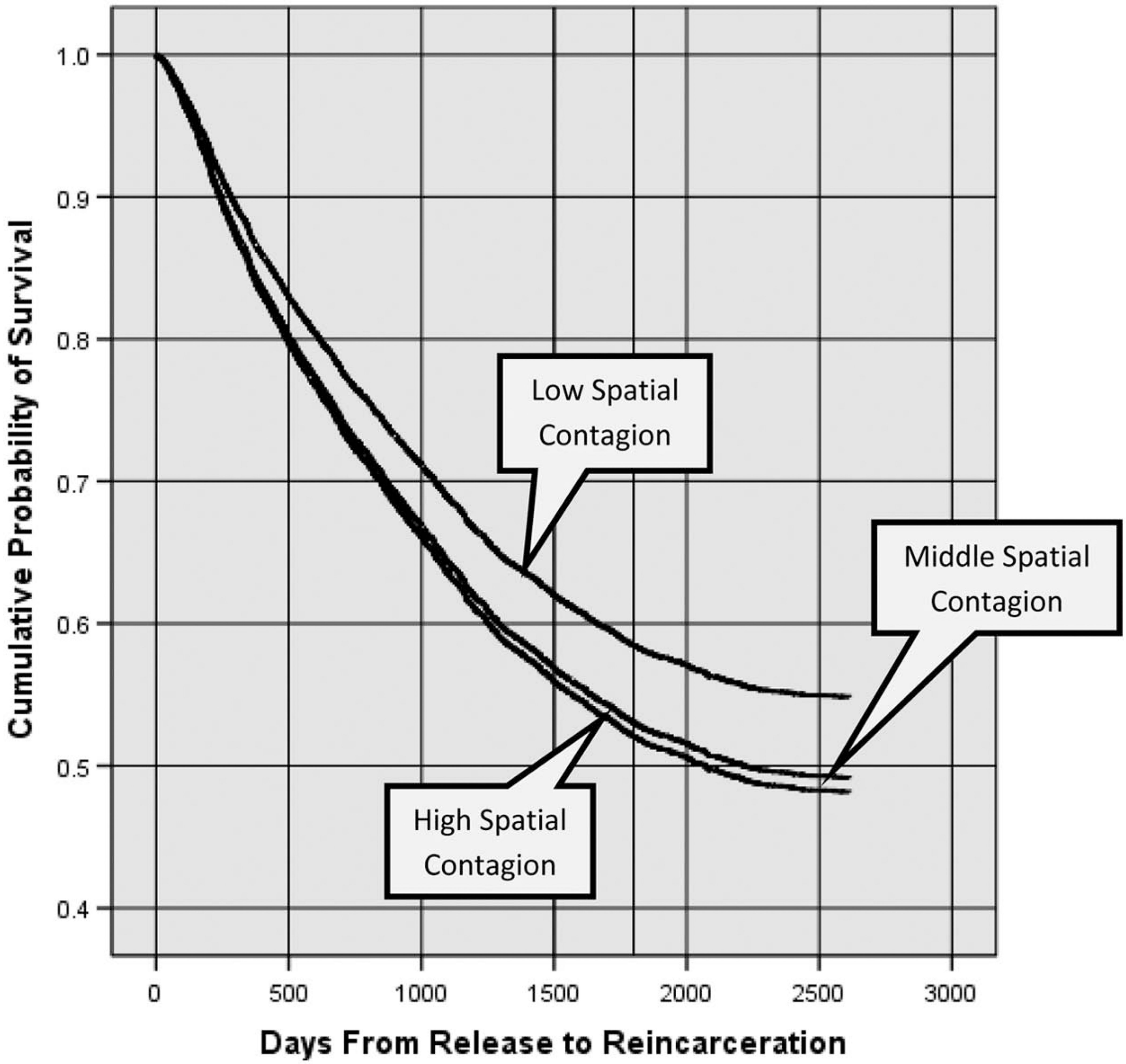

Figure 3.
Survival Function From Release to Reincarceration of Ex-Offenders at Different Levels of Spatial Contagion, While Controlling for Age, Race, Gender, Marriage Status, Offense Type, and Drug Involvement

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Table 1

Characteristics of the Sample

Variable	**M**	**SD**
Age at release from prison	35	9
	N	*%*
Race		
African American	4,064	76%
Hispanic	789	15%
White/Other	501	9%
Gender		
Female	234	4%
Male	5,120	96%
Marital status		
Married	779	15%
Not married	4,575	85%
Offense type		
Violent offense	2,378	44%
Drug offense	1,846	35%
Other (nonviolent/nondrug) offense	1,130	21%
Drug involvement		
Verified drug problem	4,512	84%
No verified drug problem	842	16%
Reincarceration		
Reincarcerated within 3 years	1,882	35%
Not reincarcerated within 3 years	3,472	65%

Note. N = 5,354.

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Table 2

Logistic and Cox Regression Models Predicting Reincarceration

Variable	Model 1	Model 2	Model 3	Model 4
Age	0.78*** (57.85)	0.78*** (56.75)	0.79*** (52.59)	0.80*** (47.19)
	CI: 0.73 to 0.83	CI: 0.73 to 0.83	CI: 0.74 to 0.84	CI: 0.75 to 0.85
Race (ref = African American)	(3.02)	(4.52)	(5.08)†	(7.10)*
Hispanic	0.93 (0.71)	0.90 (1.48)	0.89 (1.80)	0.85† (3.43)
	CI: 0.79 to 1.10	CI: 0.76 to 1.07	CI: 0.76 to 1.05	CI: 0.72 to 1.01
White/Other	0.85 (2.61)	0.83† (3.48)	0.82† (3.79)	0.80* (4.47)
	CI: 0.69 to 1.04	CI: 0.67 to 1.01	CI: 0.67 to 1.00	CI: 0.65 to 0.98
Male	1.50** (6.95)	1.54** (7.74)	1.44* (5.49)	1.43* (5.11)
	CI: 1.11 to 2.04	CI: 1.14 to 2.09	CI: 1.06 to 1.96	CI: 1.05 to 1.94
Married	1.01 (0.01)	1.02 (0.04)	1.03 (0.10)	1.01 (0.03)
	CI: 0.85 to 1.19	CI: 0.86 to 1.20	CI: 0.87 to 1.21	CI: 0.86 to 1.20
Offense type (ref = other offense)		(18.54)***	(13.27)***	(14.10)***
Violent offense		0.73*** (16.49)	0.76*** (13.17)	0.75*** (14.04)
		CI: 0.63 to 0.85	CI: 0.65 to 0.88	CI: 0.64 to 0.87
Drug offense		0.89 (2.12)	0.85† (3.80)	0.84* (4.38)
		CI: 0.76 to 1.04	CI: 0.73 to 1.00	CI: 0.72 to 0.99
Drug involvement			1.38*** (13.19)	1.39*** (13.38)
			CI: 1.16 to 1.64	CI: 1.16 to 1.65
Spatial contagion				1.57*** (33.42)
				CI: 1.35 to 1.83
Constant	0.89 (0.37)	1.05 (0.05)	0.82 (0.80)	0.17** (25.87)
AUC	0.57***	0.58***	0.58***	0.60***
	CI: 0.55 to 0.58	CI: 0.56 to 0.59	CI: 0.56 to 0.60	CI: 0.58 to 0.61

Note. N = 5,354. Values reported are odds ratios, Wald statistic reported in parentheses, and confidence intervals reported below.

† $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .005$.

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Table 3

Logistic Regression Models Predicting Reincarceration for Violent, Drug, and Other (Nondrug/Nonviolent) Offenders

Variable	Model 1 Violent Offenders	Model 2 Drug Offenders	Model 3 Other Offenders
Age	0.79*** (21.28)	0.75*** (23.69)	0.88† (3.26)
	CI: 0.72 to 0.88	CI: 0.67 to 0.84	CI: 0.77 to 1.01
Race (ref = African American)	(3.91)	(1.63)	(2.34)
Hispanic	0.75† (2.90)	0.89 (1.10)	1.11 (0.21)
	CI: 0.54 to 1.04†	CI: 0.71 to 1.11	CI: 0.71 to 1.72
White/Other	0.83 (1.35)	0.82 (0.75)	0.79 (1.91)
	CI: 0.61 to 1.14	CI: 0.52 to 1.29	CI: 0.56 to 1.11
Male	1.08 (0.09)	2.13** (7.67)	1.17 (0.27)
	CI: 0.65 to 1.80	CI: 0.70 to 1.26	CI: 0.66 to 2.08
Married	1.14 (1.09)	0.94 (0.18)	0.88 (0.49)
	CI: 0.89 to 1.45	CI: 1.02 to 1.74	CI: 0.61 to 1.26
Drug involvement	1.41*** (10.34)		1.38† (3.24)
	CI: 1.14 to 1.74		CI: 0.97 to 1.96
Spatial contagion	1.71*** (20.26)	1.34* (4.54)	1.66*** (10.37)
	CI: 1.35 to 2.16	CI: 1.02 to 1.74	CI: 1.22 to 2.26
Constant	0.12*** (16.09)	0.28* (4.44)	0.11*** (10.14)
AUC	0.60***	0.59***	0.58***
	CI: 0.57 to 0.62	CI: 0.56 to 0.62	CI: 0.55 to 0.62

Note. Violent offenders N =2,378. Drug offenders N = 1,846. Other (nondrug/nonviolent) offenders N = 1,130. Values reported are odds ratios, Wald statistic reported in parentheses, and confidence intervals reported below.

† $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .005$.