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A Two-State Examination of Varied Measurement Strategies for Juvenile Reoffending

Final Project Report

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Contents

Summary of the Project

The extent and prediction of juvenile reoffending are of considerable research and policy importance. Reliable measures of reoffending enable practitioners, policymakers, and scholars to assess youths' reentry experiences, evaluate programs and interventions, allocate resources, and plan agency-level improvements (Deal et al., 2015; Harris et al., 2009). Knowledge of the predictors of reoffending enables these parties to design interventions, develop prediction tools, and direct more resources to the most at-risk youth. Despite the importance of juvenile reoffending, there is no national standard for its measurement, and we do not know the extent to which the wide variability in measures across states and studies has consequences for our understanding of reoffending. Among state agencies, juvenile reoffending is alternately defined in terms of arrest, adjudication or conviction, or commitment or incarceration, and using follow-up periods ranging anywhere from six months to four years (Pew, 2014). Some states track youth only while they are under justice system supervision (e.g., only while they are on probation). And some count only juvenile justice system contacts, and not adult criminal justice system contacts. This variability hampers efforts to make cross-state comparisons and to develop national estimates of juvenile reoffending.

In order to know what difference this variability in measurement makes, researchers would need to examine how much the prevalence and correlates of juvenile reoffending differ across measures. This would require that multiple measures of recidivism be featured in the same study. Yet most empirical works have used single measures (e.g., Craig et al., 2022; Wolff et al., 2022), and less than half of states report on multiple types of system contact (Pew, 2014). There thus is a need for systematic examinations and comparisons of the rates and predictors of measures of juvenile reoffending that vary along dimensions including type of contact, follow-up period, and offense type. There also is a need for information on how much conclusions are impacted by the inclusion of information from the adult system, or by the inclusion of system contacts for technical violations and other contacts that are not always included in summary measures. Absent this information, practitioners, policymakers, and researchers cannot know whether findings learned from the study or tracking of one type of reoffending measure would also hold for others. They also have incomplete guidance towards the creation of a unified system of measurement that would enable cross-state comparisons and national estimates.

Major Goals and Objectives

This project was a three-year effort to (1) describe states' current practices regarding the measurement of juvenile recidivism, (2) compare the rates and predictors of different measures of recidivism that varied in terms of marker events, follow-up lengths, and inclusion of adult system information, (3) compare the amount of program- and community-level variation in recidivism across different measures of recidivism, and (4) assist the state of Oregon in exploring potential changes to its current measure of juvenile recidivism. The study was a collaborative effort between Florida State University (FSU), the Florida Department of Juvenile Justice (FDJJ), and the Oregon Youth Authority (OYA). Archival data from FDJJ and OYA offered an opportunity to do what researchers had previously been unable to: analyze several different permutations of a reoffending measure based on the same sets of youth, and assess the robustness of findings across those permutations.

Research Questions

Our specific research questions were:

- Do youth demographic, risk, and protective factors differentially predict varied measures of juvenile reoffending?

- Do a series of community characteristics differentially predict varied measures of juvenile reoffending?
- Are the predictors of one- and two-year felony reoffending similar across two states?
- Do conclusions about variability in reoffending rates between different juvenile justice programs depend on how reoffending is measured?
- Do conclusions about the extent of geographic variability in juvenile reoffending depend on how reoffending is measured?
- Based on the empirical literature and on the initial results of this project, how might the measurement of juvenile reoffending in Oregon be modified?

This report describes the study contexts, the research methods, the study findings, and the main conclusions that followed from the research.

Review of Previous Literature

Issues in the Measurement of Juvenile Reoffending

Debates over the appropriate measurement of reoffending among both juveniles and adults are decades old. Researchers have outlined a range of dimensions along which measures might vary, including the population examined (e.g., arrestees), the "marker event" or type of system contact captured (e.g., new convictions), and the follow-up period used (e.g., one year; Andersen & Skardhamar, 2017; Deal et al., 2015; Fazel & Wolf, 2015; Maltz, 2001; Robert et al., 2019). These dimensions have both conceptual and empirical implications. More specifically, different definitions of reoffending are likely to result in different amounts of measurement error, to capture different offending severities, and to be useful for different research questions. For example, measures that capture earlier stages of justice system processing may include more false positives, because only cases that are supported by evidence are likely to move to the next step of processing (Maltz, 2001). For this reason, some have suggested that juvenile recidivism be operationalized in terms of adjudication/conviction instead of arrest (Harris et al., 2009). Yet that operationalization may come at the cost of missing reoffending behavior that resulted in informal sanctioning. Different follow-up periods also may have costs and benefits. Shorter periods run the risk of missing more reoffending behavior, and they leave less time for system processing to play out; however, they may be more desirable for the purposes of program improvement efforts (Deal et al., 2015; Harris et al., 2009).

Reoffending measures also vary along other lines. For example, only a minority of states produce and publish statistics on recidivism among probation youth; commitment or residential placement youth are more commonly tracked, even though they are a much smaller population (Deal et al., 2015). In addition, not all states track youth into the adult system, which likely results in lower detection of recidivism among older youth (Deal et al., 2015; Pew, 2014). Furthermore, authors differ in whether they recommend that measures include (Walsh & Weber, 2014) or exclude (Harris et al., 2009) system contacts for acts such as technical violations. Thus, the actual measurement of juvenile reoffending, and scholarly recommendations for that measurement, vary in terms of populations, measures, data sources, offenses, and follow-up periods. To account for possible differences in the conclusions that would be reached using different measures, some have recommended that information on multiple marker events and follow-up periods be collected; however, many states do not routinely do this (Deal et al., 2015; Pew, 2014; Walsh & Weber, 2014). We turn next to the existing evidence on the differences between alternative definitions of juvenile reoffending.

Measurement Issues and Rates of Reoffending

Different measures of reoffending yield dramatically different reoffending rates. One recent study found that adult recidivism rates in Norway varied from 9% to 53% depending on how, among whom, and for how long recidivism was measured (Andersen & Skardhamar, 2017). Similar variability in rates has been found among juveniles (Harris et al., 2009). For example, among previously committed youth, recidivism rates range from approximately 20% to approximately 75%, depending on which stage of system contact is examined and how long youth are tracked (Annie E. Casey Foundation, 2011). This substantial impact of measurement on rates prevents comparisons between states. In a 2014 study, Pew found that approximately one-third of states used new arrests as their reported juvenile recidivism measure, half used new adjudications, and half used new commitments (with some states using multiple measures); some did not track recidivism at all.

Measurement Issues and Predictors of Reoffending

Research has identified several youth-level characteristics that predict reoffending. Meta-analyses summarize these as involving offense history characteristics, family and peer factors, and emotional and behavioral problems (Cottle et al., 2001; Scott & Brown, 2018). In Florida, where two phases of this project took place, known predictors include demographic factors, past juvenile justice referrals, educational history and status, vocational training and employability, relationship characteristics, substance use, attitudes and skills, aggression, and impulse control (Baglivio et al., 2017; Intravia et al., 2017). Many of these domains can be operationalized in terms of risk factors or protective factors, and often both types of operationalization independently predict reoffending (Hay et al., 2018). Community-level predictors have also been identified, including rates of disadvantage—which appear to be a risk factor—and immigrant concentration—which appears to be a protective factor (Baglivio et al., 2017; Intravia et al., 2017; Wolff et al., 2018). However, not all studies have found evidence that community factors matter, and a recent meta-analysis concluded that there is inconsistent evidence on whether and which ecological characteristics predict juvenile reoffending (Jacobs et al., 2020).

As is the case for conclusions about reoffending rates, it is possible that conclusions about the predictors of reoffending will depend on how reoffending is measured. For example, gender and race may have different associations with different types of system contact among adolescents (Barrett et al., 2006). Additional suggestive evidence comes from meta-analyses of reoffending studies that examine the measurement of the outcome as a predictor of effect size. Based on these research syntheses, it appears that different types of system contact may be differentially predicted by individual risk factors as well as by global risk assessment instruments (Schwalbe, 2008; Wibbelink et al., 2017). It also is possible that predictors' effect sizes differ depending on what type of reoffending is assessed (e.g., violent, non-violent), though there is inconsistent meta-analytic evidence for this (Edens et al., 2007; Olver et al., 2009; Pusch & Holtfreter, 2018). Although meta-analyses provide important insights into the consequences of choices of measurement for conclusions about reoffending, head-to-head comparisons of different measures of reoffending are rare. There thus are unanswered questions regarding the extent to which practitioners or researchers' choice of one reoffending measure over another impacts results.

Research Gaps and Needs

The Juvenile Justice and Delinquency Prevention Act as amended by the Juvenile Justice Reform Act of 2018 calls for the establishment of "a common national juvenile recidivism measurement system" (p. 37). Recent surveys of states' recidivism measurement systems show that we are some distance from this goal. Yet perhaps even more importantly, we do not yet know what a common measurement strategy should look like. Together, the existing studies, reviews, and policy briefs on the topic indicate a pressing need for research that:

- Addresses populations beyond just committed youth (e.g., probation youth);
- Evaluates varying follow-up periods for capturing recidivism;
- Examines outcomes beyond arrest, adjudication, and commitment (e.g., technical violations);
- Compares different types and severities of recidivism;
- Assesses the uniqueness of the predictors of different measures of recidivism;
- Explores variability in program effects using different measures of recidivism; and
- Analyzes contextual variability in different measures of recidivism.

This project was a response to these research gaps and needs. The next sections of this report describe the study contexts, designs, and findings for the Florida studies and for the Oregon study.

Research Design, Collaborating Organizations, Methods, and Outcomes for the Three Studies

The following sections describe the designs, methods, analytical and data analysis techniques, collaborating organizations, and outcomes for the three phases of research that were undertaken as part of this project. This information is presented first for the Florida Youth-Level and Contextual Differences Studies, and then for the study on Evaluating Measures of Juvenile Reoffending in Oregon.

Preliminary Work: Census of Current State Measures of Juvenile Recidivism

To provide context for the project and guidance for variable selection, an initial project phase entailed collecting information about the official or reported measures of juvenile recidivism that were used by the 50 U.S. states and Washington, DC. The results of this work have been published (Casey & Siennick, 2022). Briefly, reviews of state publications and statutes were combined with information from juvenile justice agency representatives to create an updated accounting of current (as of 2020) practices in the measurement of juvenile recidivism. The results revealed that although most states tracked youth into the adult criminal justice system, there was considerable variability in the marker events and follow-up periods used. Based on these results, we identified seven measures that were commonly used nationwide (see "The Florida Analyses" below) and used those as our focal outcomes. Note that some states may collect additional measures that are not used in reporting and are not part of those states' formal definitions of juvenile recidivism. Both Florida and Oregon do this; indeed, those additional measures made this study possible. The existence of such additional measures could facilitate more cross-state comparisons than would be possible using states' official measures alone.

Phases 1 and 3: Florida Youth-Level and Contextual Differences Studies

The main analyses of the individual and contextual predictors of juvenile recidivism used data from FDJJ and a form of multilevel regression that allowed comparisons of effect sizes across different correlated outcomes. Here we provide information on the study context before describing the data, methods, and results of the Florida studies.

The Florida Department of Juvenile Justice

FDJJ was created in 1994 by the Florida legislature. Youth proceedings previously were handled by the Florida Department of Health and Rehabilitative Services, and the new FDJJ continued the prior agency's rehabilitative focus. Unlike some states (e.g., Oregon, Mississippi), the Florida juvenile justice system is centralized. FDJJ develops and coordinates services and programs statewide for the prevention, reduction, and treatment of delinquent behavior. Although legislative initiatives have periodically changed the balance of treatment and punishment in FDJJ's proceedings, the department has continually maintained its general rehabilitative focus, and since a 2011 review it has emphasized less restrictive, community-based sanctions for youth who do not pose serious threats to public safety. Currently, all 67 counties in Florida operate a range of diversion programs for less serious youth offenders.

FDJJ also maintains Florida's Juvenile Justice Information System (JJIS), a real-time tracking system for youth who have had system contact. The system, which is one of the largest state-operated juvenile justice databases in the United States, contains information on demographic characteristics, official delinquency histories, risk and protective factors, referral and placement histories, and other data elements relevant to the treatment and placement of youth. The Florida JJIS was the main source of this project's Florida data. An additional source was the Florida Department of Law Enforcement's (FDLE) Computerized Criminal History

(CCH) database, which contains information on adult arrests and convictions in Florida. Data from these sources were used in the statistical analyses described below.

The Florida Youth-Level Data

Outcomes and youth-level predictors for phases 1 and 3 came from JJIS and FDLE archival data on a release cohort of all youth who completed FDJJ programs between July 1, 2012 and June 30, 2017. This totaled 114,561 unique spells of FDJJ supervision. Youth leaving diversion (53,150 spells), probation (48,215 spells), and residential commitment (13,196 spells) were included. Similar data have been used in several prior studies of juvenile recidivism in Florida (e.g., Baglivio et al., 2017; Hay et al., 2018; Intravia et al., 2017).

At the time of this study, Florida defined juvenile recidivism as an adjudication, adjudication withheld, or adult conviction for any new law violation committed within 12 months of program completion (Office of Research and Data Integrity, 2018). Yet the JJIS data also allow the redefinition of recidivism using different marker events, data sources, offenses, and follow-up periods. Specifically, over 80 measures of recidivism are routinely available, and others were created specifically for this study. In addition, JJIS stores the results of a risk assessment screener for each youth. The screening tool captures predictors recommended by Harris and colleagues (2009), as well as additional measures of risk levels and needs as recommended by Walsh and Weber (2014). These measures are summarized in table 1. The larger assessment tool that yielded these measures has been validated among FDJJ-supervised youth (e.g., Hay et al., 2018). The data also contain demographic information.

The Florida Contextual Data

The youth-level data were combined with additional contextual data on youths' FDJJ programs and home communities. The program number came from FDJJ. To incorporate

Table 1. Youth-Level Predictors Included in the Analyses	
Demographic Predictors	Family Predictors
Gender	Out of home placements
Race/ethnicity	History of running away
Age at release	History of neglect
Delinquency History Predictors	Family history of incarceration
Age at first offense	Parental substance use
Prior misdemeanors	Prior physical abuse
Prior felonies	Prior sexual abuse
Prior weapons offenses	Youth Predictors
Prior commitments	Attitudes towards the law
Prior pickup orders	Accepts responsibility for antisocial behavior
	Delinquent peers
	Problem alcohol use
	Problem drug use

community information, youths' home addresses were geocoded to create indicators of their census tracts and counties of residence. These enabled the merging in of community context measures from the Census Bureau's American Community Survey (ACS) and the Federal Bureau of Investigation's Uniform Crime Report (UCR). The ACS variables were 5-year tract-level pooled estimates centered on the year that the youth was released from supervision. County-level UCR data were available for 2012-2016, but the source of the 2017 data did not allow true zeros to be distinguished from missing values. The county-level measures thus were missing for 2017. The contextual measures are summarized in table 2.

Listwise deletion was used to address item-missing data on the individual-level and contextual predictor variables. This resulted in a sample size of 104,354 unique spells of FDJJ supervision, including 48,616 diversion spells, 43,799 probation spells, and 11,939 residential commitment spells. This was our analytic sample.

Focal Recidivism Measures from the Florida Data

As described below, the focal analyses involved comparisons of coefficients across equations predicting different measures of recidivism. The number of predictors in conjunction

Table 2. Contextual Predictors Included in the Analyses	
Predictor	Source
Population Predictors	
Total population	ACS
Percent non-Hispanic Black	ACS
Percent Hispanic	ACS
Disadvantage Predictors	
Percent unemployed	ACS
Percent without high school diploma	ACS
Percent on public assistance	ACS
Instability Predictors	
Mobility rate	ACS
Percent renters	ACS
Crime Predictors	
Violent arrest rate	UCR
Drug arrest rate	UCR
Police per capita	UCR
Note. ACS = tract-level American Community Survey; UCR = county-level Uniform Crime Reports	

with the number of outcomes resulted in a large number of possible comparisons. For example, in predicting a single trio of recidivism outcomes, the 23 youth-level predictor measures would yield 69 coefficient comparisons (by comparing their effects across outcomes 1 and 2, 1 and 3, and 2 and 3), and the 11 contextual predictors would yield 33 comparisons. From the thousands of possible combinations of recidivism measures, we selected those that reflected measures that our census revealed were commonly used by U.S. states. These are the comparisons that are most relevant for policy and practice. Table 3 displays the comparisons made, including variations in marker events, follow-up periods, utilization of adult criminal justice system data, and types of recidivism. The combination of these sets of outcomes and the predictors examined resulted in 544 comparisons of the effects of risk and protective factors on different recidivism measures.

The Florida Analyses

The analyses proceeded in two stages. First, rates of recidivism were calculated for all measures noted in table 3. Because all of the rates were computed for the same set of youth, this

Table 3. Sets of Operationalizations of Juvenile Recidivism Selected for Comparison
1. Referral vs. adjudication vs. commitment within 12 months
2. Adjudication or conviction within 6 vs. 12 vs. 24 months
3. Referral or arrest within 12 months, with and without adult system data
4. Adjudication or conviction within 12 months, with and without adult system data
5. Referral or arrest for new offense vs. violation of probation within 12 months
6. Adjudication or conviction within 12 months for misdemeanor vs. felony
7. Adjudication or conviction within 12 months for violent vs. property vs. drug offense
8. Adjudication or conviction within 24 months, by group (diversion/probation/residential)

comparison illustrates the impact of measurement on conclusions about recidivism rates without the confounding influence of variations between the populations generating the rates.

Second, a series of multivariate multilevel models (MVMM) were estimated relating the substantive predictors to recidivism. Multilevel models are extensions of regression that adjust for the grouping or clustering of cases by incorporating an additional higher-order level of analysis for the groupings (here, spells). MVMMs are variants of basic multilevel models that allow the joint analysis of multiple outcomes in a single model (Goldstein, 2011; Hox, 2010; Snijders & Bosker, 2012). This is done through the addition of a lower-order level where the multivariate nature of the outcome is indicated. For example, one model simultaneously predicted 12-month referral, adjudication, and commitment from the demographic variables in a trio of parallel multilevel regressions. MVMMs are well-suited for cases like ours where a study's multiple outcome measures are highly correlated with each other (Snijders & Bosker, 2012). In addition, and especially relevant here, they allow tests of whether specific predictors' coefficients differ across the multiple outcomes (Baldwin et al., 2014; Pituch & Stevens, 2016). This feature allowed us to examine whether each predictor had statistically different associations with different measures of recidivism. Tests indicated that additional variance components were not consistently needed for census tract and county, so two-level models were estimated. Effect size was examined by dividing the logistic coefficients by 1.81 to compute Cohen's *d* (Chinn,

2000) and comparing the resulting quantities against recommended thresholds for small, medium, and large effects (Cohen, 1992; Rice & Harris, 2005; Sawilowsky, 2009).

The Florida Results

Rates of Recidivism across Measures

Descriptive statistics were computed to compare rates of juvenile recidivism across the measures shown in table 3. Table 4 displays the results. Recidivism rates varied considerably depending on the marker event, follow up period, and system's data used. For example, the lowest calculated rate was 4% for commitment within 12 months, and the highest was 33% for referral or arrest within 12 months. Rates were seven-fold higher when referral versus commitment was considered, and they doubled when the follow-up period for tracking adjudication increased from 6 to 24 months. They also increased by approximately 50% when a combination of juvenile and adult system data was used in place of juvenile system data alone.

Additional analyses calculated rates of recidivism for the outcome measures separately for males and females; for white youth, black youth, Hispanic youth, and youth of other racial or ethnic backgrounds; and for residential youth, probation youth, and diversion youth. These results, which are shown in appendices A1-A3, revealed that males had higher recidivism rates than non-males, by every measure and for every offense type. By some measures, the rate among males was 50% higher, while in more extreme cases, their rate was three times that of non-males. In the analyses by race, black youth had the highest recidivism rate by all measures except adjudication or conviction for a drug offense. Hispanic youths' rates across the measures resembled those of white youth, but by some measures they were slightly higher than white youths' rates. Relatively few youth were of other races and ethnicities, but those youth had the lowest recidivism rate by any measure.

Table 4. Variation in Rates of Juvenile Recidivism as Operationalized in Multiple Ways, Florida (*N* = 104,354)	
Operationalization	Proportion Recidivating by this Measure
Comparison 1	
Referral within 12 months	22.4%
Adjudication within 12 months	14.2%
Commitment within 12 months	3.6%
Comparison 2	
Adjudication or conviction within 6 months	13.2%
Adjudication or conviction within 12 months	20.7%
Adjudication or conviction within 24 months	28.8%
Comparison 3	
Referral within 12 months, without adult system data	22.4%
Referral or arrest within 12 months, with adult system data	33.4%
Comparison 4	
Adjudication within 12 months, without adult system data	14.2%
Adjudication or conviction within 12 months, with adult system data	20.7%
Comparison 5	
Referral or arrest for new offense within 12 months	27.0%
Technical violation within 12 months	7.6%
Comparison 6	
Adjudication or conviction within 12 months for a misdemeanor	15.1%
Adjudication or conviction within 12 months for a felony	10.0%
Comparison 7	
Adjudication or conviction within 12 months for violent offense	5.5%
Adjudication or conviction within 12 months for property offense	8.7%
Adjudication or conviction within 12 months for drug offense	3.6%
Comparison 8	
Adjudication or conviction within 24 months for diversion youth	22.4%
Adjudication or conviction within 24 months for probation youth	29.7%
Adjudication or conviction within 24 months for residential youth	51.2%
Source: Florida Department of Juvenile Justice and Florida Department of Law Enforcement	

Several conclusions follow from the descriptive statistics by group of youth (i.e., by initial disposition). First, residential youth had the highest rates of recidivism by all measures; in addition, by nearly all measures, these rates were at least twice as high as the rates for the other groups of youth. Second, diversion youth had higher recidivism rates than probation youth when only juvenile system data were considered, but they had lower rates when the combination of juvenile and adult system data was considered. Third, the inclusion of adult system data had the greatest impact on calculated recidivism rates for probation youth. Fourth, although recidivism rates increased with follow-up length for all groups, they increased more steeply for probation and diversion youth than for residential youth.

Differential Prediction of Recidivism Measures by Individual Factors

A series of MVMMs was estimated to compare the relative strength of association of the individual-level risk and demographic factors with the varied measures of recidivism among FDJJ youth. As a first step, 16 models were estimated to compare the predictors of measures that varied in terms of the marker event captured, the follow up period used, and whether or not data from the adult criminal justice system was included. Four models were estimated for each outcome group, such that demographic predictors, criminal history predictors, family predictors, and youth predictors were included in four separate models. Tables 5-7 show the results of the post-hoc coefficient comparisons from these models; appendices B1-B4 show the coefficients on which the comparisons are based. Three main conclusions emerged. First, many (71% of the) tests of the differences in predictors' effects across outcomes were not statistically significant. This indicates that there is much similarity in the predictors of referral, adjudication, and commitment, of 6, 12, and 24 month follow ups, and of juvenile system data alone and combined juvenile and adult system data. Of the three sets of contrasts, a minority of contrasts across marker events (26%) and follow-up periods (19%) were significant; there were more significant contrasts in the models comparing recidivism as measured using different data sources (52% and 48% for the referral and adjudication models respectively). The degrees of difference in effect sizes in the significant contrasts are discussed below.

Second, when significant differences in predictors' strength did emerge, they indicated that the predictors had weaker predictive power when earlier points of system contact and longer follow-up periods were considered. Specifically, multiple predictors were most strongly

Table 5. Summary of Differences in Individual-Level Predictors' Effects on Different Marker Events Capturing 12 Month Recidivism in the Juvenile System, Florida

Predictor	Referral vs. Adjudication	Referral vs. Commitment	Adjudication vs. Commitment
Model 1: Demographic Predictors			
Male	n.s.	<	<
Black[a]	n.s.	n.s.	<
Hispanic[a]	>	n.s.	n.s.
Other non-white race/ethnicity[a]	n.s.	n.s.	n.s.
Age at release	<[b]	<[b]	<[b]
Model 2: Delinquency History Predictors			
Age at first offense	n.s.	<[b]	<[b]
Prior misdemeanors	n.s.	>	n.s.
Prior felonies	n.s.	<	<
Prior weapons offenses	n.s.	n.s.	n.s.
Prior commitments	>[c]	n.s.	n.s.
Prior pickup orders	n.s.	n.s.	>
Model 3: Family Predictors			
Out of home placements	n.s.	n.s.	n.s.
History of running away	n.s.	<	<
History of neglect	n.s.	n.s.	n.s.
Family incarceration	n.s.	n.s.	n.s.
Parental substance abuse	n.s.	n.s.	n.s.
Physical abuse	n.s.	n.s.	n.s.
Sexual abuse	n.s.	n.s.	n.s.
Model 4: Youth Predictors			
Attitudes towards the law	n.s.	n.s.	n.s.
Takes responsibility for behavior	n.s.	n.s.	n.s.
Delinquent peers	n.s.	<	<
Problem alcohol use	n.s.	n.s.	n.s.
Problem drug use	n.s.	n.s.	n.s.

Note. Results for each set of predictors are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome.
[a]Reference category = white non-Hispanic
[b]Both coefficients are negative; all other coefficients in significant contrasts are positive
[c]Smaller coefficient is not statistically significant

associated with commitment, and there was some decay in predictive strength as the follow-up period grew longer. The latter finding could indicate that risk factors are most closely associated with recidivism that occurs close in time to their measurement. Third, in cases where the predictive power of risk factors differed when adult system data was and was not included, that power tended to be stronger when the outcome did include adult system data. This may be in part a product of recidivism among youth who age out of the juvenile system during the follow-up

Table 6. Summary of Differences in Individual-Level Predictors' Effects on Adjudication or Conviction Captured within Different Time Windows, Florida

Predictor	6 Months vs. 12 Months	6 Months vs. 24 Months	12 Months vs. 24 Months
Model 1: Demographic Predictors			
Male	n.s.	<	n.s.
Black[a]	n.s.	n.s.	n.s.
Hispanic[a]	n.s.	n.s.	n.s.
Other non-white race/ethnicity[a]	n.s.	n.s.	n.s.
Age at release	<[b]	<[b]	<[b]
Model 2: Delinquency History Predictors			
Age at first offense	<[b]	<[b]	<[b]
Prior misdemeanors	n.s.	>	>
Prior felonies	n.s.	>	>
Prior weapons offenses	n.s.	n.s.	n.s.
Prior commitments	n.s.	n.s.	n.s.
Prior pickup orders	n.s.	n.s.	n.s.
Model 3: Family Predictors			
Out of home placements	n.s.	n.s.	n.s.
History of running away	>	>	n.s.
History of neglect	n.s.	n.s.	n.s.
Family incarceration	n.s.	n.s.	n.s.
Parental substance abuse	n.s.	n.s.	n.s.
Physical abuse	n.s.	n.s.	n.s.
Sexual abuse	n.s.	n.s.	n.s.
Model 4: Youth Predictors			
Attitudes towards the law	n.s.	n.s.	n.s.
Takes responsibility for behavior	n.s.	n.s.	n.s.
Delinquent peers	n.s.	n.s.	n.s.
Problem alcohol use	n.s.	n.s.	n.s.
Problem drug use	n.s.	n.s.	n.s.

Note. Results for each set of predictors are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome.
[a]Reference category = white non-Hispanic
[b]Both coefficients are negative; all other coefficients in significant contrasts are positive

period; that recidivism would go undetected by measures that are based only on juvenile system information.

Next, a series of 12 MVMMs was estimated to compare the associations of the predictors with different offense types. The types examined were, in one set of models, 12 month referrals or arrests for new charges versus technical violations; in another set, 12 month adjudications or convictions for misdemeanors versus felonies; and in a third set, 12 month adjudications or convictions for violent versus property versus drug offenses. Tables 8-9 show the results of the

Table 7. Summary of Differences in Individual-Level Predictors' Effects on 12 Month Referral/Arrest and, Separately, 12 Month Adjudication/Conviction when Adult System Data Is Not versus Is Included, Florida

Predictor	First model: Referral vs. Referral/Arrest	Second model: Adjudication vs. Adjudication/Conviction
Models 1 and 2: Demographic Predictors		
Male	<	<
Black[a]	<	n.s.
Hispanic[a]	n.s.	n.s.
Other non-white race/ethnicity[a]	n.s.	n.s.
Age at release	>[b]	>[b]
Models 3 and 4: Delinquency History Predictors		
Age at first offense	>[b]	>[b]
Prior misdemeanors	<	<
Prior felonies	<	<
Prior weapons offenses	n.s.	>[c]
Prior commitments	<	<[c]
Prior pickup orders	<[c]	-/+
Models 5 and 6: Family Predictors		
Out of home placements	n.s.	n.s.
History of running away	n.s.	n.s.
History of neglect	n.s.	n.s.
Family incarceration	n.s.	n.s.
Parental substance abuse	n.s.	n.s.
Physical abuse	n.s.	n.s.
Sexual abuse	<[b]	<[b]
Models 7 and 8: Youth Predictors		
Attitudes towards the law	<	n.s.
Takes responsibility for behavior	n.s.	n.s.
Delinquent peers	>	>
Problem alcohol use	n.s.	n.s.
Problem drug use	<	<

Note. Results for each outcome group by set of predictors combination are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome.
[a]Reference category = white non-Hispanic
[b]Both coefficients are negative; all other coefficients in significant contrasts are positive unless otherwise noted
[c]Smaller coefficient is not statistically significant

post-hoc coefficient comparisons from these models, and appendices B5-B7 show the underlying coefficients.

Table 8 suggests three main conclusions. First, slightly more than one-third (37%) of contrasts were statistically significant, indicating that predictors typically had statistically indistinguishable effects on the likelihood of a new charge versus a technical violation and on the likelihood of a misdemeanor versus a felony. Second, when contrasts were significant, they were

Table 8. Summary of Differences in Individual-Level Predictors' Effects on 12 Month Referral/Arrest for a New Charge versus a Technical Violation, and, Separately, 12 Month Adjudication/Conviction for a Misdemeanor versus a Felony Offense, Florida		
Predictor	First model: Technical Violation vs. New Offense	Second model: Misdemeanor vs. Felony Adjudication
Models 1 and 2: Demographic Predictors		
Male	<	<
Black[a]	n.s.	<
Hispanic[a]	<[b]	<[b]
Other non-white race/ethnicity[a]	n.s.	n.s.
Age at release	>[c]	n.s.
Models 3 and 4: Delinquency History Predictors		
Age at first offense	>[c]	n.s.
Prior misdemeanors	n.s.	>
Prior felonies	<	<
Prior weapons offenses	>[b]	n.s.
Prior commitments	n.s.	n.s.
Prior pickup orders	n.s.	n.s.
Models 5 and 6: Family Predictors		
Out of home placements	<[b]	n.s.
History of running away	>	n.s.
History of neglect	n.s.	n.s.
Family incarceration	>	n.s.
Parental substance abuse	n.s.	n.s.
Physical abuse	n.s.	n.s.
Sexual abuse	<[c]	<[c]
Models 7 and 8: Youth Predictors		
Attitudes towards the law	n.s.	n.s.
Takes responsibility for behavior	n.s.	n.s.
Delinquent peers	n.s.	<
Problem alcohol use	n.s.	n.s.
Problem drug use	n.s.	n.s.

Note. Results for each outcome group by set of predictors combination are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome.
[a]Reference category = white non-Hispanic
[b]Smaller coefficient is not statistically significant
[c]Both coefficients are negative; all other coefficients in significant contrasts are positive

nearly as likely to favor the less serious recidivism type than the more serious type, indicating that the magnitudes of coefficient differences were not closely tied to the severity of the outcome. Third, substantively, demographic factors, felonies, and sexual abuse had weaker associations with less serious forms of recidivism than with more serious forms. Differences in the predictive strength of other factors were either non-significant or were inconsistent across models.

Table 9. Summary of Differences in Individual-Level Predictors' Effects on 12 Month Adjudication or Conviction for Different Offense Types, Florida			
Predictor	Violent vs. Property Offense	Violent vs. Drug Offense	Property vs. Drug Offense
Model 1: Demographic Predictors			
Male	<	<	<
Black[a]	>	+/-	+/-
Hispanic[a]	n.s.	>[b]	n.s.
Other non-white race/ethnicity[a]	n.s.	n.s.	n.s.
Age at release	>[c]	>[c]	>[c]
Model 2: Delinquency History Predictors			
Age at first offense	>[c]	>[c]	>[c]
Prior misdemeanors	n.s.	n.s.	<
Prior felonies	<	<	>
Prior weapons offenses	n.s.	n.s.	n.s.
Prior commitments	>[b]	>[b]	n.s.
Prior pickup orders	<[b]	n.s.	n.s.
Model 3: Family Predictors			
Out of home placements	>	+/-	+/-
History of running away	n.s.	>	>
History of neglect	n.s.	<	n.s.
Family incarceration	n.s.	n.s.	n.s.
Parental substance abuse	>[b]	>[b]	n.s.
Physical abuse	<[b]	<[b]	n.s.
Sexual abuse	<[c]	<[c]	n.s.
Model 4: Youth Predictors			
Attitudes towards the law	n.s.	n.s.	n.s.
Takes responsibility for behavior	>	>	>
Delinquent peers	<	<	n.s.
Problem alcohol use	n.s.	n.s.	n.s.
Problem drug use	n.s.	<	<

Note. Results for each set of predictors are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome; +/- = predictor has a positive effect on the first listed outcome and a negative effect on the second listed outcome.
[a]Reference category = white non-Hispanic
[b]Smaller coefficient is not statistically significant
[c]Both coefficients are negative; all other coefficients in significant contrasts are positive unless otherwise noted

Table 9 presents a mixed picture regarding differences in predictive strength across recidivism as measured in terms of different offense types (violent versus property versus drug recidivism). There were more significant contrasts (57%) in that model, but they did not consistently favor any one type of recidivism. In four cases, predictors had different signs depending on the outcome, a pattern that was also rarely seen in the other tables. These results could stem in part from substantive differences between violent, property, and drug recidivism that align with different constellations of risk and protective factors.

Table 10. Summary of Differences in Individual-Level Predictors' Effects on Adjudication/Conviction at 24 Months, by Initial Disposition, Florida			
Predictor	Diversion vs. Probation	Diversion vs. Residential	Probation vs. Residential
Model 1: Demographic Predictors			
Male	n.s.	>	n.s.
Black[a]	n.s.	>	>
Hispanic[a]	n.s.	n.s.	n.s.
Other non-white race/ethnicity[a]	n.s.	>	n.s.
Age at release	<[c]	<[c]	<[c]
Model 2: Delinquency History Predictors			
Age at first offense	>[c]	<[c]	<[c]
Prior misdemeanors	>	>	>
Prior felonies	>	>	>
Prior weapons offenses	>[b]	n.s.	n.s.
Prior commitments	n.s.	<[b]	<[b]
Prior pickup orders	n.s.	>[b]	>[b]
Model 3: Family Predictors			
Out of home placements	>	>	n.s.
History of running away	>	>	>
History of neglect	n.s.	n.s.	n.s.
Family incarceration	n.s.	>	>
Parental substance abuse	n.s.	n.s.	n.s.
Physical abuse	n.s.	n.s.	n.s.
Sexual abuse	n.s.	n.s.	n.s.
Model 4: Youth Predictors			
Attitudes towards the law	>	+/-	+/-
Takes responsibility for behavior	>	>[b]	>[b]
Delinquent peers	>[b]	>	n.s.
Problem alcohol use	n.s.	n.s.	n.s.
Problem drug use	<	n.s.	>[b]

Note. Results are from twelve logistic regression models, one for each pair of group of youth by set of predictors combination. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome; +/- = predictor has a positive effect on the first listed outcome and a negative effect on the second listed outcome.
[a]Reference category = white non-Hispanic
[b]Smaller coefficient is not statistically significant
[c]Both coefficients are negative; all other coefficients in significant contrasts are positive unless otherwise noted

The final set of analyses of individual-level factors involved estimating single-level logistic regression models predicting 24-month adjudication or conviction separately for residential, probation, and diversion youth. These models differ from the MVMMs presented above because the comparisons are for predictors of a single measure of recidivism across different groups of youth—residential, probation, and diversion—rather than comparing across different measures of recidivism. We used *z*-tests to compare the equality of coefficients across models (Clogg et al., 1995). Table 10 shows the results of these z-tests, and appendix B8 shows the coefficients on which they are based. Over half (55%) of these contrasts were statistically significant. Most of the significant contrasts indicated that the risk factors had stronger associations with adjudication/conviction for shallow-end youth who had not penetrated as deeply into the justice system.

Differential Prediction of Recidivism Measures by Contextual Factors

Next, a series of MVMMs was estimated to compare the relative strength of association of the contextual factors with different measures of recidivism among FDJJ youth. These analyses were identical in structure and outcomes used to the analyses of individual-level predictors, but they featured the contextual predictors shown in table 2 in place of the individual-level predictors shown in table 1. The first analyses compared the strength of the associations of the contextual factors with recidivism as measured via different marker events, under different follow-up periods, and with and without adult system data.

Table 11 shows the results for the marker event model. Nearly half (48%) of these coefficient contrasts were statistically significant, though the directions of the differences were not consistent. Seven of the significant contrasts indicated that the contextual predictor was more strongly associated with less serious system contact (e.g., referral rather than adjudication), six indicated that the predictor was more strongly associated with more serious contact, and three indicated that the predictor had a positive association with recidivism as measured by one marker event but a negative association with a different marker event. In addition, one-fourth (25%) of the contrasts involved cases where the contextual predictor significantly predicted one marker event but was not significantly associated with another. There thus was greater variability in the associations of contextual predictors with different marker events than there was in the associations of individual-level predictors with different marker events.

Table 11. Summary of Differences in Contextual Predictors' Effects on Different Marker Events Capturing 12 Month Recidivism in the Juvenile System, Florida

Predictor	Referral vs. Adjudication	Referral vs. Commitment	Adjudication vs. Commitment
Model 1: Population Predictors			
Total population	>[a]	n.s.	n.s.
Percent non-Hispanic Black	n.s.	<	<
Percent Hispanic	+/-	+/-	n.s.
Model 2: Disadvantage Predictors			
Percent unemployed	n.s.	<	<
Percent without high sch. diploma	>	n.s.	n.s.
Percent on public assistance	n.s.	>	>
Model 3: Instability Predictors			
Mobility rate	n.s.	>[bc]	n.s.
Percent renters	n.s.	n.s.	n.s.
Model 4: Crime Predictors			
Violent arrest rate	n.s.	<[c]	<[c]
Drug arrest rate	n.s.	>	n.s.
Police per capita	>[bc]	-/+	n.s.

Note. sch. = school. Results for each set of predictors are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome; +/- = predictor has a positive effect on the first listed outcome and a negative effect on the second listed outcome; -/+ = predictor has a negative effect on the first listed outcome and positive effect on the second listed outcome.
[a]Both coefficients are negative; all other coefficients in significant contrasts are positive unless otherwise noted
[b]Significant coefficient is negative
[c]Smaller coefficient is not statistically significant

Table 12 shows the results for the comparison of different follow-up periods. Only two coefficient contrasts were statistically significant, indicating that the contextual predictors generally had statistically indistinguishable associations with adjudication/conviction as measured at 6 months, 12 months, and 24 months. This parallels the low rate of differences found in the individual-level predictor models of these outcomes.

Table 13 shows the results for the comparisons of recidivism measures based on data from the juvenile justice system versus those based on data from the juvenile and adult systems combined. Fourteen percent of coefficient contrasts were statistically significant, and only 5% involved cases where a contextual factor was significantly associated with one version of the outcome but not with another. These findings indicate considerable uniformity in contextual predictors' effects on recidivism regardless of data source.

Table 12. Summary of Differences in Contextual Predictors' Effects on Adjudication or Conviction Captured within Different Time Windows, Florida

Predictor	6 Months vs. 12 Months	6 Months vs. 24 Months	12 Months vs. 24 Months
Model 1: Population Predictors			
Total population	n.s.	n.s.	n.s.
Percent non-Hispanic Black	n.s.	n.s.	n.s.
Percent Hispanic	n.s.	n.s.	n.s.
Model 2: Disadvantage Predictors			
Percent unemployed	n.s.	n.s.	n.s.
Percent without high sch. diploma	n.s.	n.s.	n.s.
Percent on public assistance	n.s.	n.s.	n.s.
Model 3: Instability Predictors			
Mobility rate	n.s.	n.s.	n.s.
Percent renters	n.s.	<	<
Model 4: Crime Predictors			
Violent arrest rate	n.s.	n.s.	n.s.
Drug arrest rate	n.s.	n.s.	n.s.
Police per capita	n.s.	n.s.	n.s.

Note. sch. = school. Results for each set of predictors are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; < = predictor has a weaker effect on the first listed outcome.

Table 13. Summary of Differences in Contextual Predictors' Effects on 12 Month Referral/Arrest and, Separately, 12 Month Adjudication/Conviction when Adult System Data Is Not versus Is Included, Florida

Predictor	First model: Referral vs. Referral/Arrest	Second model: Adjudication vs. Adjudication/Conviction
Model 1: Population Predictors		
Total population	n.s.	n.s.
Percent non-Hispanic Black	n.s.	n.s.
Percent Hispanic	<[a]	>[b]
Model 2: Disadvantage Predictors		
Percent unemployed	n.s.	n.s.
Percent without high sch. diploma	n.s.	n.s.
Percent on public assistance	n.s.	n.s.
Model 3: Instability Predictors		
Mobility rate	n.s.	n.s.
Percent renters	n.s.	n.s.
Model 4: Crime Predictors		
Violent arrest rate	n.s.	n.s.
Drug arrest rate	>	n.s.
Police per capita	n.s.	n.s.

Note. sch. = school. Results for each outcome group by set of predictors combination are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome.

[a]Smaller coefficient is not statistically significant

[b]Both coefficients are negative; all other coefficients in significant contrasts are positive

Tables 14 and 15 show the contextual results for the comparisons of recidivism measures that captured different offense types. Table 14 shows results for a comparison of new offenses versus technical violations and misdemeanors versus felonies, and table 15 shows results for violent, property, and drug offenses. Over half (59%) of the contrasts in table 14 were statistically significant. In these significant cases, stronger prediction was typically seen for the more serious infraction (new offenses and felonies). In addition, percent Hispanic was negatively associated with technical violations and misdemeanors but positively associated with new offenses and felonies. Table 15 shows a different pattern; somewhat fewer (42% of) contrasts were significant, and many more coefficients (30%) had different signs across models. The latter sign differences typically stemmed from negative associations of the contextual predictors with drug offenses, and positive associations of those predictors with other offense types.

Table 16 shows variation in the effects of contextual predictors across different groups of youth. Nearly half (46%) of these coefficient contrasts were statistically significant; in addition, over one-fourth (27%) involved cases where a predictor's effect was significant for one group but not another. In nearly all cases, where effects differed by group, they were stronger for groups that had not penetrated as deeply into the juvenile justice system. For example, effects tended to be stronger for diversion youth than for probation or residential youth. The exception to this pattern involved the drug arrest rate, which was more strongly associated with re-adjudication among youth who had progressed further into the system. Overall, relative to the variability in contextual factors' effects across marker events, follow-up periods, and systems, tables 14-16 indicate greater variability in the effects of contextual factors when recidivism is operationalized in terms of different offense types or for different populations of justice-involved youth.

Table 14. Summary of Differences in Contextual Predictors' Effects on 12 Month Referral/Arrest for a New Charge versus a Technical Violation, and, Separately, 12 Month Adjudication/Conviction for a Misdemeanor versus a Felony Offense, Florida		
Predictor	First model: Technical Violation vs. New Offense	Second model: Misdemeanor vs. Felony Adjudication
Model 1: Population Predictors		
Total population	>[a]	n.s.
Percent non-Hispanic Black	<	<
Percent Hispanic	-/+	-/+
Model 2: Disadvantage Predictors		
Percent unemployed	n.s.	n.s.
Percent without high sch. diploma	<[a]	<[a]
Percent on public assistance	n.s.	n.s.
Model 3: Instability Predictors		
Mobility rate	n.s.	<[a]
Percent renters	n.s.	<
Model 4: Crime Predictors		
Violent arrest rate	n.s.	<[a]
Drug arrest rate	>	>[a]
Police per capita	>[b]	n.s.

Note. sch. = school. Results for each outcome group by set of predictors combination are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome; -/+ = predictor has a negative effect on the first listed outcome and positive effect on the second listed outcome.
[a]Smaller coefficient is not statistically significant
[b]Both coefficients are negative; all other coefficients in significant contrasts are positive

Table 15. Summary of Differences in Individual-Level Predictors' Effects on 12 Month Adjudication or Conviction for Different Offense Types, Florida			
Predictor	Violent vs. Property Offense	Violent vs. Drug Offense	Property vs. Drug Offense
Model 1: Population Predictors			
Total population	n.s.	>[a]	n.s.
Percent non-Hispanic Black	n.s.	+/-	+/-
Percent Hispanic	n.s.	n.s.	n.s.
Model 2: Disadvantage Predictors			
Percent unemployed	n.s.	+/-	+/-
Percent without high sch. diploma	n.s.	>[a]	>[a]
Percent on public assistance	n.s.	n.s.	n.s.
Model 3: Instability Predictors			
Mobility rate	n.s.	-/+	-/+
Percent renters	n.s.	+/-	+/-
Model 4: Crime Predictors			
Violent arrest rate	<	+/-	+/-
Drug arrest rate	n.s.	n.s.	n.s.
Police per capita	n.s.	n.s.	n.s.

Note. sch. = school. Results for each set of predictors are from a single multivariate multilevel model. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome; +/- = predictor has a positive effect on the first listed outcome and a negative effect on the second listed outcome; -/+ = predictor has a negative effect on the first listed outcome and positive effect on the second listed outcome.
[a]Smaller coefficient is not statistically significant

Table 16. Summary of Differences in Contextual Predictors' Effects on Adjudication/Conviction at 24 Months, by Initial Disposition, Florida			
Predictor	Diversion vs. Probation	Diversion vs. Residential	Probation vs. Residential
Model 1: Population Predictors			
Total population	>[a]	n.s.	n.s.
Percent non-Hispanic Black	>	>[b]	>[b]
Percent Hispanic	n.s.	n.s.	n.s.
Model 2: Disadvantage Predictors			
Percent unemployed	n.s.	>[b]	>[b]
Percent without high sch. diploma	>	>	>
Percent on public assistance	n.s.	n.s.	n.s.
Model 3: Instability Predictors			
Mobility rate	n.s.	>	n.s.
Percent renters	>	>	n.s.
Model 4: Crime Predictors			
Violent arrest rate	n.s.	n.s.	n.s.
Drug arrest rate	<	<	<
Police per capita	n.s.	n.s.	n.s.

Note. sch. = school. Results are from twelve logistic regression models, one for each pair of group of youth by set of predictors combination. n.s. = no significant difference in the predictor's effects on the two listed outcomes; > = predictor has a stronger effect on the first listed outcome; < = predictor has a weaker effect on the first listed outcome.
[a]Both coefficients are negative; all other coefficients in significant contrasts are positive
[b]Smaller coefficient is not statistically significant

Considering Differences in Effect Size Across Operationalizations of Recidivism

Across all of the previously described models, most (61% of) comparisons indicated no significant differences in the effects of a given predictor on two different operationalizations of recidivism. Moreover, in the 39% of cases that did reveal significant differences, those differences typically did not mean differences of substantive significance. To better understand whether these differences corresponded with differences in effect size, each coefficient was transformed to Cohen's d (see appendices C1-C16 for Cohen's d values). For nearly all coefficients, Cohen's d was either small (between .2 and .5) or very small (< .2); however, three coefficients (all involving the *male* predictor) had moderate effect sizes (Cohen's d between .5 and .8). These three coefficients were part of five significant coefficient comparisons. These significant contrasts involved the small *male* coefficient in predicting referral (d = .247) versus the moderate *male* coefficient in predicting commitment (d = .510), the small *male* coefficient in predicting adjudication (d = .278) versus the moderate *male* coefficient for commitment, the small *male* coefficient in predicting misdemeanor offenses (d = .297) versus the moderate *male* coefficient for felony offenses (d = .621), the moderate *male* coefficient in predicting drug offenses (d = .674) versus the very small *male* coefficient for violent offenses (d = .166), and the moderate *male* coefficient for drug offenses versus the small *male* coefficient for property offenses (d = .413).

Most of the significant comparisons found were between two small effect sizes or two very small effect sizes. For example, among the individual level predictors for adjudication/ conviction at 24 months by youth group, we found several significant contrasts for the *age of release* predictor. One such contrast involved the very small *age of release* coefficient for predicting adjudication among diversion youth (d = -0.062) and the very small coefficient of *age of release* for probation youth (d = -0.093). The other significant contrasts involving this predictor and outcome combination also featured one small and one very small coefficient each. In total, 39 coefficient contrasts involved such combinations of small and very small coefficients. The remaining significant contrasts—167, or 79% of the total number of significant contrasts—involved significant differences between two small effects or between two very small effects. Overall, this analysis of effect sizes suggests that even where significant contrasts emerged, they tended to be between effects that were both substantively small.

Consistency of Associations of Recidivism with Specific Predictors

Across all models combined, each predictor was used in 16 different coefficient comparisons. We examined whether some predictors had more consistent effects across operationalizations of recidivism than did other predictors. To do this, we calculated the percentage of a predictor's contrasts that yielded a significant contrast. Table 17 shows the results. All predictors, except for problem alcohol use, were part of at least one significant

Table 17. Number and Percent of Significant Contrasts across Models for each Individual-Level and Contextual Predictor	
Operationalization	Number (%) of Significant Contrasts
Demographic Predictors	
Male	11 (68.8%)
Black	8 (50.0%)
Hispanic	4 (25.0%)
Other non-white race/ethnicity	1 (6.3%)
Age at release	15 (93.8%)
Delinquency History Predictors	
Age at first offense	14 (87.5%)
Prior misdemeanors	10 (62.5%)
Prior felonies	14 (87.5%)
Prior weapons offenses	3 (18.8%)
Prior commitments	7 (43.8%)
Prior pickup orders	6 (37.5%)
Family Predictors	
Out of home placements	6 (37.5%)
History of running away	10 (62.5%)
History of neglect	1 (6.3%)
Family incarceration	3 (18.8%)
Parental substance abuse	2 (12.5%)
Physical abuse	2 (12.5%)
Sexual abuse	6 (37.5%)
Youth Predictors	
Attitudes towards the law	4 (25.0%)
Takes responsibility for behavior	6 (37.5%)
Delinquent peers	9 (56.3%)
Problem alcohol use	0 (0.0%)
Problem drug use	6 (37.5%)
Population Predictors	
Total population	4 (25.0%)
Percent non-Hispanic Black	9 (56.3%)
Percent Hispanic	6 (37.5%)
Disadvantage Predictors	
Percent unemployed	6 (37.5%)
Percent without high sch. diploma	8 (50.0%)
Percent on public assistance	2 (12.5%)
Instability Predictors	
Mobility rate	5 (31.3%)
Percent renters	7 (43.8%)
Crime Predictors	
Violent arrest rate	6 (37.5%)
Drug arrest rate	7 (43.8%)
Police per capita	3 (18.8%)
Note: See tables 5-16 for results for individual contrasts.	

contrast. When the different predictor domains were considered, the predictive strength of demographic and delinquency history predictors varied more across recidivism measures than did the predictive strength of other predictors. The predictors in the family domain tended to have especially consistent effects across outcome measures. Because these results suggest that many factors that are commonly used in risk assessment may have statistically different associations with different measures of recidivism, the scoring systems and thresholds for tools and scores that include these factors may need to be tailored to specific operationalizations of recidivism (cf. Siennick & Pupo, 2023).

Conclusions about Differential Prediction of Recidivism Measures

The preceding results support five general conclusions, as follows:

- All categories of predictors showed differences in predictive strength across operationalizations of recidivism. The strengths of the associations of demographic and criminal history predictors with recidivism were least robust.
- The variability in the predictive strength of criminal history in relation to recidivism was especially high in comparisons involving whether or not the recidivism measure included data from the adult system.
- Changing the follow-up window had little impact on the prediction of recidivism.
- Many risk factors had weaker effects for deeper-end youth (e.g., residential youth).
- The direction (i.e., positive or negative sign) of the associations of risk factors with recidivism was most variable in analyses involving contextual predictors and those involving comparisons of violent, property, and drug offenses.

Phase 2: Evaluating Measures of Juvenile Reoffending in Oregon

Here we provide context for the Oregon study before describing the methods and results of that portion of the project.

The Oregon Youth Authority

The juvenile justice system in Oregon comprises 36 independent county systems that operate under the umbrella of a single state system. The OYA, the centralized agency of the Oregon system, was established in 1995 by the Oregon legislature. OYA handles youth ages 12 to 24 who commit crimes before the age of 18. It operates correctional and transitional facilities and provides probation and community parole services. Many of the youth served by OYA are more serious youth offenders, youth who were unsuccessful at the county level, or youth who require more resources than counties can provide.

OYA also created and maintains Oregon's JJIS, which includes both state data and data from 34 of the 36 counties (Brazeau & Peterson, 2000). Like Florida's JJIS, Oregon's tracks youth in the Oregon juvenile justice system in real time. The system allows Oregon's county juvenile departments and OYA to instantly share records electronically through a common database. It was also the source of this project's Oregon data.

Overview of Research Activities in Oregon

The Oregon portion of the project entailed several activities. In the study's initial phase, FSU had numerous meetings with OYA's research director, OYA data analysts, and a research officer from the adult system. Meetings with the first two parties were aimed at understanding juvenile justice operations in Oregon, the contents and format of the JJIS, and Oregon's currently available measures of juvenile recidivism. The meeting with the adult system representative was aimed at understanding what would be required for OYA to track youth misdemeanors into the adult system when creating its recidivism measure. In this phase, FSU also reviewed OYA's risk assessment tool as well as sample recidivism and risk assessment files from the JJIS.

The Oregon Data

In the next phase, OYA provided FSU with recidivism, risk-needs assessment, and status and placement history information on all probation and parole youth with open cases between July 1, 2012 through June 30, 2016. This totaled 2,743 unique spells of supervision, 1,616 for youth on probation and 1,127 for youth on parole. The included predictor variables were the same as those provided by FDJJ and listed in table 1, with two exceptions: prior commitments and prior pickup orders were not included due to low prevalence (among probationers for commitments, and among the full sample for pickup orders) and related sparse data problems. Also, the Oregon analyses rely on individual level data; we did not have addresses for these youth and thus were unable to match their records with contextual data from the ACS and UCR.

Focal Recidivism Measures from the Oregon Data

The varied juvenile recidivism measures that could be constructed with OYA's routinely collected data involved different follow-up lengths. Specifically, using the available data it was possible to examine felony adjudication or conviction within 12, 24, or 36 months, and parole revocations within 12, 24, and 36 months.

The Oregon Analyses

The OYA JJIS data were used in a series of logistic regression models with bootstrapped standard errors predicting adjudication or conviction for a felony within 12, 24, or 36 months of the date on which the youth was committed to probation or parole. The models featured the same categories of youth-level predictors that were used in the Florida analyses. Exploratory analyses indicated that multilevel models—specifically MVMMs—were not needed for these outcomes, and indeed those models would not converge in many cases. For comparison with FDJJ probationers—the one category of youth that was present in both datasets—a second set of models replicated the first set among probation youth only. A third, similar set of models predicted parole revocations within 12, 24, or 36 months of the date on which the youth was committed to parole from the same predictor categories. Finally, a fourth set of models used the adjudication or conviction outcome measured at 36 months to assess any potential differences in the effects of the predictors based on race or ethnicity.

The Oregon Results

Rates of Recidivism across Measures

Descriptive statistics were calculated to compare the proportions of OYA youth recidivating across the three time frames. Rates were also calculated separately among OYA probation youth. This was to facilitate comparisons with the FDJJ data, which also included that category of youth. Descriptive statistics for Florida probation youth were calculated using the felony adjudication measures, which was the offense type captured by the Oregon measures, and at 12 and 24 months because those two time windows were available in both data sources.

Table 18 shows the results. In Oregon, recidivism rates more than doubled between the 12- and 24-month windows, and then increased by another 50% by the 24 month window. Recidivism rates were somewhat higher in the Florida data than in the Oregon data. Specifically, they were over 50% higher among Florida versus Oregon youth at 12 months and nearly 20% higher among them at 24 months. This was true despite efforts to compare similar subsets of youth and similar operationalizations of recidivism. The difference in prevalence rates indicates that caution may be warranted when trying to generalize findings based on a specific state's data.

Table 18. Rates of Adjudication or Conviction for a Felony Within Different Time Windows Among the Oregon Full Sample, Oregon Probation Youth, and Florida Probation Youth			
	Proportion Recidivating by this Measure		
Population of Youth	12 months	24 months	36 months
OYA Full Sample (n=2,743)	7.5%	17.2%	25.5%
OYA Probation Youth (n=1,616)	6.6%	13.6%	--
FDJJ Probation Youth (n=43,799)	10.5%	16.1%	--

Still, there was evidence that the recidivism rate among OYA youth grew closer to the rate among FDJJ youth as the follow-up period increased.

Prediction of Recidivism Measures by Individual Factors

Next, we examined the associations of the individual-level risk and demographic factors with recidivism among OYA youth as captured at varying follow-up windows. As in the Florida analyses, demographic predictors, criminal history predictors, family predictors, and youth predictors were included in separate models. In combination with the three outcome measures, these predictor groupings resulted in the estimation of 12 separate logistic regression models.

Table 19 shows the results. Several findings emerged. First, there was consistency across outcomes with respect to significant predictors; a predictor that was associated with one version of the recidivism outcome tended to also be associated with others. Second, when there was inconsistency in prediction, it sometimes reflected predictors' being significantly associated with recidivism as measured by longer but not shorter time windows. This was especially true for the predictors in the youth domain, none of which predicted 12-month recidivism but several of which predicted 24- or 36-month recidivism. Third, there was no clear pattern of increasing or decreasing strength of associations across the follow-up periods examined. That is, the demographic and risk-needs assessment items were not consistently stronger or weaker predictors of recidivism as the time window for observing that recidivism increased. Fourth, as

Table 19. Coefficients from Logistic Regression Models Estimating Individual-Level Predictors' Effects on Felony Adjudication or Conviction Captured within Different Time Windows, Oregon (N = 2,743)									
	12 Months			24 Months			36 Months		
Predictor	b	SE		b	SE		b	SE	
Models 1-3: Demographic Predictors									
Male	0.571	(0.230)	*	0.883	(0.171)	***	0.846	(0.139)	***
Black[a]	0.621	(0.238)	**	0.656	(0.171)	***	0.633	(0.157)	***
Hispanic[a]	0.436	(0.170)	**	0.294	(0.121)	*	0.297	(0.105)	**
Other non-white race/ethnicity[a]	-0.156	(0.336)		-0.296	(0.228)		-0.225	(0.190)	
Age at release	-0.066	(0.048)		-0.028	(0.034)		-0.008	(0.030)	
Models 4-6: Delinquency History Predictors									
Age at first offense	0.016	(0.081)		0.067	(0.056)		0.098	(0.049)	*
Prior misdemeanors	0.269	(0.066)	***	0.310	(0.048)	***	0.289	(0.040)	***
Prior felonies	0.183	(0.085)	*	0.185	(0.059)	**	0.200	(0.051)	***
Prior weapons offenses	0.339	(0.225)		0.385	(0.162)	*	0.317	(0.147)	*
Models 7-9: Family Predictors									
Out of home placements	-0.048	(0.071)		0.088	(0.051)		0.132	(0.044)	**
History of running away	0.112	(0.045)	*	0.136	(0.034)	***	0.113	(0.030)	***
History of neglect	0.018	(0.176)		0.023	(0.123)		-0.012	(0.107)	
Family incarceration	0.065	(0.167)		0.144	(0.120)		0.161	(0.104)	
Parental substance abuse	-0.049	(0.162)		-0.017	(0.113)		-0.064	(0.098)	
Physical abuse	-0.147	(0.175)		-0.174	(0.126)		-0.219	(0.112)	
Sexual abuse	-0.530	(0.217)	*	-0.522	(0.145)	***	-0.594	(0.126)	***
Models 10-12: Youth Predictors									
Attitudes towards the law	-0.022	(0.111)		-0.037	(0.074)		0.077	(0.065)	
Takes responsibility for behavior	0.014	(0.120)		0.086	(0.080)		0.008	(0.071)	
Delinquent peers	0.522	(0.312)		0.551	(0.204)	**	0.346	(0.161)	*
Problem alcohol use	0.170	(0.194)		0.357	(0.141)	*	0.365	(0.123)	**
Problem drug use	0.386	(0.235)		0.304	(0.164)		0.296	(0.141)	*

Note. Results for each combination of a set of predictors and an outcome are from a single logistic regression model with bootstrapped standard errors. All models included controls for year, probation versus parole status, if the individual had both a probation and parole record during the study window, and whether the risk-needs assessment instrument was administered within 90 days of status onset.
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

was the case in the Florida analyses, measures from all four categories were significantly associated with recidivism.

Comparing the Predictors of Recidivism in Oregon and Florida

To examine whether comparable factors predicted recidivism in Oregon and Florida, we limited the Oregon and Florida samples to include only probation youth and we estimated models from each state using the same outcome measures—felony adjudication or conviction at 12 or 24 months—and the same individual-level predictor variables. The same strategy of

Table 20. Coefficients from Logistic Regression Models Estimating Individual-Level Predictors' Effects on Felony Adjudication or Conviction Captured within Different Time Windows, Oregon and Florida Probation Youth

	Oregon (n=1,616 probation youth)				Florida (n=43,799 probation youth)			
	12 Months		24 Months		12 Months		24 Months	
Predictor	b	SE	b	SE	b	SE	b	SE
Models 1-4: Demographic Predictors								
Male	0.357	(0.297)	0.682	(0.229)**	1.123	(0.050)***	1.088	(0.040)***
Black[a]	0.408	(0.369)	0.303	(0.277)	0.539	(0.036)***	0.577	(0.030)***
Hispanic[a]	0.243	(0.238)	0.069	(0.178)	0.141	(0.051)**	0.168	(0.042)***
Other non-white race/ethnicity[a]	-0.271	(0.497)	-0.481	(0.353)	-0.039	(0.287)	0.056	(0.223)
Age at release	-0.122	(0.077)	-0.087	(0.056)	-0.091	(0.010)***	-0.132	(0.009)***
Models 5-8: Delinquency History Predictors								
Age at first offense	0.031	(0.113)	0.009	(0.083)	-0.097	(0.015)***	-0.149	(0.013)***
Prior misdemeanors	0.207	(0.094)*	0.209	(0.070)**	0.233	(0.017)***	0.212	(0.014)***
Prior felonies	0.153	(0.126)	0.138	(0.091)	0.392	(0.016)***	0.360	(0.014)***
Prior weapons offenses	-0.075	(0.423)	0.424	(0.254)	-0.005	(0.053)	-0.006	(0.045)
Models 9-12: Family Predictors								
Out of home placements	-0.187	(0.104)	0.040	(0.076)	0.046	(0.030)	0.043	(0.026)
History of running away	0.089	(0.060)	0.143	(0.048)**	0.098	(0.015)***	0.091	(0.013)***
History of neglect	0.185	(0.252)	0.121	(0.178)	0.261	(0.067)***	0.247	(0.057)***
Family incarceration	-0.185	(0.228)	-0.096	(0.170)	0.332	(0.033)***	0.334	(0.028)***
Parental substance abuse	0.018	(0.230)	0.179	(0.164)	0.013	(0.059)	0.009	(0.050)
Physical abuse	-0.010	(0.234)	-0.213	(0.183)	-0.099	(0.058)	-0.069	(0.048)
Sexual abuse	-0.483	(0.307)	-0.768	(0.237)***	-0.630	(0.085)***	-0.599	(0.069)***
Models 13-16: Youth Predictors								
Attitudes towards the law	0.050	(0.157)	-0.120	(0.114)	0.172	(0.031)***	0.209	(0.027)***
Takes responsibility for behavior	-0.127	(0.165)	0.126	(0.122)	0.170	(0.033)***	0.123	(0.028)***
Delinquent peers	0.335	(0.403)	0.768	(0.314)*	0.154	(0.032)***	0.135	(0.027)***
Problem alcohol use	-0.085	(0.256)	0.071	(0.190)	-0.057	(0.072)	-0.128	(0.063)*
Problem drug use	0.348	(0.296)	0.403	(0.224)	0.458	(0.043)***	0.425	(0.037)***

Note. Results for each combination of a set of predictors and an outcome are from a single logistic regression model with bootstrapped standard errors. All models included controls for year. Oregon models included controls for whether the individual had both a probation and parole record during the study window, and whether the risk-needs assessment instrument was administered within 90 days of status onset.
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

separately modeling the demographic predictors, criminal history predictors, family predictors, and youth predictors was used in these analyses.

The results of the comparisons are presented in table 20. Several noteworthy findings emerged. First, there were more statistically significant effects in the Florida models than in the Oregon models. This may be due to the much larger sample size for the Florida analyses, which allowed the detection of modest associations. Next, the directions of effects were similar across the two states; if a predictor was positively associated with recidivism in Oregon, it tended also to be positively associated with recidivism in Florida. In no case did a pair of analogous statistically significant coefficients have opposite signs across the two states. This suggests that the predictors included in the analyses operate similarly in the two juvenile justice systems. Finally, consistent with the models presented above for the full OYA sample, the effects of the predictors often appeared to be similar in size across follow-up periods. However, among OYA probationers, four predictors had modest and non-significant associations with 12-month recidivism and larger and significant associations with 24-month recidivism.

Examining the Inclusion of Misdemeanors in Oregon's Recidivism Measure

OYA's official juvenile recidivism measure—that is, the measure that was used in its recidivism reporting and internal publications as of the beginning of this project—was felony adjudication or conviction in the juvenile or adult system within 36 months among first-time releasees. To put this into national context, in 2020, 70% of states used adjudication/conviction as the focal marker event, 52% used a 36-month follow-up, and 80% tracked recidivism into the adult system (Casey & Siennick, 2022). Most states did not limit their measure to felony adjudications/convictions as did Oregon. The exclusion of misdemeanors in Oregon was due to variation across counties in how misdemeanors were recorded, most notably in the adult system. This is discussed in more detail below.

One goal of this project was to assist OYA in evaluating potential changes to its current measure of juvenile recidivism. One potential change that was discussed at the beginning of the project was the expansion of the measure to include not only felonies, but also misdemeanors. The barrier to doing that was the unavailability of data on misdemeanors occurring after youth were no longer under the jurisdiction of the juvenile court. Oregon's Criminal Justice Commission (CJC), the centralized state (adult) criminal justice agency, did not share adult misdemeanor data with OYA. As alluded to above, the CJC did not have complete data on adult misdemeanors for all counties. County-level municipal and justice courts process DUIs, trespassing cases, and other low-level misdemeanors, and those data were not recorded in the same system as other misdemeanors. It was unknown how many misdemeanors were missed in the central database. In addition, the matching process by which the CJC tracked misdemeanor recidivism had some error. State offender identification numbers are unique assigned identifiers that are given to all people in the CJC's records and to most youth in OYA's records. When SID numbers were missing (often due to a lack of fingerprinting), matching was done by name and date of birth. Data entry errors, absent fingerprints, and multiple matches could result in unmatched records or overmatched records.

In addition to these data quality issues, there were practical barriers to merging adult misdemeanor data with JJIS data. Data sharing agreements in Oregon are very specific, and must describe the particular data elements that are to be shared between agencies. Although OYA and the CJC already had a data sharing agreement regarding the sharing of adult felony data, that existing agreement would need to be updated to cover the transfer of adult misdemeanor data before such a transfer occurred. Although this did not occur before the end of the project period, the discussions that emerged from this project helped prompt working group discussions on the development of a standardized interagency data sharing agreement that in the future will remove some of the practical barriers to merging data across systems. It thus is possible that misdemeanor data from the adult system will one day be available to OYA.

Examining Parole Revocations as an Alternative Recidivism Measure

Discussions then turned to other potentially desirable modifications to OYA's current recidivism measure. OYA was particularly interested in exploring forms of juvenile reoffending that were not captured by felony adjudication and conviction data. One theme that was present throughout the discussions was the possibility of using a broader definition of reoffending. For example, the possibility of measuring offenses committed while youth were still in OYA placements was discussed. Another new form of reoffending to potentially examine involved "revocations" or violations of the conditions of parole (this measure would be available only for parole youth). Revocation data might be considered useful recidivism information in that revocations (1) constitute new behaviors beyond those that led to initial system involvement, (2) could signify the potential ineffectiveness of OYA's or other providers' programming and intervention efforts, (3) could have potential consequences for the youth's career in the justice system, and (4) require OYA resources to be tracked and addressed. It thus is important to understand the predictors of revocations, including the extent to which they are predicted by different factors as compared to OYA's main recidivism measure.

To determine the extent to which tracking revocations might impact conclusions about recidivism among OYA-involved youth, we estimated descriptive statistics and regression models that paralleled those estimated for OYA's current recidivism measure, but that substituted revocations as the focal outcomes. We found that 39%, 46%, and 48% of parole youth were revoked within 12, 24, and 36 months respectively.

Table 21 shows the regression results. Notably, fewer risk-needs assessment items predicted revocations among parole youth than predicted felony re-adjudication/reconviction among the full sample (see table 19 for reference). For example, gender, race/ethnicity, prior weapons offenses, history of sexual abuse, and delinquent peers, among other items, predicted OYA's main recidivism measure in the earlier analysis but not this alternative recidivism measure in the current analysis. Still, there was consistency in the predictors of the three parole

Table 21. Coefficients from Logistic Regression Models Estimating Individual-Level Predictors' Effects on Revocations Captured within Different Time Windows, Oregon Parole Youth (*N* = 1,127)									
	12 Months			24 Months			36 Months		
Predictor	b	SE		b	SE		b	SE	
Models 1-3: Demographic Predictors									
Male	-0.199	(0.166)		-0.119	0.165		-0.061	0.164	
Black[a]	0.324	(0.227)		0.353	0.228		0.322	0.228	
Hispanic[a]	0.175	(0.155)		0.063	0.153		0.035	0.152	
Other non-white race/ethnicity[a]	0.181	(0.230)		0.116	0.229		0.129	0.229	
Age at release	-0.083	(0.046)		-0.196	0.048	***	-0.225	0.049	***
Models 4-6: Delinquency History Predictors									
Age at first offense	-0.012	(0.070)		-0.066	(0.068)		-0.105	(0.068)	
Prior misdemeanors	0.131	(0.058)	*	0.116	(0.057)	*	0.098	(0.057)	
Prior felonies	0.138	(0.071)		0.123	(0.070)		0.123	(0.070)	
Prior weapons offenses	0.101	(0.199)		0.021	(0.199)		-0.014	(0.198)	
Models 7-9: Family Predictors									
Out of home placements	0.119	(0.060)	*	0.112	(0.058)		0.105	(0.058)	
History of running away	0.133	(0.042)	**	0.111	(0.042)	**	0.089	(0.042)	*
History of neglect	0.163	(0.155)		0.352	(0.151)	*	0.388	(0.149)	**
Family incarceration	0.356	(0.154)	*	0.417	(0.149)	**	0.398	(0.148)	**
Parental substance abuse	-0.042	(0.145)		-0.212	(0.143)		-0.190	(0.142)	
Physical abuse	0.161	(0.152)		0.069	(0.150)		0.070	(0.149)	
Sexual abuse	0.070	(0.154)		0.124	(0.152)		0.154	(0.151)	
Models 10-12: Youth Predictors									
Attitudes towards the law	0.038	(0.087)		0.081	(0.086)		0.082	(0.086)	
Takes responsibility for behavior	0.142	(0.095)		0.097	(0.093)		0.098	(0.092)	
Delinquent peers	0.480	(0.227)	*	0.302	(0.216)		0.215	(0.210)	
Problem alcohol use	0.049	(0.175)		-0.022	(0.171)		-0.132	(0.171)	
Problem drug use	0.032	(0.201)		0.050	(0.196)		0.070	(0.195)	

Note. Results for each combination of a set of predictors and an outcome are from a single logistic regression model with bootstrapped standard errors. All models included controls for year, whether the individual had both a probation and parole record during the study window, and whether the risk-needs assessment instrument was administered within 90 days of status onset.
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

revocation measures; when a predictor was statistically significantly associated with one measure, it tended to also be significantly associated with the others. Furthermore, consistent with the models predicting adjudication/conviction, the directions of the predictors' effects were consistent across revocation follow-up lengths. In the latter models, no predictor had a positive and significant association with one outcome but a negative and significant association with another.

Other similarities with the models predicting adjudication/conviction were observed. In general, if a predictor was positively or negatively associated with parole revocations, its association with adjudication/conviction tended also to be in the same direction. Finally, as in the adjudication/conviction models, there was no clear pattern of consistently increasing or decreasing strength of associations across follow-up lengths. That is, the risk-needs assessment items were not consistently stronger or weaker predictors of recidivism as the time window for observing recidivism increased.

Examining Whether the Predictors of Recidivism Differ Across Race/Ethnicity

One final issue that was of particular interest to OYA was whether the predictors of recidivism varied across racial and ethnic groups. To examine this, we replicated our earlier models predicting adjudication or conviction measured at the 36-month follow-up separately for white, black, Hispanic, and other non-white race/ethnicity groups. The results are shown in table 22. Several findings emerged.

First, different risk factors emerged as significant predictors of recidivism for different groups. For example, delinquency history predicted recidivism among white and Hispanic but not black youth, and running away was a significant predictor among white and black youth but not Hispanic and other race youth. The models for white and Hispanic youth yielded the largest numbers of significant coefficients, but this could be due to the larger sample sizes for those groups. Second, the most notable group difference in the sizes of significant coefficients was seen for male gender, which appeared to be more strongly associated with recidivism in the models for black and Hispanic youth. Third, there were no pairs of analogous significant coefficients that had opposite signs for different racial or ethnic groups. Finally, although having a history of running away was positively associated with recidivism for white and black youth, indicators of abuse were negatively associated with recidivism for white and Hispanic youth.

Table 22. Coefficients from Logistic Regression Models Estimating Individual-Level Predictors' Effects on Felony Adjudication or Conviction Captured at 36 months by Race and Ethnicity, Oregon												
	White (n=1,653)			Black (n=216)			Hispanic (n=651)			Other Race (n=223)		
Predictor	*b*	SE		*b*	SE		*b*	SE		*b*	SE	
Models 1-4: Demographic Predictors												
Male	0.619	(0.173)	***	1.488	(0.582)	*	1.301	(0.366)	***	0.683	(0.503)	
Age at release	-0.059	(0.038)		-0.081	(0.103)		0.236	(0.075)	**	-0.092	(0.120)	
Models 5-8: Delinquency History Predictors												
Age at first offense	0.063	(0.065)		-0.074	(0.189)		0.199	(0.104)		0.196	(0.213)	
Prior misdemeanors	0.294	(0.054)	***	0.145	(0.146)		0.298	(0.084)	***	0.337	(0.197)	
Prior felonies	0.150	(0.068)	*	0.057	(0.190)		0.382	(0.107)	***	0.079	(0.225)	
Prior weapons offenses	0.215	(0.213)		0.556	(0.469)		0.112	(0.283)		1.307	(0.685)	
Models 9-12: Family Predictors												
Out of home placements	0.089	(0.062)		0.156	(0.162)		0.103	(0.092)		0.658	(0.239)	**
History of running away	0.128	(0.040)	***	0.286	(0.100)	**	0.036	(0.063)		0.083	(0.152)	
History of neglect	0.041	(0.143)		-0.133	(0.403)		0.195	(0.216)		-0.971	(0.645)	
Family incarceration	0.098	(0.136)		0.244	(0.392)		0.353	(0.205)		-0.652	(0.530)	
Parental substance abuse	-0.035	(0.130)		0.134	(0.376)		-0.034	(0.213)		0.055	(0.492)	
Physical abuse	-0.154	(0.143)		0.070	(0.413)		-0.510	(0.252)	*	0.537	(0.554)	
Sexual abuse	-0.529	(0.158)	***	-0.551	(0.504)		-0.884	(0.326)	**	-0.417	(0.505)	
Models 13-16: Youth Predictors												
Attitudes towards the law	0.047	(0.087)		0.079	(0.243)		0.219	(0.141)		0.149	(0.246)	
Takes responsibility for behavior	0.074	(0.094)		-0.183	(0.271)		-0.120	(0.146)		0.072	(0.318)	
Delinquent peers	0.404	(0.209)		0.695	(0.628)		-0.085	(0.406)		-0.742	(0.587)	
Problem alcohol use	0.206	(0.161)		0.540	(0.416)		0.596	(0.257)	*	0.976	(0.631)	
Problem drug use	0.553	(0.197)	**	-0.020	(0.433)		0.232	(0.284)		-0.212	(0.661)	

Note. Results for each combination of a set of predictors and an outcome are from a single logistic regression model with bootstrapped standard errors. All models included controls for year, probation versus parole status, if the individual had both a probation and parole record during the study window, and whether the risk-needs assessment instrument was administered within 90 days of status onset.
* $p < .05$; ** $p < .01$; *** $p < .001$

This latter finding runs counter to what might be expected for those predictors. In sum, there were both similarities and differences across racial and ethnic groups in the associations of risk factors with recidivism.

Conclusions from the Oregon Phase

The preceding results support four general conclusions, as follows:

- Youth-level risk factors for juvenile recidivism may operate similarly across disparate state contexts.
- There may be racial and ethnic differences in the ability of risk factors to predict juvenile recidivism.

- Agencies with smaller caseloads may be less able to detect associations of risk factors with juvenile recidivism.
- Organizational and logistical barriers may prevent states from adopting alternate measures of juvenile recidivism.

Phase 3: Florida Place Variation Study

The third phase of the project responded to calls for examinations of variability in juvenile reoffending across programs and geographic contexts (Walsh & Weber, 2014). Specifically, it examined whether conclusions about the amount of variation in the juvenile recidivism rates of different FDJJ programs, or of different geographic places in Florida, differed across operationalizations of recidivism. The analyses combined the FDJJ-provided individual-level outcomes from Phase 1 with additional identifiers for the FDJJ program that youths completed and for youths' home communities.

The Place Variation Analyses

The analyses for this phase involved statistical comparisons of the amounts of between-program and, separately, between-county variability in juvenile reoffending as assessed by different measures. To achieve these comparisons, we estimated a series of two-level multilevel models, each predicting a different version of the reoffending outcome. In these models, individual youth were nested within either programs or counties. The focal results of interest were the estimates of the amounts of variability in reoffending that lie between these higher-order units versus at the lower-order youth level. (Due to the dichotomous nature of the outcomes, the level one [youth-level] variance was calculated as π2/3 [Rodriguez & Elo, 2003]). More specifically, intraclass correlation coefficients (ICCs) were computed for each outcome measure. These coefficients gave the proportion of the variance in the measure that was accounted for by the program and county levels, rather than the individual level. We then used post-estimation significance tests developed for dependent ICCs (Donner & Zou, 2002; Zou & Donner, 2004) to determine whether those proportions differed significantly between the versions of the reoffending measure. Where they did, it indicated that the choice of reoffending measure affected conclusions about how much reoffending rates varied across programs and geographic contexts. Differences in ICCs are first examined using models estimated without control variables, results of which are presented in the lefthand columns of tables 23 and 24. Differences that were statistically significant in the null models were then re-estimated to control for a handful of key demographic characteristics including gender, race and ethnicity, and age, with results presented in the righthand columns of tables 23 and 24.

The Place Variation Results

Variation in Different Recidivism Measures by Program

The results presented in table 23 show whether the amount of variation in reoffending that is explained by FDJJ programs varied depending on which reoffending outcomes were used. A total of 13 comparisons were made, each generating a pair of ICCs that can be interpreted as the proportion of variation in reoffending for the given outcome measure that is attributable to differences across programs. One conclusion from these results can be observed by scanning down the columns presenting the ICCs for each outcome. Nearly all these coefficients were below 0.10, indicating that less than 10% of the variation in most of these outcomes was attributable to differences across FDJJ programs. The largest ICC was for commitment within 12 months (0.176), meaning 17.6% of the variation in commitment was explained at the program level, with a similar amount of 17.4% for technical violations.

A second conclusion comes from an examination of the differences in ICCs across outcomes. Of the thirteen comparisons, only five were statistically significant. For example, the first three comparisons were for different marker events—referral, adjudication, and commitment within 12 months. The ICC for referral was 0.097, indicating that nearly 10% of the variation in referral within 12 months was accounted for by variation across FDJJ programs. This is

Table 23. Comparison of Intraclass Coefficients across Programs								
	Without Controls				With Controls			
Outcomes Compared	ICC 1	ICC 2	% Diff.		ICC 1	ICC 2	% Diff.	
Referral vs adjudication within 12 months	0.097	0.103	6.5					
Referral vs commitment within 12 months	0.097	0.176	57.8	*	0.090	0.209	80.2	*
Adjudication vs commitment within 12 months	0.103	0.176	51.8	*	0.099	0.209	71.9	*
Adjudication or conviction within 6 vs 12 months	0.078	0.068	13.8					
Adjudication or conviction within 6 vs 24 months	0.078	0.057	31.3					
Adjudication or conviction within 12 vs 24 months	0.068	0.057	17.7					
Referral/arrest within 12 months without vs with adult system data	0.097	0.080	19.0					
Adjudication within 12 months without vs with adult system data	0.103	0.068	42.0	*	0.099	0.069	36.0	
New offense vs technical violation within 12 months	0.061	0.174	95.8	*	0.050	0.176	111.2	*
Misdemeanor vs felony adjudication within 12 months	0.048	0.093	64.9	*	0.046	0.078	50.3	
Adjudication/conviction for violent vs property offense within 12 months	0.050	0.072	35.8					
Violent vs drug offense within 12 months	0.050	0.036	31.1					
Property vs drug offense within 12 months	0.072	0.036	65.1					

* $p < .05$

compared with the ICC for adjudication within 12 months of 0.103, indicating that the variation attributable to programs was only slightly higher for adjudication than for referral. Since these ICCs are very similar, with a difference of just 6.5%, it is not surprising that the difference between them was not statistically significant. However, the other two pairwise comparisons between marker events—referral and adjudication compared with commitment—yielded larger differences in ICCs that were both statistically significant. Specifically, FDJJ programs explained 57.8% more relative variation in commitment compared with referral, and 51.8% more relative variation in commitment than adjudication. Significantly larger ICCs were also observed for adjudication within 12 months without adult system data versus with adult data (a 42.0% difference in ICCs), for technical violations compared with new offenses (a 95.8% difference), and for felonies compared with misdemeanors (a 64.9% difference). Differences in ICCs for varying follow-up periods, for referral/arrest with and without adult system data, and for varying offense types were not statistically significant.

For the ICC differences that were statistically significant, we next re-estimated the models while controlling for a set of demographic characteristics—gender, race and Hispanic origin, and age at release—to account for the possibility that any differences in explained variation across programs may be due to differences in the composition of youth who participate in those programs rather than the programs themselves. The first two significant differences were for referral versus commitment and adjudication versus commitment. After controlling for demographic composition, the differences in ICCs remained statistically significant, and they actually increased from 57.8% and 51.8%, respectively, to 80.2% and 71.9%. This suggests that differences in the demographic characteristics of individuals across programs were obscuring some of the differences in variation in these outcomes that can be attributed to programs. It appears that the greater observed differences in program-level variation after including controls is primarily due to an increase in the ICC for commitment (0.176 to 0.209), while the ICCs for referral and adjudication showed little change. Though the difference in ICCs for adjudication with and without adult system data was significant in the model without controls, it declined slightly after including controls—from a difference of 42.0% to 36.0%—and the difference was no longer statistically significant. This difference in ICCs for misdemeanor and felony adjudication also was no longer significant after including controls. However, the difference for new offenses versus technical violations remained statistically significant, and increased from a difference of 95.8% to 111.2%, largely due to a decline in the proportion of variation at the individual level for new offenses.

Variation in Different Recidivism Measures by County

Table 24 presents a similar set of ICC comparisons, but now examining the proportion of variation in reoffending attributable to counties. In general, the ICCs in this table show that counties explained a smaller relative proportion of variation in every outcome compared with FDJJ programs, with ICCs lower than 0.04 for nearly every outcome, reaching a high of 0.093 for technical violations. Thus, county differences accounted for only about 2-4% of the variation in reoffending, with a maximum of 9.3% for technical violations. Only three of the 13 comparisons yielded significant differences, all of which were also significantly different in the analysis of variation across programs detailed above. Differences in ICCs for referral vs. commitment (67.9% difference) and adjudication vs. commitment (69.2% difference) were statistically significant, and the size of the differences was somewhat larger for these two contrasts than what was observed for FDJJ programs. A significant difference was also observed for new offenses compared with technical violations, where the proportion of variation attributable to counties was nearly 10% for technical violations (0.093), but only about 4% for new offenses (0.039).

Next, we re-estimated the models with significant ICC differences while controlling for demographic characteristics. Like the results for program differences above, we observed that the differences in ICCs for commitment compared with referral and adjudication remained statistically significant, and they were greater after accounting for these compositional differences. We see a similar finding for new offenses versus technical violations, where the ICC difference was larger after including individual-level controls and it remained statistically significant.

Table 24. Comparison of Intraclass Coefficients across Counties

Outcomes Compared	Without Controls				With Controls			
	ICC 1	ICC 2	% Diff.		ICC 1	ICC 2	% Diff.	
Referral vs adjudication within 12 months	0.038	0.037	1.6					
Referral vs commitment within 12 months	0.038	0.076	67.9	*	0.021	0.076	113.6	*
Adjudication vs commitment within 12 months	0.037	0.076	69.2	*	0.030	0.076	87.7	*
Adjudication or conviction within 6 vs 12 months	0.028	0.028	1.2					
Adjudication or conviction within 6 vs 24 months	0.028	0.039	31.5					
Adjudication or conviction within 12 vs 24 months	0.028	0.039	32.7					
Referral/arrest within 12 months without vs with adult system data	0.038	0.039	2.2					
Adjudication within 12 months without vs with adult system data	0.037	0.028	27.7					
New offense vs technical violation within 12 months	0.039	0.093	82.8	*	0.024	0.090	116.2	*
Misdemeanor vs felony adjudication within 12 months	0.023	0.021	10.3					
Adjudication/conviction for violent vs property offense within 12 months	0.017	0.024	34.6					
Violent vs drug offense within 12 months	0.017	0.032	59.8					
Property vs drug offense within 12 months	0.024	0.032	26.6					

* $p < .05$

Conclusions from the Place Variation Study

The preceding results support five general conclusions, as follows:

- Most of the variation in juvenile recidivism was between youth, rather than between programs or counties.
- There was greater contextual variation in commitment than in other marker events.
- Programs and counties explained statistically equivalent amounts of variation in juvenile recidivism as measured over different time periods. Similarly, the inclusion of adult system data had little impact on the amount of contextual variation in recidivism.
- There was more contextual variation in technical violations than in new offenses.
- The amount of contextual variation in juvenile recidivism was similar across offense types.

Implications, Expected Applicability, Limitations, and Conclusion

Implications

Overall, the three studies revealed considerable similarities across different operationalizations of juvenile recidivism. In many cases, predictors of recidivism had comparable associations with different marker events, with recidivism as measured within different time windows, with recidivism as measured by different data sources, and with the recidivism of different racial and ethnic groups. When differences in associations were found, they typically were differences in the magnitude of associations, not differences in their presence or direction. The descriptive findings show that choices of operationalization of juvenile recidivism affect calculated recidivism rates; however, the combined results suggest that if one's interest is in the presence (versus strength) of a predictor's association, different recidivism measures may be more interchangeable than previously had been assumed.

If predictive strength is of interest, additional conclusions are worth noting. There may be substantive differences between marker events that warrant measuring multiple types. In addition, predictors may have stronger associations with measures of recidivism that follow youth into the adult criminal justice system. They also may have more variable associations with different offense types, and with contextual predictors. Finally, risk factors may have stronger associations with lower-risk youth than with youth who have had more serious juvenile justice system contact. Thus, although most effects were consistent across recidivism measures, in some cases conclusions involving specific predictor-outcome combinations may be affected by features of measurement and of the sample.

These less common but still visible differences across recidivism measures bolster prior recommendations that agencies track multiple operationalizations of recidivism. Having such data available would facilitate comparisons of risk factors' effects across outcomes, as well as comparisons of recidivism across agencies. Indeed, it was this type of multifaceted data collection that made the current set of studies possible. However, although this data collection might be desirable, in practice organizational and logistical barriers may prevent agencies from implementing it. Marker events are defined differently in different jurisdictions, lengthy follow-up periods may not always be possible, and data sharing across agencies may be hampered by technical, privacy, and bureaucratic issues. These factors may pose important barriers to the Juvenile Justice Reform Act's call for a national system of measurement of juvenile recidivism.

Expected Applicability of the Research

This project used data from two state agencies that varied considerably in their size, in the organization of their juvenile justice systems, in the populations they served, and in their information-sharing with other state agencies. Despite this, the substantive conclusions were largely similar across the two state contexts. This provides some reassurance that the findings would generalize to additional states and agencies. The consistency of the findings with those of the limited number of previous studies on this topic provides additional reassurance. Still, it will be important for future researchers to examine these issues in other contexts in order to confirm that we have uncovered broadly applicable patterns, rather than patterns that apply only in states like Florida and Oregon.

One motivator for the original NIJ solicitation to which this project responded was the call for a national system of measurement of juvenile recidivism. Our work with Oregon revealed that bureaucratic and other system-level factors may impede states' adoption of whatever recidivism measure ultimately is chosen for this national system. Our census of states' current practices indicated that the U.S. is closer to a national system than it previously was, and our results indicated that it is reasonable to export knowledge about the predictors of juvenile recidivism from one state to another. However, we are some distance from the scenario where all states include the same operationalization—for example, two-year adjudication or conviction, as recommended in previous literature—among their collected measures.

Limitations

This project's implications must be considered in light of its limitations. First, like many states, Florida does not use social security numbers to track youth involved in the juvenile justice system. Although this protects the privacy of juvenile records, it also makes it difficult to match those records to other data sources—including data from the adult criminal justice system. Interagency matches are done using a combination of name and date of birth, which can result in both multiple matches and unmatched records. This is one potential source of error in the recidivism data, and it is a source that also may be relevant to other agencies' efforts to follow youth across systems.

Second, during the study window, Oregon changed its approach to drug offenses. In 2014 marijuana possession was decriminalized, and in August 2017 the possession of most other drugs was redefined as a misdemeanor. In February 2020, at the very end of the study window, the possession of most drugs was decriminalized. This could have reduced felony recidivism rates among our sample, and if our predictors differentially predicted drug offenses it also could have impacted the observed correlations. It also would have affected rates of misdemeanor recidivism, had OYA's data sharing agreement with the CJC resulted in the collection of that information. Examinations of recidivism across time periods (e.g., across multiple years) should be interpreted in the context of relevant changes in policy and practice.

Third, the use of any single recidivism measure may mask nuances regarding the specific actions that constituted the reoffending. For instance, our examination of commitment did not distinguish commitments that were due to new offenses from those that were due to technical violations. Agencies and researchers should consider the behaviors that may be captured by their chosen measures of recidivism.

Fourth, many state juvenile justice systems—including those in California, Mississippi, and, relevant to this study, Oregon—are decentralized. Although the local organization of juvenile justice services can have benefits, it also can result in variation in recidivism definitions, recordkeeping practices, and other factors that affect efforts to measure and predict recidivism. Decentralization thus may be another factor that may impact states' abilities to shape the measurement and tracking of juvenile recidivism.

Conclusion

The current project revealed that choices of operationalization of juvenile recidivism have a large impact on calculated recidivism rates and a smaller impact on conclusions about the predictors of recidivism. Recidivism rates were higher for earlier points of system contact, when adult system data were included, and for longer follow-up periods. Nearly two-thirds of the time, predictors had statistically equivalent effects on different recidivism measures. When differences were found, they typically involved the magnitude of associations, not differences in their presence or direction. Observed differences also tended to indicate weaker predictive power for earlier points of system contact, longer tracking periods, and measures that lacked adult system information. While these findings suggest potential benefits of utilizing multiple measures of juvenile recidivism, logistical and bureaucratic challenges may impede such data collection efforts. Future research should continue to assess how measurement variability affects conclusions about other established correlates of juvenile reoffending, thus advancing our progress toward identifying an optimal uniform measurement system of juvenile recidivism.

Artifacts

Publications

Casey, William M., and Sonja E. Siennick. 2022. Juvenile recidivism: An examination of state measurement strategies. *American Journal of Criminal Justice*, 48, 786–807. https://doi.org/10.1007/s12103-022-09684-7

Siennick, Sonja E., and Jhon A. Pupo. 2023. Exploring variation in the strength of association of a validated recidivism risk score with seven common measures of juvenile recidivism: A research note. *Youth Violence and Juvenile Justice*, *21*(1), 72–80. https://doi.org/10.1177/15412040221115056

Conference Presentations

Casey, William M., and Sonja E. Siennick. 2022. An examination of the relationship between social ties and recidivism: Does the association change when using different follow-up lengths? Paper presented at the annual meetings of the American Society of Criminology.

Casey, William M., and Sonja E. Siennick. 2023. Race/ethnicity, risk, and juvenile recidivism: Does outcome variation matter? Paper presented at the annual meetings of the American Society of Criminology.

Cowell, Dequan. 2023. A social learning approach to juvenile recidivism. Paper presented at the annual meetings of the American Society of Criminology.

Cowell, Dequan, Brian J. Stults, and Sonja E. Siennick. 2022. The effect of concentrated disadvantage on juvenile recidivism: Variation by race, economic capital, and operationalization of recidivism. Paper presented at the annual meetings of the American Society of Criminology.

Siennick, Sonja E., and William M. Casey. 2022. Measurement matters: Comparing different operationalizations of juvenile recidivism through point estimates and multivariate multilevel models. Paper presented at the annual meetings of the American Society of Criminology.

Siennick, Sonja E., Jacob Judd, and Jennifer Copp. 2023. Family-related adversity and recidivism among residentially committed youth. Paper presented at the annual meetings of the American Society of Criminology.

Siennick, Sonja E., George B. Pesta, and Mayra Picon. 2020. New research to better understand recidivism: A two-state examination of varied measurement strategies for juvenile reoffending. Paper presented at the National Conference on Juvenile Justice (virtual meeting).

Stults, Brian J., Dequan Cowell, and Sonja E. Siennick. 2022. Inconsistency in the measurement of juvenile reoffending and its impact on assessments of community variation. Paper presented at the annual meetings of the American Society of Criminology.

Stults, Brian J., and Sonja E. Siennick. 2023. The importance of county characteristics for juvenile recidivism: Explaining differences across measures of reoffending. Paper presented at the annual meetings of the American Society of Criminology.

Datasets

The Measuring Juvenile Reoffending Study: Florida Studies Data

A person-level file featuring the juvenile recidivism measures, individual-level predictors, and contextual predictors described in the sections of this report that discuss Phases 1 and 3 of the project.

The Measuring Juvenile Reoffending Study: Oregon Study Data

A person-level file featuring the juvenile recidivism measures and individual-level predictors describe in the section of this report that discusses Phase 2 of the project.

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Appendices

Appendix A. Recidivism Rates for Subgroups of Youth

Table A1. Variation in Rates of Recidivism as Operationalized in Multiple Ways, by Gender

Operationalization	Proportion Recidivating by this Measure	
	Males (*N* = 75,103)	Non-males (*N* = 29,251)
Comparison 1		
Referral within 12 months	24.5%	16.9%
Adjudication within 12 months	15.8%	9.9%
Commitment within 12 months	4.5%	1.5%
Comparison 2		
Adjudication or conviction within 6 months	15.3%	7.7%
Adjudication or conviction within 12 months	23.8%	12.6%
Adjudication or conviction within 24 months	32.8%	18.4%
Comparison 3		
Referral within 12 months, without adult system data	24.5%	16.9%
Referral or arrest within 12 months, with adult system data	37.3%	23.3%
Comparison 4		
Adjudication within 12 months, without adult system data	15.8%	9.9%
Adjudication or conviction within 12 months, with adult system data	23.8%	12.6%
Comparison 5		
Referral or arrest for new offense within 12 months	30.3%	18.4%
Technical violation within 12 months	8.7%	4.5%
Comparison 6		
Adjudication or conviction within 12 months for a misdemeanor	17.1%	9.8%
Adjudication or conviction within 12 months for a felony	12.5%	3.8%
Comparison 7		
Adjudication or conviction within 12 months for violent offense	6.0%	4.1%
Adjudication or conviction within 12 months for property offense	10.3%	4.6%
Adjudication or conviction within 12 months for drug offense	4.6%	1.3%

Source: Florida Department of Juvenile Justice and Florida Department of Law Enforcement

Table A2. Variation in Rates of Recidivism as Operationalized in Multiple Ways, by Race and Ethnicity				
Operationalization	Proportion Recidivating by this Measure			
	White youth (*N* = 42,001)	Black youth (*N* = 45,429)	Hispanic youth (*N* = 16,307)	Youth of other racial groups (*N*= 617)
Comparison 1				
Referral within 12 months	18.5%	27.1%	19.8%	11.3%
Adjudication within 12 months	11.6%	17.5%	11.7%	5.8%
Commitment within 12 months	2.4%	5.2%	2.6%	1%
Comparison 2				
Adjudication or conviction within 6 months	10.6%	16.5%	10.9%	6.0%
Adjudication or conviction within 12 months	17.0%	25.2%	17.7%	9.2%
Adjudication or conviction within 24 months	24.1%	34.5%	25.1%	15.9%
Comparison 3				
Referral within 12 months, without adult system data	18.5%	27.1%	19.8%	11.3%
Referral or arrest within 12 months, with adult system data	27.7%	39.6%	31.2%	19.8%
Comparison 4				
Adjudication within 12 months, without adult system data	11.6%	17.5%	11.7%	5.8%
Adjudication or conviction within 12 months, with adult system data	17.0%	25.2%	17.7%	9.2%
Comparison 5				
Referral or arrest for new offense within 12 months	22.4%	32.2%	24.6%	14.4%
Technical violation within 12 months	5.7%	10.0%	5.8%	3.2%
Comparison 6				
Adjudication or conviction within 12 months for a misdemeanor	12.8%	18.0%	12.9%	7.0%
Adjudication or conviction within 12 months for a felony	7.2%	13.3%	8.6%	3.7%
Comparison 7				
Adjudication or conviction within 12 months for violent offense	3.9%	7.3%	4.5%	2.9%
Adjudication or conviction within 12 months for property offense	6.7%	11.2%	7.0%	3.1%
Adjudication or conviction within 12 months for drug offense	3.7%	3.5%	3.8%	1.5%
Source: Florida Department of Juvenile Justice and Florida Department of Law Enforcement				

Table A3. Variation in Rates of Recidivism as Operationalized in Multiple Ways, by Initial Disposition			
Operationalization	Proportion Recidivating by this Measure		
	Diversion youth (*N* = 48,616)	Probation youth (*N* = 43,799)	Residential youth (*N* = 11,939)
Comparison 1			
Referral within 12 months	21.8%	16.5%	46.8%
Adjudication within 12 months	12.7%	11.0%	32.0%
Commitment within 12 months	1.2%	2.5%	17.7%
Comparison 2			
Adjudication or conviction within 6 months	8.6%	13.1%	32.2%
Adjudication or conviction within 12 months	14.6%	21.2%	43.5%
Adjudication or conviction within 24 months	22.4%	29.7%	51.2%
Comparison 3			
Referral within 12 months, without adult system data	21.8%	16.5%	46.8%
Referral or arrest within 12 months, with adult system data	25.6%	34.9%	59.4%
Comparison 4			
Adjudication within 12 months, without adult system data	12.7%	11.0%	32.0%
Adjudication or conviction within 12 months, with adult system data	14.6%	21.2%	43.5%
Comparison 5			
Referral or arrest for new offense within 12 months	22.8%	25.7%	48.5%
Technical violation within 12 months	4.7%	4.7%	29.7%
Comparison 6			
Adjudication or conviction within 12 months for a misdemeanor	11.8%	15.8%	25.8%
Adjudication or conviction within 12 months for a felony	6.1%	10.5%	24.5%
Comparison 7			
Adjudication or conviction within 12 months for violent offense	4.5%	5.2%	10.7%
Adjudication or conviction within 12 months for property offense	6.6%	8.0%	19.4%
Adjudication or conviction within 12 months for drug offense	2.9%	3.9%	5.9%
Source: Florida Department of Juvenile Justice and Florida Department of Law Enforcement			

Appendix B. Coefficient Tables from the Florida Studies

Appendix B1. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on Different Marker Events Capturing 12 Month Recidivism in the Juvenile System, Florida

	Referral			Adjudication			Commitment		
Predictor	b	SE		b	SE		b	SE	
Model 1: Demographic Predictors									
Male	0.447	(0.024)	***	0.504	(0.032)	***	0.923	(0.068)	***
Black[a]	0.404	(0.023)	***	0.352	(0.029)	***	0.503	(0.053)	***
Hispanic[a]	0.104	(0.032)	***	-0.003	(0.041)		0.111	(0.080)	
Other non-white race/ethnicity[a]	-0.512	(0.165)	**	-0.710	(0.231)	**	-0.699	(0.510)	
Age at release	-0.445	(0.006)	**	-0.477	(0.008)	***	-0.633	(0.017)	***
Model 2: Delinquency History Predictors									
Age at first offense	-0.413	(0.009)	***	-0.437	(0.012)	***	-0.557	(0.027)	***
Prior misdemeanors	0.247	(0.013)	***	0.235	(0.016)	***	0.183	(0.025)	***
Prior felonies	0.141	(0.014)	***	0.160	(0.017)	***	0.287	(0.027)	***
Prior weapons offenses	-0.095	(0.039)	*	-0.194	(0.049)	***	-0.244	(0.075)	**
Prior commitments	0.091	(0.035)	**	-0.055	(0.044)		0.062	(0.065)	
Prior pickup orders	-0.026	(0.019)		-0.070	(0.023)	**	0.027	(0.034)	
Model 3: Family Predictors									
Out of home placements	0.068	(0.021)	**	0.035	(0.026)		0.055	(0.040)	
History of running away	0.143	(0.010)	***	0.164	(0.013)	***	0.219	(0.019)	***
History of neglect	0.228	(0.045)	***	0.216	(0.055)	***	0.313	(0.086)	***
Family incarceration	0.420	(0.021)	***	0.437	(0.027)	***	0.448	(0.048)	***
Parental substance abuse	-0.018	(0.038)		-0.020	(0.047)		-0.015	(0.076)	
Physical abuse	-0.038	(0.036)		-0.083	(0.045)		-0.090	(0.074)	
Sexual abuse	-0.274	(0.047)	***	-0.258	(0.058)	***	-0.437	(0.102)	***
Model 4: Youth Predictors									
Attitudes towards the law	0.182	(0.021)	***	0.217	(0.026)	***	0.241	(0.044)	***
Takes responsibility for behavior	0.176	(0.022)	***	0.179	(0.027)	***	0.254	(0.046)	***
Delinquent peers	0.310	(0.021)	***	0.285	(0.026)	***	0.407	(0.048)	***
Problem alcohol use	-0.269	(0.052)	***	-0.248	(0.064)	***	-0.249	(0.098)	*
Problem drug use	0.195	(0.032)	***	0.134	(0.039)	***	0.229	(0.062)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* p < .05; ** p < .01; *** p < .001

Appendix B2. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on Adjudication or Conviction Captured within Different Time Windows, Florida

	6 Months			12 Months			24 Months		
Predictor	b	SE		b	SE		b	SE	
Model 1: Demographic Predictors									
Male	0.736	(0.038)	***	0.794	(0.032)	***	0.823	(0.025)	***
Black[a]	0.463	(0.033)	***	0.466	(0.028)	***	0.497	(0.023)	***
Hispanic[a]	0.001	(0.047)		0.031	(0.040)		0.046	(0.032)	
Other non-white race/ethnicity[a]	-0.563	(0.257)	**	-0.745	(0.215)	***	-0.462	(0.157)	***
Age at release	-0.154	(0.010)	***	-0.179	(0.008)	***	-0.224	(0.006)	***
Model 2: Delinquency History Predictors									
Age at first offense	-0.129	(0.014)	***	-0.176	(0.011)	***	-0.251	(0.009)	***
Prior misdemeanors	0.408	(0.018)	***	0.406	(0.016)	***	0.336	(0.014)	***
Prior felonies	0.398	(0.019)	***	0.365	(0.016)	***	0.310	(0.014)	***
Prior weapons offenses	-0.134	(0.054)	**	-0.069	(0.048)		-0.071	(0.040)	
Prior commitments	0.185	(0.046)	***	0.181	(0.041)	***	0.157	(0.040)	***
Prior pickup orders	0.138	(0.025)	***	0.106	(0.023)	***	0.092	(0.019)	***
Model 3: Family Predictors									
Out of home placements	0.013	(0.029)		0.040	0.026		0.045	(0.022)	*
History of running away	0.222	(0.014)	***	0.183	0.013	***	0.157	(0.011)	***
History of neglect	0.230	(0.064)	***	0.209	0.057	***	0.183	(0.047)	***
Family incarceration	0.401	(0.031)	***	0.438	0.027	***	0.424	(0.022)	***
Parental substance abuse	0.001	(0.054)		0.007	(0.048)		0.000	(0.039)	
Physical abuse	-0.104	(0.052)	*	-0.126	(0.045)	**	-0.052	(0.037)	
Sexual abuse	-0.543	(0.070)	***	-0.469	(0.060)	***	-0.479	(0.049)	***
Model 4: Youth Predictors									
Attitudes towards the law	0.264	(0.030)	***	0.268	(0.026)	***	0.267	(0.021)	***
Takes responsibility for behavior	0.159	(0.032)	***	0.180	(0.028)	***	0.155	(0.023)	***
Delinquent peers	0.280	(0.031)	***	0.258	(0.026)	***	0.257	(0.021)	***
Problem alcohol use	-0.155	(0.071)	*	-0.149	(0.063)	*	-0.177	(0.053)	***
Problem drug use	0.349	(0.044)	***	0.328	(0.039)	***	0.304	(0.033)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B3. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Referral/Arrest when Adult System Data Is Not versus Is Included, Florida

	Referral Without FDLE Data			Referral with FDLE Data		
Predictor	b	SE		b	SE	
Model 1: Demographic Predictors						
Male	0.481	(0.026)	***	0.630	(0.022)	***
Black[a]	0.413	(0.024)	***	0.507	(0.020)	***
Hispanic[a]	0.100	(0.034)	**	0.171	(0.028)	***
Other non-white race/ethnicity[a]	-0.534	(0.176)	**	-0.368	(0.133)	**
Age at release	-0.469	(0.007)	***	-0.061	(0.006)	***
Model 2: Delinquency History Predictors						
Age at first offense	-0.433	(0.010)	***	-0.83	(0.008)	***
Prior misdemeanors	0.251	(0.014)	***	0.426	(0.012)	***
Prior felonies	0.149	(0.014)	***	0.349	(0.012)	***
Prior weapons offenses	-0.100	(0.042)	*	-0.021	(0.035)	
Prior commitments	0.073	(0.037)	*	0.210	(0.031)	***
Prior pickup orders	-0.020	(0.020)		0.217	(0.017)	***
Model 3: Family Predictors						
Out of home placements	0.068	(0.022)	**	0.055	(0.019)	**
History of running away	0.147	(0.011)	***	0.160	(0.010)	***
History of neglect	0.237	(0.047)	***	0.179	(0.042)	***
Family incarceration	0.436	(0.022)	***	0.397	(0.020)	***
Parental substance abuse	-0.018	(0.040)		-0.012	(0.035)	
Physical abuse	-0.039	(0.037)		-0.074	(0.033)	*
Sexual abuse	-0.281	(0.049)	***	-0.415	(0.043)	***
Model 4: Youth Predictors						
Attitudes towards the law	0.192	(0.022)	***	0.256	(0.019)	***
Takes responsibility for behavior	0.182	(0.023)	***	0.159	(0.020)	***
Delinquent peers	0.315	(0.022)	***	0.248	(0.019)	***
Problem alcohol use	-0.270	(0.053)	***	-0.175	(0.047)	***
Problem drug use	0.203	(0.033)	***	0.401	(0.029)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B4. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication/Conviction when Adult System Data Is Not versus Is Included, Florida						
	Adjudication Without FDLE Data			Adjudication with FDLE Data		
Predictor	b	SE		b	SE	
Model 1: Demographic Predictors						
Male	0.499	(0.031)	***	0.706	(0.026)	***
Black[a]	0.347	(0.028)	***	0.405	(0.023)	***
Hispanic[a]	0.007	(0.040)		0.029	(0.032)	
Other non-white race/ethnicity[a]	-0.691	(0.227)	**	-0.619	(0.173)	***
Age at release	-0.462	(0.008)	***	-0.126	(0.007)	***
Model 2: Delinquency History Predictors						
Age at first offense	-0.427	(0.012)	***	-0.129	(0.009)	***
Prior misdemeanors	0.218	(0.016)	***	0.348	(0.013)	***
Prior felonies	0.150	(0.016)	***	0.320	(0.013)	***
Prior weapons offenses	-0.183	(0.046)	***	-0.055	(0.038)	
Prior commitments	-0.041	(0.040)		0.147	(0.033)	***
Prior pickup orders	-0.057	(0.022)	*	0.095	(0.018)	***
Model 3: Family Predictors						
Out of home placements	0.033	(0.025)		0.031	(0.021)	
History of running away	0.157	(0.012)	***	0.155	(0.010)	***
History of neglect	0.210	(0.053)	***	0.177	(0.046)	***
Family incarceration	0.425	(0.026)	***	0.369	(0.022)	***
Parental substance abuse	-0.019	(0.045)		0.006	(0.038)	
Physical abuse	-0.079	(0.043)		-0.105	(0.037)	**
Sexual abuse	-0.249	(0.056)	***	-0.421	(0.049)	***
Model 4: Youth Predictors						
Attitudes towards the law	0.204	(0.025)	***	0.228	(0.021)	***
Takes responsibility for behavior	0.170	(0.026)	***	0.147	(0.022)	***
Delinquent peers	0.277	(0.025)	***	0.217	(0.021)	***
Problem alcohol use	-0.235	(0.061)	***	-0126	(0.050)	*
Problem drug use	0.137	(0.038)	***	0.288	(0.031)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B5. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Referral/Arrest for a New Charge versus a Technical Violation, Florida						
	New Charge			Technical Violation		
Predictor	b	SE		b	SE	
Model 1: Demographic Predictors						
Male	0.576	(0.019)	***	0.431	(0.036)	***
Black[a]	0.401	(0.017)	***	0.346	(0.031)	***
Hispanic[a]	0.115	(0.024)	***	0.017	(0.046)	
Other non-white race/ethnicity[a]	-0.446	(0.124)	***	-0.388	(0.253)	
Age at release	-0.182	(0.005)	***	-0.367	(0.009)	***
Model 2: Delinquency History Predictors						
Age at first offense	-0.185	(0.007)	***	-0.334	(0.014)	***
Prior misdemeanors	0.306	(0.010)	***	0.277	(0.016)	***
Prior felonies	0.248	(0.010)	***	0.199	(0.167)	***
Prior weapons offenses	-0.023	(0.030)		-0.221	(0.048)	***
Prior commitments	0.098	(0.026)	***	0.105	(0.038)	**
Prior pickup orders	0.060	(0.014)	***	0.082	(0.022)	***
Model 3: Family Predictors						
Out of home placements	0.057	(0.016)	***	-0.017	(0.026)	
History of running away	0.114	(0.008)	***	0.188	(0.012)	***
History of neglect	0.174	(0.035)	***	0.171	(0.055)	**
Family incarceration	0.341	(0.017)	***	0.491	(0.029)	***
Parental substance abuse	-0.010	(0.029)		0.033	(0.047)	
Physical abuse	-0.061	(0.028)	*	-0.058	(0.046)	
Sexual abuse	-0.372	(0.037)	***	-0.235	(0.060)	***
Model 4: Youth Predictors						
Attitudes towards the law	0.192	(0.016)	***	0.191	(0.027)	***
Takes responsibility for behavior	0.150	(0.017)	***	0.145	(0.029)	***
Delinquent peers	0.230	(0.016)	***	0.209	(0.029)	***
Problem alcohol use	-0.169	(0.040)	***	-0.146	(0.061)	*
Problem drug use	0.260	(0.024)	***	0.294	(0.039)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B6. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication/Conviction for a Misdemeanor versus a Felony Offense, Florida

	Misdemeanor Adjudication			Felony Adjudication		
Predictor	b	SE		b	SE	
Model 1: Demographic Predictors						
Male	0.537	(0.024)	***	1.124	(0.035)	***
Black[a]	0.301	(0.021)	***	0.538	(0.027)	***
Hispanic[a]	-0.020	(0.030)		0.162	(0.038)	***
Other non-white race/ethnicity[a]	-0.584	(0.169)	***	-0.553	(0.229)	*
Age at release	-0.137	(0.006)	***	-0.128	(0.007)	***
Model 2: Delinquency History Predictors						
Age at first offense	-0141	(0.009)	***	-0.141	(0.011)	***
Prior misdemeanors	0.324	(0.012)	***	0.212	(0.014)	***
Prior felonies	0.200	(0.012)	***	0.431	(0.014)	***
Prior weapons offenses	-0.067	(0.036)		-0.038	(0.040)	
Prior commitments	0.030	(0.031)		0.071	(0.033)	*
Prior pickup orders	0.051	(0.017)	**	0.089	(0.019)	***
Model 3: Family Predictors						
Out of home placements	0.036	(0.019)		0.035	(0.023)	
History of running away	0.113	(0.010)	***	0.107	(0.011)	***
History of neglect	0.123	(0.042)	**	0.181	(0.050)	***
Family incarceration	0.329	(0.020)	***	0.293	(0.025)	***
Parental substance abuse	0.042	(0.035)		-0.039	(0.043)	
Physical abuse	-0.110	(0.034)	**	-0.098	(0.041)	*
Sexual abuse	-0.299	(0.046)	***	-0.638	(0.060)	***
Model 4: Youth Predictors						
Attitudes towards the law	0.189	(0.020)	***	0.162	(0.023)	***
Takes responsibility for behavior	0.134	(0.021)	***	0.132	(0.025)	***
Delinquent peers	0.187	(0.020)	***	0.253	(0.024)	***
Problem alcohol use	-0.148	(0.048)	**	-0.141	(0.054)	**
Problem drug use	0.209	(0.029)	***	0.268	(0.034)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B7. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication or Conviction for Different Offense Types, Florida

	Violent Offense			Property Offense			Drug Offense		
Predictor	b	SE		b	SE		b	SE	
Model 1: Demographic Predictors									
Male	0.300	(0.035)	***	0.748	(0.032)	***	1.220	(0.056)	***
Black[a]	0.523	(0.033)	***	0.425	(0.026)	***	-0.161	(0.038)	***
Hispanic[a]	0.140	(0.047)	**	0.035	(0.038)		-0.028	(0.050)	
Other non-white race/ethnicity[a]	-0.187	(0.248)		-0.683	(0.241)	**	-0.866	(0.341)	*
Age at release	-0.262	(0.009)	***	-0.232	(0.007)	***	-0.071	(0.011)	***
Model 2: Delinquency History Predictors									
Age at first offense	-0.317	(0.014)	***	-0.230	(0.011)	***	-0.049	(0.015)	**
Prior misdemeanors	0.230	(0.017)	***	0.202	(0.014)	***	0.262	(0.021)	***
Prior felonies	0.157	(0.018)	***	0.343	(0.015)	***	0.209	(0.021)	***
Prior weapons offenses	-0.151	(0.052)	**	-0.136	(0.042)	**	-0.003	(0.060)	
Prior commitments	0.116	(0.042)	**	-0.034	(0.034)		-0.043	(0.051)	
Prior pickup orders	-0.035	(0.024)		0.050	(0.020)	*	0.035	(0.028)	
Model 3: Family Predictors									
Out of home placements	0.112	(0.026)	***	0.043	(0.023)		-0.079	(0.037)	*
History of running away	0.112	(0.013)	***	0.126	(0.011)	***	0.037	(0.017)	*
History of neglect	0.087	(0.059)		0.216	(0.049)	***	0.306	(0.072)	***
Family incarceration	0.315	(0.030)	***	0.279	(0.025)	***	0.276	(0.036)	***
Parental substance abuse	-0.121	(0.052)	*	0.010	(0.042)		0.093	(0.061)	
Physical abuse	0.069	(0.048)		-0.094	(0.041)	*	-0.220	(0.063)	***
Sexual abuse	-0.153	(0.063)	*	-0.527	(0.059)	***	-0.544	(0.094)	***
Model 4: Youth Predictors									
Attitudes towards the law	0.186	(0.028)	***	0.155	(0.023)	***	0.149	(0.034)	***
Takes responsibility for behavior	0.233	(0.029)	***	0.127	(0.025)	***	0.029	(0.036)	
Delinquent peers	0.136	(0.030)	***	0.274	(0.024)	***	0.231	(0.035)	***
Problem alcohol use	-0.201	(0.072)		-0.095	(0.056)		-0.152	(0.075)	*
Problem drug use	0.049	(0.043)		0.136	(0.035)	***	0.526	(0.046)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).

[a]Reference category = white non-Hispanic

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

Appendix B8. Coefficients from Logistic Regression Models Estimating Individual-Level Predictors' Effects on Adjudication in the Juvenile or Adult System within 24 Months by Initial Disposition, Florida

	Diversion Youth			Probation Youth			Residential Youth		
Predictor	b	SE		b	SE		b	SE	
Models 1-3: Demographic Predictors									
Male	0.721	(0.025)	***	0.677	(0.027)	***	0.579	(0.060)	***
Black[a]	0.454	(0.024)	***	0.427	(0.024)	***	0.270	(0.044)	***
Hispanic[a]	0.038	(0.033)		0.036	(0.033)		0.134	(0.067)	*
Other non-white race/ethnicity[a]	-0.665	(0.169)	***	-0.267	(0.178)		0.473	(0.377)	
Age at release	-0.112	(0.006)	***	-0.168	(0.007)	***	-0.617	(0.017)	***
Models 4-6: Delinquency History Predictors									
Age at first offense	-0.185	(0.009)	***	-0.154	(0.010)	***	-0.362	(0.022)	***
Prior misdemeanors	0.734	(0.023)	***	0.229	(0.012)	***	0.056	(0.018)	**
Prior felonies	0.494	(0.020)	***	0.235	(0.012)	***	0.073	(0.021)	***
Prior weapons offenses	-0.155	(0.060)	**	0.009	(0.038)		-0.102	(0.049)	*
Prior commitments	-0.510	(0.294)		0.014	(0.033)		0.323	(0.036)	***
Prior pickup orders	0.133	(0.052)	*	0.151	(0.016)	***	-0.017	(0.022)	
Models 7-9: Family Predictors									
Out of home placements	0.116	(0.028)	***	0.030	(0.021)		-0.021	(0.028)	
History of running away	0.257	(0.014)	***	0.103	(0.010)	***	0.053	(0.013)	***
History of neglect	0.163	(0.057)	**	0.187	(0.047)	***	0.063	(0.065)	
Family incarceration	0.360	(0.024)	***	0.352	(0.022)	***	0.209	(0.039)	***
Parental substance abuse	-0.019	(0.046)		0.055	(0.040)		-0.074	(0.055)	
Physical abuse	-0.018	(0.043)		-0.070	(0.038)		-0.039	(0.053)	
Sexual abuse	-0.363	(0.056)	***	-0.379	(0.051)	***	-0.449	(0.070)	***
Models 10-12: Youth Predictors									
Attitudes towards the law	0.351	(0.024)	***	0.225	(0.021)	***	-0.109	(0.035)	**
Takes responsibility for behavior	0.257	(0.025)	***	0.121	(0.023)	***	-0.059	(0.037)	
Delinquent peers	0.324	(0.023)	***	0.126	(0.022)	***	0.113	(0.038)	**
Problem alcohol use	-0.052	(0.075)		-0.123	(0.053)	*	-0.165	(0.061)	**
Problem drug use	0.172	(0.043)	***	0.354	(0.031)	***	0.054	(0.043)	

Note. Results for each combination of set of predictors and group of youth are from a single logistic regression model. All models also included controls for year.
[a]Reference category = white non-Hispanic
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix B9. Coefficients from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on Different Marker Events Capturing 12 Month Recidivism in the Juvenile System, Florida									
	Referral			Adjudication			Commitment		
Predictor	b	SE		b	SE		b	SE	
Model 1: Population Predictors									
Total population	-0.00002	(0.000)	***	-0.00002	(0.000)	***	-0.00002	(0.000)	**
Percent non-Hispanic Black	0.005	(0.000)	***	0.005	(0.000)	***	0.007	(0.001)	***
Percent Hispanic	0.001	(0.001)	**	-0.004	(0.001)	***	-0.004	(0.001)	**
Model 2: Disadvantage Predictors									
Percent unemployed	0.009	(0.002)	***	0.010	(0.002)	***	0.020	(0.005)	***
Percent without high sch. dipl.	0.009	(0.001)	***	0.004	(0.001)	**	0.009	(0.003)	**
Percent on public assistance	0.025	(0.004)	***	0.025	(0.004)	***	0.007	(0.009)	
Model 3: Instability Predictors									
Mobility rate	-0.005	(0.002)	**	-0.002	(0.002)		0.003	(0.003)	
Percent renters	0.007	(0.001)	***	0.006	(0.001)	***	0.009	(0.001)	***
Model 4: Crime Predictors									
Violent arrest rate	0.00003	(0.000)		0.0002	(0.000)		0.0009	(0.000)	***
Drug arrest rate	0.0006	(0.000)	***	0.0005	(0.000)	***	0.0002	(0.000)	
Police per capita	-0.019	(0.005)	***	-0.005	(0.006)		0.011	(0.009)	

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix B10. Coefficients from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on Adjudication or Conviction Captured within Different Time Windows, Florida									
	6 Months			12 Months			24 Months		
Predictor	b	SE		b	SE		b	SE	
Model 1: Population Predictors									
Total population	-0.00002	(0.000)	***	-0.00002	(0.000)	***	-0.00002	(0.000)	***
Percent non-Hispanic Black	0.005	(0.001)	***	0.006	(0.000)	***	0.006	(0.000)	***
Percent Hispanic	-0.003	(0.001)	**	-0.002	(0.001)	***	-0.002	(0.001)	***
Model 2: Disadvantage Predictors									
Percent unemployed	0.008	(0.003)	**	0.011	(0.003)	***	0.013	(0.002)	***
Percent without high sch. dipl.	0.004	(0.002)	*	0.005	(0.002)	**	0.007	(0.001)	***
Percent on public assistance	0.025	(0.006)	***	0.027	(0.005)	***	0.023	(0.004)	***
Model 3: Instability Predictors									
Mobility rate	-0.004	(0.002)		-0.004	(0.002)		-0.002	(0.002)	
Percent renters	0.007	(0.001)	***	0.006	(0.001)	***	0.007	(0.001)	***
Model 4: Crime Predictors									
Violent arrest rate	0.0002	(0.000)	*	0.0002	(0.000)	*	0.0001	(0.000)	
Drug arrest rate	0.0005	(0.000)	***	0.001	(0.000)	***	0.001	(0.000)	***
Police per capita	-0.005	(0.007)		-0.0003	(0.006)		-0.004	(0.005)	

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix B11. Coefficients from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on 12 Month Referral/Arrest when Adult System Data Is Not versus Is Included, Florida						
	Referral Without FDLE Data			Referral with FDLE Data		
Predictor	b	SE		b	SE	
Model 1: Population Predictors						
Total population	-0.00002	(0.000)	***	-0.00002	(0.000)	***
Percent non-Hispanic Black	0.005	(0.000)	***	0.006	(0.000)	***
Percent Hispanic	0.001	(0.001)		0.004	(0.000)	***
Model 2: Disadvantage Predictors						
Percent unemployed	0.009	(0.002)	***	0.009	(0.002)	***
Percent without high school diploma	0.009	(0.001)	***	0.010	(0.001)	***
Percent on public assistance	0.026	(0.004)	***	0.023	(0.004)	***
Model 3: Instability Predictors						
Mobility rate	-0.005	(0.002)	**	-0.007	(0.001)	***
Percent renters	0.007	(0.001)	***	0.008	(0.001)	***
Model 4: Crime Predictors						
Violent arrest rate	0.0002	(0.000)		0.0002	(0.000)	*
Drug arrest rate	0.001	(0.000)	***	0.0004	(0.000)	***
Police per capita	-0.018	(0.005)	***	-0.017	(0.004)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B12. Coefficients from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on 12 Month Adjudication/Conviction when Adult System Data Is Not versus Is Included, Florida						
	Adjudication Without FDLE Data			Adjudication with FDLE Data		
Predictor	b	SE		b	SE	
Model 1: Population Predictors						
Total population	-0.0002	(0.000)	***	-0.00002	(0.000)	***
Percent non-Hispanic Black	0.005	(0.000)	***	0.005	(0.000)	***
Percent Hispanic	-0.004	(0.001)	***	-0.002	(0.001)	***
Model 2: Disadvantage Predictors						
Percent unemployed	0.009	(0.002)	***	0.010	(0.002)	***
Percent without high school diploma	0.004	(0.001)	**	0.004	(0.001)	***
Percent on public assistance	0.024	(0.005)	***	0.022	(0.004)	***
Model 3: Instability Predictors						
Mobility rate	-0.002	(0.002)		-0.003	(0.002)	
Percent renters	0.006	(0.001)	***	0.005	(0.001)	***
Model 4: Crime Predictors						
Violent arrest rate	0.0002	(0.000)		0.0002	(0.000)	
Drug arrest rate	0.0005	(0.000)	***	0.0004	(0.000)	***
Police per capita	-0.005	(0.006)		-0.0006	(0.005)	

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B13. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Referral/Arrest for a New Charge versus a Technical Violation, Florida						
	New Charge			Technical Violation		
Predictor	b	SE		b	SE	
Model 1: Population Predictors						
Total population	-0.00002	(0.000)	***	-0.00003	(0.000)	***
Percent non-Hispanic Black	0.005	(0.000)	***	0.002	(0.001)	**
Percent Hispanic	0.002	(0.000)	***	-0.005	(0.001)	***
Model 2: Disadvantage Predictors						
Percent unemployed	0.008	(0.002)	***	0.002	(0.003)	
Percent without high school diploma	0.007	(0.001)	***	0.003	(0.002)	
Percent on public assistance	0.020	(0.003)	***	0.027	(0.005)	***
Model 3: Instability Predictors						
Mobility rate	-0.005	(0.001)	***	-0.001	(0.002)	
Percent renters	0.006	(0.000)	***	0.005	(0.001)	***
Model 4: Crime Predictors						
Violent arrest rate	0.0001	(0.000)		-0.00001	(0.000)	
Drug arrest rate	0.0004	(0.000)	***	0.001	(0.000)	***
Police per capita	-0.009	(0.004)	*	-0.032	(0.007)	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B14. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication/Conviction for a Misdemeanor versus a Felony Offense, Florida						
	Misdemeanor Adjudication			Felony Adjudication		
Predictor	b	SE		b	SE	
Model 1: Population Predictors						
Total population	-0.00001	(0.000)	***	-0.00001	(0.000)	***
Percent non-Hispanic Black	0.003	(0.000)	***	0.007	(0.000)	***
Percent Hispanic	-0.003	(0.000)	***	0.001	(0.001)	*
Model 2: Disadvantage Predictors						
Percent unemployed	0.008	(0.002)	***	0.011	(0.002)	***
Percent without high school diploma	0.002	(0.001)		0.008	(0.001)	***
Percent on public assistance	0.021	(0.004)	***	0.017	(0.004)	***
Model 3: Instability Predictors						
Mobility rate	0.001	(0.001)		-0.007	(0.002)	***
Percent renters	0.003	(0.001)	***	0.008	(0.001)	***
Model 4: Crime Predictors						
Violent arrest rate	-0.00009	(0.000)		0.001	(0.000)	***
Drug arrest rate	0.0005	(0.000)	***	0.000	(0.000)	
Police per capita	0.007	(0.004)		-0.006	(0.005)	

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B15. Coefficients from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication or Conviction for Different Offense Types, Florida									
	Violent Offense			Property Offense			Drug Offense		
Predictor	b	SE		b	SE		b	SE	
Model 1: Population Predictors									
Total population	-0.00002	(0.000)	***	-0.00001	(0.000)	***	-0.00001	(0.000)	
Percent non-Hispanic Black	0.006	(0.001)	***	0.006	(0.000)	***	-0.004	(0.001)	***
Percent Hispanic	-0.001	(0.001)		-0.001	(0.001)		-0.002	(0.001)	*
Model 2: Disadvantage Predictors									
Percent unemployed	0.013	(0.003)	***	0.009	(0.002)	***	-0.014	(0.004)	***
Percent without high sch. dipl.	0.007	(0.002)	***	0.005	(0.001)	***	-0.003	(0.002)	
Percent on public assistance	0.016	(0.005)	**	0.020	(0.004)	***	0.017	(0.007)	*
Model 3: Instability Predictors									
Mobility rate	-0.006	(0.002)	**	-0.004	(0.002)	*	0.005	(0.003)	*
Percent renters	0.006	(0.001)	***	0.007	(0.001)	***	-0.002	(0.001)	*
Model 4: Crime Predictors									
Violent arrest rate	0.0003	(0.000)	**	0.001	(0.000)	***	-0.0004	(0.000)	**
Drug arrest rate	0.0002	(0.000)	**	0.0002	(0.000)	**	0.0003	(0.000)	**
Police per capita	-0.004	(0.007)		-0.003	(0.005)		-0.008	(0.009)	

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix B16. Coefficients from Logistic Regression Models Estimating Contextual Predictors' Effects on Adjudication in the Juvenile or Adult System within 24 Months by Initial Disposition, Florida									
	Diversion Youth			Probation Youth			Residential Youth		
Predictor	b	SE		b	SE		b	SE	
Models 1-3: Population Predictors									
Total population	-0.00002	(0.000)	***	-0.000007	(0.000)	*	-0.00002	(0.000)	**
Percent non-Hispanic Black	0.008	(0.000)	***	0.004	(0.000)	***	0.001	(0.001)	
Percent Hispanic	-0.001	(0.001)		-0.002	(0.001)	***	-0.003	(0.001)	**
Models 4-6: Disadvantage Predictors									
Percent unemployed	0.014	(0.002)	***	-0.010	(0.002)	***	0.001	(0.004)	
Percent without high sch. dipl.	0.009	(0.001)	***	0.003	(0.001)	**	-0.002	(0.002)	
Percent on public assistance	0.018	(0.004)	***	0.014	(0.004)	***	0.028	(0.007)	***
Models 7-9: Instability Predictors									
Mobility rate	-0.004	(0.002)	*	-0.001	(0.002)		0.002	(0.003)	
Percent renters	0.007	(0.001)	***	0.004	(0.001)	***	0.002	(0.001)	*
Models 10-12: Crime Predictors									
Violent arrest rate	0.0001	(0.000)		0.0001	(0.000)		0.00002	(0.000)	
Drug arrest rate	0.0001	(0.000)		0.001	(0.000)	***	0.001	(0.000)	***
Police per capita	0.002	(0.006)		-0.003	(0.005)		-0.006	(0.007)	

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year.
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix C. Coefficients and Cohen's d for Florida Models

Appendix C1. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on Different Marker Events Capturing 12 Month Recidivism in the Juvenile System, Florida

	Referral			Adjudication			Commitment		
Predictor	b	d		b	d		b	d	
Model 1: Demographic Predictors									
Male	0.447	0.247	***	0.504	0.278	***	0.923	0.510	***
Black[a]	0.404	0.223	***	0.352	0.194	***	0.503	0.278	***
Hispanic[a]	0.104	0.057	***	-0.003	-0.002		0.111	0.061	
Other non-white race/ethnicity[a]	-0.512	-0.283	**	-0.710	-0.392	**	-0.699	-0.386	
Age at release	-0.445	-0.246	**	-0.477	-0.264	***	-0.633	-0.350	***
Model 2: Delinquency History Predictors									
Age at first offense	-0.413	-0.228	***	-0.437	-0.241	***	-0.557	-0.308	***
Prior misdemeanors	0.247	0.136	***	0.235	0.130	***	0.183	0.101	***
Prior felonies	0.141	0.078	***	0.160	0.088	***	0.287	0.159	***
Prior weapons offenses	-0.095	-0.052	*	-0.194	-0.107	***	-0.244	-0.135	**
Prior commitments	0.091	0.050	**	-0.055	-0.030		0.062	0.034	
Prior pickup orders	-0.026	-0.014		-0.070	-0.039	**	0.027	0.015	
Model 3: Family Predictors									
Out of home placements	0.068	0.038	**	0.035	0.019		0.055	0.030	
History of running away	0.143	0.079	***	0.164	0.091	***	0.219	0.121	***
History of neglect	0.228	0.126	***	0.216	0.119	***	0.313	0.173	***
Family incarceration	0.420	0.232	***	0.437	0.241	***	0.448	0.248	***
Parental substance abuse	-0.018	-0.010		-0.020	-0.011		-0.015	-0.008	
Physical abuse	-0.038	-0.021		-0.083	-0.046		-0.090	-0.050	
Sexual abuse	-0.274	-0.151	***	-0.258	-0.143	***	-0.437	-0.241	***
Model 4: Youth Predictors									
Attitudes towards the law	0.182	0.101	***	0.217	0.120	***	0.241	0.133	***
Takes responsibility for behav.	0.176	0.097	***	0.179	0.099	***	0.254	0.140	***
Delinquent peers	0.310	0.171	***	0.285	0.157	***	0.407	0.225	***
Problem alcohol use	-0.269	-0.149	***	-0.248	-0.137	***	-0.249	-0.138	*
Problem drug use	0.195	0.108	***	0.134	0.074	***	0.229	0.127	***

Note. behav. = behavior. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* p < .05; ** p < .01; *** p < .001

Appendix C2. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on Adjudication or Conviction Captured within Different Time Windows, Florida									
	6 Months			12 Months			24 Months		
Predictor	b	d		b	d		b	d	
Model 1: Demographic Predictors									
Male	0.736	0.407	***	0.794	0.439	***	0.823	0.455	***
Black[a]	0.463	0.256	***	0.466	0.257	***	0.497	0.275	***
Hispanic[a]	0.001	0.001		0.031	0.017		0.046	0.025	
Other non-white race/ethnicity[a]	-0.563	-0.311	**	-0.745	-0.412	***	-0.462	-0.255	***
Age at release	-0.154	-0.085	***	-0.179	-0.099	***	-0.224	-0.124	***
Model 2: Delinquency History Predictors									
Age at first offense	-0.129	-0.071	***	-0.176	-0.097	***	-0.251	-0.139	***
Prior misdemeanors	0.408	0.225	***	0.406	0.224	***	0.336	0.186	***
Prior felonies	0.398	0.220	***	0.365	0.202	***	0.310	0.171	***
Prior weapons offenses	-0.134	-0.074	**	-0.069	-0.038		-0.071	-0.039	
Prior commitments	0.185	0.102	***	0.181	0.100	***	0.157	0.087	***
Prior pickup orders	0.138	0.076	***	0.106	0.059	***	0.092	0.051	***
Model 3: Family Predictors									
Out of home placements	0.013	0.007		0.040	0.022		0.045	0.025	*
History of running away	0.222	0.123	***	0.183	0.101	***	0.157	0.087	***
History of neglect	0.230	0.127	***	0.209	0.115	***	0.183	0.101	***
Family incarceration	0.401	0.222	***	0.438	0.242	***	0.424	0.234	***
Parental substance abuse	0.001	0.001		0.007	0.004		0.000	0.000	
Physical abuse	-0.104	-0.057	*	-0.126	-0.070	**	-0.052	-0.029	
Sexual abuse	-0.543	-0.300	***	-0.469	-0.259	***	-0.479	-0.265	***
Model 4: Youth Predictors									
Attitudes towards the law	0.264	0.146	***	0.268	0.148	***	0.267	0.148	***
Takes responsibility for behav.	0.159	0.088	***	0.180	0.099	***	0.155	0.086	***
Delinquent peers	0.280	0.155	***	0.258	0.143	***	0.257	0.142	***
Problem alcohol use	-0.155	-0.086	*	-0.149	-0.082	*	-0.177	-0.098	***
Problem drug use	0.349	0.193	***	0.328	0.181	***	0.304	0.168	***

Note. behav. = behavior. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix C3. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Referral/Arrest when Adult System Data Is Not versus Is Included, Florida						
	Referral Without FDLE Data			Referral with FDLE Data		
Predictor	b	d		b	d	
Model 1: Demographic Predictors						
Male	0.481	0.266	***	0.630	0.348	***
Black[a]	0.413	0.228	***	0.507	0.280	***
Hispanic[a]	0.100	0.055	**	0.171	0.094	***
Other non-white race/ethnicity[a]	-0.534	-0.295	**	-0.368	-0.203	**
Age at release	-0.469	-0.259	***	-0.061	-0.034	***
Model 2: Delinquency History Predictors						
Age at first offense	-0.433	-0.239	***	-0.830	-0.459	***
Prior misdemeanors	0.251	0.139	***	0.426	0.235	***
Prior felonies	0.149	0.082	***	0.349	0.193	***
Prior weapons offenses	-0.100	-0.055	*	-0.021	-0.012	
Prior commitments	0.073	0.040	*	0.210	0.116	***
Prior pickup orders	-0.020	-0.011		0.217	0.120	***
Model 3: Family Predictors						
Out of home placements	0.068	0.038	**	0.055	0.030	**
History of running away	0.147	0.081	***	0.160	0.088	***
History of neglect	0.237	0.131	***	0.179	0.099	***
Family incarceration	0.436	0.241	***	0.397	0.219	***
Parental substance abuse	-0.018	-0.010		-0.012	-0.007	
Physical abuse	-0.039	-0.022		-0.074	-0.041	*
Sexual abuse	-0.281	-0.155	***	-0.415	-0.229	***
Model 4: Youth Predictors						
Attitudes towards the law	0.192	0.106	***	0.256	0.141	***
Takes responsibility for behavior	0.182	0.101	***	0.159	0.088	***
Delinquent peers	0.315	0.174	***	0.248	0.137	***
Problem alcohol use	-0.270	-0.149	***	-0.175	-0.097	***
Problem drug use	0.203	0.112	***	0.401	0.222	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix C4. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication/Conviction when Adult System Data Is Not versus Is Included, Florida

	Adjudication Without FDLE Data			Adjudication with FDLE Data		
Predictor	b	d		b	d	
Model 1: Demographic Predictors						
Male	0.499	0.276	***	0.706	0.390	***
Black[a]	0.347	0.192	***	0.405	0.224	***
Hispanic[a]	0.007	0.004		0.029	0.016	
Other non-white race/ethnicity[a]	-0.691	-0.382	**	-0.619	-0.342	***
Age at release	-0.462	-0.255	***	-0.126	-0.070	***
Model 2: Delinquency History Predictors						
Age at first offense	-0.427	-0.236	***	-0.129	-0.071	***
Prior misdemeanors	0.218	0.120	***	0.348	0.192	***
Prior felonies	0.150	0.083	***	0.320	0.177	***
Prior weapons offenses	-0.183	-0.101	***	-0.055	-0.030	
Prior commitments	-0.041	-0.023		0.147	0.081	***
Prior pickup orders	-0.057	-0.031	*	0.095	0.052	***
Model 3: Family Predictors						
Out of home placements	0.033	0.018		0.031	0.017	
History of running away	0.157	0.087	***	0.155	0.086	***
History of neglect	0.210	0.116	***	0.177	0.098	***
Family incarceration	0.425	0.235	***	0.369	0.204	***
Parental substance abuse	-0.019	-0.010		0.006	0.003	
Physical abuse	-0.079	-0.044		-0.105	-0.058	**
Sexual abuse	-0.249	-0.138	***	-0.421	-0.233	***
Model 4: Youth Predictors						
Attitudes towards the law	0.204	0.113	***	0.228	0.126	***
Takes responsibility for behavior	0.170	0.094	***	0.147	0.081	***
Delinquent peers	0.277	0.153	***	0.217	0.120	***
Problem alcohol use	-0.235	-0.130	***	-0126	-0.070	*
Problem drug use	0.137	0.076	***	0.288	0.159	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix C5. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Referral/Arrest for a New Charge versus a Technical Violation, Florida

	New Charge			Technical Violation		
Predictor	b	d		b	d	
Model 1: Demographic Predictors						
Male	0.576	0.318	***	0.431	0.238	***
Black[a]	0.401	0.222	***	0.346	0.191	***
Hispanic[a]	0.115	0.064	***	0.017	0.009	
Other non-white race/ethnicity[a]	-0.446	-0.246	***	-0.388	-0.214	
Age at release	-0.182	-0.101	***	-0.367	-0.203	***
Model 2: Delinquency History Predictors						
Age at first offense	-0.185	-0.102	***	-0.334	-0.185	***
Prior misdemeanors	0.306	0.169	***	0.277	0.153	***
Prior felonies	0.248	0.137	***	0.199	0.110	***
Prior weapons offenses	-0.023	-0.013		-0.221	-0.122	***
Prior commitments	0.098	0.054	***	0.105	0.058	**
Prior pickup orders	0.060	0.033	***	0.082	0.045	***
Model 3: Family Predictors						
Out of home placements	0.057	0.031	***	-0.017	-0.009	
History of running away	0.114	0.063	***	0.188	0.104	***
History of neglect	0.174	0.096	***	0.171	0.094	**
Family incarceration	0.341	0.188	***	0.491	0.271	***
Parental substance abuse	-0.010	-0.006		0.033	0.018	
Physical abuse	-0.061	-0.034	*	-0.058	-0.032	
Sexual abuse	-0.372	-0.206	***	-0.235	-0.130	***
Model 4: Youth Predictors						
Attitudes towards the law	0.192	0.106	***	0.191	0.106	***
Takes responsibility for behavior	0.150	0.083	***	0.145	0.080	***
Delinquent peers	0.230	0.127	***	0.209	0.115	***
Problem alcohol use	-0.169	-0.093	***	-0.146	-0.081	*
Problem drug use	0.260	0.144	***	0.294	0.162	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix C6. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication/Conviction for a Misdemeanor versus a Felony Offense, Florida

	Misdemeanor Adjudication			Felony Adjudication		
Predictor	b	d		b	d	
Model 1: Demographic Predictors						
Male	0.537	0.297	***	1.124	0.621	***
Black[a]	0.301	0.166	***	0.538	0.297	***
Hispanic[a]	-0.020	-0.011		0.162	0.090	***
Other non-white race/ethnicity[a]	-0.584	-0.323	***	-0.553	-0.306	*
Age at release	-0.137	-0.076	***	-0.128	-0.071	***
Model 2: Delinquency History Predictors						
Age at first offense	-0141	-0.078	***	-0.141	-0.078	***
Prior misdemeanors	0.324	0.179	***	0.212	0.117	***
Prior felonies	0.200	0.110	***	0.431	0.238	***
Prior weapons offenses	-0.067	-0.037		-0.038	-0.021	
Prior commitments	0.030	0.017		0.071	0.039	*
Prior pickup orders	0.051	0.028	**	0.089	0.049	***
Model 3: Family Predictors						
Out of home placements	0.036	0.020		0.035	0.019	
History of running away	0.113	0.062	***	0.107	0.059	***
History of neglect	0.123	0.068	**	0.181	0.100	***
Family incarceration	0.329	0.182	***	0.293	0.162	***
Parental substance abuse	0.042	0.023		-0.039	-0.022	
Physical abuse	-0.110	-0.061	**	-0.098	-0.054	*
Sexual abuse	-0.299	-0.165	***	-0.638	-0.352	***
Model 4: Youth Predictors						
Attitudes towards the law	0.189	0.104	***	0.162	0.090	***
Takes responsibility for behavior	0.134	0.074	***	0.132	0.073	***
Delinquent peers	0.187	0.103	***	0.253	0.140	***
Problem alcohol use	-0.148	-0.082	**	-0.141	-0.078	**
Problem drug use	0.209	0.115	***	0.268	0.148	***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C7. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication or Conviction for Different Offense Types, Florida									
	Violent Offense			Property Offense			Drug Offense		
Predictor	b	d		b	d		b	d	
Model 1: Demographic Predictors									
Male	0.300	0.166	***	0.748	0.413	***	1.220	0.674	***
Black[a]	0.523	0.289	***	0.425	0.235	***	-0.161	-0.089	***
Hispanic[a]	0.140	0.077	**	0.035	0.019		-0.028	-0.015	
Other non-white race/ethnicity[a]	-0.187	-0.103		-0.683	-0.377	**	-0.866	-0.478	*
Age at release	-0.262	-0.145	***	-0.232	-0.128	***	-0.071	-0.039	***
Model 2: Delinquency History Predictors									
Age at first offense	-0.317	-0.175	***	-0.230	-0.127	***	-0.049	-0.027	**
Prior misdemeanors	0.230	0.127	***	0.202	0.112	***	0.262	0.145	***
Prior felonies	0.157	0.087	***	0.343	0.190	***	0.209	0.115	***
Prior weapons offenses	-0.151	-0.083	**	-0.136	-0.075	**	-0.003	-0.002	
Prior commitments	0.116	0.064	**	-0.034	-0.019		-0.043	-0.024	
Prior pickup orders	-0.035	-0.019		0.050	0.028	*	0.035	0.019	
Model 3: Family Predictors									
Out of home placements	0.112	0.062	***	0.043	0.024		-0.079	-0.044	*
History of running away	0.112	0.062	***	0.126	0.070	***	0.037	0.020	*
History of neglect	0.087	0.048		0.216	0.119	***	0.306	0.169	***
Family incarceration	0.315	0.174	***	0.279	0.154	***	0.276	0.152	***
Parental substance abuse	-0.121	-0.067	*	0.010	0.006		0.093	0.051	
Physical abuse	0.069	0.038		-0.094	-0.052	*	-0.220	-0.122	***
Sexual abuse	-0.153	-0.085	*	-0.527	-0.291	***	-0.544	-0.301	***
Model 4: Youth Predictors									
Attitudes towards the law	0.186	0.103	***	0.155	0.086	***	0.149	0.082	***
Takes responsibility for behav.	0.233	0.129	***	0.127	0.070	***	0.029	0.016	
Delinquent peers	0.136	0.075	***	0.274	0.151	***	0.231	0.128	***
Problem alcohol use	-0.201	-0.111		-0.095	-0.052		-0.152	-0.084	*
Problem drug use	0.049	0.027		0.136	0.075	***	0.526	0.291	***

Note. behav. = behavior. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
[a]Reference category = white non-Hispanic
* $p < .05$; ** $p < .01$; *** $p < .001$

Appendix C8. Cohen's d Effect sizes from Logistic Regression Models Estimating Individual-Level Predictors' Effects on Adjudication in the Juvenile or Adult System within 24 Months by Initial Disposition, Florida									
	Diversion Youth			Probation Youth			Residential Youth		
Predictor	b	d		b	d		b	d	
Models 1-3: Demographic Predictors									
Male	0.721	0.398	***	0.677	0.374	***	0.579	0.320	***
Black[a]	0.454	0.251	***	0.427	0.236	***	0.270	0.149	***
Hispanic[a]	0.038	0.021		0.036	0.020		0.134	0.074	*
Other non-white race/ethnicity[a]	-0.665	-0.367	***	-0.267	-0.148		0.473	0.261	
Age at release	-0.112	-0.062	***	-0.168	-0.093	***	-0.617	-0.341	***
Models 4-6: Delinquency History Predictors									
Age at first offense	-0.185	-0.102	***	-0.154	-0.085	***	-0.362	-0.200	***
Prior misdemeanors	0.734	0.406	***	0.229	0.127	***	0.056	0.031	**
Prior felonies	0.494	0.273	***	0.235	0.130	***	0.073	0.040	***
Prior weapons offenses	-0.155	-0.086	*	0.009	0.005		-0.102	-0.056	*
Prior commitments	-0.510	-0.282		0.014	0.008		0.323	0.178	***
Prior pickup orders	0.133	0.073	*	0.151	0.083	***	-0.017	-0.009	
Models 7-9: Family Predictors									
Out of home placements	0.116	0.064	***	0.030	0.017	***	-0.021	-0.012	
History of running away	0.257	0.142	***	0.103	0.057	***	0.053	0.029	***
History of neglect	0.163	0.090	**	0.187	0.103	***	0.063	0.035	
Family incarceration	0.360	0.199	***	0.352	0.194	***	0.209	0.115	***
Parental substance abuse	-0.019	-0.010		0.055	0.030		-0.074	-0.041	
Physical abuse	-0.018	-0.010		-0.070	-0.039		-0.039	-0.022	
Sexual abuse	-0.363	-0.201	***	-0.379	-0.209	***	-0.449	-0.248	***
Models 10-12: Youth Predictors									
Attitudes towards the law	0.351	0.194	***	0.225	0.124	***	-0.109	-0.060	**
Takes responsibility for behav.	0.257	0.142	***	0.121	0.067	***	-0.059	-0.033	
Delinquent peers	0.324	0.179	***	0.126	0.070	***	0.113	0.062	**
Problem alcohol use	-0.052	-0.029		-0.123	-0.068	*	-0.165	-0.091	**
Problem drug use	0.172	0.095	***	0.354	0.196	***	0.054	0.030	

Note. behav. = behavior. Results for each combination of set of predictors and group of youth are from a single logistic regression model. All models also included controls for year.

[a]Reference category = white non-Hispanic

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

Appendix C9. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on Different Marker Events Capturing 12 Month Recidivism in the Juvenile System, Florida						
	Referral		Adjudication		Commitment	
Predictor	b	d	b	d	b	d
Model 1: Population Predictors						
Total population	-0.00002	-0.00001***	-0.00002	-0.00001***	-0.00002	-0.00001**
Percent non-Hispanic Black	0.005	0.003***	0.005	0.003***	0.007	0.004***
Percent Hispanic	0.001	0.001**	-0.004	-0.002***	-0.004	-0.002**
Model 2: Disadvantage Predictors						
Percent unemployed	0.009	0.005***	0.010	0.006***	0.020	0.011***
Percent without high sch. dipl.	0.009	0.005***	0.004	0.002**	0.009	0.005**
Percent on public assistance	0.025	0.014***	0.025	0.014***	0.007	0.004
Model 3: Instability Predictors						
Mobility rate	-0.005	-0.003**	-0.002	-0.001	0.003	0.002
Percent renters	0.007	0.004***	0.006	0.003***	0.009	0.005
Model 4: Crime Predictors						
Violent arrest rate	0.00003	0.00002	0.0002	0.0001	0.001	0.001***
Drug arrest rate	0.001	0.0003***	0.0005	0.0003***	0.0002	0.0001
Police per capita	-0.019	-0.010***	-0.005	-0.003	0.011	0.006

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C10. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on Adjudication or Conviction Captured within Different Time Windows, Florida						
	6 Months		12 Months		24 Months	
Predictor	b	d	b	d	b	d
Model 1: Population Predictors						
Total population	-0.00002	-0.00001***	-0.00002	-0.00001***	-0.00002	-0.00001***
Percent non-Hispanic Black	0.005	0.003***	0.006	0.003***	0.006	0.003***
Percent Hispanic	-0.003	-0.002**	-0.002	-0.001***	-0.002	-0.001***
Model 2: Disadvantage Predictors						
Percent unemployed	0.008	0.004**	0.011	0.0061***	0.013	0.007***
Percent without high sch. dipl.	0.004	0.002*	0.005	0.0028**	0.007	0.004***
Percent on public assistance	0.025	0.014***	0.027	0.015***	0.023	0.013***
Model 3: Instability Predictors						
Mobility rate	-0.004	-0.002	-0.004	-0.002	-0.002	-0.001
Percent renters	0.007	0.004***	0.006	0.003***	0.007	0.004***
Model 4: Crime Predictors						
Violent arrest rate	0.0002	0.0001*	0.0002	0.0001*	0.0001	0.0001
Drug arrest rate	0.0005	0.0003***	0.001	0.001***	0.001	0.001***
Police per capita	-0.005	-0.003	-0.0003	-0.0002	-0.004	-0.002

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C11. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on 12 Month Referral/Arrest when Adult System Data Is Not versus Is Included, Florida				
	Referral Without FDLE Data		Referral with FDLE Data	
Predictor	b	d	b	d
Model 1: Population Predictors				
Total population	-0.00002	-0.00001***	-0.00002	-0.00001***
Percent non-Hispanic Black	0.005	0.003***	0.006	0.003***
Percent Hispanic	0.001	0.001	0.004	0.002***
Model 2: Disadvantage Predictors				
Percent unemployed	0.009	0.005***	0.009	0.005***
Percent without high school diploma	0.009	0.005***	0.01	0.006***
Percent on public assistance	0.026	0.014***	0.023	0.013***
Model 3: Instability Predictors				
Mobility rate	-0.005	-0.003**	-0.007	-0.004***
Percent renters	0.007	0.004***	0.008	0.004***
Model 4: Crime Predictors				
Violent arrest rate	0.0002	0.0001	0.0002	0.0001*
Drug arrest rate	0.001	0.001***	0.0004	0.0002***
Police per capita	-0.018	-0.010***	-0.017	-0.009***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C12. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Contextual Predictors' Effects on 12 Month Adjudication/Conviction when Adult System Data Is Not versus Is Included, Florida				
	Adjudication Without FDLE Data		Adjudication with FDLE Data	
Predictor	b	d	b	d
Model 1: Population Predictors				
Total population	-0.0002	-0.0001***	-0.00002	-0.00001***
Percent non-Hispanic Black	0.005	0.003***	0.005	0.003***
Percent Hispanic	-0.004	-0.002***	-0.002	-0.001***
Model 2: Disadvantage Predictors				
Percent unemployed	0.009	0.005***	0.010	0.006***
Percent without high school diploma	0.004	0.002**	0.004	0.002***
Percent on public assistance	0.024	0.013***	0.022	0.012***
Model 3: Instability Predictors				
Mobility rate	-0.002	-0.001	-0.003	-0.002
Percent renters	0.006	0.003***	0.005	0.003***
Model 4: Crime Predictors				
Violent arrest rate	0.0002	0.0001	0.0002	0.0001
Drug arrest rate	0.001	0.0003***	0.0004	0.0002***
Police per capita	-0.005	-0.003	-0.001	-0.0003

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C13. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Referral/Arrest for a New Charge versus a Technical Violation, Florida				
	New Charge		Technical Violation	
Predictor	b	d	b	d
Model 1: Population Predictors				
Total population	-0.00002	-0.00001***	-0.00003	-0.00002***
Percent non-Hispanic Black	0.005	0.003***	0.002	0.001**
Percent Hispanic	0.002	0.001***	-0.005	-0.003***
Model 2: Disadvantage Predictors				
Percent unemployed	0.008	0.004***	0.002	0.001
Percent without high school diploma	0.007	0.004***	0.003	0.002
Percent on public assistance	0.020	0.011***	0.027	0.015***
Model 3: Instability Predictors				
Mobility rate	-0.005	-0.0028***	-0.001	-0.001
Percent renters	0.006	0.0033***	0.005	0.003***
Model 4: Crime Predictors				
Violent arrest rate	0.0001	0.0001	-0.00001	-0.00001
Drug arrest rate	0.0004	0.0002***	0.001	0.001***
Police per capita	-0.009	-0.005*	-0.032	-0.018***

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C14. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication/Conviction for a Misdemeanor versus a Felony Offense, Florida				
	Misdemeanor Adjudication		Felony Adjudication	
Predictor	b	d	b	d
Model 1: Population Predictors				
Total population	-0.00001	-0.00001***	-0.00001	-0.00001***
Percent non-Hispanic Black	0.003	0.002***	0.007	0.004***
Percent Hispanic	-0.003	-0.002***	0.001	0.001*
Model 2: Disadvantage Predictors				
Percent unemployed	0.008	0.004***	0.011	0.006***
Percent without high school diploma	0.002	0.001	0.008	0.004***
Percent on public assistance	0.021	0.012***	0.017	0.009***
Model 3: Instability Predictors				
Mobility rate	0.001	0.001	-0.007	-0.004***
Percent renters	0.003	0.002***	0.008	0.004***
Model 4: Crime Predictors				
Violent arrest rate	-0.0001	-0.00005	0.001	0.001***
Drug arrest rate	0.001	0.0003***	0.000	0.000
Police per capita	0.007	0.004	-0.006	-0.003

Note. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C15. Cohen's d Effect sizes from Multivariate Multilevel Models Estimating Individual-Level Predictors' Effects on 12 Month Adjudication or Conviction for Different Offense Types, Florida

	Violent Offense		Property Offense		Drug Offense	
Predictor	b	d	b	d	b	d
Model 1: Population Predictors						
Total population	-0.00002	-0.00001***	-0.00001	-0.00001***	-0.00001	-0.00001
Percent non-Hispanic Black	0.006	0.003***	0.006	0.003***	-0.004	-0.002***
Percent Hispanic	-0.001	-0.001	-0.001	-0.001	-0.002	-0.001*
Model 2: Disadvantage Predictors						
Percent unemployed	0.013	0.007***	0.009	0.005***	-0.014	-0.008***
Percent without high sch. dipl.	0.007	0.004***	0.005	0.003***	-0.003	-0.002
Percent on public assistance	0.016	0.009**	0.02	0.011***	0.017	0.009*
Model 3: Instability Predictors						
Mobility rate	-0.006	-0.003**	-0.004	-0.002*	0.005	0.003*
Percent renters	0.006	0.003***	0.007	0.004***	-0.002	-0.001*
Model 4: Crime Predictors						
Violent arrest rate	0.0003	0.0002**	0.001	0.0006***	-0.0004	-0.0002**
Drug arrest rate	0.0002	0.0001**	0.0002	0.0001**	0.0003	0.0002**
Police per capita	-0.004	-0.002	-0.003	-0.002	-0.008	-0.004

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year and initial disposition (probation or diversion; residential was the reference category).
* *p* < .05; ** *p* < .01; *** *p* < .001

Appendix C16. Cohen's d Effect sizes from Logistic Regression Models Estimating Contextual Predictors' Effects on Adjudication in the Juvenile or Adult System within 24 Months by Initial Disposition, Florida

	Diversion Youth		Probation Youth		Residential Youth	
Predictor	b	d	b	d	b	d
Models 1-3: Population Predictors						
Total population	-0.00002	-0.00001***	-0.000007	-0.000004*	-0.00002	-0.00001**
Percent non-Hispanic Black	0.008	0.004***	0.004	0.002***	0.001	0.001
Percent Hispanic	-0.001	-0.001	-0.002	-0.001**	-0.003	-0.002**
Models 4-6: Disadvantage Predictors						
Percent unemployed	0.014	0.008***	-0.01	-0.006***	0.001	0.001
Percent without high sch. dipl.	0.009	0.005***	0.003	0.002**	-0.002	-0.001
Percent on public assistance	0.018	0.010***	0.014	0.008***	0.028	0.015***
Models 7-9: Instability Predictors						
Mobility rate	-0.004	-0.002*	-0.001	-0.001	0.002	0.001
Percent renters	0.007	0.004***	0.004	0.002***	0.002	0.001*
Models 10-12: Crime Predictors						
Violent arrest rate	0.0001	0.0001	0.0001	0.0001	0.00002	0.00001
Drug arrest rate	0.0001	0.0001	0.001	0.001***	0.001	0.001***
Police per capita	0.002	0.001	-0.003	-0.002	-0.006	-0.003

Note. sch. dipl. = school diploma. Results for each set of predictors are from a single multivariate multilevel model. All models also included controls for year.
* *p* < .05; ** *p* < .01; *** *p* < .001