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Neighborhood Risk Factors for Recidivism: For Whom Do They Matter?

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Abstract

Justice-involved people vary substantially in their risk of reoffending. To date, recidivism prediction and prevention efforts have largely focused on individual-level factors like antisocial traits. Although a growing body of research has examined the role of residential contexts in predicting reoffending, results have been equivocal. One reason for mixed results may be that an individual's susceptibility to contextual influence depends upon his or her accumulated risk of reoffending. Based on a sample of 2,218 people on probation in San Francisco, California, this study draws on observational and secondary data to test the hypothesis that individual risk moderates the effect of neighborhood factors on recidivism. Results from survival analyses indicate that individual risk interacts with neighborhood concentrated disadvantage and disorder—these factors increase recidivism among people relatively low in individual risk, but not those at higher risk. This is consistent with the disadvantage saturation perspective, raising the possibility that some people classified as low risk might not recidivate but for placement in disadvantaged and disorderly neighborhoods. Ultimately, residential contexts "matter" for lower risk people and may be useful to consider in efforts to prevent recidivism.

Keywords

risk assessment; recidivism; disadvantage saturation; neighborhood effects; disadvantage; disorder

After incarceration, people are often released to "prison places" (Clear, 2009)—neighborhoods that lack the institutional and social features that help control crime (Sampson, 2012). Theoretically, this could promote reoffending (Cullen, Eck, & Lowenkamp, 2002; Kirk, 2015). After adjusting for individual-level risk factors, however, the association between neighborhood factors and re-offending is decidedly small and uneven across studies (Jacobs et al., 2020b). Partly for this reason, neighborhood factors play little role in the "Risk-Need-Responsivity" (RNR) model of correctional rehabilitation (Bonta & Andrews, 2016)—which guides a variety of justice reform efforts across the U.S. (see Council of State Governments, 2017). According to the RNR model, efforts to prevent

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recidivism "are best based on an understanding of the criminal conduct of *individuals* rather than theories of community-wide crime rates" (Andrews, 2012, p. 129). So, correctional services are largely geared toward reducing individual risk by targeting factors like substance abuse and antisocial traits—leaving aside neighborhood disadvantage as largely "non-criminogenic" (Andrews, 2012).

In our view and in accordance with the values of community psychology highlighted in this special issue of the *American Journal of Community Psychology*, it is unwise to dismiss neighborhood factors as irrelevant to preventing recidivism. Inconsistent effects observed in past research may reflect the fact that neighborhood factors predict reoffending more strongly among *some* subgroups than others (see, e.g., Huebner & Pleggenkuhle, 2015; Hipp, Petersilia, & Turner, 2010). Even proponents of the RNR model (Bonta & Andrews, 2003, p. 26) have called for research that examines "…*for whom* residential contexts matter" (Sharkey & Faber, 2014, p. 572). Ultimately, examining the interaction between individual and ecological characteristics holds promise for fostering resilience among justice-involved persons.

In this study, we test whether individual-level risk for recidivism moderates the effect of neighborhood factors on reoffending. People differ in their likelihood of recidivism, based on the overall balance of risk and protective factors they have accumulated. Based on the disadvantage saturation perspective (Hannon, 2003) discussed below, people high in individual-level risk should be *least* adversely affected by neighborhood risk factors. Before detailing the study aims and approach, we first highlight relevant past research to provide context. We briefly summarize studies of the relationship between specific neighborhood factors and recidivism, then shift to research on how individual characteristics moderate that relationship.

Which Neighborhood Factors Most Robustly Predict Recidivism?

Just as people vary in risk so too do neighborhoods. Neighborhoods differ in their material, institutional, and social resources and composition. An extensive body of research has examined the sociohistorical bases for this variation, especially focusing on its contribution to racial inequality and crime (see Massey & Denton, 1993; Wilson, 2012). This work indicates that a complex interaction of political and policy actions (e.g., Jim Crow and housing policies that segregated communities), economic conditions (e.g., deindustrialization), and population shifts (e.g., population growth during a time of economic retraction) explain the unequal distribution of resources and crime between neighborhoods. Over the past two decades, scholars have moved beyond the study of neighborhoods and crime to also study the relation between neighborhoods and recidivism, using a variety of theoretical frameworks (e.g., Chamberlain & Wallace, 2015; Hipp et al., 2010; Huebner & Pleggenkuhle, 2015; Mears, Wang, Hay, & Bales, 2008; Miller, Caplan, & Ostermann, 2016; Stahler et al., 2013; Tillyer & Vose, 2011; Wallace, 2015; Wang et al., 2014; Wang, Mears, & Bales, 2010; Wehrman, 2010). The majority of these studies indicate that at least one neighborhood characteristic predicts recidivism—above and beyond individual-level characteristics— though effects are not consistent across factors.

Of neighborhood conditions tested, constructs relevant to social disorganization theory—concentrated disadvantage, residential instability, and ethnoracial diversity—have received the most attention. From a social disorganization perspective (Shaw & McKay, 1942; Sampson & Groves, 1989), these constructs may increase recidivism by reducing formal and informal sources of social control that can reduce crime and promote successful reentry. Empirically, *concentrated disadvantage* predicts recidivism in about half of studies where it is tested, with no clear methodological differences between studies that do (e.g., Hipp et al., 2010; Kubrin & Stewart, 2006; Wallace, 2015) and do not (e.g., Chamberlain & Wallace, 2016; Miller et al., 2016; Stahler et al., 2013) find it adds incremental utility to individual factors in predicting recidivism.[1] A recent meta-analysis (k = 32) by (Jacobs et al., 2020b) found no significant relationship between concentrated disadvantage and recidivism after analyses adjust for individual risk (log OR=0.03). *Residential instability* often predicts recidivism weakly, above and beyond individual factors-- though at times in an unanticipated direction (Chamberlain & Wallace, 2016; Hipp et al., 2010; Huebner & Pleggenkuhle, 2015; Tillyer & Vose, 2011). Most studies find that factors akin to *ethnoracial diversity* fail to independently increase recidivism (Chamberlain & Wallace, 2016; Hipp et al., 2010; Wang et al., 2014; c.f. Miller et al., 2016).

Two other neighborhood factors are less commonly investigated, but promising: density of residents with criminal records and disorder. From a social learning perspective, th*e density of residents with criminal records* may indirectly increase offending by modeling illegal behavior (Dishion, McCord, & Poulin, 1999; Warr & Stafford, 1991). Given that exposure of lower risk people to the deviant influence of their higher-risk peers theoretically causes "contagion" of delinquency and offending (see Dodge, Lansford, & Dishion, 2006; Lowenkamp & Latessa, 2004), placement in neighborhoods densely populated by other crime-involved people could especially cause (low risk) people to recidivate. Empirically, two studies indicate that the density of people on parole or proximity to those who have recidivated predict recidivism, above and beyond individual and other neighborhood factors (Chamberlain & Wallace, 2016; Stahler et al., 2013).

As for *disorder*, broken windows theory suggests that physical signs of disorder provide cues that promote disorderly behavior and crime, and induce a sense of danger in communities (Kelling & Wilson, 1982; see also Sampson & Raudenbush, 1999). According to Kelling and Wilson (1982), such cues indicate that norms can be violated and that norm-violating behavior comes with little cost to the violator. Field studies find that signs of disorder can promote illegal activity among pedestrians (i.e., non-justice involved people at low risk of offending; Keizer, Lindenberg, & Steg, 2008). Two studies find disorder, represented by crime density (Gottfredson & Taylor, 1986) and alcohol outlet density (Hipp et al., 2010), predicts recidivism.

In summary, though several theories provide plausible explanations for their relationship, empirical evidence on the relation between neighborhood factors and recidivism is mixed.

[1]Three of the five studies dismissing concentrated disadvantage also included variables representing the density of nearby parolees or features of disorder, potentially swamping the effect of concentrated disadvantage (Chamberlain & Wallace, 2016; Miller, Caplan, & Ostermann, 2016; Stahler et al., 2013). In addition, one of these studies examined effects at the county-level, which likely weakened the effect of concentrated disadvantage, since disadvantage can vary considerably within a county.

The most commonly studied variable—concentrated disadvantage—has only mixed support. Disorder and density of justice-involved residents appear promising but have been tested in few studies.

For Which Justice-involved Persons do Disadvantaged Neighborhoods Matter?

These inconsistent results could partially reflect sample differences that, in turn, alter the strength of the relationship between neighborhood factors and recidivism. Because neighborhood factors likely predict reoffending more strongly among *some* groups than others, there has long been a call for "research to focus on the interactions between offender and environmental characteristics" (Kubrin & Stewart, 2006, p. 187). In examining recidivism, several researchers have tested potential interactions between neighborhood factors and individuals' demographic characteristics (Huebner & Pleggenkuhle, 2015; Hipp et al., 2010; Mears et al., 2008; Wang et al., 2010; Wehrman, 2010), socioeconomic state (i.e., financial problems, job instability, etc; Gottfredson & Taylor, 1986), and criminal history (Gottfredson & Taylor, 1986; Raphael & Weiman, 2007; Reisig, Bales, Hay, & Wang, 2007; Wang et al., 2014). Several interactions have been found, but few are theoretically coherent and even fewer have been replicated.

As noted above, we posit that a justice-involved persons' risk of recidivism moderates the effect of neighborhood factors on reoffending. From a disadvantage saturation perspective (Hannon, 2003), people who experience significant or have accrued multiple risk factors should be *least* adversely affected by disadvantaged neighborhoods. People high in risk already have a multitude of risk factors that place them at substantial likelihood of reoffending—their level of risk may have reached a point of saturation where any additional risk factor does little to further increase that likelihood (i.e., a point of diminishing negative returns). In contrast, people who have experience less significant or have accrued fewer risk factors should be *most* adversely affected by disadvantaged neighborhoods. People low in risk are unlikely to reoffend *but for* exposure to risk factors like placement in highly disadvantaged neighborhoods (see Kirk, 2009; Wikström & Loeber, 2000). Because people classified as low risk have experienced less adversity, the impact of neighborhood disadvantage would be felt more strongly. This perspective is consistent with other theories that "the negative impact of any one risk factor or stressor on the life course is diluted, for individuals who experience multiple stressors" (Turanovic, 2018, p. 105).

This hypothesis is not new—but also has not been rigorously tested. Four studies have *indirectly* tested this hypothesis, using criminal history as a proxy for individual risk of recidivism. Together, these studies yield promising results. Gottfredson and Taylor (1986) explored the interaction between neighborhood disorder and two proxies of recidivism risk, criminal history (n=382) and socioeconomic state (n = 286). The authors found that neighborhood disorder interacted with these proxies to add modest predictive utility for some recidivism indices (time to and severity of arrest), but not others (arrest). Wang et al. (2014) found the effect of residential mobility on recidivism was relatively high for those with less serious criminal histories (although there were no such interactions with neighborhood disadvantage, urbanism, or racial segregation; n = 54,359). Similarly, in a sample of 418,199 people on parole, Raphael & Weiman (2007) found the effect of neighborhood unemployment rates was relatively strong for those with limited criminal histories. Lastly, Reisig et al. (2007) found county economic hardship among Black families had a relatively strong effect on Black ex-prisoners with shorter criminal histories (n = 21,484).

Present Study

In this study, we directly and rigorously test our hypothesis that individual risk moderates the relationship between neighborhood risk factors and reoffending. From a differential saturation perspective, the impact of neighborhood factors on reoffending will be greatest among low-risk people. It is likely that low-risk people will most keenly experience the impact of placement in neighborhoods marked by disorder, deprived of economic and social resources essential to re-entry, and populated by crime-involved peers.

We tested our hypothesis based on a sample of 2,218 people on probation who were assessed with a purpose-built, comprehensive, validated risk assessment instrument (the COMPAS; Brennan, Dieterich, & Ehret, 2009) that distills 15 different individual risk factors into a single score. Administrative data from a probation agency was used to characterize the sample and recidivism. We triangulated census data with online systematic social observation based on Google Street View (Odgers et al., 2012) to obtain a comprehensive picture of concentrated disadvantage, ethnoracial diversity, residential stability, disorder, and probationer density in each neighborhood. To avoid criterion contamination (i.e., correlating a construct with itself), we excluded most direct indices of criminal behavior from our measure of disorder.

Method

Sample

Our sample (n = 2,218) was drawn from a population of people on probation who entered community supervision between October of 2011 and June of 2014 in San Francisco, California (see Table 1). The maximum observation period for the study sample is 1,000 days (approximately 2.75 years), and over 75% were observed for at least 12 months (the period in which the majority of recidivism occurs; Ostermann, Salerno, & Hyatt, 2015). We included people regardless of observation length because we used survival analysis, which adjusts for censored observations, and censoring was “non-informative” (i.e., based on non-significant correlation between start date and recidivism risk score, individuals who enter probation in 2014 are at no greater risk of recidivism than those who enter in 2011; Allison, 2010).[2]

We excluded people (n = 3,566) who had no mappable address in San Francisco (59%; i.e., relocated/transferred outside the city, documented as homeless, or lacked a residential address) or who were not assessed for risk with the COMPAS at the start of probation

[2]The study period overlaps with California’s Public Safety Realignment Act, which makes county probation departments responsible for supervision of non-violent, non-serious, and non-sex offender registered felony offenders, previously supervised by parole. Realignment may have led to a qualitative change in the sample, but did not increase the sample’s risk; correlating start date and risk score yielded an insignificant result ($r = -.04$, p = .07). Thus, Realignment did not likely alter study aims.

(46%).[3] Our inclusion rate (38%) is low but comparable to similar studies (e.g., Wolff et al., 2018), especially given this region's high rate of homelessness (see Jacobs & Gottlieb, 2020). To assess potential selection bias, we compared the characteristics of our final sample with those excluded. Although our sample was slightly older (mean age of 38 vs. 36; t=6.01, p=<001) and more likely to be Black (−7% percent; $X^2 = 30.5$, p<.001) than those excluded, the two groups were similar in gender, COMPAS risk classifications ($X^2 = 4.44$, p = .11, comparing our sample with the 56% of those excluded who had COMPAS data), and recidivism rates (β =.04, p = .34). Overall, results provide little evidence of selection bias.

Measures

Individual predictors.

Recidivism risk.: We operationalized each persons risk of recidivism with the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS; Brennan, Fretz, & Wells, 2003; Brennan et al., 2009). We used both COMPAS scores and risk classifications in analyses. Given that COMPAS risk classifications should be calibrated to particular contexts, we created three categories by cutting COMPAS risk scores in this sample into tertiles. We define these categories as *low*, *moderate*, and *high risk*, with respective COMPAS raw score ranges of −2.94 to −.30, - .31 to .41, and .42 to 1.99.

In San Francisco, the COMPAS is completed by probation officers during pre-sentence investigations, in the period between a person's conviction and the start of their supervision. The version of COMPAS used in San Francisco consists of 135 items—but it is unclear how items are weighted and summed to produce risk scores because that information is proprietary (see Wisconsin v. Loomis, 2016). According to Brennan et al. (2009), Northpointe Inc. created an overall risk score by regressing "new offenses" on participants' scores across 15 different sub-scales: prior criminal involvement, history of noncompliance, history of violence, current violence, criminal associates, substance abuse, financial problems, vocational/educational problems, family criminality, social environment, leisure, residential instability, social isolation, criminal attitudes, and criminal personality.

To better understand the COMPAS risk score, we regressed the risk score on sub-scales and found risk scores are most strongly represented by prior criminal involvement (β = 0.77), young age (β = −0.53), vocational/educational problems (β = 0.30) and substance abuse problems (β = 0.12). We also found COMPAS scores strongly predicted recidivism (AUC = .74). This is consistent with a past independent evaluation of the COMPAS (AUC=.70; Farabee, Zhang, Roberts & Yang, 2010) and with a meta-analysis that included three COMPAS studies and indicated that COMPAS (AUC=.67) predicted recidivism as strongly as other commonly used risk assessment instruments (AUC = .57 - .74; Desmarais, Johnson and Singh, 2016). In sum, the COMPAS distills many robust individual risk factors into a single score designed to maximally predict reoffending.

[3]Of those excluded due to lack of a mappable address within San Francisco, the majority were due to homelessness or relocation out of the observed area. The vast majority of remaining addresses were mappable; Addresses were initially automatically geocoded with a spelling sensitivity tolerance of 70%, and after reviewing and mapping any remaining mappable addresses by hand, we successfully geocoded 98% of participants' residential addresses within San Francisco.

Demographics.: We included gender (male=1), age (at start), and race (Black=1) as covariates, given that these demographic variables weakly but robustly predict recidivism (Gendreau, Little, & Goggin, 1996; McGovern, Demuth, & Jacoby, 2009)—and sometimes add incremental utility to risk scores in predicting recidivism (Skeem, Monahan, & Lowenkamp, 2016; Monahan, Skeem, Lowenkamp, 2017). Our goal was to capture major individual risk factors for recidivism, when estimating the independent effect of neighborhoods. These data were drawn from county probation case records and checked against county court records.

Neighborhood predictors.: Based on participants' addresses, as documented in probation case records, we observed street blocks within their immediate environments (n = 420) and collected data for the Census block groups in which these street blocks were nested (n = 338; see technical supplement).[4] Because measuring neighborhood qualities in large spatial units can neglect within unit heterogeneity, exacerbate the uncertain geographic context problem (UGCP), and attenuate effects, we followed recommendations to measure neighborhood qualities in small units within participants' immediate residential context, as detailed below (Oberwittler & Wikström, 2009; Smith et al., 2000; Weisburd et al., 2012). We also examined convergent and divergent validity of these measures at multiple units of aggregation, to ensure our measurement strategy yielded theoretically meaningful relationships between variables. Results of these analyses supported block groups as reasonable units of aggregation.[5] Below, we describe the coding of secondary data, the collection of SSO data, and the distillation of these data sources to represent neighborhood variables.

Coding secondary data.: To measure factors related to disadvantage, residential instability, and ethnoracial diversity, we collected estimates at the block group level from the U.S. Census' *American Community Survey 2009-2013* for the following indicators: poverty, median income, unemployment, median length of residence, percent of homes owned, and race/ethnicity. To reduce skew, we transformed length of residence taking the natural log. For race/ethnicity data, we calculated a diversity score (labeled "ethnoracial diversity") using the Herfindahl index (Hipp et al., 2010), where lower values indicate homogeneity and larger values indicate diversity.

To measure factors related to disorder and the density of people on probation we geolocated and aggregated alcohol outlet, drug crime, and density data at the block group level. We drew point data for alcohol outlets, drug crimes, and participant addresses from the California Board of Alcohol Beverage Control license records, San Francisco Police crime incidents, and the San Francisco Department of Adult Probation, respectively. For drug crime incidents and density of people on probation, we included only incidents and residences within the year prior to observation start. These counts were normalized by

[4]Because less than 10% of participants in our sample had a documented residential move prior to failure or censor, we use a single address documented at probation start to represent participants' neighborhoods.
[5]As Morrison et al. (2015) recommend, we conducted sensitivity analyses for measures aggregated at multiple geographic levels. Using the approach taken by Wooldredge (2002), we correlated measures (when available) within a .5 mile buffer of each probationer, at the block group- and census tract levels. We found little variation in associations between predictor variables and recidivism between these levels.

population size (see Table 1). To reduce skew, we transformed alcohol outlet density and drug crime density, taking the natural log, and density of people on probation, taking the square root.

Assessing primary data.: We applied Odgers and colleagues' (2012) online SSO approach to collect primary data capturing objective and subjective measures of disorder (for detailed procedures, see Electronic Supplement). To do so, we identified units of observation (i.e., block faces) within a maximum of 250 feet from each participant's residential address. Following Odgers et al., we used Google Earth Pro to observe blocks by taking virtual walks up and down blocks, observing Street View images, and recording observations in an electronic survey.

Odgers et al.'s electronic survey, which we used to direct observations, was adapted from a previously validated SSO instrument (Earls, Raudenbush, Reiss, & Sampson, 2005). The survey includes disorder and perceived danger. Disorder is a seven-item scale indicating the presence (0 – 1) of physical and social disorder (litter or garbage, graffiti, painted over graffiti, vandalized signs, abandoned or burned out cars, loitering, homeless encampments).[6] Perceived danger ranges from zero to eight and is comprised of responses to two questions: would you "feel safe walking in this area at night?" and does this appear "a safe place to live?" (coded 0-4 and reversed for analysis). These items were then averaged to create a single disorder and danger score for each participant's block group.

We examined the reliability and validity of these measures. Based on a subsample of 43 observations completed by two raters and assessed via one-way interclass correlation (ICC; Cicchetti, 1994; Hallgren, 2012), inter-rater reliability was good for the disorder (ICC = .73), and perceived danger (ICC = .63) scales. Based on the full sample, disorder (alpha = .73) and danger (alpha = .93) had acceptable and excellent levels of internal consistency (Nunally, 1978), in keeping with past research (Odgers et al., 2012). Aligning with Odgers et al. (2012), the block group average of our online SSO ratings manifested a theoretically coherent pattern of relationships with neighborhood variables coded from administrative data. For example, disorder correlated inversely with income ($r = -.25$), positively with poverty ($r = .22$), and positively and more strongly with drug crime ($r = .37$; see Electronic Supplement Table 1).

Distilling neighborhood variables into fewer components.: In sum, we coded eleven main variables from primary and secondary sources. All but one variable (ethnoracial diversity) was moderately to strongly associated with other neighborhood variables (see Electronic Supplement Table 1). We conducted a principal components analysis (PCA; with varimax rotation) to reduce these 11 variables into a few meaningful dimensions of correlated neighborhood characteristics, as recommended by Land, McCall, and Cohen (1990) and using the "psych" package in R (Revelle, 2018). Applying the default approach of extracting components with eigenvalues above 1 and removing variables that fail to load discretely, we found eight variables loaded on three interpretable components (variance explained = 77%).

[6]The presence of homeless encampments was not an item on the scale adapted by Odgers and colleagues. However, we added the item as an indicator of social disorder because of their significance and contribution to disorder in the city under observation.

The first component (eigenvalue= 2.09), which we labeled *concentrated disadvantage*, includes unemployment (.81), income (−.77), and poverty (.79). The second component (eigenvalue= 2.05), which we labeled *residential stability*, includes percent of owner-occupied homes (.86) and length of residence (.82). The third component (eigenvalue= 2.00), which we labeled *disorder*, includes disorder (.86), perceived danger (.82), and drug crime density (.65).[7]

We calculated standardized scores for each component (mean = 0, sd = 1; see Revelle, 2018) to represent concentrated disadvantage, residential stability, and disorder in analyses. Although two neighborhood variables—*ethnoracial diversity* and *probationer density*—did not load discretely on any component, but are theoretically relevant, we also included them as independent variables in our analyses. To facilitate interpretation and comparison, we calculated standardized scores for these variables (mean = 0, sd = 1). Thus, a one-unit change in each predictor variable is equivalent to a one-standard deviation change in that measure. In summary, the distillation process reduced 11 neighborhood variables into the following five: concentrated disadvantage, residential stability, disorder, ethnoracial diversity and density of people on probation.

Recidivism criterion.: The outcome variable for this study was time to recidivism, as documented in probation and court records. Time was measured as days under probation supervision, beginning with probation start date and ending with a recidivism or censor date. We defined recidivism as rearrest for a new offense or revocation. We adopted this liberal definition of recidivism because both rearrest and revocation indicate probation failure, and neighborhood factors could compromise one's ability to avoid criminal behavior and to abide by the terms of probation. This definition of recidivism also avoids overestimation of post-release "successes" (e.g., counting as successes those who violate community supervision; Matejkowski, Conrad, & Ostermann, 2017; Ostermann et al., 2015).

Of those in our sample, 1,058 (48%) recidivated during the study period (average time to recidivism = 210 days). Most "recidivism" reflects rearrest: 751 (71%) of incidents were arrests for new offenses, and 308 (29%) were for revocations. New offenses included crimes against persons (20%), property (30%), drug (31%), and minor (26%) offenses. Given limitations in the way data were coded, revocations included violations and petitions (i.e., administrative revocations). However, upon inspection of arrest records beyond initial recidivism dates, we found half of those who failed due to revocation (53%) were later arrested for a new charge. Even with the inclusion of petitions, then, revocation is a reasonable indicator of continued involvement in crime.

Statistical Analyses: We used Cox proportional hazards models to test the effects of both individual- and neighborhood factors on time to recidivism and their potential interaction. Cox regression estimates the probability of failure (i.e., recidivism) at a specific point in time, given one has survived up until that point in time (i.e., hazard rate; Hosmer,

[7]Disorder is often operationalized as visible attributes of physical disorder (litter, graffiti, and other signs of 'urban landscape deterioration') and social disorder (loitering, public intoxication, and other behavior "usually involving strangers and considered threatening"; Sampson & Raudenbush, 1999, p. 603; see also Skogan, 2015).

Lemeshow, & May, 2011). To account for the fact that people are clustered within block groups, we computed robust standard errors using coxph from the survival package in R (Therneau, 2018). The Cox model with robust standard errors is a semi-parametric approach that provides population-level estimates with unbiased estimates of significance (Stedman et al., 2012).

The most viable alternative to this approach for dealing with clustered data is a parametric mixed effects model. Although mixed effect models offer additional information regarding the variance explained by cluster units and the variation in effects across units, they require unverifiable assumptions regarding the distribution of unobserved data when extended to non-linear models (Stedman et al., 2012) and perform no better than the Cox model with robust standard errors in terms of Type I error, bias, coverage probability and mean standard error. Thus, results based on a mixed effects framework are relegated to the Electronic Supplement.

While assessing the size of a hazard ratio is complicated by the fact that hazard rates lack a standard deviation, the natural log of an exponentially distributed survival time provides a common variance ($\pi^2/6$) and this variance can be used to estimate effect size (*r*; Azuero, 2016). When the hazard rate is converted to effect size (*r*) using this common variance, the midpoint between a small and moderate effect size ($r = .35$) is equivalent to a hazard ratio of 1.3. Thus, we consider a hazard ratio of about 1.3 to be meaningfully (i.e., clinically) significant, and we consider effects small, moderate, or large when hazard ratios are approximately 1.14, 1.47, or 1.9 respectively (for continuous predictors).

Results

Sample Description

As shown in Table 1, the sample was predominantly male, with a mean age of 38 years, and half were Black. About half recidivated—and rates of recidivism increased across COMPAS risk categories (23% of low-, 52% of moderate-, and 70% of high-risk people recidivated). Compared to San Francisco neighborhoods on average, people on probation lived in neighborhoods with a higher poverty rate (22% vs. 14%), higher unemployment rate (13% vs. 8%), lower median income ($57,857 vs. $75,604), greater ethnoracial diversity (.60 vs. .50), fewer owner occupied homes (32% vs. 42%) and more drug crime (32 vs. 8 per 1,000 persons).

Individual and Neighborhood Predictors of Recidivism

To contextualize our main analyses, we conducted two survival analyses for each predictor. In the first model, we enter the index variable alone as a predictor of recidivism. In the second model, we enter the index predictor alongside all other individual and neighborhood predictors. These analyses allowed us to estimate each variable's bivariate and independent association with recidivism.

As shown in the Unadjusted Effects column of Table 2, nearly all individual and neighborhood variables significantly predicted recidivism, prior to adjusting for other variables. Except for age, individual-level variables moderately to strongly predicted recidivism. For example, those classified as high risk were over five times more likely to recidivate than those classified as low risk (HR = 5.37). Neighborhood factors predicted recidivism more weakly. Effect sizes were strongest for ethnoracial diversity and density of people on probation, and disorder; and weakest for concentrated disadvantage and residential instability.[8]

As shown in the Independent Effects column of Table 2, adjusting for association with other risk factors reduced the effect size of some individual predictors (e.g., race, risk classification), but all remained statistically significant. Risk classifications had a strong independent effect on recidivism (HR = 4.80). With respect to neighborhood factors, only disorder had a significant independent effect on a recidivism (HR = 1.11)—the remaining variables did not predict time to recidivism, after controlling for other factors.[9]

Does Individual Criminal Risk Moderate the Effect of Neighborhood Factors on Recidivism?

To test whether participants' COMPAS risk classification moderated the relationship between neighborhood factors and time to recidivism, we completed five Cox regressions—one for each neighborhood variable (i.e., disadvantage, residential stability, ethnoracial diversity, disorder, or probationer density). Each model included the interaction term between the neighborhood variable and risk classification (i.e., low vs. moderate risk and low vs. high risk). In addition to these interaction terms, each model included the index variables' main effect and controlled for individual-level predictors (i.e., gender, race, and age) and all neighborhood-level variables. This is a conservative test of whether risk moderates the effect of a particular neighborhood variable on recidivism—once one has controlled for participants' demographics and other neighborhood factors.

As shown in Table 3, results indicate that criminal risk significantly interacted with three of the five neighborhood risk factors. Specifically, as participants' risk classification decreased, the power of concentrated disadvantage, disorder, and probationer density in predicting recidivism increased. With interaction terms ranging from −.26 (HR = 0.77) to −0.17 (HR = .84), the largest difference in slopes were for disorder and disadvantage, indicating a greater effect for low than high-risk participants. Figure 1 illustrates how the effect of these neighborhood variables becomes less pronounced across low and higher risk groups. The interaction between density of people on probation and risk was weaker and statistically significant only when comparing low to moderate risk people.

[8]To assess the robustness of neighborhood parameter estimates, we re-ran the adjusted model substituting the COMPAS risk assessment score with the 15 risk/need sub-scale scores (see Methods for a complete list of subscales). Adjusting for this vast array of competing exposures and potential confounders did not substantively change parameter estimates; concentrated disadvantage, residential instability, ethnoracial diversity, and probationer density had coefficients ranging from HR = 0.97 – 1.05, and disorder had a HR of 1.10.

[9]It is possible that effects were dependent on our operationalization of recidivism (i.e., rearrest for a new offense or revocation), so we ran the same models with recidivism defined only as rearrest and only as revocation. We found the direction, size, and statistical non-significance of residential instability, concentrated disadvantage, ethnoracial diversity, and probationer density were similar for rearrests and revocations. Disorder remained the largest coefficient, with statistically significant effects for new offenses (HR = 1.11, p = .027) and approaching statistical significance at the .05 level for revocations (HR = 1.12, p = .083). In sum, we find little evidence that effects are outcome dependent.

In these interaction models, the main effect of each neighborhood factor represents the effect of that factor for the reference group (i.e., low-risk people). Taking interactions into account then, concentrated disadvantage (HR = 1.24) and disorder (HR = 1.35), have small but meaningful effects on recidivism for low-risk people. Put another way, at one year, 15% more low-risk people would recidivate if living in a highly disadvantaged neighborhood (+2 SD disadvantage; predicted S(365 days) = 0.72), compared to a modestly disadvantaged neighborhood (−2 SD disadvantage; predicted S(365 days) = 0.87). Similarly, 21% more low-risk people would recidivate living in a high disorder neighborhood (+2 SD disorder; predicted S(365 days) = 0.68), compared to a neighborhood with little disorder (−2 SD disorder; predicted S(365 days) = 0.89). These results were robust to variation in statistical modeling. As shown in the Electronic Supplement (Table 2), coefficients from mixed effects survival models were similar to those produced with marginal models; with significant interactions between criminal risk and neighborhood disadvantage and disorder.

In short, low-risk people on probation experience meaningful differences in their probability of recidivating depending on where they live. Criminal risk significantly moderates the effect of some neighborhood factors on recidivism: Lower risk people on probation appear more susceptible to contextual influences than their higher risk counterparts—with most robust effects for disorder.

Discussion

Leading models of correctional intervention, such as the “Risk-Need-Responsivity” model (Bonta & Andrews, 2016), target individual risk factors to prevent re-offending—virtually to the exclusion of neighborhood risk factors. The results of this study indicate that it is premature to dismiss neighborhood factors as irrelevant to recidivism reduction. Some neighborhood risk factors clearly “matter” for some people on probation. Specifically, we found that risk of recidivism moderated the effect of neighborhood conditions on reoffending. People on probation at relatively low risk were more likely to reoffend when they lived in disadvantaged and high disorder neighborhoods—whereas neighborhoods had little influence on people on probation at relatively high risk.

Our findings advance knowledge about the relation between neighborhoods and recidivism. Past studies indicate that a variety of neighborhood factors affect recidivism but are mixed regarding which factors are relevant and how strongly they shape criminal justice outcomes. We hypothesized that differences in samples may explain such variation in study findings and our results are consistent with this supposition. We found that neighborhood factors weakly and inconsistently predicted recidivism, until we accounted for the interaction between neighborhood factors and individual characteristics. Examining main effects of neighborhood characteristics on recidivism for the full sample, we found that only disorder reached statistical significance with a small effect (HR = 1.11). When interactions were examined, however, concentrated disadvantage and disorder emerged as meaningful predictors of recidivism for people at low-risk of recidivism. Hazards are over three times larger amongst those low in individual-level risk to those high in individual-level risk. This pattern of results—with disadvantage and disorder significantly interacting with individuals’ risk level to predict recidivism—was replicated when we employed multilevel models.

Ultimately, this suggests that the effects of concentrated disadvantage and disorder depend on who is examined. The typically null or small effects found in similar studies may inappropriately characterize the relationship between neighborhood conditions and offending, leading some to incorrectly and categorically interpret them as inconsequential for recidivism.

The finding that individual-level risk and neighborhood-level risk interact makes sense in light of the disadvantage saturation perspective (Hannon, 2003). In general, the disadvantage saturation perspective argues that low-risk people are most adversely affected by additional risk factors, while high-risk people are least adversely affected by additional risk factors. As applied to neighborhood risk factors and recidivism, disadvantage saturation suggests that low-risk people on probation who have accrued fewer or less meaningful criminal risk factors feel the impact of neighborhood risk factors more strongly than their relatively high-risk counterparts. In other words, those who already face serious challenges to successful reentry are likely to recidivate regardless of additional neighborhood-level risk factors, but those who face few or minor challenges to reentry may not recidivate but for risk factors present in their residential contexts.

Of neighborhood risk factors, we found concentrated disadvantage and disorder particularly meaningful for people low in risk. Concentrated disadvantage is a key construct in social disorganization theory, which argues environments characterized by disadvantage have limited social control to protect against crime. Since social disorganization theory has usually been applied to crime rates in the general population, which is comprised of people lower in criminal risk than those in justice-involved samples, it logically follows that when applied to individual reoffending, disadvantage would predict recidivism most strongly among people on probation classified as low-risk. This variation in effects may also explain why other studies with relatively high-risk samples fail to find disadvantage predictive of recidivism (see Jacobs et al., 2020a; Jacobs et al., 2020b).

As for disorder, broken windows theory suggests that visible signs of disorder provide cues that norm-violating behavior is common in a setting and that when it occurs it will go unchecked (Kelling & Wilson, 1982). As a result, the theory argues that disorder promotes crime. Experiments observe that pedestrians engage in uncivil and even low-level criminal behavior when in visibly disordered spaces (Keizer et al., 2008), which suggests that disorder can induce antisocial behavior within the general population. Our finding that disorder predicts recidivism among people on probation classified as low-risk makes sense in light of these studies—like the general public, contextual cues may elicit antisocial behavior from people on probation who would otherwise not engage in such behavior.

Before discussing the implications of these findings, we note three study limitations. First, the sample represents only 38% of the probation population. Although we found little evidence of selection bias (see Methods), results may not generalize beyond people on probation with residential addresses who were assessed for risk near probation intake. Second, we used participants' addresses at the start of probation to characterize their neighborhood, even though some participants moved after probation began. We used participants' addresses at the start of probation because this is when addresses were most reliably documented and because most participants did not have a residential move during the observation period (see Jacobs & Gottlieb, 2020). Third, our use of data related to residential contexts immediately proximate to participants did not fully address error that can arise based on how geographic units are defined (the modifiable areal unit problem; MAUP) and may not reflect contextual influences that participants predominately experience, if they spend much time elsewhere (i.e., the uncertain geographic context problem; UGCP). We did assess the relationships of interest across multiple units of analysis and used this information when selecting block groups, alleviating some concern regarding the potential for weakened effects due to MAUP. Further, our focus on relatively small areas surrounding participants' residences and our use of temporally proximate observational data facilitated measurement of a neighborhood factor like disorder within areas participants are likely to spend at least some time and alleviating some concern regarding the UGCP.

With these limitations in mind, we unpack the implications of this study—beginning with its immediate implications for this special issue of the *American Journal of Community Psychology*. This study illustrates how community psychology values can inform criminal justice research in two primary ways. First, this study goes beyond an individual focus to examine how ecological influences can promote or inhibit successful re-entry for people involved in the justice system. As noted in the introduction, most research on risk factors for criminal recidivism has focused on individual-level characteristics. This focus situates the potential source of the problem and the need for change within individuals; largely neglecting the role that socio-structural factors play in re-offending.

Second, this study illustrates how ecologically-oriented research might be applied to promote resilience among a highly stigmatized social group—people involved in the justice system. Building resilience may depend less upon practitioners' knowledge about individual *or* ecological risk factors than on their understanding that individual *and* ecological characteristics interact with one another (Berardi, Glaantsman & Whipple, 2019). There have long been calls for research that examines variation in risk factors across sub-groups of justice-involved persons *or* research that examines the role of ecological risk factors for reoffending (Andrews & Bonta, 2016; Kubrin & Stewart, 2006; Sharkey & Faber, 2014). Only a minority of studies—like the present study—respond to both calls simultaneously (see, e.g., Gottfredson & Taylor, 1986; Huebner & Pleggenkuhle, 2015). As a result, practitioners typically take a one-size-fits-all approach to "risk and needs assessment" for people on probation. The results of this study imply that resilience could be better promoted if practitioners considered the interaction between individual-level risk and ecological factors (disorder and disadvantage) to better identify needs and target interventions.

In terms of research, this study demonstrates that observational data has the capacity to overcome several limitations of administrative data and that primary data coded using Odgers et al.'s (2012) approach provides meaningful information about neighborhood features in relation to recidivism. Future researchers should continue to develop methods and use observational data on neighborhood qualities that may be relevant to recidivism (e.g., protective factors like social cohesion). Further, to overcome the UGCP, future researchers should explore emerging methods (e.g., ecological momentary analysis; Browning & Soller,

2014) that can provide detailed information on where justice-involved persons spend their time and the effects of those locations on recidivism.

As for practice, probation and parole should not dismiss neighborhood contexts as non-criminogenic. Instead, community supervision models, like Risk-Need-Responsivity, should attend to place for low-risk justice-involved people. “Risk-needs” assessment should consider disadvantage and disorder in residential contexts in directing service provision for people low in risk. Meanwhile, models of supervision should seek to mitigate both contextual and individual risk factors to reduce recidivism (e.g., Schaefer, Cullen, & Eck, 2015).

Conclusion

Social outcomes often reflect interactions between social circumstances and individual characteristics. This study indicates that neighborhood disadvantage and disorder “matter” for reoffending when interacted with individual recidivism risk. In line with the disadvantage saturation perspective, people on probation who are classified as low risk are more likely to recidivate when they live in highly disadvantaged and disorderly neighborhoods, unlike those classified as high risk. Recidivism researchers and interventionists would be wise to the heed calls for more nuanced investigation of the relationships between residential contexts and outcomes; in some cases, preventing recidivism will require considering specific neighborhood dynamics for specific groups of justice-involved people.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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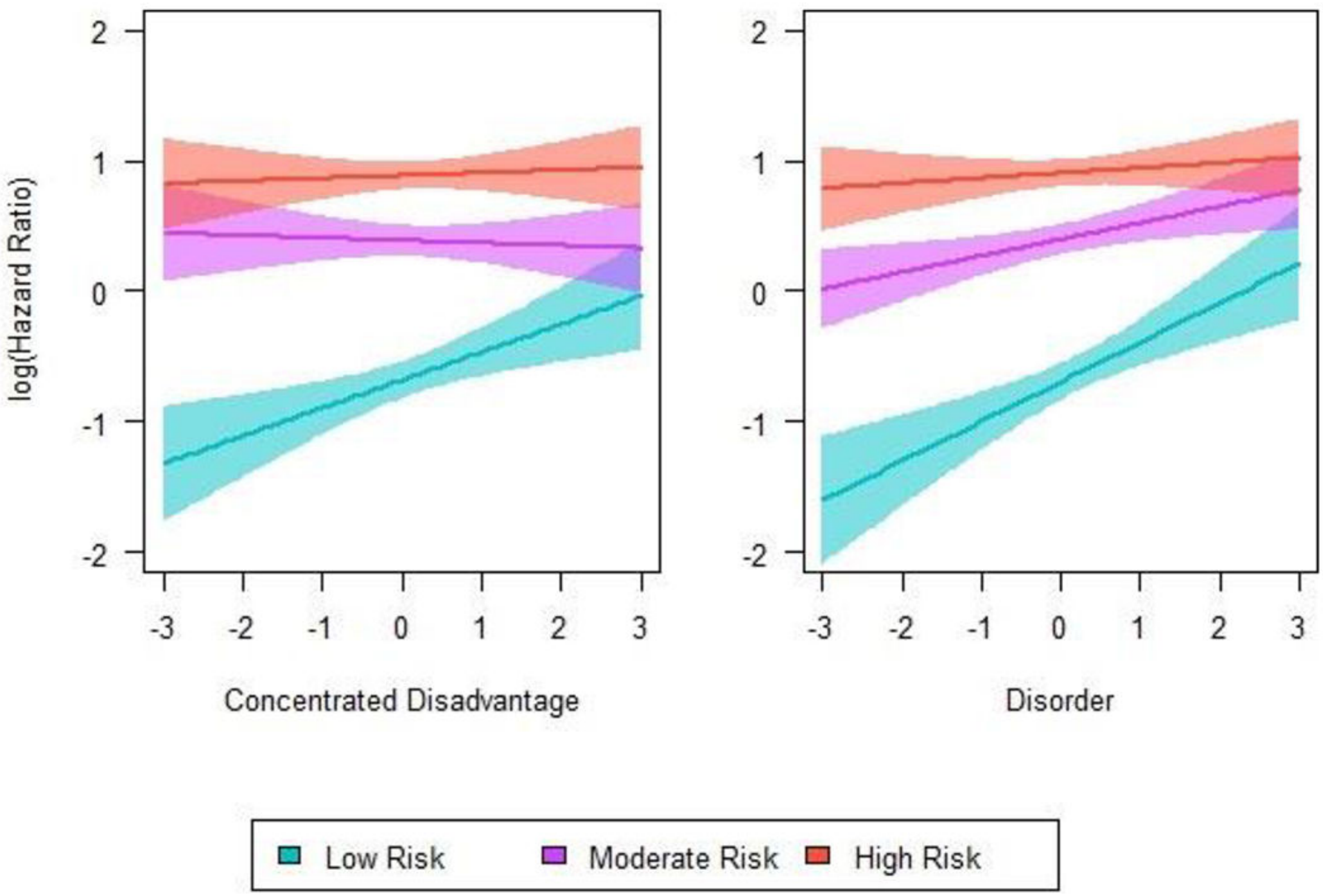

Figure 1.

Effect of Concentrated Disadvantage and Disorder for People on Probation Classified as Low, Moderate, and High Risk

Notes: These graphs plot statistically significant interactions between neighborhood risk factors and individual-level recidivism risk, as modeled in Table 4. Bands represent confidence intervals (95th percentile).

Table 1.

Variable Definitions and Descriptive Statistics

Variable	Definition and coding	Mean (count)	SD (%)
Individual Characteristics			
Male	yes = 1, no = 0	(1868)	(84%)
Black	yes = 1, no = 0	(1139)	(51%)
Age	Age (in years) at probation start	38	12
Recidivism risk	Low COMPAS risk category (yes = 1)	(776)	(35%)
	Moderate COMPAS risk category (yes = 1)	(729)	(33%)
	High COMPAS risk category (yes = 1)	(713)	(32%)
Neighborhood Factors			
Concentrated disadvantage	Component score	0.00	1.00
	Median household income	$57,857	$35,110
	Percent below the poverty line	22%	16
	Percent unemployed	13%	10
Residential stability	Component score	0.00	1.00
	Average length of residence (years)	9.99	3.28
	Percent of homes owner occupied	32%	26
Ethnoracial diversity	Herfindahl index score (0-1)	0.62	0.11
Disorder	Component score	0.00	1.00
	Observed social and physical disorder (0-7)	2.41	1.69
	Perceived danger (0-8)	4.14	2.22
	Drug crime per capita	31.71	48.26
Probationer density	Adult population on probation per 100 residents	1.69	1.78
Outcome variable			
Recidivism	Rearrested or revoked (yes = 1, no = 0)	(1058)	(48%)
Time to recidivism	Days until rearrest or revocation	210	185

Notes: N=2,218; SD = standard deviation; Neighborhood factors represent block groups

Table 2.

Effects of Individual- and Neighborhood-level Variables on Recidivism

	Unadjusted Effects[a]			Independent Effects[b]		
Individual-level variables	**HR**	**SE**	**p-value**	**HR**	**SE**	**p-value**
Male	1.38	0.09	<0.001	1.38	0.09	<0.001
Black	1.57	0.06	<0.001	1.23	0.07	0.002
Age	1.00	0.00	0.895	1.00	0.00	0.478
Risk category (moderate)	3.08	0.09	<0.001	2.93	0.09	<0.001
Risk category (high)	5.37	0.09	<0.001	4.80	0.09	<0.001
Neighborhood-level variables						
Concentrated disadvantage	1.13	0.03	<0.001	1.04	0.04	0.326
Residential instability	1.11	0.03	0.005	1.04	0.03	0.277
Ethnoracial diversity	1.18	0.03	<0.001	1.05	0.04	0.195
Disorder	1.16	0.03	<0.001	1.11	0.03	0.008
Density of people on probation	1.17	0.03	<0.001	0.96	0.04	0.329

Notes:

[a] In the Unadjusted column, each row represents results from a Cox proportional hazard model, which regresses the predictor variable on the hazard of recidivating. Standard errors are robust to clustering. All continuous variables are standardized ($\bar{x} = 0$, SD = 1).

[b] In the Independent column, results from a single Cox proportional hazard model are represented. Each coefficient represents the effect for the index variable, conditional on all other variables (individual and neighborhood level). Standard errors are robust to clustering. All continuous variables are standardized ($\bar{x} = 0$, SD = 1). HR= hazard ratio; SE = Standard error.

Table 3.

Interactive Effects of Risk Classification and Neighborhood Factors on Recidivism

	HR	SE	p-value
Concentrated disadvantage (CD)	1.24	0.08	0.002
Moderate risk x CD	0.79	0.09	0.004
High risk x CD	0.82	0.09	0.027
Residential instability (RS)	1.04	0.07	0.522
Moderate risk x RS	0.99	0.09	0.864
High risk x RS	1.01	0.09	0.91
Ethnoracial diversity (ED)	1.15	0.08	0.057
Moderate risk x ED	0.88	0.09	0.204
High risk x ED	0.9	0.09	0.275
Disorder	1.35	0.08	<0.001
Moderate risk x Disorder	0.84	0.09	0.034
High risk x Disorder	0.77	0.09	<0.001
Density of people on probation (DP)	1.09	0.08	0.235
Moderate risk x DP	0.83	0.09	0.025
High risk x DP	0.87	0.09	0.052

Notes: The interaction between each neighborhood-level variable and individual-level recidivism risk has been tested via a Cox proportional hazard model with robust standard errors. Each of the five models includes the main effect of the neighborhood factor, and the interactions between risk categories and the neighborhood factor (low risk = 0). Interactions are conditioned on individual-level covariates (i.e., gender, race, age) and all neighborhood-level variables. The table does not contain values for these controls. All continuous variables are standardized ($\overline{x} = 0$, SD = 1). HR= hazard ratio; SE= standard error.