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Recidivism Among Justice-Involved Youth: Findings From JJ-TRIALS

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Abstract

Recidivism, and the factors related to it, remains a highly significant concern among juvenile justice researchers, practitioners, and policy makers. Recent studies highlight the need to examine multiple measures of recidivism as well as conduct multilevel analyses of this phenomenon. Using data collected in a National Institute on Drug Abuse (NIDA)-funded Juvenile Justice-Translational Research on Interventions for Adolescents in the Legal System (JJ-TRIALS)

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SUPPLEMENTAL MATERIAL
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cooperative agreement, we examined individual- and site-level factors related to 1-year recidivism among probation youth in 20 sites in five states to answer research questions related to how recidivism rates differ across sites and the relationships between individual-level variables and a county-level concentrated disadvantage measure and recidivism. Our findings of large site differences in recidivism rates, and complex relationships between individual and county-level predictors of recidivism, highlight the need for more nuanced, contextually informed, multilevel approaches in studying recidivism among juveniles.

Keywords

recidivism among justice involved youth; recidivism; juvenile justice; predictors of juvenile recidivism

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Preventing recidivism among juveniles remains a priority for the juvenile justice (JJ) system. In addition to the significant costs associated with juvenile delinquency (Welsh et al., 2008), problems such as increased rates of substance use (SU) (Welty et al., 2017), dropping out of school (kirk & Sampson, 2013), and continued offending into adulthood (Stouthamer-Loeber, 2010) are also correlated with juvenile offending. given these far-reaching effects and the commonly-held goal across JJ systems of reducing recidivism (Harris et al., 2009), recidivism rates have been a traditional metric of program effectiveness within JJ.

MEASURING RECIDIVISM

Measuring and reporting recidivism is vital for tracking probation outcomes; for evaluating the effectiveness of interventions; and for informing JJ policy, practice, and resource allocation, yet no consensus exists with respect to defining recidivism or the length of follow-up period for determining occurrences of recidivism (Deal et al., 2015). A new offense or rearrest is the most commonly used indicator by researchers and program evaluators (Harris, Lockwood, et al., 2011). Other commonly used definitions include delinquency adjudication within the juvenile system (the equivalent of conviction in the adult criminal justice system) for a subsequent arrest and re-incarceration/commitment to a juvenile correctional facility (Cottle et al., 2001). Some have argued that rearrest rates are better for understanding offending patterns in the community, while delinquency adjudication rates, which may result in more intensive community supervision or out-of-home placements, are better for guiding probation practices and programming for high-risk youth (Hyatt & Barnes, 2017). Among 40 states responding to a survey, researchers found that JJ agencies typically utilized more than one measure and that nearly half (48%) used adjudication and/or commitment decisions to define recidivism (Harris et al., 2009).

The definition (i.e., new offense/rearrest, adjudication, or re-incarceration/commitment), the length of the tracking period, and youth characteristics used influence recidivism rates differently. Because the number of youth decreases at each subsequent case processing decision point (Snyder & Sickmund, 2006), the use of rearrest as an indicator of recidivism produces higher rates than adjudication, since only a subset of youth arrested will be adjudicated. For example, the 12-month rates for juveniles on probation in Virginia were 34.1% and 23.3% in 2015 (Virginia Department of Juvenile Justice, 2018).

The duration of the follow-up period is also important, as a longer tracking period offers more opportunity for youth to come back into contact with the justice system (Deal et al., 2015). Among those who recidivate, the recidivism event is most likely to occur within the first year, but the percentage who recidivate continues to rise over longer follow-up periods (Mulder et al., 2011). For example, rates were 22.0% within six months, 34.1% within 12 months, 51.2% within 24 months, and 61.2% within 36 months (Virginia Department of Juvenile Justice, 2018).

The population of interest also affects the recidivism rate. In a series of studies of Florida juveniles who completed community-based services, the rearrest rate for all youth was 19.4% (Wolff et al., 2015), but the rate for a sample was 41% (Wolff et al., 2016). The difference in these rates is attributed to the proportion of youth assessed as low risk for reoffending (i.e., 75.5% in the population vs. 39% in the sample) and higher rates of males and Black youth in the sample. Studies of recidivism among juveniles committing serious offenses have found 1-year rearrest rates of 67% among males returning to New Jersey communities from juvenile correctional facilities (LeBaron, 2002).

Recidivism is important for determining the effectiveness of JJ interventions and for informing JJ policy. However, no consensus on the definition or tracking period exists. In response to issues related to measuring and using recidivism data to inform policy, practice, and resource allocation, the Council of State governments Justice Center (2014) developed several recommendations, including measuring recidivism multiple ways and analyzing recidivism data to account for youth risk levels as well as other key characteristics, such as service needs.

JURISDICTIONAL DIFFERENCES IN RECIDIVISM

Another issue in the study of juvenile recidivism is the generalizability of findings across studies. Even if recidivism is defined in the same way and similar types of individuals are tracked for the same amount of time, recidivism rates can vary considerably across studies (Cottle et al., 2001), by state (Snyder & Sickmund, 2006), within the same state (Wolff et al., 2015), and even among neighborhoods within a single municipality (grunwald et al., 2010). The few studies that have examined recidivism across multiple sites have found significant differences across sites (Aalsma et al., 2015; Schweitzer et al., 2017). Neither study, however, included site-specific or contextual level variables that might help explain the site differences in recidivism rates.

Given growing empirical support for the effects of community context on delinquency and crime (Sampson, 2012; Sampson & groves, 1989), a number of juvenile recidivism studies have included contextual variables, especially neighborhood socioeconomic disadvantage. The results are mixed. Two studies did not find an association between contextual factors and recidivism (Harris, Mennis et al., 2011; Leverso et al., 2015), while others have found significant and positive relationships with juvenile recidivism (kalist et al., 2015; Wolff, Baglivio, Intravia, et al., 2017; Wolff et al., 2015, 2016; yan, 2009).

Finally, some studies found that the impact of neighborhood context matters for some. Neighborhood-level disadvantage and social capital were associated with drug offense recidivism, but not with violent, property or general recidivism among delinquent males (grunwald et al., 2010). While not directly associated with self-reported violence and delinquent behavior post-release, residence in a disadvantaged neighborhood was associated with witnessing violence, which in turn was associated with violent and delinquent behaviors among Black girls (Chauhan & Reppucci, 2009). A study analyzing the effects of concentrated disadvantage on reoffending by racial/ethnic groups (i.e., Black, White, and Latinx) identified concentrated disadvantage as a significant predictor among Black youth (Craig et al., 2017).

Recidivism rates can vary significantly across geographic units, suggesting that context matters. However, findings from juvenile recidivism studies that included concentrated disadvantage as a contextual factor are mixed. Multisite research reporting the range of recidivism rates across sites, rather than an overall or average rate, and research including contextual and other site-specific factors are needed to help explain why recidivism rates may vary across sites.

The current article uses data collected as part of the National Institute on Drug Abuse (NIDA)–funded Juvenile Justice-Translational Research on Interventions for Adolescents in the Legal System (JJ-TRIALS) cooperative agreement to measure recidivism in two ways and explore the relationships between individual-level and county-level factors, specifically addressing three research questions:

1. How do rates of rearrest/re-referral and adjudication differ across 20 sites?
2. Is county-level concentrated disadvantage associated with re-arrest/re-referral recidivism?
3. Do relationships between individual-level variables and recidivism risk vary across sites? If so, which factors help to explain site differences in recidivism?

METHOD

SAMPLE

Data were drawn from the NIDA-funded JJ-TRIALS cooperative agreement, which consisted of six research centers (RCs) and a coordinating center. The primary aim of JJ-TRIALS was to improve the delivery of evidence-based SU services for JJ involved youth by working with JJ agencies providing community supervision (e.g., diversion, probation, parole) and their community-based SU services partners to implement customized organizational-level changes. The JJ-TRIALS study involved representatives from state-level JJ agencies throughout the study development, design, and implementation (Leukefeld et al., 2017). Each RC submitted the JJ-TRIALS protocol to their respective institutional review board (IRB) and received approval (see knight et al., 2016 for additional details about the JJ-TRIALS protocol).

Although there were 33 research sites participating in JJ-TRIALS, this investigation only uses youth case records from 20 sites with accurate baseline data capable of determining recidivism according to the two definitions. The baseline phase, March 2014 through August 2015, occurred prior to the implementation of strategies to promote SU problem identification and linkage to services among participating sites. After excluding 98 cases that were either missing data on race/ethnicity or classified as mixed race, the analytic sample included a total of 6,771 youths at risk for recidivism for at least one year.

PROCEDURES

RCs obtained electronic JJ case records from participating sites and extracted de-identified information pertaining to youth demographics, alleged offenses/reasons for referral, and justice referral, JJ agency intake, and court hearing/case disposition dates. Unique youth identification numbers were used to track juveniles over time to identify subsequent contact with the JJ system.

MEASURES

Recidivism—Two measures of recidivism were selected, with the first defined as a new arrest or subsequent referral to the JJ system within the 12 months following the youth's initial intake into the JJ agency. Because of jurisdiction-related idiosyncrasies related to intake documentation within electronic data systems and the collapsing of multiple cases occurring within a short time period, a uniform standard was applied to all sites in which a subsequent referral/arrest was counted as recidivism only if it occurred 30 or more days after the initial JJ intake date.

The second measure of recidivism, adjudication, is defined as a judicial finding of delinquency for an offense related to a subsequent referral/arrest. Owing to system delays in the handling of juvenile court cases, adjudication may not occur within 12 months. However, our JJ partners were particularly interested in this measure of recidivism because rearrest or re-referral to the JJ system does not necessarily result in the case moving beyond intake. Because the lag time between intake and adjudication hearing dates varied considerably across sites, RCs categorized cases using a distinct coding system. Cases diverted away from the system or cases where either no action was taken or the youth was not found delinquent were coded "no." Cases were coded "yes" only when there was a hearing in which the juvenile was adjudicated delinquent. There was also a subset of youth who were rearrested/re-referred (18.8%) that were coded as "case pending." This occurred in instances when there was evidence that the case had proceeded beyond intake, such as the filing of a court petition or a hearing date being noted, but the disposition of the case was not yet entered into the JJ database.

Demographics—Gender and race/ethnicity variables are included among the individual-level predictors. Male gender is a consistent predictor of recidivism (Cottle et al., 2001). There is also evidence of racial differences in recidivism rates. Compared with White youth, Black youth are more likely to be arrested and to recidivate (kakade et al., 2012; Wolff et al., 2015). To make the classification of race and ethnicity comparable across sites, youth were placed into one of three categories: Non-Latinx White, Non-Latinx Black, and Latinx.

Offense types—RCs obtained the specific reason(s) for referral/arrest and classified the charges into offense types. For this study, we focused on violent offenses (e.g., homicide, rape, robbery, aggravated assault, simple assault, other violent offenses), property offenses (e.g., burglary, larceny-theft, motor vehicle theft, arson, vandalism, trespassing, shoplifting), probation/parole violations (PPV), and alcohol or other drug (AOD)–related law violations (e.g., driving under the influence, public intoxication, drug distribution, manufacture, or possession).

Felony—Each RC was also responsible for determining the charge level of the most serious offense as felony, misdemeanor, summary/citation, or status. In many cases, unless the charge grade was part of the JJ case record, it was difficult to determine the maximum charge level. Because there was a large amount of missing data for maximum charge level, we recoded the variable as felony (1) versus all other charge levels and missing (0).

Level of supervision—We created a variable whereby the case disposition was coded as “more” (coded 2) if the youth was placed on formal community supervision (i.e., probation or parole) or in a juvenile drug treatment court program, “less” (coded 1) if the youth was handled informally or diverted, and a catch-all “other” group (coded 0) for all dispositions not involving community supervision, such as paying a fine or doing community service.

Need for Su services—Juveniles with SU problems have more risk factors for recidivism (Van der Put et al., 2014) and are more likely to recidivate compared with those without such problems (McReynolds et al., 2010; Schubert et al., 2011). Furthermore, youth with SU disorders reoffended more frequently and committed more severe offenses when they reoffended (Hoeve et al., 2013). Determination of need for SU services (yes = 1, no = 0) was based on the presence of one or more of the following indicators: referral to the court for AOD-related offenses; results from drug testing, screening tools, and clinical assessments; JJ staff recommendations; and judicial mandates.

Concentrated disadvantage—We constructed a measure of concentrated disadvantage in line with previous research examining contextual effects on juvenile recidivism (e.g., grunwald et al., 2010; Wolff et al., 2016; yan, 2009). Because we did not have access to youth addresses, our measure is at the county level as we were unable to use zip code or census tract to address neighborhood context. While not ideal, there is some justification for considering surrounding neighborhoods and “geographic spillover” rather than just focusing on the neighborhood of residence (Sampson, 2012) and prior studies have also measured contextual effects at the county level (Mears et al., 2008; Tillyer & Vose, 2011). Furthermore, all of our research sites were county youth courts and juvenile probation departments, and all youth resided within the JJ agency county of jurisdiction.

Using 2015 census data, we constructed a composite measure of concentrated disadvantage consisting of (1) percentage receiving Supplemental Nutrition Assistance Program (SNAP)/ Food Stamp benefits, (2) unemployment rate, (3) percentage of families with children under the poverty line, (4) percentage of single-parent households with children, and (5) percentage of adults 25 years and older without a high school diploma or equivalent (α = .89). Factor analysis using principal axis factoring indicated the measures loaded on a single factor with a kaiser-Meyer-Olkin (kMO) measure of sampling adequacy of .78, indicating a distinct and reliable factor (Field, 2013). We retained the factor scores as the values of our scale. The difference between our operationalization of county-level disadvantage and that used in previous research is that we did not include median family income because it substantially decreased the reliability of the scale and financial disadvantage is already represented by measures of poverty and public assistance.

DATA ANALYSIS

Data analyses were conducted using IBM SPSS software (Version 26) and *R* (Version 3.5.2). SPSS was used to generate descriptive statistics and chi-square tests of independence for contingency tables. R was used to conduct all the other analyses, including exploratory analyses of each variable and relationships among the variables using correlation matrix and multilevel regression modeling for predicting recidivism.

Multilevel analyses were only conducted on predictors of re-arrest/re-referral recidivism. We elected not to examine adjudication recidivism using multilevel modeling because of reduction in sample size from excluding those cases pending an adjudication hearing. First, we estimated the proportion of the total variance in the recidivism risks (rates) that was attributable to between-county differences. This was done by performing a one-way random effects analysis of variance (ANOVA) model that included an intercept and county as a random effect (Mcgraw & Wong, 1996). On the basis of this model, we calculated the intraclass correlation coefficient (ICC), also called variance partition coefficient (VPC). The ICC here was estimated using the latent variable approach, where the logistic distribution for the level-one residual implies a variance of $\pi^2/3 = 3.29$, and this implies that for a two-level logistic random intercept model with an intercept variance of $\tau_0{}^2$, the ICC is $\tau_0^2 / \tau_0^2 + 3.29$ (Snijders & Bosker, 1999).

Second, a hierarchical generalized linear mixed effect model (HgLM) was used to estimate the associations of the individual-level variables and county-level disadvantage with the recidivism risks, in which the response variable was the binary outcome for recidivism. This modeling technique can be applied to any situation where there are lower-level units (e.g., individual-level variables) nested within higher-level units (e.g., county-level variables) (Woltman et al., 2012). For these analyses, the intercept is assumed as a random effect and the effects of predictors are assumed to be fixed effects. These random effects capture how the recidivism risks vary across counties. These HgLM models were fitted using R, using the generalized linear mixed-effects model (gLMM) or glmer function of package lme4 (Finch et al., 2014). The regression coefficients of the predictors characterize the population-level associations between each individual-level or county-level factor and recidivism risk when the other predictors were held constant. In addition, to investigate the proportion of total variance that can be explained by the individual-level and county-level predictors, we fit a HgLM model with individual-level fixed effects only and a HgLM model with both individual-level and county-level fixed effects, respectively. It should be kept in mind that the individual-level variance and the county-level variance are not directly comparable. While the county-level residual variance is on the logistic scale, the individual-level residual variance is on the probability scale. To address this technical issue, we applied the latent variable approach proposed by Snijders and Bosker to transform the individual-level and county-level components of the variance into the same scale before computing VPC or ICC (Snijders & Bosker, 1999). The total variance is decomposed into the individual-level residual variance, which is fixed to 3.29 as above, the county-level intercept variance $\tau_0{}^2$ and the variance $\sigma_F{}^2$ of the linear predictor from the fixed effects of the model.

Then VPC can be evaluated by $\tau_0^2 / \left(\tau_0^2 + \sigma_F^2 + 3.29\right)$, and this is the proportion of the total variance that can be explained by county-level random effects.

Third, after the fixed effects were inspected, we examined whether the association between the recidivism risks and individual-level predictors varied across counties. This was done by the forward selection method. We started with a model with a random intercept for county as the only random effect. We compared it with a larger model which includes an additional random effect of the interaction between the county and each individual-level predictor. We used the likelihood ratio test to test for the significance of the additional random effect. Under the null hypothesis that the random interaction is not significant, the statistic follows a chi-square distribution with the degrees of freedom equal to the difference of the number of parameters in the two models (Hox et al., 2017). If all random interactions are non-significant, then associations do not vary across counties; otherwise, we selected the most significant random interaction. We continued adding another random interaction between the counties and each of the remaining individual-level predictors to identify the most significant one. The selection process stopped when none of the additional random interactions were significant.

RESULTS

DESCRIPTIVE STATISTICS

Table 1 presents descriptive statistics for youth characteristics. A quarter of the sample is female. The sample is also diverse, as non-Latinx Blacks comprise 47.3% of the sample, followed by non-Latinx Whites (29.5%), and Latinx (23.2%). Over a quarter of the sample were charged with a violent offense (27.4%) or with a property offense (29.1%), and 7.6% violated conditions of probation or parole; 35% committed a felony offense. In addition, the disposition of half (50.2%) of the cases was to place the youth on a “more” intensive level of community supervision, whereas 46.4% received “less” intensive or informal supervision, and the remainder (3.4%) received some other disposition that did not involve community supervision. Just over half (52.6%) of youth were determined to be in need of treatment services for SU problems, while 18.2% had an AOD-related charge.

While the overall rate for rearrest-based recidivism was 33.1%, rearrest recidivism rates for each of the 20 sites ranged from 6.9% to 69.2% (see Figure 1). Overall, 11.6% of youth were adjudicated delinquent for a new offense, 15.3% were not adjudicated (either the case was not carried forward for a hearing or the youth was found “not delinquent”), and 6.2% were pending an adjudication hearing. Across the 20 sites, adjudication recidivism rates ranged from 1.9% to 27.8%, non-adjudication rates ranged from zero to 65%, and the percentage with cases pending adjudication hearings ranged from zero to 19.6%. Because a substantial proportion of the cases were awaiting an adjudication hearing in some sites, it is difficult to know the true rate of recidivism based on adjudication status. For these reasons, subsequent analyses focus on rearrest/re-referral recidivism.

Bivariate analyses (not displayed) of the characteristics of the 20 sites revealed potentially important differences between the counties. Based on the 2013 Rural-Urban Continuum Codes, eleven of the sites are in metropolitan areas of one million population or more and six other counties were considered urban with populations between 250,000 and one million; 95% of the sample reside in these urban counties. The percentage of families with children in the county living below the poverty line ranged from 8.3% to 42.0%, while families receiving SNAP benefits ranged from 5.9% to 25.0%. The percentage of single-parent households with children ranged from 7.6% to 14.8%. The unemployment rate ranged from 4.5% to 12.6%, and the rate of adults without a high school education ranged from 6.5% to 20.4%.

The composition of the justice-involved youth at each site varied significantly. The percentage of females across the 20 sites ranged from 9.1% to 46.4%, the percentage of Black youth ranged from 1.1% to 94.5%, and the percentage of Latinx youth ranged from zero to 49.9%. The types of offenses and level of supervision also varied significantly. The percentage of youth charged with violent offenses ranged from 1.6% to 46.1%, while the percentage with property offenses ranged from 6.4% to 56.6%. The percentage with felony offenses ranged from 10.4 to 83.6, and the percentage with PPVs ranged from zero to 32.0. keeping in mind that sanctions imposed upon youth are influenced by state laws, JJ agency policies and practices, and judicial discretion, the percentage of cases placed on the most intensive level of supervision ranged from 17.8% to 100%. The percentage of juveniles in need of SU treatment services ranged from 13.4% to almost all (99.5%). The rates of SU service need observed across JJ-TRIALS sites probably reflect differing SU screening practices rather than true differences in juvenile SU problems across our study sites.

Also displayed in Table 1 are recidivism rates for each youth characteristic based on the two definitions of recidivism used in this study. Using the rearrest/re-referral recidivism definition, males; youth of color; youth referred to the court for violent, property, or felony offenses; youth placed on more intensive community supervision; and youth in need of SU treatment services were more likely to recidivate than their counterparts. An initial referral for an AOD-related charge was not associated with recidivism in bivariate analyses. This variable was dropped from multivariate analyses because having an AOD-related charge is one of the indicators used to determine need for SU services. The rates for adjudication recidivism were significantly related to being male, youth of color, more supervision, and need for SU treatment services.

CORRELATIONAL ANALYSES AMONG POTENTIAL PREDICTORS

Bivariate correlations among all variables and rearrest recidivism are displayed in Table 2. Most correlations are small to moderate in size (Cohen, 1992) and several correlations are of note. First, need of SU service was negatively associated with less supervision (i.e., informal community supervision or diversion, ($r = -.29$), while more intensive community supervision was positively associated ($r = .32$). Second, concentrated disadvantage is associated with all variables except for PPV. Notably, youth residing in counties with higher levels of concentrated disadvantage are less likely to be White ($r = -.22$), more likely to be Black ($r = .15$), less likely to receive less intensive supervision ($r = -.35$), and more likely to recidivate ($r = .09$).

MULTILEVEL ANALYSES

The purpose of the one-way random effects ANOVA model (Model 1 in Table 3) was to assess the amount of variability in re-arrest recidivism across counties and the type of analysis needed. The random intercept is significant with the estimate of 0.75 ($p < .001$) using the likelihood ratio test. This indicates that the recidivism risks varied significantly across counties. In addition, the ICC was 0.18, which indicates that 18.46% of the total variability in the recidivism risk is due to the counties, while the remaining 81.54% is due to systematic differences between individuals.

A model with random intercept and individual-level fixed effects only (Model 2) was fitted. Compared with Model 1, this model included all the individual-level variables as fixed effects. The third model (Model 3) included a county-level variable, concentrated disadvantage, in addition to the individual-level effects. The estimated regression coefficients, estimated odds ratios, and estimated variance of the random effects are reported in Table 3. The results show that the county-level disadvantage variable is not significantly associated with recidivism. Also, both Model 2 and Model 3 produced the same estimates of between-county variance, 0.83, and the corresponding VPCs are 0.18 for Model 2 and 0.18 for Model 3, which implies that the county-level disadvantage variable had almost no contribution in explaining the variation in recidivism risks.

In the next step, a forward selection method was implemented to choose significant random interaction between the county and individual-level predictors. This step leads to the fourth model (Model 4), in which the fixed effects are the same as Model 3, but the random effects include a random effect for counties and a random interaction effect between counties and need for SU service. Although other random interactions with violent charge ($\chi^2 = 10.798$, $p = .005$), property charge ($\chi^2 = 25.64$, $p < .001$), PPV ($\chi^2 = 12.81$, $p = .002$), felony offense ($\chi^2 = 8.95$, $p = .011$), and levels of supervision ($\chi^2 = 61.34$, $p < .001$) are significant, the random interaction with the need for SU service is the most significant ($\chi^2 = 66.13$, $p < .001$) via likelihood ratio tests among all the interaction between counties and each individual-level predictor. Findings from all the candidate models on the random interaction with violent charge, property charge, PPV, felony offense, and levels of supervision respectively are available in the supplemental materials (see Table A1).

Table 3 reports the estimated regression coefficients for the fixed effects with their standard errors and corresponding odds ratio for each model. In Model 4, most of the individual-level predictors were significantly associated with recidivism risk, except male gender, felony charge, and need for SU services. Male gender and need for SU services are highly correlated ($r = .14$, $p < .001$). By controlling the need for SU service, the effect of male gender is not significant because the need for SU service has explained the variation in the recidivism risks. In other words, the association of male gender and recidivism risks is confounded by the need for SU services. We tested a model without need for SU services and found that being male is significantly associated with rearrest recidivism. The model is available in the supplemental materials (see Table 2A). With respect to race/ethnicity, being non-Latinx Black (odds ratio, OR = 1.67, $p < .001$) or being Latinx (OR = 1.20, $p = .042$) increased the odds of rearrest/re-referral by 66.7% and 19.6%, respectively, over being non-Latinx White when controlling for all other predictors. Regarding the types of offense, the results also show that there is a higher rearrest/re-referral recidivism risk among those with a violent offense charge (OR = 1.22, $p = .005$), a property offense charge (OR = 1.44, $p < .001$), or a probation or parole violation (OR = 2.50, $p < .001$). Interestingly, the results did not find recidivism risk to be significantly related to felony charge (OR = 0.92, $p = .209$) or need of SU treatment service (OR = 1.08, $p = .761$). The youth who were coded as "more" on supervision level, when compared to those coded as "less," had the highest odds of being rearrested or re-referred (OR = 2.62, $p < .001$). In addition, similar to Model 3, county-level concentrated disadvantage was not significantly related to recidivism.

In Model 4, both the random effects of counties and random interaction between counties and need for SU services are significant, implying that the impact of need for SU services ($\chi^2 = 66.13$, $p < .001$) is significantly different across counties. Note that this predictor is not significant as a fixed effect in Model 4, meaning that the effect of need for SU services on recidivism is not significant on average over the whole population (pooling the data from all the counties). Specifically, when we compare a youth with need for SU services versus one without need while controlling for all the other factors, the overall OR of recidivism risk is 1.08 ($p = .761$), given that the subjects are randomly chosen from the population in the 20 counties. However, if we look into individual counties, the relationship between SU service need and recidivism varies substantially across different JJ agencies. Therefore, when addressing need for SU services as a predictor of recidivism based on rearrest/re-referral, it needs to be done separately for each county. For example, in county 23, the odds of recidivism for a youth with need for SU services is 18.5% of that for a youth without the need, but in county 42, the odds of a youth with the need is about twice that of a youth without the need. A caterpillar plot and a table showing the random effects estimate of need for SU services by county (see Figure A) and a table of the odds ratio in each county (see Table 3A) are available in supplemental materials.

DISCUSSION

Guided by recommendations to measure recidivism multiple ways (Council of State governments Justice Center, 2014), we defined recidivism for the cohorts of youth entering participating sites as rearrest or new referral and adjudication on a subsequent offense occurring within 12 months of the initial intake into the JJ agency. Overall, 33% of youth in our study reoffended within 1 year, and the adjudication recidivism rate was roughly one-third of the rate for rearrest/re-referrals. Our 12-month rearrest recidivism rate is similar to that of juvenile probationers in Virginia (34%), but our adjudication recidivism rate is half that of the Virginia rate (23%, Virginia Department of Juvenile Justice, 2018). Although some have argued for generalizability of findings to other jurisdictions with similar socioeconomic and demographic profiles (kubrin & Stewart, 2006), comparisons across jurisdictions may not be meaningful even when using the same definition of recidivism and tracking youth for the same time period.

There are several possible explanations for differences in recidivism rates across jurisdictions. The variation in recidivism rates may be (1) due to contextual-level factors independent of the types of youth who reside there, (2) due to the characteristics of juveniles who reside within the jurisdiction, (3) a function of JJ policies and procedures, or (4) some combination of these factors.

With regards to contextual factors, we found an association between concentrated disadvantage and rearrest recidivism in bivariate analyses but not in multivariate models controlling for all individual-level predictors. The lack of convergence in our findings with the concentrated disadvantage literature reviewed earlier may be due to the county-level measure of concentrated disadvantage we used in our analyses. A county may be too large a geographic area, encompassing both urban and rural areas, with census tracts containing multiple communities with varying degrees of social disorganization (Osgood & Chambers, 2000). It is possible that limited variation in disadvantage across a small number of counties in our study explains our finding. At the same time, even studies with large numbers of "neighborhoods" as the Level 2 unit of analyses found that the magnitude of neighborhood disadvantage was small and that most of the variance in recidivism was attributable to individual-level factors (Wolff et al., 2015).

Given the mixed support for the hypothesis that individual risk for reoffending is increased by residing in a socioeconomically disadvantaged community, it may be that other community characteristics associated with socioeconomic disadvantage are better contextual-level predictors of recidivism. There is ample evidence that disadvantaged communities expose residents to violence and victimization (Attar et al., 1994; Chauhan & Reppucci, 2009; Sampson et al., 1997) as well as deviant peer groups (Harris, Mennis, et al., 2011), both associated with recidivism. Furthermore, the co-occurrence of living in a high-poverty and high-crime neighborhood may affect some residents more than others (Chauhan & Reppucci, 2009; Craig et al., 2017; Wolff, Baglivio, & Piquero, 2017). We found that concentrated disadvantage was negatively associated with being White and positively associated with being Black or Latinx.

Another explanation for site differences in recidivism rates is the characteristics of the youth who reside within the jurisdiction of the JJ agency. The majority of variation between our sites was accounted for by individual-level factors. We found that JJ agencies differed with respect to the percentage of youth of color and the type and severity of crimes committed by the youth in their jurisdictions. Sites with the above-average recidivism rates also had the highest percentage of youth of color. This is not surprising given well-established, disproportionate overrepresentation of youth of color in the JJ system (Donnelly, 2017). In addition, the two sites with the highest reoffending recidivism rates also had the highest percentage of property and felony offenses. Furthermore, when testing possible random effects of all individual-level variables, the relationship between offense types and recidivism differed by site. Therefore, the site differences in youth demographic characteristics and offending behaviors appears to account for noted differences in recidivism rates across jurisdictions.

A third explanation for site differences in recidivism rates is that there are differences in agency policies and practices. Jurisdictions differ in how they respond to youth having contact with law enforcement. Some jurisdictions will arrest and process youth involved in status offenses (e.g., a child being considered ungovernable), some have pre-arrest diversion programs for youth having contact with law enforcement for minor misdemeanor offenses (e.g., petit theft), whereas other jurisdictions primarily arrest and process youth engaging in more serious offenses (e.g., aggravated assault, grand larceny). Our sites also differed significantly in their handling of juvenile cases in terms of community supervision. In our sample, juveniles placed on a "more" intensive level of community supervision were more likely to recidivate than youth receiving other dispositions. This finding is consistent with research on the impact of intensive supervision on youth outcomes that found mixed results for reducing reoffending (i.e., either no different from standard probation or higher reoffending rates) but noted increases in probation violations and increases in incarceration (Hyatt & Barnes, 2017; Petersilia & Turner, 1993). Evidence-based juvenile case management practices dictate that the duration and frequency of community supervision be based upon the level of risk and that the delivery of services be based on an assessment of needs (Hyatt & Barnes, 2017). This is particularly true for high-risk juveniles. Match between assessed needs and interventions that addressed identified needs was associated with a 37.9% reduction in the likelihood of recidivism; the absence of interventions to address identified needs was associated with an 81.7% increase in likelihood of recidivism (Luong & Wormith, 2011).

Another indication of differences in JJ policies and practices across our sites is that the identification of youth in need of SU services varied significantly across our sites and that the relationship between SU service need and recidivism varied substantially across different JJ agencies. Our findings suggest that the interplay between SU treatment need and recidivism is complex and is likely a result of a combination of contextual, agency, and youth factors. A national study found that few JJ community supervision agencies provide mental health and SU treatment services directly to youth and families but rely on community-based providers for these services (Scott et al., 2019). However, more intensive SU and mental health, aftercare, and recovery support services were limited in availability (Scott et al., 2019). Rates of screening for SU problems varied across all 33 JJ-TRIALS sites and among those in need of services only about 15% were referred to SU treatment and about 10% initiated treatment (Dennis et al., 2019). Our findings related to site differences in the identification of need for SU services and recidivism may reflect agencies referral practices and the availability of services in the community.

LIMITATIONS

Several limitations to the study should be noted. First, this study represents the experiences of 20 sites located in five states and is not a random sample of JJ agencies. Second, for certain variables (e.g., charge level and disposition), information was missing because of the varying record keeping practices of the JJ offices, so that missing data provided a challenge to interpretation. It is possible that those sites that collected more systematic information differed in other ways from those that did not, perhaps further contributing to the site differences observed. Each site (or state) relied on its own data system or systems. Even state data systems did not guarantee uniform record-keeping practices and policies across JJ agencies. This may further explain the considerable variability across sites in several areas.

Being restricted to gathering a small set of common variables available from participating JJ agencies limited our ability to examine a broader range of individual-level predictors, including dynamic factors such as recidivism risk level. While most JJ agencies use some method for assessing risk, information on recidivism risk level was either not comparable across JJ-TRIALS sites or not available from all research sites. We examined youth demographic and offense characteristics commonly used as individual-level predictors in recidivism research (Cottle et al., 2001), and our findings are similar to those of other studies, with one exception. Contrary to prior research (Craig et al., 2017; Wolff et al., 2015; yan, 2009), being male was not associated with increased risk for recidivism once other factors were taken into consideration. This seemingly anomalous finding is due to the high correlation between male gender and need for SU services. When we ran the multivariate model without the need for SU services variable, male gender was significantly associated with rearrest recidivism.

Another limitation is the length of the follow-up period. We recognize that a 12-month follow-up period may not be long enough when recidivism is defined as adjudication of a subsequent offense as additional time may be needed for judicial processing of the case. However, a 12-month follow-up is commonly used by state JJ agencies and program evaluators regardless of how recidivism is defined (Harris, Lockwood, et al., 2011). Furthermore, of the few studies examining adjudication/conviction recidivism (Lowenkamp et al., 2010; Sullivan & Latessa, 2011; Tillyer & Vose, 2011; Wolff et al., 2018), Wolff and colleagues (2018) tracked juveniles for 365 days from the youth's completion of community-based supervision or court-ordered services.

Finally, our Level 2 sample size of 20 JJ sites is underpowered. A sample of 20 for the Level 2 unit of analysis is at the lower bounds of Level 2 sample size for powering multilevel modeling if Level 1 (youth within JJ jurisdictions) sample sizes are relatively large (Browne, 2006). Unfortunately, the number of youth per site was unbalanced (ranging from 54 to 1023), and after conducting a power analysis, we determined that we are underpowered for some of the variables in our multilevel models (Browne et al., 2009).

CONCLUSION

Despite these limitations, our findings add to the recidivism literature in several ways. First, findings of large differences in recidivism rates across sites in five states suggests a lack of generalizability of rates from one state to another even when recidivism is measured in the same way on the same type of youth. These findings also point to a continued need to account for both contextual and individual-level factors across sites when studying recidivism, as those have a potentially differential impact on recidivism risk. Our findings also stress the importance of identifying and addressing significant site differences in recidivism. Differences in youth demographic characteristics and offending behaviors across jurisdictions as well as agency practices with regards to case disposition and SU screening appear to account for noted differences in recidivism rates across jurisdictions. It is also likely that other site-specific and contextual factors not measured in our study account for differences in recidivism rates. Finally, the complex relationships between individual- and county-level predictors of recidivism require more nuanced, contextually informed, multilevel approaches in studying juvenile recidivism.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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REFERENCES

Aalsma MC, White LM, Lau KS, Perkins A, Monahan P, & grisso T. (2015). Behavioral health care needs, detention-based care, and criminal recidivism at community reentry from juvenile detention: A multisite survival curve analysis. American Journal of Public Health, 105(7), 1372–1378. 10.2105/ajph.2014.302529 [PubMed: 25973804]

Attar BK, Guerra NG, & Tolan PH (1994). Neighborhood disadvantage, stressful life events, and adjustment in urban elementary-school children. Journal of Clinical Child Psychology, 23(4), 391–400. 10.1207/s15374424jccp2304_5

Browne WJ (2006). Sample size calculations in multilevel modelling. ESRC Research Methods Festival. https://seis.bristol.ac.uk/~frwjb/materials/ssize.ppt

Browne WJ, Lahi MG, & Parker RM (2009). A guide to sample size calculations for random effect models via simulation and the mlpowsim software package. School of Clinical Veterinary Sciences, University of Bristol.

Chauhan P, & Reppucci ND (2009). The impact of neighborhood disadvantage and exposure to violence on self-report of antisocial behavior among girls in the juvenile justice system. Journal of Youth and Adolescence, 38(3), 401–416. 10.1007/s10964-008-9326-3 [PubMed: 19636753]

Cohen J. (1992). A power primer. Psychological Bulletin, 112(1), 155–159. 10.1037/0033-2909.112.1.155 [PubMed: 19565683]

Cottle CC, Lee RJ, & Heilbrun K. (2001). The prediction of criminal recidivism in juveniles: A meta-analysis. Criminal Justice and Behavior, 28(3), 367–394. 10.1177/0093854801028003005

Council of State governments Justice Center. (2014). Measuring and using juvenile recidivism data to inform policy, practice, and resource allocation. The National Reentry Resource Center. https://nicic.gov/measuring-and-using-juvenilerecidivism-data-inform-policy-practice-and-resource-allocation

Craig JM, Baglivio MT, Wolff KT, Piquero AR, & Epps N. (2017). Do social bonds buffer the impact of adverse childhood experiences on reoffending? Youth Violence and Juvenile Justice, 15(1), 3–20. 10.1177/1541204016630033

Deal T, Rackow A, & Wachter A. (2015). Measuring subsequent offending in juvenile probation [JJGPS Statescan]. https://nicic.gov/measuring-subsequent-offending-juvenile-probation

Dennis ML, Smith CN, Belenko S, knight D, McReynolds L, Rowan G, ... Wiley T. (2019). Operationalizing a behavioral health services cascade of care model: Lessons learned from a 33-site implementation in juvenile justice community supervision. Federal Probation, 83(2), 52–64. [PubMed: 34366438]

Donnelly EA (2017). The disproportionate minority contact mandate: An examination of its impacts on juvenile justice processing outcomes (1997–2011). Criminal Justice Policy Review, 28(4), 347–369. 10.1177/0887403415585139

Field A. (2013). Discovering statistics using IBM SPSS statistics. SAGE.

Finch WH, Bolin JE, & Kelley K. (2014). Multilevel modeling using R. CRC Press.

Grunwald HE, Lockwood B, Harris PW, & Mennis J. (2010). Influences of neighborhood context, individual history and parenting behavior on recidivism among juvenile offenders. Journal of Youth and Adolescence, 39(9), 1067–1079. 10.1007/s10964-010-9518-5 [PubMed: 20204686]

Harris P, Lockwood B, & Mengers L. (2009). A CJCA white paper: Defining and measuring recidivism. Council of Juvenile Correctional Administrators. http://cjca.net/wp-content/uploads/2018/02/CJCA-Recidivism-White-Paper.pdf

Harris P, Lockwood B, Mengers L, & Stoodley BH (2011). Measuring recidivism in juvenile corrections. Journal of Juvenile Justice, 1(1), 1–16.

Harris P, Mennis J, Obradovic Z, Izenman AJ, & grunwald HE (2011). The coaction of neighborhood and individual effects on juvenile recidivism. Cityscape, 13(3), 33–55.

Hoeve M, McReynolds LS, Wasserman GA, & McMillan C. (2013). The influence of mental health disorders on severity of reoffending in juveniles. Criminal Justice and Behavior, 40(3), 289–301. 10.1177/0093854812459639

Hox JJ, Moerbeek M, Van de & Schoot R. (2017). Multilevel analysis: Techniques and applications. Routledge.

Hyatt JM, & Barnes g. C. (2017). An experimental evaluation of the impact of intensive supervision on the recidivism of high-risk probationers. Crime & Delinquency, 63(1), 3–38. 10.1177/0011128714555757

Kakade M, Duarte CS, Liu X, Fuller CJ, Drucker E, Hoven CW, . . . Wu P. (2012). Adolescent substance use and other illegal behaviors and racial disparities in criminal justice system involvement: Findings from a US national survey. American Journal of Public Health, 102(7), 1307–1310. 10.2105/AJPH.2012.300699 [PubMed: 22594721]

Kalist DE, Lee DY, & Spurr SJ (2015). Predicting recidivism of juvenile offenders. The B.E. Journal of Economic Analysis & Policy, 15(1), 329–351. 10.1515/bejeap-2013-0188

Kirk DS, & Sampson RJ (2013). Juvenile arrest and collateral educational damage in the transition to adulthood. Sociology of Education, 86(1), 36–62. 10.1177/0038040712448862

Knight DK, Belenko S, Wiley T, Robertson AA, Arrigona N, Dennis M, . . . Leukefeld C. (2016). Juvenile justice—Translational research on interventions for adolescents in the legal system (JJ-TRIALS): A cluster randomized trial targeting system-wide improvement in substance use services. Implementation Science, 11(1), 1–18. 10.1186/s13012-016-0423-5 [PubMed: 26727969]

Kubrin CE, & Stewart EA (2006). Predicting who reoffends: The neglected role of neighborhood context in recidivism studies. Criminology, 44(1), 165–197. 10.1111/j.1745-9125.2006.00046.x

LeBaron J. (2002). Examining the relative influence of community context on juvenile offender post-confinement recidivism. Rutgers University.

Leukefeld CG, Cawood M, Wiley T, Robertson AA, Fisher JH, Arrigona N, . . . Marks KR (2017). The benefits of community and juvenile justice involvement in organizational research. Journal of Juvenile Justice, 6(1), 112–124. [PubMed: 28828202]

Leverso J, Bielby W, & Hoelter LF (2015). Back on the streets: Maturation and risk factors for recidivism among serious juvenile offenders. Journal of Adolescence, 41, 67–75. 10.1016/j.adolescence.2015.02.008 [PubMed: 25828549]

Lowenkamp CT, Makarios MD, Latessa EJ, Lemke R, & Smith P. (2010). Community corrections facilities for juvenile offenders in Ohio: An examination of treatment integrity and recidivism. Criminal Justice and Behavior, 37(6), 695–708. 10.1177/0093854810363721

Luong D, & Wormith JS (2011). Applying risk/need assessment to probation practice and its impact on the recidivism of young offenders. Criminal Justice and Behavior, 38(12), 1177–1199. 10.1177/0093854811421596

Mcgraw KO, & Wong SP (1996). Forming inferences about some intraclass correlation coefficients. Psychological Methods, 1(1), 30–46. 10.1037/1082-989X.1.1.30

McReynolds LS, Schwalbe CS, & Wasserman GA (2010). The contribution of psychiatric disorder to juvenile recidivism. Criminal Justice and Behavior, 37(2), 204–216. 10.1177/0093854809354961

Mears DP, Wang X, Hay C, & Bales WD (2008). Social ecology and recidivism: Implications for prisoner reentry. Criminology, 46(2), 301–340. 10.1111/j.1745-9125.2008.00111.x

Mulder E, Brand E, Bullens R, & Van Marle H. (2011). Risk factors for overall recidivism and severity of recidivism in serious juvenile offenders. International Journal of Offender Therapy and Comparative Criminology, 55(1), 118–135. 10.1177/0306624X09356683 [PubMed: 20181776]

Osgood DW, & Chambers JM (2000). Social disorganization outside the metropolis: An analysis of rural youth violence. Criminology, 38(1), 81–116. 10.1111/j.1745-9125.2000.tb00884.x

Petersilia J, & Turner S. (1993). Intensive probation and parole. Crime and Justice, 17, 281–335. 10.1086/449215

Sampson RJ (2012). Great American city: Chicago and the enduring neighborhood effect. University of Chicago Press.

Sampson RJ, & groves WB (1989). Community structure and crime: Testing social-disorganization theory. American Journal of Sociology, 4, 774–802. 10.1086/229068

Sampson RJ, Raudenbush SW, & Earls F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. Science, 277(5328), 918–924. 10.1126/science.277.5328.918 [PubMed: 9252316]

Schubert CA, Mulvey EP, & glasheen C. (2011). Influence of mental health and substance use problems and criminogenic risk on outcomes in serious juvenile offenders. Journal of the American Academy of Child & Adolescent Psychiatry, 50(9), 925–937. 10.1016/j.jaac.2011.06.006 [PubMed: 21871374]

Schweitzer M, Labrecque RM, & Smith P. (2017). Reinvesting in the lives of youth: A targeted approach to reducing recidivism. Criminal Justice Policy Review, 28(3), 207–219. 10.1177/0887403415579262

Scott CK, Dennis ML, grella CE, Funk RR, & Lurigio AJ (2019). Juvenile justice systems of care: Results of a national survey of community supervision agencies and behavioral health providers on services provision and cross-system interactions. Health & Justice, 7(1), 1–18. 10.1186/s40352-019-0093-x [PubMed: 30612284]

Snijders TA, & Bosker RJ (1999). Multilevel analysis: An introduction to basic and advanced multilevel modeling. SAGE.

Snyder HN, & Sickmund M. (2006). Juvenile offenders and victims: 2006 national report. Office of Juvenile Justice and Delinquency Prevention.

Stouthamer-Loeber M. (2010). Persistence and desistance in offending. University of Pittsburgh.

Sullivan CJ, & Latessa E. (2011). The coproduction of outcomes: An integrated assessment of youth and program effects on recidivism. Youth Violence and Juvenile Justice, 9(3), 191–206. 10.1177/1541204010393754

Tillyer MS, & Vose B. (2011). Social ecology, individual risk, and recidivism: A multilevel examination of main and moderating influences. Journal of Criminal Justice, 39(5), 452–459. 10.1016/j.jcrimjus.2011.08.003

Van der Put CE, Creemers HE, & Hoeve M. (2014). Differences between juvenile offenders with and without substance use problems in the prevalence and impact of risk and protective factors for criminal recidivism. Drug and Alcohol Dependence, 134, 267–274. 10.1016/j.drugalcdep.2013.10.012 [PubMed: 24238911]

Virginia Department of Juvenile Justice. (2018). Data resource guide: Fiscal year 2018.

Welsh BC, Loeber R, Stevens BR, Stouthamer-Loeber M, Cohen MA, & Farrington DP (2008). Costs of juvenile crime in urban areas: A longitudinal perspective. Youth Violence and Juvenile Justice, 6(1), 3–27. 10.1177/1541204007308427

Welty LJ, Hershfield JA, Abram KM, Han H, Byck GR, & Teplin LA (2017). Trajectories of substance use disorder in youth after detention: A 12-year longitudinal study. Journal of the American Academy of Child & Adolescent Psychiatry, 56(2), 140–148. 10.1016/j.jaac.2016.10.018 [PubMed: 28117060]

Wolff KT, Baglivio MT, Intravia J, Greenwald MA, & Epps N. (2017). The mobility of youth in the justice system: Implications for recidivism. Journal of Youth and Adolescence, 46(7), 1371–1393. 10.1007/s10964-016-0498-y [PubMed: 27216200]

Wolff KT, Baglivio MT, Intravia J, & Piquero AR (2015). The protective impact of immigrant concentration on juvenile recidivism: A statewide analysis of youth offenders. Journal of Criminal Justice, 43(6), 522–531. 10.1016/j.jcrimjus.2015.05.004

Wolff KT, Baglivio MT, & Piquero AR (2017). The relationship between adverse childhood experiences and recidivism in a sample of juvenile offenders in community-based treatment. International Journal of Offender Therapy and Comparative Criminology, 61(11), 1210–1242. 10.1177/0306624X15613992 [PubMed: 26567183]

Wolff KT, Baglivio MT, Piquero AR, Vaughn MG, & DeLisi M. (2016). The triple crown of antisocial behavior: Effortful control, negative emotionality, and community disadvantage. Youth Violence and Juvenile Justice, 14(4), 350–366. 10.1177/1541204015599042

Wolff KT, Intravia J, Baglivio MT, & Piquero AR (2018). The protective impact of immigrant concentration on juvenile recidivism: A multilevel examination of potential mechanisms. Crime & Delinquency, 64(10), 1271–1305. 10.1177/0011128717739608

Woltman H, Feldstain A, Mackay JC, & Rocchi M. (2012). An introduction to hierarchical linear modeling. Tutorials in Quantitative Methods for Psychology, 8(1), 52–69.

Yan J. (2009). A multidisciplinary study on juvenile recidivism and multilevel impacts: Risk factors, neighborhood features, and juvenile justice intervention [Unpublished thesis]. 10.32469/10355/6128

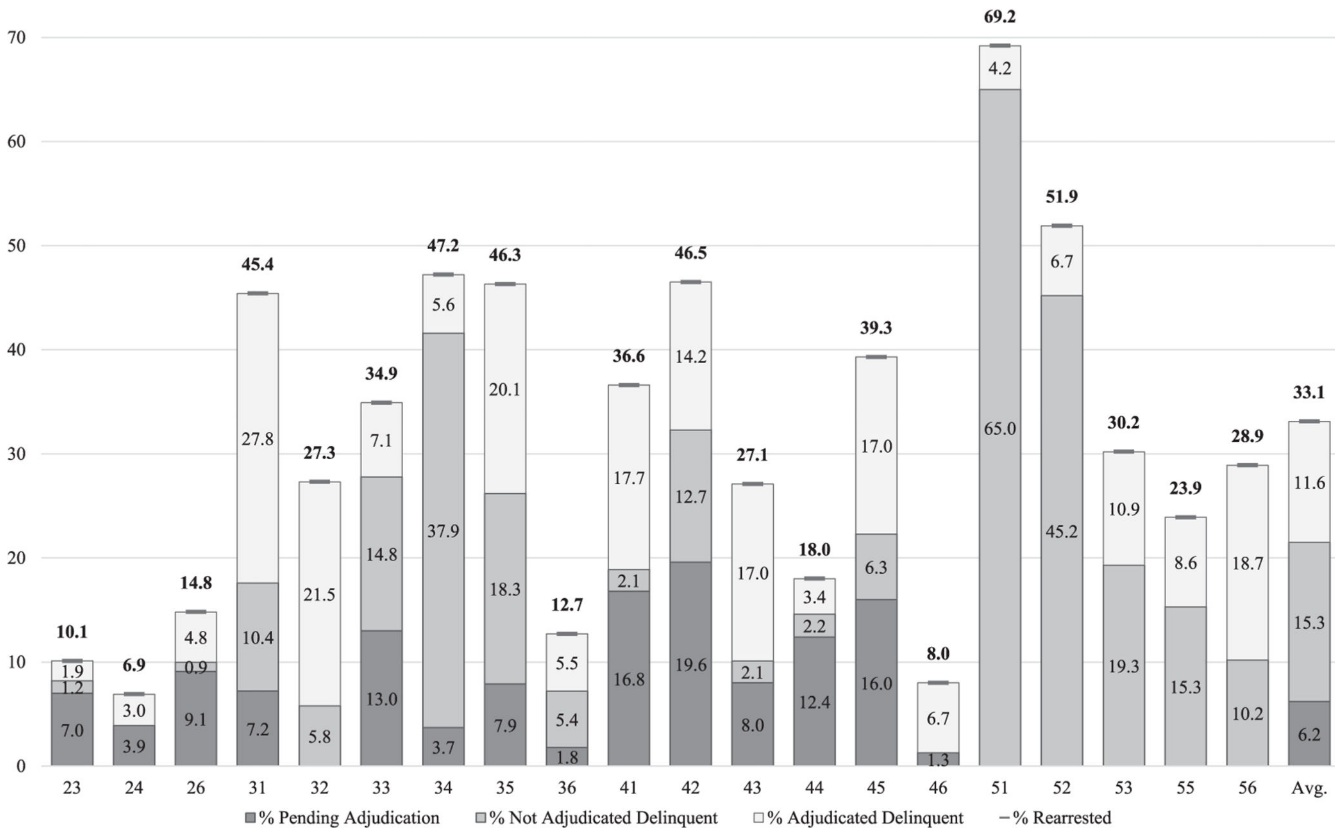

Figure 1:
Youth Recidivism by Rate of adjudication

Table 1:

Descriptive Statistics for Individual-Level Predictors and Recidivism Rates (N = 6,771)

Variables	% individual-level predictors	% rearrested/re-referred	% adjudicated delinquent
Overall rate		33.3	11.7
Gender		***	***
Female	25.5	28.0	9.2
Male	74.5	35.0	12.5
Race/ethnicity		***	***
Non-Latinx White	29.5	23.4	8.8
Non-Latinx Black	47.3	38.2	12.8
Latinx	23.2	35.8	13.0
AOD-related charge			
No	81.8	33.3	11.6
Yes	18.2	32.9	11.8
Violent charge		***	
No	72.6	31.9	11.8
Yes	27.4	36.8	11.4
Property charge		***	
No	70.9	29.4	11.0
Yes	29.1	42.7	13.4
Probation/parole Violation		***	***
No	92.4	31.8	10.9
Yes	7.6	51.1	21.6
Felony offense		***	
No	65.0	30.6	11.8
Yes	35.0	38.1	11.4
Level of supervision		***	***
Other	3.4	28.9	9.6
Less	46.4	22.8	7.6
More	50.2	43.3	15.6
Need for SU services		***	***
No	47.4	25.4	8.8
Yes	52.6	40.4	14.3

Note. Chi-square test. SU = substance use; AOD = alcohol or other drug.

[*] $p < .05$.

[**] $p < .01$.

[***] $p < .001$.

Table 2:

Bivariate Correlations Among Individual-Level Variables, County-Level Disadvantage, and Rearrest Recidivism ($N = 6,771$)

Variables	Male	Black	White	Latinx	Violent charge	Property charge	Felony offense	PPV	Supervision less	Supervision more	Supervision other	Need for SU service	Concentrated county disadvantage
Black	.00	—											
White	−.06**	−.61**	—										
Latinx	.06**	−.52**	−.36**	—									
Violent charge	−.06**	.06**	−.08**	.01	—								
Property charge	.11**	.05**	−.10**	.05**	−.21**	—							
Felony offense	.14**	.08**	−.09**	.00	.11**	.27**	—						
PPV	.03*	.06**	−.06**	−.01	−.07**	−.02	−.06**	—					
Supervision less	−.12**	−.08**	.15**	−.06**	−.06**	−.18**	−.28**	−.09**	—				
Supervision more	.12**	.03**	−.12**	.09**	.06**	.18**	.27**	.09**	−.93**	—			
Supervision other	.00	.13**	−.06**	−.08**	.02*	.00	.02*	.00	−.18**	−.20**	—		
Need for SU service	.14**	−.09**	−.04**	.15**	−.12**	.07**	.10**	.12**	−.29**	.32**	−.09**	—	
Concentrated county disadvantage	.10**	.15**	−.22**	.06**	.03*	.15**	.28**	.00	−.35**	.26**	.25**	.04**	—
Recidivism	.06**	.10**	−.14**	.03*	.05**	.13**	.08**	.11**	−.21**	.21**	−.02	.16**	.09**

Note. Individuals nested within 20 juvenile justice agencies. PPV = probation/parole violations; SU = substance use.

* $p < .05$.

** $p < .01$.

Table 3:

Hierarchical Generalized Linear Models of Rearrest/Re-Referral Recidivism Risk (N = 6,771)

	Model 1			Model 2			Model 3			Model 4		
	One-way random effects (AN OVA)			**HGLM with individual-level fixed effects only**			**HGLM with both individual-level and site-level fixed effects**			**HGLM with both fixed and random effects**		
Fixed effect	**Coefficient**	***SE***	**OR**	**Coefficient**	***SE***	**OR**	**Coefficient**	***SE***	**OR**	**Coefficient**	***SE***	**OR**
Intercept	−0.91 ***	.20	0.4	−2.27***	.23	0.10	−2.27**	.23	.104	−2.15***	.17	0.12
Individual level												
Male	—	—	—	0.13	.07	1.13	0.13	.07	1.13	0.12	.07	1.13
Race (Non-Latinx White)												
Non-Latinx Black	—	—	—	0.52***	.07	1.68	0.52***	.07	1.68	0 51***	.07	1.67
Latinx	—	—	—	0.22*	.09	1.25	0.22*	.09	1.25	0.18*	.09	1.20
Violent charge	—	—	—	0.17*	.07	1.19	0.17*	.07	1.19	0.20**	.07	1.22
Property charge	—	—	—	0.36***	.07	1.43	0.36***	.07	1.43	0.36***	.07	1.44
Felony offense	—	—	—	−0.14*	.07	0.87	−0.14*	.07	0.87	−0.09	.07	0.92
Probation/parole	—	—	—	0.83***	.11	2.29	0.83***	.11	2.29	0.91***	.12	2.50
Violation												
Level of supervision (less)												
More	—	—	—	0.90 ***	.07	2.46	0.90***	.07	2.47	0.96 ***	.07	2.62
Other	—	—	—	−0.01	.18	1.00	−0.004	.18	1.00	−0.0002	.19	1.00
Need for SU services	—	—	—	0.54 ***	.06	1.72	0.54 ***	.07	1.72	0.07	.24	1.08
County level												
Concentrated county	—	—	—	—	—	—	−0.02	.21	0.98	0.15	.15	1.17
Disadvantage												
Random effect	*Variance*	*SD*	Chi-square	*Variance*	*SD*	Chi-square	*Variance*	*SD*	Chi-square	*Variance*	*SD*	Chi-square
Intercept	.75 ***	.86	689.31	.83 ***	.91	553.09	.83 ***	.91	551.6	.32	.57	—

	Model 1			Model 2			Model 3			Model 4		
	One-way random effects (ANOVA)			HGLM with individual-level fixed effects only			HGLM with both individual-level and site-level fixed effects			HGLM with both fixed and random effects		
Fixed effect	Coefficient	*SE*	OR	Coefficient	*SE*	OR	Coefficient	*SE*	OR	Coefficient	*SE*	OR
Need for SU Services	—	—	—	—	—	—	—	—	—	.92 ***	.96	66.13

Note. Individuals nested within 20 sites. ANOVA = analysis of variance; HGLM = hierarchical generalized linear mixed effect model; OR = odds ratio.

* $p < .05$.

** $p < .01$.

*** $p < .001$.