Center for Evidence-Based Corrections
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Assessing Performance of the CSRA after California's Public Safety Realignment and Proposition 47

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1 Introduction

The California Static Risk Assessment (CSRA) was rolled out by the California Department of Corrections (CDCR) in the spring of 2009, based on development work by the Center for Evidence-Based Corrections beginning in late 2007 with extensions and refinements added over the course of 2008. The computer code of Automated Scoring Program (ASP) was further refined under the guidance of experts in the reading and interpretation of rap sheets from CDCR's Division of Adult Parole Operations in April to July of 2009. The 2009 version of the CSRA continues in use today. The only changes come through updates of the tables that map offenses to the risk indicating items on the CSRA instrument, reflecting changes in the law. The data used for developing the CSRA was based on a cohort of prisoners released in fiscal year 2002-2003, chosen at that time to allow for a minimum of a three year follow-up period for the purposes of capturing recidivism.

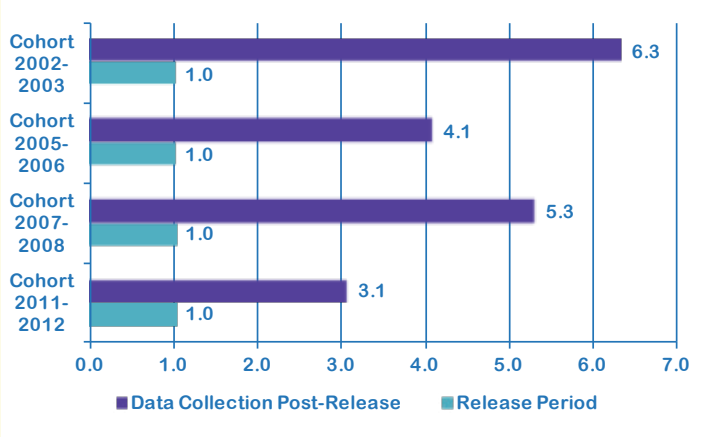
In the time since the implementation of the CSRA, the population of California and offenders supervised by the CDCR have changed, dramatically so for the CDCR population in the wake of the corrections reforms of AB109 and AB117, effective as of October 1st 2011 and popularly known as "realignment", and Proposition 47, which became effective on November 5th of 2014. During this time criminal justice agencies have also changed their practices to a lesser or greater extent, which can affect recidivism rates. Past research shows that the performance of a risk assessment instrument can vary with the population and the jurisdiction to which it is applied. This raises the important question of whether or not the CSRA continues to perform as reported at adoption by the CDCR. In this report we break this question down into three components: The general performance of the CSRA over time, whether the performance has been affected by realignment, and whether the performance has been affected by Proposition 47. We assess performance by predictive ability, the distribution of the population among the different risk groups defined by the CSRA, and the levels of recidivism within each risk group. An additional aspect of CSRA performance over time which we investigate is the evolution of missing data on specific charges, especially in convictions records, and how well the ASP recovers the missing charge information found in the automated criminal history records provided by the California Department of Justice. For our investigation we use five datasets (composed of two or more actual files) supplied to the Center for Evidence-Based Corrections (CEBC) by the CDCR. The first three are release cohorts for fiscal years 2002-03, 2005-06, and 2007-08. The fourth is a post-realignment release cohort for the year beginning October 1st 2011; this was shifted from the July 1st start of a fiscal year to begin as soon as possible after the new laws went into effect in order to maximize the follow-up time for capturing recidivism (See Table 1.1 and Figure 1.1). Assessing the impact of Proposition 47 requires an additional step. Validation of the CSRA has been based on predicting recidivism over three years after release. We do not have three years of recidivism data following the implementation Proposition 47 in 2014. Lacking actual data, we created a proxy dataset for this analysis.[1] The final dataset, used to help construct this proxy for the post-Proposition 47 population, is based on the standing population of CDCR institutions as of November 1st 2014. This is necessary in order to contrast releases due to Proposition 47 with other releases and those not released, analogous to using case and control groups, to refine estimated profiles of the offenders affected by the proposition.

1 *Data on new arrests and most convictions should be available by December of 2017; for full recovery of convictions recidivism we would need another year to allow charges to proceed through to trial and sentencing. This is covered in more detail in the section on the effects of realignment.*

Table 1.1 Dates of release and data cutoff dates, by cohorts

Group	Release Date From	Release Date To	Data Cutoff
Cohort 2002-2003	07/01/2002	06/30/2003	10/26/2009
Cohort 2005-2006	01/07/2005	06/30/2006	07/28/2010
Cohort 2007-2008	01/07/2007	06/30/2008	10/17/2013
Cohort 2011-2012	10/01/2011	09/30/2012	10/22/2015
CrossSection Nov 1, 2014	11/01/2014	12/16/2015	12/16/2015

Figure 1.1 Years of data post-release by cohort



2. Compiling a Criminal History

The first step in risk assessment is compiling the information necessary for completing the risk instrument questionnaire. The CSRA uses 22 risk items. The first two are demographic, the age at assessment and the sex of the offender. The other 20 items construct a criminal history of misdemeanor and felony convictions and supervision violations. Accuracy in compiling the record is important to the ability of the instrument to predict risk. Several issues can cause a loss of accuracy over time. The first, particularly for an automated assessment, is whether it maintains coverage of criminal law as it evolves. The second relates to data completeness and quality. This section reports on the work of the CEBC to maintain the accuracy and completeness of the constructed criminal history and examines the performance of the ASP recovering offense charges over time.

2.1 Updating Mapping Tables

The CSRA constructs a criminal history by counting the number of misdemeanor and felony offenses and supervision violations in general categories such as assault, domestic violence, property, and drug crimes. The process uses rap sheet data drawn from the California Department of Justice (DOJ) Automated Criminal History System (ACHS), which records charges either under specific sections of California statue codes or as a 5 digit Criminal Justice Information System (CJIS) code. Two tables are used to map statute and CJIS codes to CSRA criminal history items. Changes in California law require periodic updates to these mapping tables; without updates the creation of new statute codes will lead to missed charges in the criminal history. The original mapping tables were finalized in 2009, and subsequently updated with new data provided by the DOJ on March 5th 2013. The DOJ provided the latest update on February 17th 2015. As the changes will affect a relatively small number of recent charges, they are not expected to have much impact on CSRA performance. Only the 2011-12 release cohort has records of a significant number of events after the 2013 mapping table update.

We created new mapping tables on the basis of the 2015 data provided by the DOJ and ran the data for the 2011-12 cohort through the ASP with both the 2009 and 2015 mappings. Table 2.1 shows the improvement in coverage for the updated mapping. The 2015 table reduces the initial percentage of unrecovered charges by 7% from 7.56% to 7.02%. The Adjusted column shows the percentage of unrecovered charges after identifying charges recorded in comments fields (more on this below); the reduction from 2.41% to 1.70% is a 30% improvement.[2] The Individual column shows the percentage of persons in the cohort with an unrecovered charge in one or more of their records; here the improvement is about 27%. The Final column shows the percentage of individuals with a conviction for which no charge was recovered; here the improvement from 0.66% to 0.58% is a reduction of 12%. Table 2.2 compares the performance of the CSRA with the 2013 and 2015 tables using the AUC measure of overall predictive ability[3] and shows that results are essentially unchanged. All subsequent analysis with the 2011-12 cohort uses the 2015 mapping table unless otherwise noted.

Table 2.1 Unrecovered charges, mapping table 03/05/2013 versus 09/18/2009

Mapping Table	*Initial*	*Adjusted*	*Individual*	*Final*
2013	7.56%	2.41%	13.18%	0.66%
2015	7.02%	1.70%	9.57%	0.58%

Table 2.2 Cohort 2011-2012. AUC, mapping table 03/05/2013 versus 09/18/2009

Mapping Table	*Any Felony*	*Drug Felony*	*Property Felony*	*Violent Felony*
2013	0.695	0.689	0.704	0.689
2015	0.694	0.689	0.702	0.690

2.2 Recovery of Offense Charges

In this section we look at the changes in the sources and effects of bad and missing data over time and the success rate of efforts to recover unresolved charges from the rap sheet data. Creating a criminal history record requires acquiring the necessary information on the type and the seriousness of each charged offense. Bad or missing data can make this task difficult or impossible. This problem is not infrequent in the DOJ's Automated Criminal History System (ACHS) database and is particularly a problem for capturing convictions. A major function of the ASP is to compensate for this problem as far as it is possible, assembling information from diverse fields and using tables of authorities to determine or infer charges. Comparing the data across the four release cohorts shows that the level of this problem has risen over time. To meet this increasing problem, we have made revisions to sections of the ASP code as covered below. As more missing data leads to less precision in assessing instrument performance, to make the best assessment of CSRA performance we use this revised code for all the subsequent analysis here unless noted otherwise.[4]

Normatively, charges in the DOJ ACHS are recorded by entering the CJIS code in the OFFENSE field of criminal history records in CONREP files. However, the ACHS provides an alternative: entering the charges and various other information as written text in a comments field. In these cases, the CJIS code of 66085 in the OFFENSE field

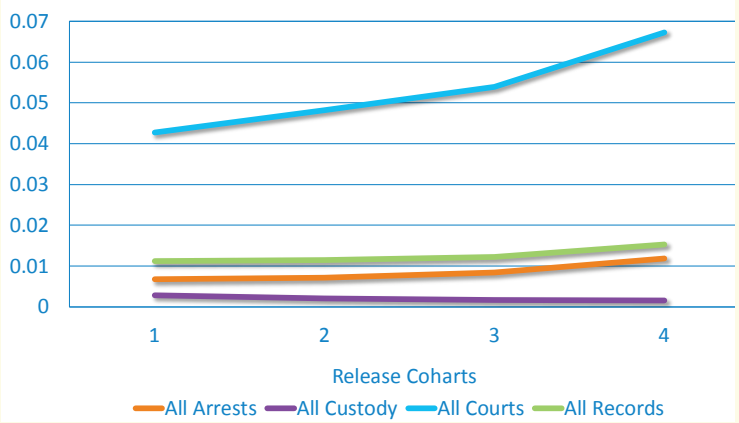
[2] *The ASP identifies convictions by the disposition of a charge. Dispositions indicating a conviction are found in both Arrest and Court records. When not all charges associated with a conviction can be identified, the ASP flags the record as an unrecovered charge.*

[3] *AUC is shorthand for the Area Under the Curve of the Receiver Operating Characteristic (ROC) Curve. The curve plots the rise in levels of true positive predictions (the Y axis) versus false positives (the X axis) as the criterion for a positive prediction is loosened. A perfect prediction will capture all true positives before adding false positives; the curve will rise vertically from (X,Y) 0,0 to 0,1 and then travel horizontally to 1,1; the entire area of the plot is under the curve and the AUC is 1.0. An instrument with no predictive ability will add false positives just as fast as true positives, cutting the area of the plot in half for an AUC of 0.5. Unlike measures of predictive performance such as accuracy, error rate, sensitivity, positive predictive value, etc., the AUC does not require a priori decisions about the cut point between positive and negative predictions and is not sensitive to base rates for the outcome.*

[4] *The revised code, providing more complete recovery of offense charges and eliminating double-counting of offenses in certain circumstances, provides a more accurate criminal history. This will also increase the reliability of CSRA results in practice; we anticipate adoption of the revised code by the CDCR following approval based on the analysis on this report.*

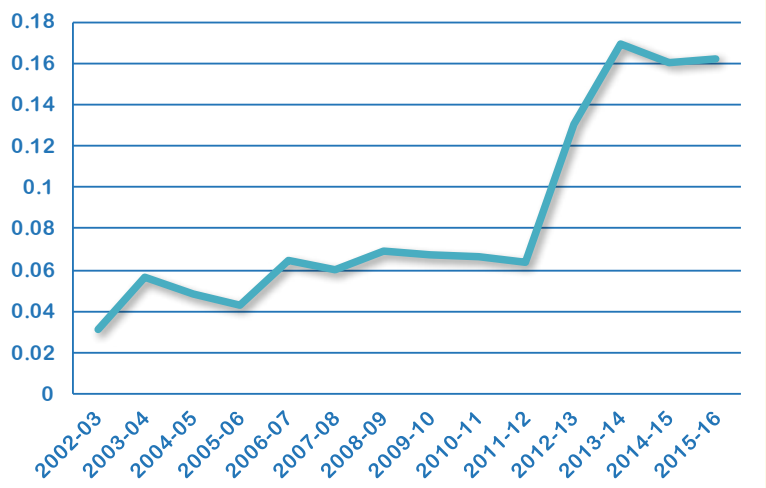
indicates that the charges will be found in the comments field. As the text fields are often unstructured, information is left incomplete, and data entry errors are made, these cases present the major challenge to compiling a criminal history in terms of number of charges affected, programmer effort, and lines of code in the final ASP.

Figure 2.1 Percentage of Records with Charges in Comments, by Cohort



Note: All records, breakdown by Arrest, Court, and Custody records.

Figure 2.2 Conviction Records, Charges in Comments Averaged Across Cohorts, by Year



Charges recorded in comments have been rising over time. Figure 2.1 shows the percentage of records with the 66085 code, broken out by arrest, court, and custody records, for each of the four release cohorts. It is clear that the biggest problem occurs in court records with 4% to 7% of charges entered as comments. Although the level for arrests is around 1%, this remains sufficient to be a concern; if each individual averages 10 arrests and the charges in comments are randomly distributed, almost 10% of individuals would be potentially missing a charge. Figure 2.2 examines convicted charges by year, which may in somewhat rare cases be found in an arrests record, averaging across cohorts.[5] This shows a dramatic rise in fiscal year 2012-2013, reaching

[5] *In some cases, a custody booking implies a conviction although a conviction disposition is not recorded in a Court or Arrest record. The ASP searches for such cases and adds the controlling custody charge to the criminal history. As the charges don't occur in records with a conviction disposition, we don't include them in tracking the recovery of conviction charges. Added after conviction charges recovery, they account for about 2% of final convictions.*

a level of 16% to 17% in 2013-14 and later years. As of the current study, this occurs after the release date for individuals in the last cohort and will have limited impact on the criminal history record. This increase however raises concerns and warrants further investigation.

2.3 Recovery of unresolved charges by old vs new code

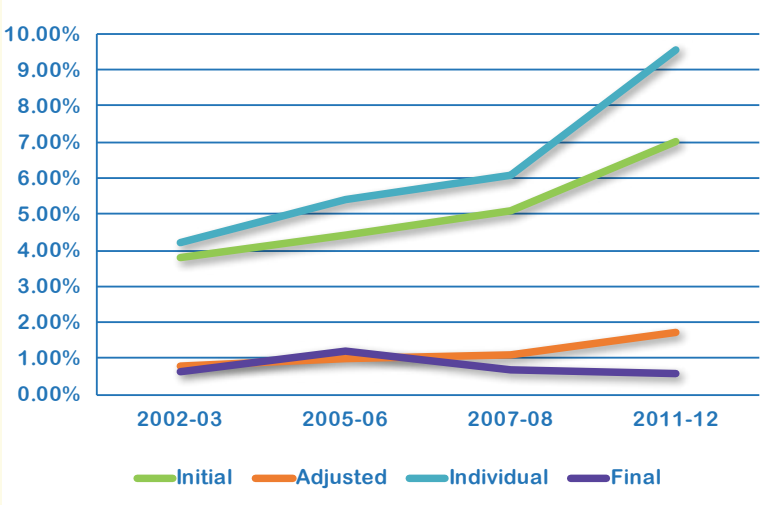
Table 2.3 Recovery of Unresolved Charges; old vs new code, Cohorts 2002-2003 and 2011-2012 Charges Recovery Gains with Modified ASP

Cohort	*Code Version*	*Initial*	*Adjusted*	*Change*	*Gain*
2002-2003	**Baseline**	3.8%	0.9%	75.2%	
	Modified	3.8%	0.8%	79.3%	105.5%
2011-2012	**Baseline**	7.0%	3.1%	55.2%	
	Modified	7.0%	1.7%	75.8%	137.4%

Table 2.4 Percentage of Unresolved Charges, All Cohorts
Percentage of Unresolved Charges by ASP stage and Cohort

Cohort	*Initial*	*Adjusted*	*Individual*	*Final*
2002-03	3.81%	0.79%	4.23%	0.62%
2005-06	4.41%	1.00%	5.41%	1.19%
2007-08	5.10%	1.11%	6.10%	0.71%
2011-12	7.02%	1.70%	9.57%	0.58%

Figure 2.3 Recovery of Unresolved Charges, All Cohorts



Especially in light of the rising use of the comments section to record charges by data entry staff, we investigated whether it was possible to improve the accuracy of the compiled criminal history, and developed several modifications to the ASP code. While in a very few cases, unresolved charges are initially due to no charges entered in the OFFENSE field of the record for a conviction, in over 98% of the cases it is due to charges recorded in a comments field. A section of the ASP code parses the text in the comments field to identify these charges. The modifications of the ASP code which reduce unresolved charges augment this section. Additional modifications eliminate the double-counting of charges which can occur in some circumstances, but these modifications do not recover additional unresolved charges.

Table 2.3 shows the improvements in the recovery of charges in comments achieved by modifications to the ASP for the 2002-2003 and 2011-2012 cohorts. This is based on convictions records as the CSRA criminal history counts convictions rather than arrest charges.[6] Table 2.3 compares the initial percentage of unresolved charges in conviction records with the percentage of unresolved charges remaining after recovery of charges from the comments field. As the percentage of records with charges in comments increased over time, the impact of ASP modifications is greater for the 2011-2012 cohort than for the 2002-2003 cohort. For the earlier cohort, the baseline code recovered 75% of the unresolved charges while the modified code recovered 79%, an improvement of about 6%. For the latest cohort, the baseline code recovered only 55% of the unresolved charges while the modified code recovered 76%, an improvement of about 37%.

Table 2.4 and Figure 2.3 are based on the modified ASP. Table 2.4 shows the reduction of unresolved charges at successive stages of records processing by the ASP. The first two columns are based on the number of records with unresolved charges, and show the gains achieved by parsing comments fields to recover charges. The final two columns are based on aggregating all records for an individual. As most individuals have multiple convictions, an unresolved charge in any of these records will leave an unresolved charge in their criminal history, so the percentage of individuals with unresolved charges is higher than the percentage of records with unresolved charges. The first three columns use all convictions records, while the fourth column labeled "Final" differs in two ways. First it is based only on the records which constitute the CSRA criminal history used in compiling risk item counts and calculating risk scores, i.e., records prior to release from prison, and dropping convictions occurring after release.[7]

In addition, the CSRA criminal history is based on selecting the most serious convicted charge in a criminal history cycle. A criminal history cycle begins with an arrest and follows the charges through to a disposition.[8] If a criminal history cycle includes an unresolved charge along with one or more resolved charges, the most serious of the resolved charges is used on the presumption that more serious charges are more carefully recorded and the pragmatic consideration of using the best information available.[9] The percentage of unresolved charges in the final column therefore indicates the percentage of criminal history cycles for which no resolved charge is available. Table 2.4 and Figure 2.3 demonstrate that despite the rising percentage of charges recorded in the comments field, with the modified ASP the final percentage of individuals with a useable criminal history exceeds 98.8% and is comparable across cohorts.

3 CSRA PERFORMANCE WITH POST-REALIGNMENT DATA

In this section we assess the impact of realignment on the CSRA, using the results for the 2002-2003 cohort published online at the CEBC website as the baseline for comparison, and extend the comparison to subgroups of the release population defined by sex and race/ethnicity. We expand on the stability of CSRA results over time with a supplemental table documenting general predictive ability for all four release cohorts.

Prior to realignment, the vast majority of prisoners released by the CDCR were placed on parole. Following realignment, inmates released after serving a commitment for non-serious, non-violent, or non-high-risk sex offenses (regardless of prior convictions), are diverted to Post-Release Community Supervision (PRCS) and supervised by local county probation departments. Thus the ex-prisoners under Parole and PRCS are distinct populations, and we examine the performance of the CSRA for each.

[6] *Because convictions are drawn from both Arrest and Court records and records not including a conviction disposition are dropped, the percentages of unresolved charges differ from the raw percentage of charges in comments identified in Table 2.1.*

[7] *As Figures 2.1 and 2.2 indicate, the percentage of charges in comments increases in the years after release, particularly for this 2011-12 cohort. The differences between the 3rd and 4th columns in Table 2.3 in part reflect that the records with the highest percentage on unresolved charges occur after release.*

[8] *More formally, in the DOJ rap sheet data, a criminal history cycle is initiated by the transmission of fingerprints to the DOJ on an arrest or a booking into custody. Thus a custody following a conviction initiates a new cycle.*

[9] *We tested using all offenses rather that the most serious offense only and found it made little difference.*

Following examination of the CSRA's predictive ability, we look at the distribution of releases across risk groups over time using all four release cohorts, and then compare recidivism rates within risk groups focusing on the 2002-2003 and 2011-2012 cohorts. For the 2011-2012 group, we break out recidivism by the type of post-release supervision.

In the CSRA, recidivism is based on a new offense within 3 years following release. Our interest is in when offender behavior occurs, not when cases are resolved by the judicial process. Therefore convictions recidivism is based on a new arrest within three years after release leading to a conviction; the ASP looks at dispositions through the 4th year after release to allow time for most cases to work their way through the system.[10] In the 2011-12 cohort, the censoring of data at three years from the last release date causes the loss of some convictions that should be counted as recidivism to maintain consistency with both instrument intent and the evaluation of other cohorts. Below in Section 4 we impute the "lost" data for purposes of comparing recidivism across cohorts. However, the imputation is limited to aggregate recidivism, not to individual cases. Therefore the imputed data cannot be used to assess predictive ability or to assign risk groups. We use the empirical data only in sections 3.1 and 3.2.

3.1 AUC Comparison

Table 3.1 AUC by Felony type for All Cohorts vs. Cohort 2002-2003

Cohort	*Felony Conviction*	*Felony Drug Conviction*	*Felony Violent Property Conviction*	*Felony Violent Conviction*
2002-2003 (Old Code)	0.655	0.674	0.673	0.679
2002-2003	0.652	0.664	0.677	0.674
2005-2006	0.650	0.666	0.679	0.678
2007-2008	0.655	0.673	0.681	0.683
2011-2012	0.694	0.689	0.702	0.690

The primary consideration in evaluating the performance and continued validity of the CSRA over time is whether it retains the same ability to predict recidivism. The first row of Table 3.1 gives the predictive ability of the CSRA on the development cohort at adoption as reported in our 2009 working paper, Development of the California Static Risk Assessment Instrument (CSRA).[11] For the sake of a cleaner comparison, the second and subsequent rows all use the same, modified version of the ASP and the 2015 mapping tables. For the first three cohorts, variations in the AUC range from plus to minus one percent, indicating stability in predictive ability. Looking at whether realignment has had an adverse impact on CSRA performance, we find that to the contrary, performance has improved. The AUCs increase in the post-realignment 2011-2012 cohort by 6% for Any Felony, 2% to 3% for Drug and violent Property Felony, and by 1% for Violent Felony outcome. The increases for all except the Violent Felony outcome are statistically significant. It is possible that the offenders diverted from prison custody by realignment have somewhat more erratic criminal behavior problems, making their future offenses harder to predict, leaving those with more regular behavior to CDCR custody.

Table 3.2 Cohort 2002-2003. AUC by Gender AUC by Gender, Cohort 2002-2003

Gender	*Felony Conviction*	*Felony Drug Conviction*	*Felony Violent Property Conviction*	*Felony Violent Conviction*
Males	0.655	0.675	0.669	0.662
Females	0.641	0.661	0.701	0.638
Total	0.655	0.674	0.673	0.679

[10] *This is in accord with the recidivism definition adopted by the California Board of State and Community Corrections. See www.bscc.ca.gov.*

[11] *http://ucicorrections.seweb.uci.edu/files/2009/11/CSRA-Working-Paper.pdf*

Table 3.3 Cohort 2011-2012. AUC by Gender

Gender	Felony Conviction	Felony Drug Conviction	Felony Violent Property Conviction	Felony Violent Conviction
Males	0.700	0.696	0.704	0.694
Females	0.678	0.679	0.707	0.674
Total	0.699	0.694	0.704	0.694

A second consideration in evaluating the performance and continued validity of the CSRA over time is whether its performance remains equitable across groups defined by sex and race/ethnicity. Table 3.2 gives the baseline performance for the 2002-2003 cohort by gender, with table 3.3 providing the same information for the 2011-12 cohort. At the baseline, the CSRA generally performs less well for women than men – a 2% decline for Any Felony and Drug Felony, a 4% decline for Violent Felony, but a 5% increase for Property Felony. However, only the Property Felony difference is statistically significant. We find a similar pattern for the post-realignment cohort, except that the Property Felony AUC is now essentially the same for men and women (-3%, -2%, 0%, -2% left to right). This again indicates stable performance for the CSRA.

Table 3.4 Cohort 2011-2012. AUC by Ethnicity
AUC by Ethnicity, Cohort 2002-2003

Ethnicity	Felony Conviction	Felony Drug Conviction	Felony Violent Property Conviction	Felony Violent Conviction
White	0.693	0.682	0.684	0.672
Black	0.680	0.678	0.652	0.650
Hispanic	0.698	0.663	0.680	0.681
Other	0.700	0.739	0.677	0.649
Total	0.655	0.674	0.673	0.679

Table 3.5 Cohort 2011-2012. AUC by Ethnicity
AUC by Ethnicity, Cohort 2011-2012

Ethnicity	Felony Conviction	Felony Drug Conviction	Felony Violent Property Conviction	Felony Violent Conviction
White	0.698	0.686	0.715	0.690
Black	0.650	0.695	0.678	0.687
Hispanic	0.725	0.695	0.717	0.701
Other	0.721	0.745	0.702	0.672
Total	0.694	0.689	0.702	0.690

Tables 3.4 and 3.5 give a similar picture for differences in CSRA performance by ethnicity. First we note that behavior seems somewhat more consistent within ethnic groups, making prediction a bit easier. Out of 16 comparisons with the AUC for the whole baseline cohort (4 groups by 4 outcomes), 6 have higher AUCs, 6 are within one percent, and only four are lower by 2% to 4%. Post-realignment, consistency gains are similar – 6 comparisons of the AUC for an ethnic group with the cohort total show an increase, 7 are within one percent, and three are lower.

Comparing across ethnic groups with whites as the reference group in each cohort, we find performance generally equivalent with a few exceptions. Within the 2002-2003 cohort, performance for blacks is lower, by from -1% (Drug) to -5% (Property). Post-realignment, the disparity for blacks is worse for Any Felony (-7%), with Property unchanged at -5%, a 1% higher AUC for Drug, and no difference for Violent Felony recidivism. For Hispanics, within the baseline cohort the difference is biggest for Drug recidivism (-3%), and essentially

the same (within plus or minus one percent) for the other outcomes. Looking at Hispanics post-realignment we find essentially no difference for Drug and Property Felonies and slight improvements for Violent (2%) and Any Felony (4%) outcomes. For the mixed group of other ethnicities, we find similar patterns across the two cohorts, generally with shifts of one or two percent in the differences from whites. Any Felony AUCs are 1% to 3% better; Drug felony differences are a more dramatic 8% to 9% improvement; Property and Violent Felony AUCs are 1% to 3% lower. Overall, with the sole difference of a slip in performance for blacks in predicting Any Felony from 2% lower to 7% lower, the post-realignment performance of the CSRA across ethnicities remains similar to or slightly better than the baseline.

3.2 Compare results for offenders assigned to PAROLE and PRCS

Table 3.6 Cohort 2011-2012 Validation Sample, Releases to PAROLE and PRCS

Released to	*Frequency*	*Percent*
Parole	12,159	39.93
PRCS	18,290	60.07

Table 3.7 Cohort 2011-2012. AUC by Post-Release Supervision
AUC by Post-Release Supervision

Released To	*Felony Conviction*	*Felony Drug Conviction*	*Felony Property Conviction*	*Felony Violent Conviction*
Parole	0.700	0.697	0.693	0.678
PRCS	0.687	0.661	0.710	0.702
Total	0.699	0.690	0.707	0.691

In 2011-2012, close to 60% of prisoners were released to community supervision, PRCS, and 40% were released to CDCR parole supervision (Table 3.6). Table 3.7 shows the AUCs for these two groups. Differences go both ways; CSRA performance for the PRCS group in comparison with the Parole group is slightly lower for Any Felony (-4%) and Drug Felony recidivism (-2%), while for Property (+2%) and Violent Felony (+4%) the PRCS group performance is somewhat better than results for Parole. The differences in results for the two supervision groups are modest.

Table 3.8 Cohort 2011-2012. AUC by Post-Release Supervision and Gender
PAROLE

Gender	*Felony Conviction*	*Felony Drug Conviction*	*Felony Property Conviction*	*Felony Violent Conviction*
Males	0.705	0.698	0.689	0.665
Females	0.705	0.708	0.740	0.690
Total	0.700	0.697	0.693	0.678

PRCS

Gender	*Felony Conviction*	*Felony Drug Conviction*	*Felony Property Conviction*	*Felony Violent Conviction*
Males	0.684	0.666	0.706	0.696
Females	0.658	0.655	0.693	0.667
Total	0.687	0.661	0.710	0.702

Table 3.9 Cohort 2011-2012. AUC by Post-Release Supervision and Ethnicity

PAROLE

Ethnicity	*elony Conviction*	*Felony Drug Conviction*	*Felony Property Conviction*	*Felony Violent Conviction*
White	0.716	0.704	0.709	0.675
Black	0.655	0.668	0.660	0.668
Hispanic	0.725	0.706	0.709	0.673
Other	0.749	0.771	0.713	0.693
Total	0.700	0.697	0.693	0.678

PRCS

Ethnicity	*Felony Conviction*	*Felony Drug Conviction*	*Felony Property Conviction*	*Felony Violent Conviction*
White	0.679	0.656	0.713	0.699
Black	0.635	0.676	0.688	0.701
Hispanic	0.713	0.665	0.716	0.721
Other	0.682	0.712	0.683	0.662
Total	0.687	0.661	0.710	0.702

Tables 3.8 and 3.9 break down performance for both post-release supervision groups by gender and ethnicity. As it would be both tedious and of little practical use to discuss these with the same level of detail as above, we rely instead on broader characterizations of the patterns. In the Parole supervision group, performance for both males and females tends to be slightly above the results for the group as a whole but within one or two percent of the total. The performance for females for Property recidivism is anomalously high at +7%, possibly an artifact of chance given the small size of this group.[12] Within the PRCS supervision group (Table 3.8), performance for females it is 2% to 4% percent weaker than for males. There seems to be a mild interaction between supervision and gender; the prediction for females is equal to or stronger that the prediction for males in the Parole Group but weaker in the PRCS group.

For ethnicity the pattern is similar for both supervision groups. Whites are within a percent or two of the group figures. This is close enough that we get the same results for the other ethnic groups whether we compare them to whites or the total cohort. For blacks the Any Felony and Property AUCs are respectively 8% and 3% lower than for the group or for whites. For Violent recidivism the predictions are equivalent. For Drug recidivism, Black AUCs are 4% lower for those on Parole but 2% higher for those on PRCS. AUCs for Hispanics are generally equivalent to or slightly higher than for whites, reaching a 4% improvement for Any Felony predictions. The small size of the mixed ethnicity Other may lead to more chance variation; while AUCs are 2% to 11% higher in the Parole group, they range from 6% lower to 8% higher in the PRCS group. The differences within supervision groups largely mirror the overall pattern for ethnicity; there is no evidence of an interaction between ethnicity and supervision type.

3.3 Recidivism by Risk Groups

The assignment of individuals to risk groups and rates of recidivism with risk groups are not primary performance issues for the CSRA. Rather they are secondary issues driven by the interaction between the ability of the CSRA to discriminate between future recidivists and non-recidivists, and policy decisions on how to manage the population under CDCR supervision in light of trade-offs between public safety and perceptions, department resources, and the costs and benefits of different types of supervision and services. This section then is less concerned with revalidation of the CSRA and more advisory. It answers the question, given the policy decisions made at the adoption of the CSRA, what are the consequences for the population distribution across risk groups

[12] *In the Validation subset of the data, 6% of parolees or 736 individuals are women.*

and recidivism levels within risk groups following realignment and other changes in policy and practice since our original report?

Figure 3.1 Population Distribution by Risk Group, All Cohorts

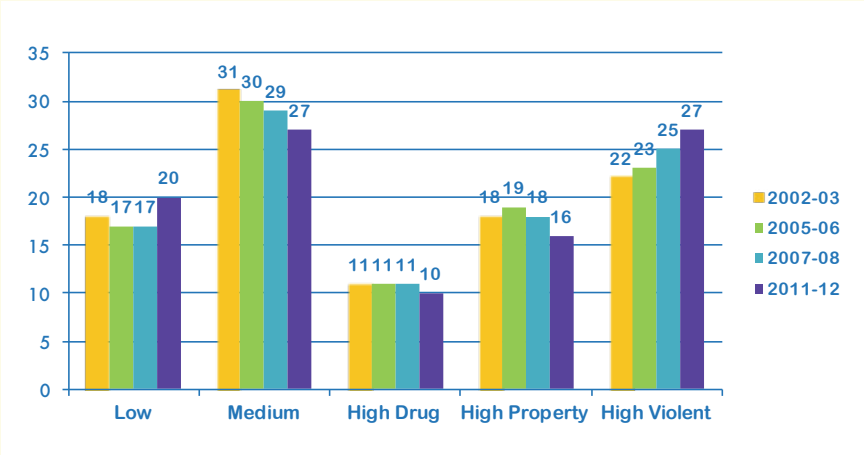
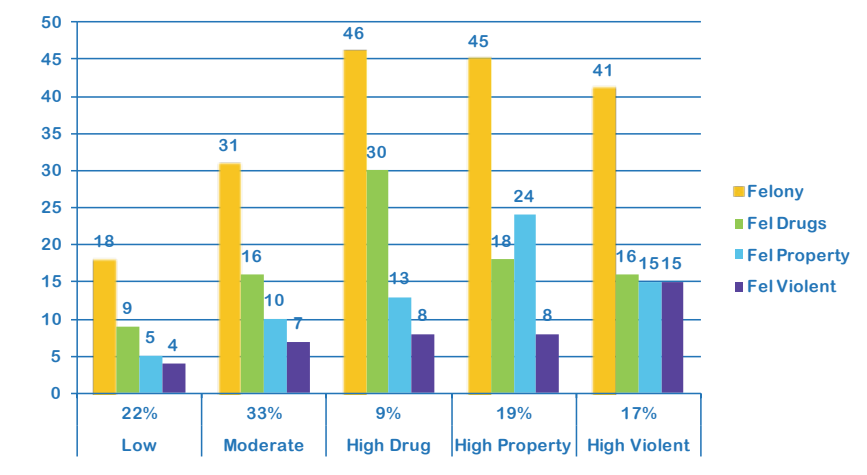


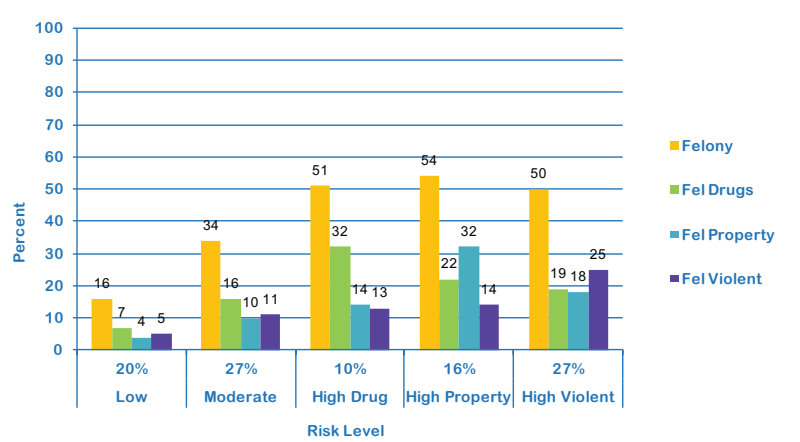
Figure 3.1 shows the evolution of the population distribution across risk groups over time using the four release cohorts available.[13] It shows a trend in the decreasing proportion of the population classified as a Medium recidivism risk of roughly 1 percentage point per cohort or 0.5 percentage points per year, and a corresponding rise in the proportion classified as High risk for a new violent felony conviction. Pre-realignment (Cohorts 2002-03, 2005-06, 2007-08), the other (Low, High Drug, High Property, and High Violent Felony) risk groups varied in size by a percentage point or less from cohort to cohort. Following realignment the trends reducing the Medium risk group and increasing the High Violent risk group size strengthen a bit along with a new rise in the Low Risk proportion and declines in High Drug and High Property assignments. As realignment diverts low stakes but often high risk drug and property offenders to the counties, the prison population is increasingly High Violent risk offenders, possibly plus high stakes offenders who do not yet have enough of a criminal record to lead to a high risk classification. (See Figure 3.4 below.)

Figure 3.2 Recidivism by Risk Group, 2002-2003 Cohort



[13] *The 2002-2003 numbers in this section do not correspond exactly with those reported in the 2009 working paper. As we have to use the modified ASP code and 2015 mapping table to get the best results with the 2011-2012 cohort, consistency and comparability require that we use this code on the older cohort too.*

FIGURE 3.3 RECIDIVISM BY RISK GROUP, 2011-2012 COHORT



Comparing the cohorts (Figures 3.2 and 3.3) shows that recidivism has increased. Recidivism was fairly stable from the baseline through the 2005-2006 and 2007-2008 cohorts with shifts of a percentage point or two.[14] For the 2011-2012 post-realignment cohort (table not shown), overall, Drug Felony recidivism rose about 10% from 16% to 18%, Violent Property and Any Felony rose a bit less than 20%, respectively from 13% to 15% and from 34% to 40%. Violent Felony recidivism rose 80%, from 8% to 14%. The increase in Violent recidivism in particular impacted rates in all groups, but not proportionately: In the low risk group, the Violent rate rose only 25%, (1 percentage point), while in other groups in increased by 60% to 75%. (4, 5,6, and 10 percentage points respectively for Moderate, High Drug, High Property, amnd High Violent risk groups).

Given the overall increase, how did the risk groups perform? Excluding Violent Felony recidivism, the Low Risk group actually has lower recidivism rates post-realignment than at the baseline, declining for Any Felony, Drug, and Property respectively by 11%, 22%, and 20%. The Moderate Risk group holds the line on Drug and Property recidivism with no change while the rate for Any Felony rises by 10%, or a bit more than half of the rate of the overall increase of 17%. The overall rise in recidivism was reflected most in the increased rates in the high risk groups, as expected. Excluding Violent Felony recidivism, rates rose in the neighborhood of 10% for the High Drug risk group, 20% to 40% for the High Property risk group, and around 20% for the High Violent risk group.

TABLE 3.10 COHORT 2002-03 VS 2011-12. RISK GROUP DISCRIMINATION BY RECIDIVISM TYPE

Supervision	*Recidivism Rate*	*Any Felony Conviction*	*Drug Felony Conviction*	*Property Felony Conviction*	*Violent Felony Conviction*
2002-2003	**Not High**	25	14	11	7
	High	44	30	24	15
	Discrimination	1.80	2.11	2.23	2.22
2011-2012	**Not High**	25	16	12	11
	High	52	32	32	25
	Discrimination	2.07	2.00	2.78	2.33
Ratio PRCS/Parole		1.15	0.95	1.25	1.05

[14] *The charts are included in the appendix.*

Another way of assessing risk group performance is to ask how well the groups differentiate recidivism rates; for example, whether the Drug recidivism rate is higher in the High Drug risk group than in other groups, and by how much. We calculated a rough measure, which divides the rate of recidivism in the risk group intended to maximize it by the unweighted average recidivism in the other risk groups. For Any Felony, we combined the three high risk groups into one and compared this to the combined Low and Moderate risk groups. Since this measure restricts itself to comparisons within a particular type of recidivism, it is unaffected by different recidivism rates across offense-specific outcomes. The results are given in Table 3.10. For the 2002-2003 cohort, this measure of discrimination ranges from 1.8 for Any Felony to 2.2 for Property and Violent recidivism. For the 2011-2012 cohort, this measure ranges from 2.0 for Drug Felony to 2.8 for Property recidivism. Comparing this measure of discrimination for the post-realignment to the baseline cohort, it decreased by 5% for Drug recidivism, and increased respectively by 15%, 25%, and 5% for Any Felony, Property, and Violent recidivism. We conclude that the risk groups continue to discriminate between rates of recidivism for the different outcomes, at least as well post-realignment as for the pre-realignment CDCR population released from prison.

Figure 3.4 Population Distribution by Risk Group, 2011-2012 Cohort, Parole versus PRCS

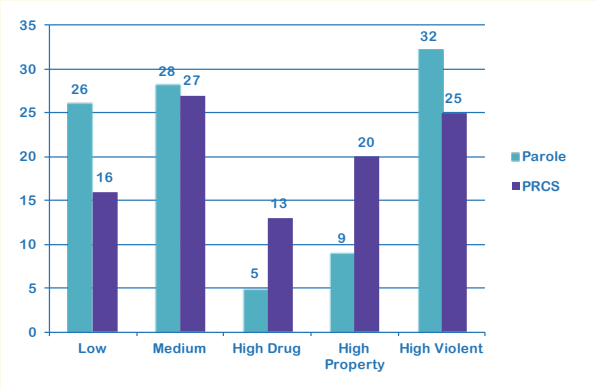


Figure 3.5 Recidivism by Risk Group, 2011-2012 Cohort, Release to Parole

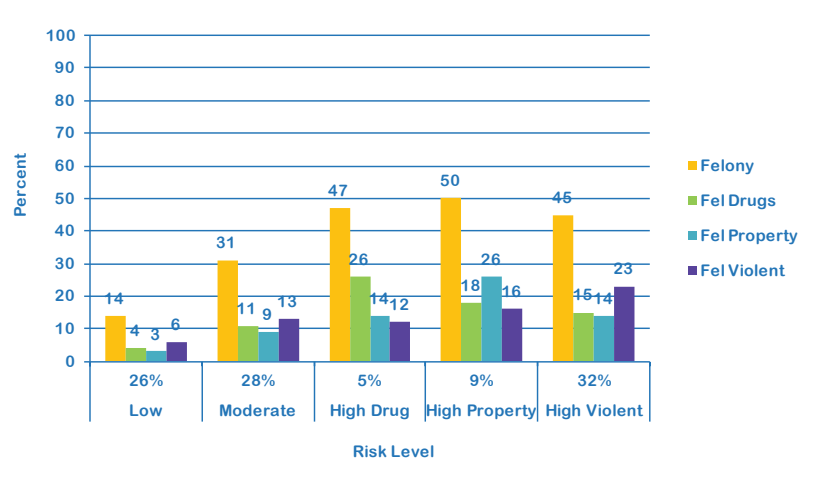
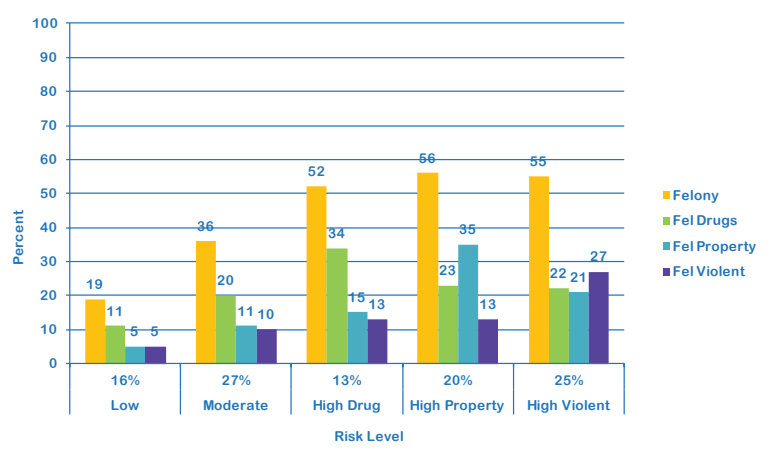


FIGURE 3.6 RECIDIVISM BY RISK GROUP, 2011-2012 COHORT, RELEASE TO PRCS



Here we turn again to our break out of the 2011-2012 cohort by post-release supervision. Figure 3.4 compares the population distribution across risk groups for Parole and PRCS supervision groups. Both groups have roughly the same proportion assigned to the Moderate risk group. Parole has roughly 40% more individuals assigned to Low risk and 20% more assigned to High Violent risk than PRCS, with relatively few in High Drug (5% versus 13% for PRCS, an increase of 160%) and High Property (9% versus 20%, an increase of 120% for PRCS). The effect of realignment is that the combined total of those at high risk for drug and violent property felonies is roughly 1 in 7 of the Parole group, but 1 in 3 of the PRCS group.

While overall recidivism rates have increased, the increase is not equally divided between Parole and PRCS supervision groups, with the exception of Violent Felony recidivism, in which the rates of both groups are equal to each other and the overall 180% increase from the 2002-2003 baseline. Otherwise, rates for the Parole groups are equivalent to (Any Felony) or lower than for the baseline (-25% for Drug and -15% for Property recidivism). The rising rates are found in the PRCS group, with increases over the Parole rates for Any Felony, Drug Felony, and Violent Property Felony respectively at 32%, 83%, and 66%.

This difference between supervision groups has an impact on recidivism rates within risk groups. For Any Felony, Drug Felony, and Violent Property Felony, these rates are higher for PRCS than Parole risk groups by levels ranging from +5% (Property recidivism in the High Drug risk group, 15% vs 14% respectively) to +175% or a factor of almost 2.8 times for Drug recidivism in the Low risk group, with rates for PRCS and Parole respectively at 11% and 4%. Generally the increases within risk groups for PRCS supervision over Parole range from 10% to 80% for these three outcomes, averaging out to 43%.[15] Contrarily, for Violent Felony recidivism, the rate for PRCS as opposed to Parole is lower by around 20% in Low, Moderate, and High Property risk groups, up by 17% in the High Violent risk group, and up by 8% in the High Drug group.

The Low risk group shows the biggest changes in recidivism rates when change is measured as a percentage of an initial rate, as the low rates in the Parole group amplify the effects of differences of a few percentage points in the PRCS group. This assessment of relative change has been our usual method of representing differences. In this case the unweighted average recidivism rates for PRCS over Parole increase by 65% for Low risk group, 24% for the Moderate, 14% for the High Drug and High Property, and 34% for the High Violent risk group. If we look at the differences as absolute changes in percentage points, not dividing them by an initial rate, the rates for

[15] *For Drug recidivism in the Low risk group, the increased rate of PRCS over Parole spikes at 175% based on rates of 11% versus 4%; see the following paragraph for a comment on the effects of a low baseline rate.*

both Low and Moderate risk groups increase by about 3 percentage points; the rates for both High Drug and High Property risk groups increase by about 4 percentage points; and the rate for the High Violent risk group increases by 7 percentage points. These two measures give different pictures of the impact of higher overall recidivism rates on rates within risk groups. The relative differences between Parole and PRCS groups in particular may raise questions on whether these constitute two distinct populations and whether they should be normed separately in assigning risk classifications.

Table 3.11 Cohort 2011-12, Parole vs PRCS. Risk Group Discrimination by Recidivism Type

Supervision	*Recidivism Rate*	*Any Felony Conviction*	*Drug Felony Conviction*	*Property Felony Conviction*	*Violent Felony Conviction*
Parole	**Not High**	23	12	10	12
	High	47	26	26	23
	Discrimination	2.10	2.17	2.60	1.96
PRCS	**Not High**	28	19	13	10
	High	54	34	35	27
	Discrimination	1.98	1.79	2.69	2.63
Ratio PRCS/Parole		0.94	0.83	1.04	1.35

For another assessment of risk group performance in these two supervision groups we look again at our rough measure of discrimination (Table 3.11). For the Parole group, this measure of discrimination ranges from 2.0 for Violent to 2.6 for Property recidivism with Any Felony (2.1) and Drug Felony (2.2) in between. For the PRCS group, this measure ranges from 1.8 for Drug Felony to 2.7 for Property recidivism with Any Felony (2.0) and Violent Felony (2.6) in between. These ranges are similar to those both for the cohort overall and for the 2001-2003 baseline cohort. Comparing this measure of discrimination for the PRCS to the Parole group, it decreased by about 6% for Any Felony recidivism and 17% for Drug recidivism, Discrimination in the PRCS group is higher by 4% for Property recidivism and 35% for Violent recidivism. Another way of looking at this is to note that in the Parole group, while discrimination for other outcomes was around 2.0 plus or minus 10%, for Property it was 2.6, reflecting the relatively strong AUC of .707. In the PRCS group discrimination for the Violent outcome rises to about the same level as for Property (2.6 and 2.7 respectively), again reflecting a rising AUC. For both the AUC and discrimination measure, a higher score indicates a greater similarity of behavior among people who have similar scores. If this is due to supervision interventions increasing normative behavior, we might expect lower recidivism in the group with higher AUCs and higher discrimination, but we don't find a consistent relationship between recidivism, discrimination, and supervision. This leaves us suspecting that the differences arise in how realignment affects which segments of the sentenced population are sent to prison and who is assigned to Parole or PRCS. Answering the questions raised by these differences in predictive ability and discrimination lie beyond the scope of this project. However, we find that the risk groups continue to discriminate between rates of recidivism for the different outcomes, with a rough equivalence in the range of discrimination for both the Parole and PRCS supervision groups that equals or improves the discrimination in the baseline cohort.

4 Impact of missing data in the 4th year after release

Table 4.1A Cohort 2007-2008 Baseline. Convictions by Years after Release

Year of Recidivation	Cumulative Number	Percent	Percent	Percent of Recidivism
None	71,825	66.45	66.45	
1st	17,558	16.24	82.89	48.41
2nd	11,009	10.18	92.88	30.36
3rd	7,699	7.12	100	21.23

Table 4.1B Cohort 2007-2008, Censored Data. Convictions by Years after Release

Year of Recidivation	Cumulative Number	Percent	Percent	Percent of Recidivism	Change from Baseline
None	72,107	66.71	66.71		99.66
1st	17,540	16.23	82.94	48.74	100.10
2nd	10,965	10.14	93.08	30.47	100.40
3rd	7,479	6.92	100	20.78	102.94

Table 4.1C Cohort 2011-2012. Convictions by Years after Release

Year of Recidivation	Cumulative Number	Percent	Percent	Percent of Recidivism
None	37,380	61.15	61.15	
1st	13,539	22.15	83.3	57.01
2nd	7,343	12.01	95.31	30.92
3rd	2,868	4.69	100	12.08

Table 4.1D Cohort 2011-2012. Imputed Convictions by Years after Release

Year of Recidivation	Cumulative Number	Percent	Percent	Percent of Recidivism	Change from Baseline
None	37,252	60.94	60.94		99.66
1st	13,553	22.17	83.11	56.76	100.10
2nd	7,372	12.06	95.17	30.88	100.40
3rd	2,952	4.83	100.00	12.36	102.94

Table 4.2: Imputed Recidivism by Risk Group, 2011-2012 Cohort
Would require breaking down recidivism by years after release by risk group.

As noted above, while in the CSRA recidivism is based on a new offense within 3 years following release, it requires four years of data to capture conviction dispositions in order to allow for normal delays in the judicial process.[16] In the 2011-2012 cohort the censoring of data at three years from the last release date (see Figure 1.1) causes the loss of some convictions that should be counted as recidivism to maintain consistency with both instrument intent and the evaluation of other cohorts. In this section we impute the missing recidivism using the 2007-2008 cohort as the basis for imputation, given that it is the closest in time and most likely to resemble the 2011-2012 cohort on composition and case processing. For brevity, we limit our analysis to the Any Felony outcome which includes the more offense-specific recidivism events.

[16] *While the delays from arrest to conviction can take more than a year, we adopted the 4 year cutoff due to the pragmatic concerns that few additional convictions would added in the 5th year, and that increases in accuracy of measuring recidivism would be offset by limiting us to analyses that would not be able to keep up with changes in corrections policy and practice due to the need to wait 5 years for evaluation.*

Our method for imputing recidivism is simple. We broke down total recidivism in the 2007-2008 cohort into recidivism within one, two, or three years based on the date of arrest (Table 4.1A). We then created a dataset in which we censored all events which occurred more than three years after the final release date of June 30th 2008, and again ran the data through the CSRA ASP and measured recidivism within one, two, or three years. For each of the three years, we divide the number of incidents of recidivism based on four years of follow up by the number of incidents of recidivism based on three years of follow up to estimate the additional recidivism that would have been measured in each year with an additional year for convictions to take place and end up in the data record (Table 4.1B).[17] We then applied this factor to the recorded Any Felony recidivism in the 2011-2012 cohort (Table 4.1C) to estimate the recidivism we would have observed with a fourth year of follow-up. To calculate the estimated number of non-recidivists we summed the estimated total recidivism across all three years and subtracted it from the number in the cohort.

Table 4.1D gives the results. We estimate that given a fourth year of data, measured recidivism would rise by 0.1% in the first year, 0.4% in the second year, and 2.9% in the third year. The estimated level of Felony recidivism rises from 38.85% to 39.06%, 0.21 percentage points or by a factor of 0.5%. We judge that this difference is not sufficient to affect any of our analyses or conclusions.

5 Analysis of Remapping PC290 Sex Offender Registration from Escape to Supervision Violation.

Under California Penal Code section 290, offenders convicted of many types of sex crimes are required to register as sex offenders and update their information in the registry annually, or when they change residence or begin attending classes on a college campus. In the 2009 version of the tables mapping statute codes to CSRA risk items, violations of PC 290 were classified as escapes. In the DOJ automated rap sheet data used to reconstruct a criminal history, few escape charges were recovered, given the stage of the ASP code at the time when risk item weights were determined; 2.5 % of criminal histories included a felony escape and 0.05 included a misdemeanor escape. Escapes were found to have little use in predicting recidivism. In the six models predicting recidivism to used assign risk groups (two measures of recidivism as a new arrest or a new conviction, by three outcomes, i.e. Felony, Property, and Violent outcomes), escapes are given a weight of zero and contribute nothing to the prediction.[18] Violations of supervision conditions on the other hand have positive weights in all six models. We asked whether re-classifying failures to register as a sex offender as violations of supervision conditions would add information to the recidivism predictions and improve CSRA performance. Accordingly, we created versions of the two mapping tables in which PC 290 and PC 290.4 violations were reclassified as supervision violations. As violations of sex offender registration requirements are generally regarded to be serious offenses, we assigned these a seriousness level of 8 to ensure that they were selected above other supervision violations for inclusion in the criminal history which are assigned a seriousness level of 6.

Table 5.1 AUC by Felony type for Cohort 2007-2008, PC290 as Escape vs Supervision Violation

PC290 Mapping	*Felony Conviction*	*Felony Drug Conviction*	*Felony Violent Property Conviction*	*Felony Violent Conviction*
Escape	0.694	0.689	0.702	0.690
Supervision Violation	0.696	0.691	0.706	0.699

[17] *As we do not have data on how long on average it takes a conviction disposition in the courts to enter the DOJ database, we did not attempt to include this factor, which may lower our estimate by a few tenths of a percent.*

[18] *With the lastest modifications to the ASP, the identification of escapes rises to 6.3% for felony escape and 3.2 percent for misdemeanor escape.*

Table 5.1 shows the results of our analysis. In this analysis we reclassified PC 290 violations in the mapping tables but did not re-estimate our recidivism prediction models and modify risk item weights. For each outcome, the remapping of PC 290 offenses leads to slight increases in the AUC. Although these changes are not substantial or statistically significant, they support the proposed remapping which has the virtue of assuring stakeholders that these offenses are included in risk predictions.

The change in mapping for PC 290 leads to small changes in the distribution of cases across risk groups and as a consequence, the rates of recidivism within risk groups. However, none of these shifts are large enough to remain visible when numbers are rounded to the nearest percent for creating charts, so we do not include a separate figure for these results.

6 Proposition 47 Impact on CSRA

California voters passed Proposition 47, titled on the ballot as **"Criminal Sentences. Misdemeanor Penalties. Initiative Statute"** on November 4th, 2014. Proposition 47 reclassifies non-serious non-violent offenses formerly chargeable as felonies to misdemeanors. It also allows people previously convicted of a felony under one of the affected California code sections to apply for a reduction in their sentence. A sentence reduction would render anyone serving a felony prison sentence eligible for release.

The changes in California criminal law under Proposition 47 potentially impact the performance of the CSRA through two paths. First, behavior which was once classified as a felony and counted as such in the CSRA is now reclassified, which will change risk scores and risk group assignments, and consequently the population distribution across risk groups. Second, as individuals affected by Proposition 47 are diverted from prison or released, it will change the characteristics of the population under CDCR supervision. The CSRA predictions were calibrated using a specific release cohort from a prison population which is no longer a match to the current population. Both these paths require analysis of how they affect performance of the current CSRA instrument and consideration whether the CSRA needs recalibration.

6.1 Proposition 47 Scope: Offense Definitions

Analysis of the impact of proposition 47 requires determining the scope of the ballot measure. While it explicitly addressed specific statutes of California Penal Code and Health and Safety Code by section designation, the proposition also includes general language referring to classes of offenses and a requirement that "This Act shall be liberally construed to effectuate its "purposes" (Section 18)." This leaves the scope of the measure open to interpretation, and interpretations have been provided by the CDCR, the California Legislative Analyst's Office, the Administrative Office of the Courts (AOC), and various private law firms. In our initial proxy analysis of the effects of reclassifying offenses by remapping them in the ASP mapping tables, we compared the effects of the CDCR and AOC analysis, and present here the AOC analysis.

The AOC interpretation is broader, covering more statute codes under which offenses can be filed and hence a greater number of offenses and individuals are affected. The written analysis of the application of Proposition 47 in the courts is the most extensive, provided by a retired judge of the Superior Court (J. Richard Couzens) and a presiding judge of the Court of Appeal (Tricia A. Bigelow) with a listing of implicated statues codes by a retired judge of the Superior Court (John Ryan). We judged this interpretation as the one most likely to guide the application of Proposition 47 in practice.

For our analysis of the impact of a shifting population on the CSRA we supplemented the AOC definition with one published online by a private firm, Cota Law. This interpretation extends the reach of the measure for statutes covering forgery, and in empirical checks it covers individuals released from prison under Proposition 47 not matched by the AOC definition.

6.2 Re-Mapping Offenses Effect

Our analysis of Proposition 47 was guided by a limited ability to identify those specific offenses eligible for reclassification, most severe in the case of property offenses where the criteria was the value of stolen or fraudulently obtained goods and services, which is not recorded in the data. Hence we explored a boundary condition: the effects of reclassifying all felony offenses convicted under an eligible statute code as a misdemeanor. The CSRA translates charges to risk item counts using a table which, in combination with information on felony versus misdemeanor sentencing, maps a range of statute codes to risk items. We produced a modified version of this table, setting the type of charge on all affected offenses to a maximum of a misdemeanor for analytic purposes.[19]

The CSRA obtains risk estimates by multiplying the count of offenses on 20 criminal history items by a weight and summing them (together with weighted responses on age and gender) to calculate a score. As far as weights differ for the felony and misdemeanor levels of an offense category (e.g., assault, weapons, drugs), reclassifying the offense will change the weight applied and the final risk score, and if the change in score is large enough it could lead to reassignment to a different risk group. The magnitude of the changes in scores together with the number of individuals affected determines the extent of the change to CSRA results.

6.2.1 Differences in Weights

Table 6.1 shows the change in weights when reclassifying an offense from a felony to a misdemeanor. Under Offense Category, Property stands for non-violent property offenses which are affected by Proposition 47, not violent property offenses such as robberies which remain felonies. The label "PropV" designates the scale used to estimate the risk of a new violent property felony.

Table 6.1 Changes in Weights from Proposition 47 Reclassification of Offenses

Offense Category	*Maximum Counts Score*		*Weights*					
			Felony Counts Score		*V. Property Score*		*Violent Score*	
	Fel.	**Misd.**	**Fel.**	**Misd.**	**Fel.**	**Misd.**	**Fel.**	**Misd.**
Property	5	3	3	3	6	4	0	0
Drug	3	2	3	4	-5	-1	-2	-1

The distribution of risk scores gives context to the size of these changes (Table 6.2). For property felonies, Felony and Violent Felony scores weights are not different. Each non-violent property conviction reclassified will reduce the Violent Property Felony score by two points or 0.11 standard deviations (s.d.) at a first approximation (See Table 6.2A). An additional consideration is that the counts on risk items are capped at a maximum to prevent outliers (unusually high counts) from exercising outsized leverage on the results.

The cap for property felonies is 5 while the cap for property misdemeanors is 3; insofar as the number of felonies reclassified causes the number of misdemeanors to exceed the cap some convictions will be lost and not contribute to the risk scale scores. Each lost felony property conviction will lead to a loss of 3 points on the Felony score and a loss of 6 points on the Violent Property score. If "all bases are loaded" with maximum counts for both felony and misdemeanor property offenses, the loss of 5 convictions would lower the Felony Score by a maximum of 15 points, or a change of approximately 0.65 s.d.. The maximum impact of property conviction reclassification on the Violent Property score would lower the score by 30 points, or a move of approximately 1.64 s.d.

[19] *We left infractions unchanged.*

Table 6.2A Distribution of Risk Scale Scores, Unmodified Mapping Table

Scale	*Mean*	*Std. Deviation*	*Minimum*	*Maximum*
Felony	90.9	23.1	-11.0	166.0
Violent Property	59.7	18.3	-13.0	126.0
Violent	34.8	9.4	-7.0	69.0

Panel A: Standard Mapping Table

Table 6.2B Distribution of Risk Scale Scores, Prop 47 (AOC) Mapping Table

Scale	*Mean*	*Std. Deviation*	*Minimum*	*Maximum*
Felony	88.3	22.2	-11.0	169.0
Violent Property	59.0	18.5	-13.0	126.0
Violent	35.0	9.4	-8.0	69.0

Panel B: Prop 47 Modified Mapping Table

For drug convictions, reclassification increases Felony and Violent Felony scores by one point. This is an increase of about 0.04 s.d. for Felony and 0.11 s.d. for Violent Felony scores. Each drug conviction reclassified will increase the Violent Property Felony score by 4 points (about 0.22 s.d.). The cap for drug felony counts is 3 while the cap for misdemeanors is 2; insofar as the number of felonies reclassified causes the number of misdemeanors to exceed the cap the effect on the risk score will be a loss of 3 points of the Felony score up to a maximum of 9 points (0.39 s.d.). The impact of a drug conviction reclassification on the Violent Property score is an increase of 5 points up to a maximum of 15 points (0.82 s.d.); for the Violent outcome score it is an increase of 2 points up to a maximum of 6 points (+0.64 s.d.).

In sum, the changes in scores from reclassifying felonies to misdemeanors can go in both directions – for drug offenses, a misdemeanor conviction is a stronger predictor of a future felony than a felony conviction itself. The change in scores from a single reclassified conviction is small, 4% to 22% of a standard deviation. A score shift of this magnitude would only affect the classification of individuals close to the cut points of risk category boundaries. Changing the mapping tables to reclassify all Proposition 47 felonies as misdemeanors would have a larger effect, shifting some proportion of the scores as much as 44% to 164% of a standard deviation. Table 6.2B shows the overall effect of such a remapping on the risk scores – the mean score for Felony and Violent Property decline respectively by 2.6 and 0.7 percentage points; the mean Violent score rises by 0.2 percentage points; the differences are statistically significant but substantially minor.

6.2.2 Potential Number of Offenses or Individuals Affected

For the analysis of the impact of Proposition 47 through the reclassification of offenses, we used the last cohort we had with sufficient data and the full 3-year follow-up to capture recidivism, released from CDCR prison custody in fiscal year 2007-2008.[20] In round figures, this cohort of 108,092 individuals have recoverable information on approximately 1,250,000 charges; when only the most serious offense is chosen from criminal history cycles with convictions on multiple charges, there are 950,000 convictions. Of all convicted charges, about 31% are property offenses and about 30% are drug offenses. Twenty-two percent (22%) of these are charged under statute codes that are covered by Proposition 47, 18% are felonies which are reclassified as misdemeanors in this analysis. Of the most serious conviction charges, which are the offenses counted by the CSRA, ~23% are property offenses and ~22% are drug offenses. (These lower percentages reflect the selection of more serious violent offenses when multiple charges are brought.) Sixteen percent (16%) of these are charged under statute codes that are covered by Proposition 47, 14% are felonies which are reclassified as misdemeanors in this analysis. When charges are processed and counted using the modified version of the mapping table, in the final collection of most serious charges, 28% of non-violent property offenses and 30% of drug offenses are reclassified as misdemeanors.

[20] *At the time of our analysis, we didn't have sufficient follow-up data to use the more recent 2011-12 cohort.*

Table 6.3 Changes in Risk Classification with Proposition 47 Modifications of Sentence

	Current Risk Level					
Modifed Risk Level	*High Violent*	*High Property*	*High Drug*	*Medium*	*Low*	*Total*
High Violent	26,643	375	295	220	8	27,541
% of Total	24.7	0.4	0.3	0.2	0.0	25.5
% of Column	98.1	2.0	2.4	0.7	0.0	
High Property	207	15,908	736	1,410	9	18,270
% of Total	0.2	14.7	0.7	1.3	0.0	16.9
% of Column	0.8	83.5	6.1	4.5	0.1	
High Drug	163	1,066	7,753	339	0	9,321
% of Total	0.2	1.0	7.2	0.3	0.0	8.6
% of Column	0.6	5.6	64.2	1.1	0.0	
Medium	134	1,688	3,293	26,999	564	32,678
% of Total	0.1	1.6	3.1	25.0	0.5	30.2
% of Column	0.5	8.9	27.3	86.5	3.0	
Low	5	10	0	2,257	18,010	20,282
% of Total	0.0	0.0	0.0	2.1	16.7	18.8
% of Column	0.0	0.1	0.0	7.2	96.9	
Total	27,152	19,047	12,077	31,225	18,591	108,092
Column % of Row	25.1	17.6	11.2	28.9	17.2	100.0
Change from Current Risk Level						
Higher Risk	0.0	2.0	8.5	6.3	3.1	
Lower Risk	1.9	14.5	27.3	7.2	0.0	
Any Change	1.9	16.5	35.8	13.5	3.1	
Change as a Percentage of Total	0.5	2.9	4.0	3.9	0.5	11.8

Table 6.4 Changes in Risk Classification with Proposition 47 Modifications of Sentence

	Current Risk Level		
Modifed Risk Level	*High Risk*	*Low Risk*	*Total*
High Risk	53,146	1,986	55,132
% of Total	49.2	1.8	51.0
% of Column	91.2	4.0	
Low Risk	5,130	47,830	52,960
% of Total	4.8	44.3	49.0
% of Column	8.8	96.0	
Total	58,276	49,816	108,092
	53.9	46.1	100.0
Change from Current Risk Level			
Higher Risk	0.0	4.0	
Lower Risk	8.8	0.0	
Any	8.8	4.0	
Change as Percentage of Total	4.8	1.8	6.6

Shifting the focus from offenses to offenders, the effect of the modified mapping table on risk classification is to change the assignment of 11.8% of all individuals to another group (Table 6.3). Assuming that only transitions

between High and Moderate-to-Low risk categories would require changes in supervision and impact CDCR resources, this changes the risk category of 6.6% of individuals (Table 6.4). These tables show the results, with a summary of percentages moving to higher or lower levels based on their original classification. These shifts represent the same numbers as the 'Change as a percent of the Total' row, but with the smaller denominator of a single group they work out to higher percentages.

Table 6.5 AUCs

		Recidivism Offense Type			
Outcome	*Mapping*	*Drug Any Felony*	*Violent Felony*	*Violent Property Felony*	*Felony*
Convictions	Baseline	0.652	0.671	0.680	0.682
	Prop47 Adjustment	0.650	0.671	0.677	0.682
	Change	-0.002	0.000	-0.003	0.000
Arrests	Baseline	0.697	0.672	0.682	0.673
	Prop47 Adjustment	0.679	0.659	0.666	0.675
	Change	-0.018	-0.013	-0.016	0.002

Notes
All potentially Prop47 offenses, based on AOTC guide, adjusted to a misdemeanor
Based on 2007-2008 cohort, validation sample, hybrid records excluded

6.2.3 Effect on CSRA AUCs

The remapping of potential Proposition 47 offenses to misdemeanors has minimal impact on the AUC for predictions of a new conviction on an offense committed in the 3 years following release, with a decline of 0.3% for any new felony and 0.4% for a new violent property crime, with drug and violent felony results unchanged. The impact is a bit higher for predicting a new felony arrest. The AUC declines by 2.6% for any felony, 1.9% for drug felonies, and 2.3% for violent property felonies. However, the violent felony change is a minor 0.3% improvement. Overall these are very marginal changes. The changes might be addressed by reweighting risk items, but this seems unnecessary as conviction outcome changes are so small and the arrests predictions are not used by the CDCR in practice.

Table 6.6 Risk Group Distribution & Rates

			Recidivism Rate by Offense Type			
Run	*Percent Risk Group*	*Any in Group*	*Drug Felony*	*Violent Felony*	*Violent Property Felony*	*Felony*
Baseline	High Violent	25	41	14	15	17
	High Property	18	44	16	27	9
	High Drug	11	42	27	11	7
	Moderate	29	29	14	10	7
	Low	17	16	8	4	4
AOC Prop47 Adjustment	High Violent	25	40	14	15	16
	High Property	17	44	16	27	8
	High Drug	9	44	28	13	7
	Moderate	30	30	15	10	7
	Low	19	17	9	4	4

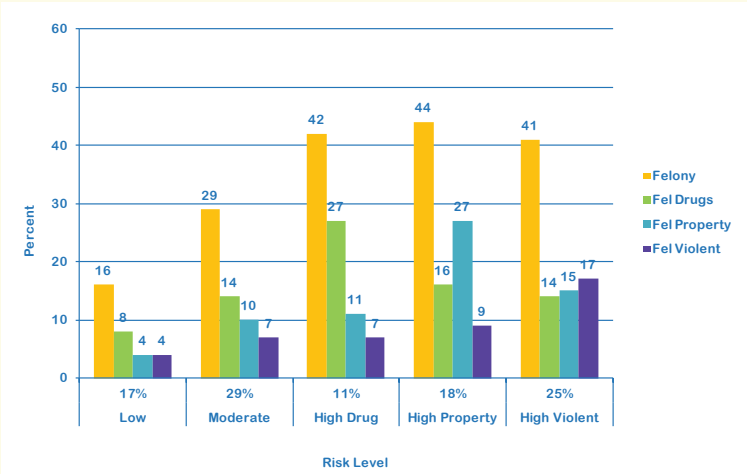
Table 6.6 Risk Group Distribution & Rates (Cont.)

Run	Risk Group	Percent in Group	Recidivism Rate by Offense Type: Any Felony	Drug Felony	Violent Property Felony	Violent Felony
Change	High Violent	0	-1	0	0	-1
	High Property	-1	0	0	0	-1
	High Drug	-2	2	1	2	0
	Moderate	1	1	1	0	0
	Low	2	1	1	0	0
	Overall Rate	*34*	*15*	*13*	*9*	

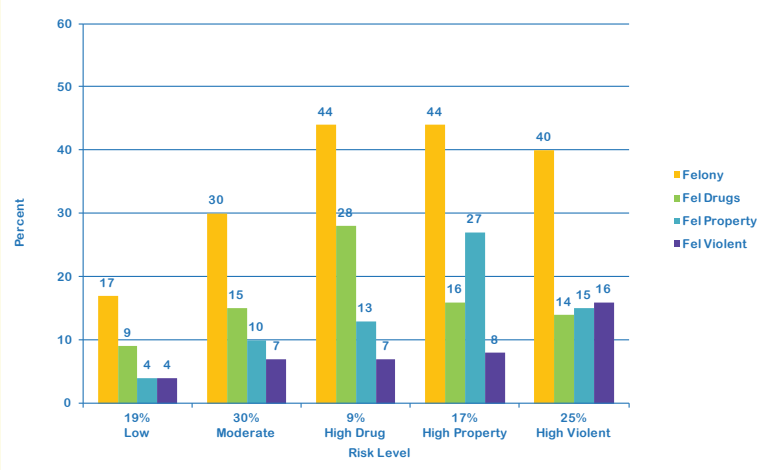
Notes: All potentially Prop47 offenses adjusted to a misdemeanor.
Based on 2007-2008 cohort, validation sample, hybrid records excluded

The remapping of potential Proposition 47 offenses to misdemeanors has minimal impact on how the population is distributed across risk groups. The size of the High Violent recidivism risk group in unchanged; the High Violent Property and High Drug groups decline one and two percentage points respectively, while the Moderate and Low risk groups increase by one and two percentage points respectively.

Figure 6.2 Recidivism Rates



Panel A: Standing Mapping Table



Panel B: Proposition 47 Adjusted Mapping Table

The remapping of potential Proposition 47 offenses to misdemeanors has minimal impact on recidivism rates. The overall rate is fixed; when individuals risk scores rise or fall enough to change risk groups their recidivism is now counted in the new group; the low percentage of net movement between groups limits the change in recidivism rates, often to within rounding error. Hence the rate of new violent felony convictions falls a percentage point in the High Violent and High Property risk groups without showing up as an increase in the High Drug, Moderate, or Low risk groups. The High Drug risk group has one to two percentage point increases in Any, Drug, and Violent Property felonies; the Moderate and Low risk groups have a one percentage point increases in Any and Drug felonies. The differentiation in recidivism rates between risk groups consequently declines by roughly the same magnitude.

6.2.4 Conclusions

There are limits to our ability to draw conclusions from this exercise due to the differences between it and the actual situation where sentence type information is available. This is primarily a concern for property offenses, where we are able to make no distinction finer than the classification as a felony or misdemeanor in the absence of an indicator of the dollar value of damages. We are constrained to making a wholesale change to the mapping of property offenses, changing the risk item counts, scores, and risk group assignments of a higher proportion of the cohort than would be realized in practice. Therefore our numbers reflect a boundary condition of maximum impact; to judge the actual change we must interpolate between the baseline measures of performance and those induced by remapping. We think this provides sufficient guidance to draw some conclusions and make recommendations.

In practice, the sentencing judge will have the information to determine whether Proposition 47 applies, so there are no concerns on that account. The question that arises is different: should the same behavior be counted differently depending on whether it is before or after some date? This question has scientific and juridical/ethical considerations. To see how and when it arises, consider first that there are four logical possibilities for responding to Proposition 47 through the mapping of offenses to risk items. The first is to leave the mapping unmodified and count convictions as they are sentenced. The others would follow from deciding that the scientific consideration, maintaining consistency in how behavior is measured, outweighs all others, and involve modification of the mapping tables, varying by when the changes are applied. The second possibility then is to impose a remapping on all convictions regardless of when they occurred. A third possibility would change the mapping as of the November 5th 2014 date that Proposition 47 went into effect; the fourth possibility would back-date the remapping of offenses to some date prior to the effective date of the proposition. The third possibility, while it has face validity, would in fact accomplish little as presumably judicial decisions should achieve the same end and so it we do not consider it further.

Leaving the mapping unchanged highlights the several concerns. This would mean that the same behavior, for example methamphetamine possession under HS 11377, could be counted as a felony if sentenced before November 5th 2014 and would always be a misdemeanor after that date. From a scientific standpoint, this means that on that date our measuring instrument and the numbers no longer represent the same phenomena that they used to represent. From a juridical/ethical standpoint, it means that individuals could receive disparate treatment despite similar behavior and levels of responsibility for harm. Proposition 47 addresses the juridical/ethical concern by allowing the convicted to petition for resentencing. We know of no mechanism operating now that would lead automatically from resentencing to reassessment and modification of supervision.

The other logical possibilities introduce a consideration, the date of a sentence versus the change in mapping, which raise different concerns for property and drug offenses. We will discuss them separately, considering first the case for drug offenses. Here the behavior didn't shift over time, just how we label and treat it. Leaving the mapping unchanged would mean that behavior once counted as a felony is now counted as a misdemeanor.

Potentially, two different degrees of offending are now combined into one and the loss of this distinction could lead to a loss of accuracy in prediction. However, this presumes that a charge and conviction as a felony actually indicated a different degree of offending, not differences in how similar behavior was processed by the criminal justice system, including strategic decisions about whether the county or state should bear the responsibility for the costs of sentences such as probation or incarceration. Additionally the distinction is inevitably lost over time as older offenders age out of the system and more offenses, post-Proposition 47, come into criminal records as misdemeanors.

The main alternatives available through adjustments to mapping are to either make drug possession offenses affected by Proposition 47 always count as felonies or always count as misdemeanors. These would impose consistency in how they are counted and to the extent that the behaviors are similar would lead to an increase in predictive accuracy. It would also change already assigned risk levels. Counting them always as felonies however would likely not survive a judicial challenge by affected offenders. Counting them always as misdemeanors might also be challenged by law enforcement agencies, prosecutors, and judges. Either change would mean that CSRA criminal histories diverge from the judicial record.

We next consider the case for property offenses affected by Proposition 47. One could argue that felony property charges came to be applied inappropriately over time as inflation led to felony charges for more minor thefts. The division between petty and grand theft as adjusted by Proposition 47 rose by a factor of almost four, from $250 to $950. Leaving the mapping tables as is will let the post-Nov 4th 2014 property convictions (as well as those reclassified on application) adjust appropriately to reflect behavior.

This however leaves a “gray” period in which the classification of offending is sometimes not consistent with the degree of offending. The alternatives considered for drug possession, remapping all Proposition 47-related property offenses to felonies or misdemeanors, do not apply here because the type of sentence often reflects true differences in the degree of offending.

However, one could argue on both scientific and juridical/ethical grounds the adjustment is too late, that the meaning of a measurement by the instrument had changed enough to require recalibration by remapping perhaps more than a decade ago. The second logical possibility for adjusting the mapping table would be to choose a date other than November 6, 2014 on which to impose a remapping of affected property or drug felonies to misdemeanors. Such a date might be chosen to split the difference between $250 and $950 at the point when inflation raised the price of generic market basket of goods from $250 at the time it was defined as the boundary between petty and grand theft to the midpoint price of $600. In practice, this adjustment would be very difficult to achieve as the CSRA data sources lack information on the value of property damages. The best we could do would be to substitute a proxy measure based on sentence characteristics, which would require extensions to and modifications of the ASP code. We have worked on this problem for the development of a proxy cohort for post-Proposition 47 releases as detailed below in this report. While we believe our proxy works well enough for the post-realignment cohort we used, we can’t presume that it would work equally well if applied to the pre-realignment CDCR population. Determining how well it would work would require difficult and extensive additional research. Even with positive results indicating possible utility in separating old offenses into nominal misdemeanors and felonies, we would be left with the significant problems noted for changes in mappings for drug offenses: it would diverge from the judicial record and lead to changes in assigned risk levels.

6.2.5 Recommendation

Having considered the relative challenges and benefits of various ways of mapping offenses to CSRA risk items, we do not recommend modifying the mapping tables as a consequence of Proposition 47. Absent

changes in mapping, we suggest that we should re-evaluate the existing caps on misdemeanor counts, as the loss of offenses counted when reclassified felony charges exceed misdemeanor caps is potentially more serious that the change in weightings.

6.3 Population Change Effect

6.3.1 The Problem: Population Composition and Risk Prediction

As individuals affected by Proposition 47 are diverted from prison or released, it changes the characteristics of the population under CDCR supervision. The CSRA predictions were calibrated using a specific release cohort from a prison population which is no longer matched to the current population. The distribution across risk groups and recidivism rates are certain to change as those who are directly affected *prima facie* tend towards high risk for property and drug crime recidivism, but the magnitude of these changes will depend on the number who are affected. The effect of Proposition 47 on the predictive ability of the CSRA as measured by the AUC is harder to anticipate and may vary for different outcomes or population subgroups.

At the time of this study, the changes following from Proposition 47 had been in place for less than a full year, limiting the follow-up time necessary to capture the 3-year recidivism rate used in developing and evaluating the CSRA. As an alternative, we construct a proxy post-Proposition 47 population using an older cohort which allows for sufficient follow-up and evaluate the performance the CSRA with the proxy.

6.3.2 Prison Releases under Proposition 47

Proposition 47 alters the prison population through two mechanisms. The one that prevails over time is the diversion of offenders who would have once received a felony sentence and been remanded for custody to the CDCR but now receive misdemeanor convictions and serve any custody sentence in jail. In the short run the biggest impact is the release of people serving felony sentences in prison who successfully petition for reclassification as misdemeanants.

Figure 6.3 All Offenders: Releases by Offense Category and Release Type

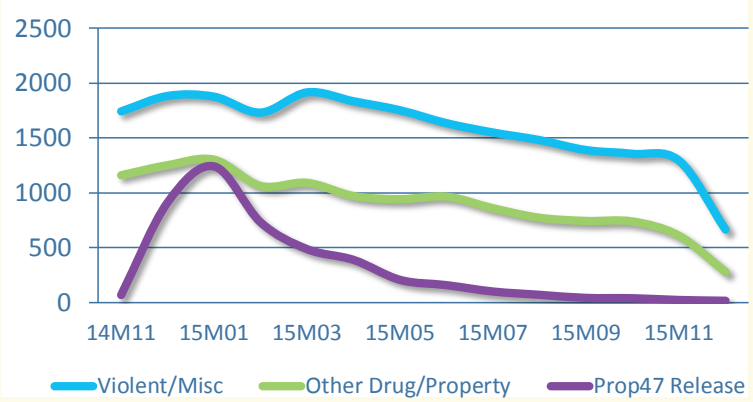
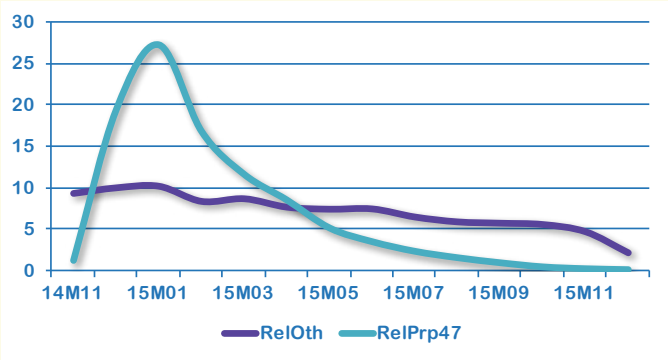
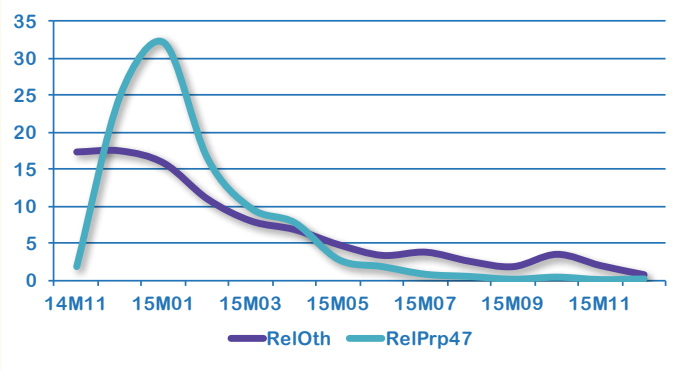


FIGURE 6.4 PROPOSITION 47 ELIGIBLE OFFENDERS: RATE OF RELEASES

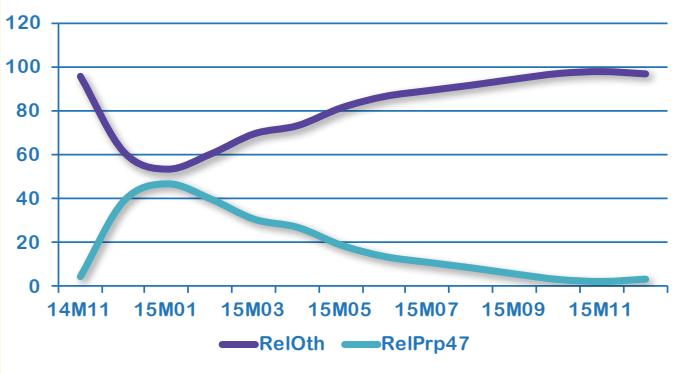


Panel A: Property Offenders

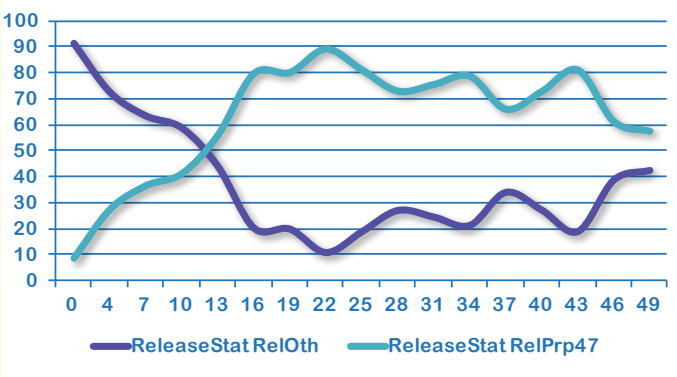


Panel B: Drug Offenders

FIGURE 6.5 ELIGIBLE OFFENDERS: PROPORTION OF RELEASES BY TYPE OF RELEASE



Panel A: Property Offenders



Panel B: Drug Offenders

Figure 6.3 shows the evolution of the number of releases from the standing population of November 1st, 2014, tracing Proposition 47 releases, other drug and property offender releases, and releases of violent/other felony offenders. Overall the numbers decline over time as earlier releases lower the size of the group remaining. With a delay from the time needed to file and resolve reclassification petitions, Proposition 47 releases rise rapidly, peak early, and fall off quickly. Figure 6.4 tightens the focus on the evolution of releases, breaking out those nominally eligible under Proposition 47 by offense category.[21] These figures graph the rate, defined as the percentage of the periods' releases per month, by type of release. Again we see the rapid rise and early peak of proposition 47 releases compared to others, with property offender releases delayed slightly compared to drug offender releases, possibly due to the more complex task of determining the value of property damages in reaching a decision on the petition. Figure 6.5 shows the proportion of releases under Proposition 47 versus those released under normal procedures by month. The proportions are complementary; together they add to 1, as reflected in the symmetry of the lines on the graphs. This view shows that at their peak, Proposition 47 releases of property offenders approached the number of regular releases, but that there were always more regular releases than those from reclassification. For drug offenders, however, the number of Proposition 47 releases exceeded regular releases from December 2014 through April 2015, averaging around two-thirds of releases for that period. Proposition 47 affected a greater proportion of drug than property offenders.[22]

Several challenges arise in the construction of a proxy population. The first, covered above, is the multiplicity of interpretations of which specific offenses are reclassified under Proposition 47. In addition to identifying the statute code sections reclassified under Proposition 47, it was also necessary to identify the prior conviction offenses that exclude one from eligibility for reclassification and a reduced sentence. For these we relied on the list compiled by Judge John Ryan for the AOC report.

The second is uncertainty arising from insufficient information in the databases available to us to determine precisely which offenses as recorded are eligible for reclassification under the proposition. In the case of drug offenses, this is a minor issue as the law is explicit in specifying that it applies to simple possession charges covered under Health and Safety statute code sections 11350, 11357, and 11377.[23] In the case of property offenses, there is an additional criterion. Proposition 47 changed the bar above which a theft can be charged as a felony to $950. The value of goods or services stolen is not recorded in CDCR or DOJ records, so applying Proposition 47 retroactively to an old cohort requires inference.

A third challenge is that practice may vary from any a priori interpretation. Judges Couzins and Bigelow discuss, in their guide for the AOC, many considerations which will depend on interpretation of case law precedents, and note indeterminacy in records available to the courts about the value of damages from a property crime. Again, inference using what data is available is necessary for coping with this problem. In particular we hoped that data on sentencing would prove useful in distinguishing a high verses low value property crime.

6.3.3 Methods

6.3.3.1 Training Data

Inference requires a dataset to use in training the prediction algorithm to recognize members of the target class. In particular to distinguish those apparently eligible under Proposition 47 criteria from those actually eligible, we

[21] *At this stage we didn't attempt to remove individuals with exclusions or adjust for the value of damages in a theft.*

[22] *The reconvergence of the drug offender release lines in the last few months reflects the greater chance variation found in a smaller number of releases, averaging fewer than 40 drug offenders released per month from August on.*

required information on individuals with potentially eligible offenses which were not reclassified and who served their regular time in prison. This requires cross-sectional data on the prison population at a particular point in time preferably prior to the first releases under the proposition, with sufficient follow-up time to capture most of the releases. The CDCR supplied a dataset covering 136,967 persons in prison as of November 1, 2014 with their controlling offense and information on releases through December 16, 2015, including a flag for 4,422 releases under Proposition 47. In addition they supplied a dataset on "walkovers" who, due to Proposition 47, passed directly to supervision or discharge without serving a term in CDCR custody. Additional information included a file with the history of conviction offenses for each individual and a file with the DOJ rap sheet data used by the CSRA ASP to extract a criminal history and provide risk predictions.

In this analysis, we concentrate on the data generated by the release mechanism in order to model Proposition 47 eligibility. This is necessary due to the requirement for a consistent set of sentenced offenses and covariates. Walkovers represent the diversion mechanisms; their sentences will be different from those of the pre-Proposition 47 cohort used to build the proxy. For walkovers, both the convictions and the prisoner data in the OBIS database used as covariates in modeling will be affected and not useful for proxy construction.

6.3.3.2 Proxy Data

As the base data for constructing our proxy population we use the data we have on the cohort of 56,860 individuals released from CDCR custody over the course of a year following the implementation of realignment in beginning November 1, 2011, with follow-up data through October 22 2015. This gives us a post-realignment population to use as the baseline for our proxy and allows for a sufficiently long follow-up.[24]

6.3.3.3 Primary Predictor

Our primary predictor of Proposition eligibility is the determination of Proposition 47 coverage by the AOC applied to the controlling offense reported by the CDCR, restricted by the identification of ineligible individuals identified by the presence of an exclusionary offense in the CDCR history of their convictions. In cases where different interpretations differed in the level specificity (by statute code, paragraph, sub-paragraph) at which detailed charges were included or excluded, we turned to the text of the statue to reconcile the differences.

In addition we included a secondary predictor based on the additional offenses covered in the interpretation of the COTA law firm in part because the AOC criteria fail to include 11% of the individuals flagged as Proposition 47 releases; this secondary predictor covers an additional 3% of released cases.

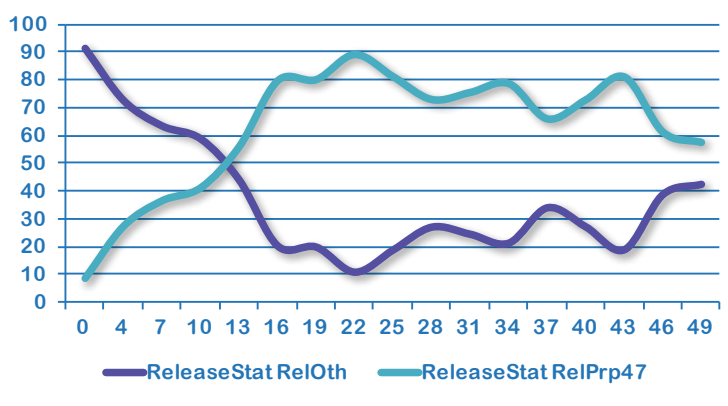
6.3.3.4 Outcome Measure

The desired outcome measure is an indicator of true eligibility for reclassification under Proposition 47 to flag individuals who would not receive a felony sentence and CDCR prison custody had the reform been in place at the time of their conviction. Determining eligibility post-sentencing requires a petition by the individual and a case review by the courts. This presents two challenges. First, we do not have access to petitions filed and accepted or denied. Therefore we have to rely on accepted petitions received and acted on by the CDCR.

[23] *The minor complication is that a section of 11350, formerly paragraph d now become paragraph c, applies to probation for a felony conviction under the statute, leading some interpreters to limit reclassification to offenses charged under paragraphs a and b. When the paragraph is not specified, this distinction can be missed.*

[24] *This cut-off date limits the capture of some convictions, as the CSRA uses arrest date for the timing of recidivism and exams records through the 4th year to allow time for case prosecution and court decisions. See the report sections on realignment.*

Figure 6.6 Eligible Offenders: Type of Release by Time to Scheduled Rele



Second, not all eligible individuals may decide to petition, for any number of reasons. One reason might be that they are anticipating an imminent release from custody and anticipate little benefit from petitioning for reclassification worth the effort to seek it. Figure 6.6 shows the proportion of individuals with a nominally eligible offense actually released under Proposition 47 versus those released under normal procedures, by the months remaining to their projected release date from November 5th of 2014, the day following passage.[25] People with less than a year left rely predominantly on their anticipated release while those with over a year remaining turn to the Proposition 47 option.[26]

Including individuals who are legitimately eligible for Proposition 47 but didn't file a petition would confound our attempt at modeling eligibility. Therefore our dependent variable for model construction is a release from CDCR custody under Proposition 47 after excluding the 34,827 who were released for another reason, leaving 102,140 in the training data.

6.3.3.5 Covariate Data Sets

We drew data on potential covariates for the prediction of Proposition 47 eligibility from CDCR-supplied Termcase, Termgroup, and Offenses files, covering several dimensions of criminal history, sentencing, and current offenses, including the controlling offense of the case, flags for serious or violent offenses in the case, sex offender registration, and other factors that may limit or vary with eligibility.

For a more comprehensive criminal history and additional sentencing information we drew on automated rap sheet data files provided by the California Department of Justice (DOJ). DOJ rap sheet data includes fields for recording up to 25 components of a sentence, including fines, restitution, probation, jail time and prison time. Additionally a specific type of record is defined within a criminal history record segment for recording extended sentencing information in a text field. We developed an additional code section for the CSRA automated scoring program to extract and compile information on these noted sentence components within each criminal justice cycle, along with information on whether multiple custody sentences were to be served concurrently or consecutively, and whether custody or monetary components of a sentence were suspended. We also explored keeping regular and extended sentence terms separate or summing them together. We then retain the sentence components for the last cycle prior to release from prison to match the case leading to CDCR incarceration.[27]

[25] *The horizontal scale is non-linear to deskew the distribution somewhat while avoiding a logarithmic or other transform in order to maintain a scale in months.*

[26] *Proposition 47 releases actually rise above regular releases at 14 months remaining to serve. The later fluctuations occur because the numbers decline over time (falling below 20 per month at 33 months) and chance variations have more influence.*

[27] *Not all individuals were matched to sentence records leading to 5.0% (n=6889) with missing data in the 2014 cross-section but only 2 cases or approximately 0% missing data for the 2011-12 release cohort.*

6.3.3.6 Prediction tools

Regression is the standard analytic tool for predicting membership in a class. The CSRA tool is based on linear regression analysis; Gerlinger and Turner in an effort similar to this one used regression to construct a proxy for the shift in the population under CDCR supervision due to Measure AB109, popularly called "Realignment." In the past few years, more analysts in the field of criminology are turning to machine learning methods, often used to implement an approach called "data mining". Rather that selecting variables and including them in a model, the analyst selects an algorithm which searches through a potentially very large data set for associations with the target outcome. We have investigated the possibility of using one such machine learning algorithm, generally known as Random Forests (RF), in the CSRA as a more powerful prediction method to replace regression.[28] While we did not find much improvement in predictions from RF, here we chose to test its application due to several advantages in exploratory analysis. We wanted to quickly test more than a few variables, suggesting possible utility for a data mining technique. RF is further a non-parametric method, not making any assumptions about the shape of variable distributions. It is not troubled by collinearity, doesn't require transformation of non-linear variables, and doesn't run the risk of non-convergence. For these reasons we initially chose to explore the proxy problem with RF as implemented in the Bootstrap Forest option of the JMP analytic software package.

The RF algorithm proved useful in identifying sets of variables useful to predicting a Proposition 47 release. It has limitations, too. Among them, it is opportunistic in picking values of variables associated with the dependent variable; the cutoff value or even the direction of association, positive or negative, can change from one branch of the tree to another. The randomness in the process can lead to somewhat comparable variables displacing one another from run to run and other shifts of relative variable importance. Achieving data reduction along with prediction requires considerable directed experimentation. Appendix A gives more detail on the lessons of working with RF.

In the end, we chose to use logistic regression on sets of variables chosen with the assistance of RF to create a predictive score for constructing the proxy population. With the same sets of variables, the performance of the two methods was closely matched, and regression gives estimates of the strength and significance of the relation of each independent variable with the dependent variable.

6.3.4 Results

Table 6.7 Cross-Section and Release Cohorts Characteristics

	Cross-Section Nov. 1, 2014			*Cohort 2011-12*
	Prison Population	*Releases Months 1-7**	*Releases Months 8-14**	*All Releases*
	n=136967	*n=24174*	*n=14735*	*n=56860*
Admission Age < 18	1.1	0.4	0.5	0.4
18-24	29.7	21.9	25.0	24.2
25-34	33.8	34.8	34.4	34.9
35-44	20.2	22.4	21.9	23.4
45-54	11.3	15.6	13.5	13.9
55+	4.0	4.9	4.6	3.2
Mean (sd)	32 (11)	34 (11)	33 (11)	33 (11)
Sex F	4.6	6.7	6.0	8.9

[28] *We found that while the Random Forest predictions were generally a bit more accurate than those from regression, the differences were very small and in only 1 of 4 comparisons on the CSRA were the differences large enough to achieve statistical significance despite a test set of nearly 50,000. Due to other criteria favoring the regression approach, we did not recommend adoption of Random Forests.*

Table 6.7 Cross-Section and Release Cohorts Characteristics (Cont.)

	Cross-Section Nov. 1, 2014			Cohort 2011-12
	Prison Population	*Releases Months 1-7**	*Releases Months 8-14**	*All Releases*
	n=136967	*n=24174*	*n=14735*	*n=56860*
Inmate Race				
American Indian/Alaskan	1.1	1.2	1.0	1.1
Asian or Pacific Islander	1.0	1.2	1.1	0.8
Black	28.8	25.5	25.7	25.2
Hispanic	41.6	41.3	41.6	40.5
Other	5.2	4.1	4.6	3.8
White	22.3	26.8	26.0	28.6
Status				
New Admission	80.2	79.2	80.1	52.7
Return w New Term	19.8	20.8	19.9	23.7
PV Return to Custody	0.0	0.0	0.0	22.4
Pending Revocation	0.0	0.0	0.0	1.2
Sentence Type				
2nd Striker	27.5	34.3	36.4	15.1
3rd Striker	27.5	0.3	0.3	0.0
Determinate	43.3	63.0	59.5	84.3
Life	20.0	2.3	3.7	0.6
Life wo Parole	3.6	0.1	0.1	0.0
Death Row	0.5	0.0	0.0	0.0
OffenseCategory				
Persons	73.6	40.7	53.1	32.8
Property	13.0	27.2	22.6	30.9
Drugs	7.5	20.4	13.1	23.8
Other	6.0	11.8	11.1	12.5
Highest Serious/Violent in Term				
Neither	24.2	62.0	48.1	70.5
Serious	14.7	19.5	22.5	15.8
Violent	61.1	18.5	29.4	13.7
Number of Prior Offenses				
0	51.9	38.5	43.3	41.5
1	9.5	11.0	10.6	11.5
2	9.7	11.2	11.1	11.7
3	7.8	9.7	9.1	9.7
4-6	10.4	13.6	12.7	12.9
7-9	8.1	12.1	10.2	9.9
10-14	1.9	3.2	2.3	2.2
15+	0.6	0.6	0.6	0.5
Number of Prior Serious Offenses				
0	74.0	67.9	72.2	81.1
1	16.1	22.2	19.2	13.8
2	5.8	6.5	5.7	3.5
3	1.9	1.8	1.5	0.9
4-6	1.3	1.1	0.9	0.5
7+	0.8	0.6	0.5	0.2

Table 6.7 Cross-Section and Release Cohorts Characteristics (Cont.)

	Cross-Section Nov. 1, 2014			Cohort 2011-12
	Prison Population	*Releases Months 1-7**	*Releases Months 8-14**	*All Releases*
	n=136967	*n=24174*	*n=14735*	*n=56860*
Number of Prior Violent Offenses				
0	88.1	87.7	88.7	93.7
1	8.8	10.3	9.2	5.2
2	1.8	1.2	1.4	0.7
3	0.6	0.4	0.2	0.2
4-6	0.4	0.2	0.3	0.1
7+	0.3	0.1	0.2	0.1
PC290 Sex Offender Registration				
Yes	16.4	8.1	10.4	9.5
Proposition 47 Offense				
Yes	12.8	33.8	17.8	31.8
Proposition 47 Extended Offense				
Yes	15.5	38.6	24.0	41.1
Have an Excluding Conviction				
Yes	36.9	9.7	13.8	8.2

** Months 1-7: Nov 2014 – May 2015. Months 8-14: Jun 2015 –Dec 2015*

Table 6.7 shows descriptive statistics on the November 1, 2014 cross-sectional population, along with releases from the population divided into two seven-month cohorts (November 2014 through May 2015 and June 2015 through December 2015), and the fiscal year 2011-12 release cohort. The two seven-month cohorts are intended to capture the process at different stages, both reflecting the evolution of releases shown in figures 6.3 to 6.5 and providing rough models for the differences we expect between the 2011-12 release cohort and the proxy post-Proposition 47 population assembled using that cohort. We expect the full 2011-12 release cohort to more closely resemble the early cross-section releases of November 2014 through May 2015 than the later releases as both come from a population with the Proposition 47-affected subpopulation largely intact. The cross-section releases from June through December 16th of 2015 come after most of that subpopulation has already been released; therefore we expect it will more closely resemble the proxy post-Proposition 47 cohort. The resemblances can only be relative at best as due to the systematic change in the CDCR population with the diversion of non-serious, non-violent, non-sex offenders to country corrections under California's Public Safety Realignment Act of 2011.[29] We find that as expected, the full 2011-12 release cohort more closely resembles the early cross-section releases than the later ones, particularly on Offense Category (with fewer violent offenders and more property and drug offenders released) and the Highest Serious/Violent offense in the prison term, with far fewer individuals with violent offenses and more with neither serious nor violent offenses. As expected, these two groups have higher percentages nominally eligible for reclassification under Proposition 47. They have very slightly better matches on age, sex and sentence type than the match of the 2011-12 cohort with the later releases from the 2014 cross-section. In contrast, the 2011-12 cohort is closer to the later releases on prior offenses.

[29] *California's Public Safety Realignment, enacted by bills AB109 and AB117, took effect October 1, 2011. In addition to diverting some offenders to county-based corrections, it made a number of other changes in sentencing, supervision, and sanctions for violations of supervision.*

Table 6.8 **Release Status versus Offense Category, All Offenders in CDCR Custody Nov. 1, 2014**

		Release Status						
	Offense Category	*Released Not Released*	*col %*	*Released Other*	*col %*	*Prop47*	*col %*	*Total*
Persons	82,901	84.8%	17,657	50.7%	191	4.3%	100,749	73.6%
row%	82.3%		17.5%		0.2%		100.0%	
Property	7,793	8.0%	7,986	22.9%	1,972	44.6%	17,751	13.0%
row%	43.9%		45.0%		11.1%		100.0%	
Drugs	3,377	3.5%	4,731	13.6%	2,173	49.1%	10,281	7.5%
row%	32.8%		46.0%		21.1%		100.0%	
Other	3,646	3.7%	4,453	12.8%	86	1.9%	8,185	6.0%
row%	44.5%		54.4%		1.1%		100.0%	
Total	97,718	100.0%	34,827	100.0%	4,422	100.0%	136,967	100.0%
	71.3%		25.4%		3.2%		100.0%	

Note: The Not Released total includes 1 case with missing data on the Offense Category

Table 6.8 breaks out releases from the November 1st 2014 cross-section by Release Status (Not Released, and Proposition 47 versus Other Releases) and the Offense Category of the controlling offense for the sentence (Persons, Property, Drugs, and Other {including Vehicular Code}). The vertical bar charts show column percentages; the horizontal charts show row percentages. Working through the offense categories, 17.7% of "persons" offenders were released, including 0.2% released through Proposition 47. Proposition 47 then accounts for about 1% of all "persons" offenders released. Of property offenders, 56.1% were released, including 11.1% released through Proposition 47, which then accounts for about 20% of all property offenders released. Of "drug" offenders, 67.1% were released, including 21.1% released through Proposition 47, which then accounts for about 32% of all drug offenders released. Of other offenders, 55.5% were released, including 1.1% released through Proposition 47, which then accounts for about 2% of all other offenders released.

Looking at releases by reading down the columns of Table 6.8, just over half of regular releases (50.7%) were persons offenders; 22.9% were property offenders, 13.6% were drug offenders, and 12.8% were other offenders. For Proposition 47 releases, 4.3% were persons offenders; 44.6% were property offenders, 49.1% were drug offenders, and 1.9% were other offenders.

This creates a minor problem in creating a proxy population in that the persons and other offenders had controlling offenses which were nominally not eligible for reclassification under Proposition 47. We did not investigate the mechanisms by which these individuals were released under Proposition 47. We did look at some of the controlling offenses recorded for these and found a few dozen cases each of robbery II, assault with a deadly weapon, domestic violence, firearms possession by a felon, and the vehicular code violation of attempted evasion of a police officer. We experimented with including some of these in a definition of Proposition 47 eligibility, but discarded them as unhelpful at best before creating our eligibility models.

Table 6.9 **Release Status versus Proposition 47 Eligibility, All Offenders in CDCR Custody Nov. 1, 2014**

	Release Status							
	Prop 47 Eligible	*Not Released*	*Released col %*	*Released Other*	*col %*	*Prop 47*	*col %*	*Total*
No	91,549	93.7%	28,156	80.8%	502	11.4%	120,207	87.8%
row%	76.2%		23.4%		0.4%		100.0%	
Yes	61,69	6.3%	6,671	19.2%	3,920	88.6%	16,760	12.2%
row%	36.8%		39.8%		23.4%		100.0%	
Total	97,718	100.0%	34,827	100.0%	4,422	100.0%	136,967	
	71.3%		25.4%		3.2%		100.0%	100.0%

Table 6.9 examines release status by eligibility for Proposition 47 reclassification. Under the AOC interpretation, 12.2% are nominally eligible. Of these, 23.4% were released under Proposition 47, 39.8% were released under the regular process, and 36.8% were not released. While some of those eligible may have not sought release for a number of reasons, and some may not have filed a petition in anticipation of a regular release in the near term, it is reasonable to infer that the nominal definition based on statute codes alone includes somewhere between 37% and 76% who are not actually eligible in fact. In addition, 502 individuals or 0.4% not eligible under the AOC interpretation were released under Proposition 47, and these amounted to 11.4% of all Proposition 47 releases.

Using the extended interpretation of Proposition 47 eligibility (table not shown), the percentage nominally eligible increases from 12.2% to 14.8% and the number of true positive predictions rises by 3% from 3,920 to 4,026. The number of false positive predictions rises faster however, so that the percentage of actual Proposition 47 releases among the eligible declines from 23.4% to 19.9%, and the percentage of ineligible individuals released under Proposition 47 declines from 11.4% to 9.0%. The extended definition increases predictor sensitivity (the percentage of positive outcomes correctly predicted) but lowers specificity (the percentage of negative outcomes correctly predicted). We deal with this trade off of increased sensitivity for reduced specificity by using AOC eligibility as a primary predictor and adding extended eligibility as a supplemental predictor.

Table 6.10 **Release Status versus Proposition 47 Eligibility, Property Offenders in CDCR Custody Nov. 1, 2014**

	Release Stat					
	Eligible	*Prop47 Released*	*col %*	*Not Released Prop47*	*col %*	*Total*
No	1,946	25.0%	160	8.1%	2,106	21.6%
row%	92.4%		7.6%		100.0%	
Yes	5,847	75.0%	1,812	91.9%	7,659	78.4%
row%	76.3%		23.7%		100.0%	
Total	7,793	100.0%	1,972	100.0%	9,765	
	79.8%		20.2%		100.0%	100.0%

As mentioned above, releases through regular procedures are a partial confound of the relationship between nominal eligibility and actual release under Proposition 47. Given this, we drop these cases from further use in the actual eligibility modeling and prediction process. Also, given differences in the criteria for reclassification between property and drug offenses and the need for proxy measures for the value criteria in predicting property reclassification, we proceed by analyzing these two subgroups of offenders separately.

Table 6.10 focuses on roughly 9,800 property offenders from the 2014 prison population cross-section. Under the AOC interpretation, 78.4% of these are nominally eligible and about 1 in 5 (20.2%) were actually released.

This includes 23.7% of the nominally eligible and 7.6% of the nominally ineligible. Of those released under Proposition 47, 91.9% were eligible while 8.1% were not. Of those not released, a substantial proportion of 75.0% were nominally eligible and 25.0% were not. The sensitivity of the predictor at 92% is good but the specificity at 25% is not. The accuracy (true positives + true negatives divided by the total) is low at 39% and the error rate of 62% is high. The AUC is only 0.584.

Table 6.11 Release Status versus Proposition 47 Eligibility, Drug Offenders in CDCR Custody Nov. 1, 2014

	Release Stat					
	Prop47 Eligible	*Released*	*col %*	*Not Released Prop47*	*col %*	*Total*
No	3,055	90.5%	65	3.0%	3,120	56.2%
row%	97.9%		2.1%		100.0%	
Yes	322	9.5%	2,108	97.0%	2,430	43.8%
row%	13.3%		86.7%		100.0%	
Total	3,377	100.0%	2,173	100.0%	5,550	
	60.8%	39.2%		100.0%	100.0%	

Table 6.11 focuses on roughly 5,600 drug offenders who were in the 2014 prison population cross-section. Under the AOC interpretation, 43.8% of these are nominally eligible. About 2 in 5 (39.2%) were actually released. This includes 86.7% of the nominally eligible and 2.1% of the nominally ineligible. Of those released under Proposition 47, 97.0% were eligible while 3.0% were not. Of those not released, 9.5% were nominally eligible and 90.5% were not. The sensitivity of the predictor at 97% is very good and the specificity at 91% is also good. The accuracy (true positives + true negatives divided by the total) is good at 93% as is the error rate of 7%. The AUC is a strong 0.937. For drug offenders then, nominal eligibility is by itself a good predictor of actual reclassification and release under Proposition 47. For property offenders, however nominal eligibility is a poor predictor; a proxy will need especially to have higher specificity while maintaining sensitivity.

6.3.4.1 Modeling Proposition 47 Impacts on the CDCR Population

Our strategy is first to use RF and logistic regression to predict which offenders will be removed from the CDCR prison population as a result of Proposition 47, and next to use the prediction scores from the modelling process to select and drop individuals from the post-realignment 2011-2012 release cohort in order to construct a proxy for a post-Proposition 47 prison release cohort. Finally, we generate CSRA risk scores for the proxy cohort and use them to predict recidivism, and compare the accuracy of the predictions on the proxy to the accuracy of the predictions on the unmodified 2011-12 cohort to provide a basis for judging whether or not the performance of the CSRA on the post-Proposition 47 prison population is comparable and adequate.

Modeling the impact of Proposition 47 requires several judgement calls on modelling approach and which cases and variables to use. We have introduced these choices above and review them here.

In this analysis we concentrate on the release mechanism due to the requirement for a consistent set of covariates, which is that they must measure the same events in both the training and the target data. Several covariates relate to offense level and sentence type, and Proposition 47 changes sentencing for new cases such as “walkovers”, that is cases affected by Proposition 47 who do not have prison terms but nevertheless come under CDCR supervision. Hence walkovers are not used in modeling. The training and the target groups were both sentenced prior to Proposition 47, so sentence-based measures will be more consistent across the datasets.

Releases through regular procedures of inmates eligible for reclassification and release under Proposition 47 are a partial confound of the relationship between nominal eligibility and actual release under Proposition 47.

Given this, we drop these cases from further use in the actual eligibility modeling and prediction process. Given differences in the ability of the primary predictor to predict property and drug offender releases, and the need for proxy measures for the value criteria in predicting property reclassification, we predict these two subgroups of offenders separately.

Because the AOC criteria fail to include 11% of the individuals flagged as Proposition 47 releases, we included a secondary predictor based on the additional offenses covered in the interpretation of the COTA law firm; this secondary predictor covers an additional 3% of released cases. We use the AOC eligibility as a primary predictor and added extended eligibility as a supplemental predictor. In addition, we found individuals released under Proposition 47 whose controlling offenses were not found among the various interpretations of the range of its application. We experimented with including some of these offenses in a definition of Proposition 47 eligibility, but found that they brought in disproportional numbers of offenders with crimes against persons. Isolating them as individual factors covering one crime type led to their dropping out of our models, and we discarded them.

We tested many combinations of independent variables particularly in applying RF to the prediction problem. We aimed for parsimonious and interpretable models, retaining only statistically significant variables in our final models. While RF was able to create highly predictive forests with many different sets of variables, it required considerable experimenter intervention to arrive at parsimonious, consistent, and interpretable variable sets.

6.3.4.2 Prediction Models

The final models are presented in Tables 6.12 to 6.16. The Drug Model has four covariates in addition to our primary and extended predictors of eligibility, and the Property Model is slightly more complex with seven covariates in addition to our primary and extended predictors.

Table 6.12 Property Model Factor Estimates

					Confidence Limits	
Effect	*Estimate*	*StdErr*	*p-value*	*Odds Ratio*	*Lower*	*Upper*
Intercept	-7.063	0.434	<.0001			
Prop47 Eligibility	2.358	0.129	<.0001	10.572	8.209	13.616
Prop47 Extended Eligibility	0.616	0.175	0.0004	1.851	1.315	2.606
Sex Offender Flag (N vs Y)	1.985	0.296	<.0001	52.951	16.620	168.699
Highest Serious/Violent (N vs V)	3.198	0.137	<.0001	241.948	114.268	512.295
Highest Serious/Violent (S vs V)	-0.908	0.153	<.0001	3.986	1.818	8.737
Sentence Type (2nd/DSL vs 3rd_Life)	0.358	0.132	0.0068	2.047	1.218	3.439
Prior Offense Count	-0.031	0.010	0.0025	0.970	0.951	0.989
Admission Age	0.029	0.004	<.0001	1.030	1.022	1.037
Prison Term	-0.472	0.044	<.0001	0.624	0.573	0.680

Table 6.13 Drug Model Factor Estimates

					Confidence Limits	
Effect	*Estimate*	*StdErr*	*p-value*	*Odds Ratio*	*Lower*	*Upper*
Intercept	-7.668	0.590	<.0001			
Prop47 Eligibility	5.659	0.190	<.0001	286.891	197.760	416.193
Prop47 Extended Eligibility	0.818	0.259	0.0016	2.266	1.363	3.767
Sex Offender Flag (N vs Y)	2.228	0.187	<.0001	86.172	41.435	179.210
Sentence Type (2nd/DSL vs 3rd_Life)	1.009	0.178	<.0001	7.526	3.744	15.129
Highest Serious/Violent (N,S vs V)	1.925	0.223	<.0001	46.972	19.634	112.373
Prison Term	-0.339	0.083	<.0001	0.713	0.605	0.839

The factors in each model and estimates of their coefficients and odds ratios are given in Tables 6.12 and 6.13. For the Property Model (Table 6.12), the dominant factor is whether they have a non-serious or violent offense conviction in the current term.[30] This is followed by the other exclusionary criterion, a Penal Code 290 sex offense. The statute-code based eligibility primary predictor is much weaker than these first two factors but comes in third with still high odds ratio of over 10 to 1. The next factor is whether they have had nonviolent serious offense in the current term. Dichotomized Sentence Type ranks fifth. The extended eligibility factors comes in sixth, followed by length of their prison term. Admission Age, which may indicate desistance from more serious crimes, and the number of prior offense convictions as a measure of the general amount of criminal history, are roughly equivalent as predictors although in opposite directions.

For the Drug Model (Table 6.13), the statute-code based eligibility primary predictor is the dominant factor, followed by two exclusionary criteria, a sex offense requiring registration under Penal Code 290, and a nonviolent (N,S) or violent offense conviction in the current term. Fourth is Sentence Type, dichotomized into those with a standard determinant sentence of a second striker versus those with 3rd strikes, life sentences, or death sentences. The extended eligibility factors comes in fifth, and the length in months of their current prison sentence is also significant.

Tables 6.14 and 6.15, equivalent to Tables 6.10 and 6.11 for Property and Drug Offenders respectively, show the results of using the models to predict a release under Proposition 47.[31] Table 6.16 summarizes the comparisons with the AUC (Area Under the Receiver Operating Characteristic Curve), a measure of general predictive ability, and several measures of accuracy.[32]

Table 6.14 Release Status versus Predicted Proposition 47 Eligibility, Property Offenders in CDCR Custody Nov. 1, 2014

	Release Stat					
Eligible	*Prop47 Released*	*col %*	*Not Released Prop47*	*col %*	*Total*	
No	6,648	89.4%	263	13.7%	6,911	73.9%
row%	96.2%		3.8%		100.0%	
Yes	785	10.6%	1,661	86.3%	2,446	26.1%
row%	32.1%		67.9%		100.0%	
Total	7,433	100.0%	1924	100.0%	9,357	
	79.4%		20.6%		100.0%	100.0%

Table 6.15 Release Status versus Predicted Proposition 47 Eligibility, Drug Offenders in CDCR Custody Nov. 1, 2014

	Release Stat					
Eligible	*Prop47 Released*	*col %*	*Not Released Prop47*	*col %*	*Total*	
No	3,127	96.0%	113	5.3%	3,240	60.1%
row%	96.5%		3.5%		100.0%	
Yes	131	4.0%	2,021	94.7%	2,152	39.9%
row%	6.1%		93.9%		100.0%	
Total	3,258	100.0%	2,134	100.0%	5,392	
	60.4%		39.6%		100.0%	100.0%

[30] While serious and violent offenses were collapsed in the Drug model as limited cell sizes led to large standard errors and low statistical significance, this problem did not arise in the Property model and keeping them distinct produced finer intervals in the predictive score, allow better control over the effects of selecting a cut point.

[31] The total number in the tables are lower (by 408 for Property and 158 for Drug Offenders) due to missing sentencing information.

[32] The AUC doesn't require an a priori decision about the probability necessary for a positive prediction. The other measures are based on a prediction of a release when the probability exceeds 50%.

Table 6.16 Comparison of Proposition 47 Release Predictions

Model	Measure AUC	Sens	Spec	Acc	Error
Property					
AOL Criteria	0.584	91.9%	25.0%	38.5%	61.5%
Full Model	0.929	86.3%	89.4%	88.8%	11.2%
Drug					
AOL Criteria	0.937	97.0%	90.5%	93.0%	7.0%
Full Model	0.972	94.7%	96.0%	95.5%	4.5%

For Property offenders (Table 6.14), the prediction from the model is much more conservative, with one-third as many releases predicted (26.1% versus 78.4%). This reduces the sensitivity by roughly 6% (from 91.9% to 86.3%, Table 6.16) but more than triples the specificity (from 25% to 89.4%), more than doubling the rate of accurate predictions (from 38.5% to 88.8%). The Property Model is dramatically better than the simple statute code-based eligibility criteria. The AUC measure shows a major improvement in general predictive ability over chance of 133% from 0.584 to 0.929 (Table 6.16).

For Drug offenders (Table 6.15), the model's performance is marginally better. The model is somewhat more conservative, with 10% fewer releases predicted (39.9% versus 43.8%). This reduces the sensitivity by roughly 2% (from 97.0% to 94.7%) and modestly improves the specificity (from 90.5% to 96.0%), only slightly improving the rate of accurate predictions (from 93.0% to 95.5%). The AUC measure shows a minor improvement in general predictive ability over chance of 8% from 0.937 to 0.972 (Table 6.16).

6.3.4.3 Proxy Models

Table 6.17 Proxy Adjustments to Cohort 2011-12 Population

Adjustment	Diverted N	Final N
None	0	61,130
Prop47 Eligible	19,025	42,105
Extended Eligible	24,628	36,502
Drug 33	4,769	56,361
Drug 36	5,338	55,792
Drug 38	5,575	55,555
Property 28	5,306	55,824
Property 33	6,297	54,833
Property 39	7,301	53,829
Low: Drug36 w Pr33	11,635	49,495
High: Drug38 w Prp39	12,876	48,254

The models based on Proposition 47 releases from the Cross-Sectional population were saved and applied to the 2011-12 release cohort, yielding a prediction of which offenders would likely have been absent from the cohort if Proposition 47 had gone into effect before that time and not entered the prison population (Table 6.17). The models predicted that 7,301 of 18,907 or 39% of Property offenders would have been diverted by the proposition and that similarly 5,575 of 14,534 or 38% of Drug offenders would have been diverted. We found the predicted diversion of Drug offenders in line with expectations, as the model predicted that 32.5%[33] of the 2014 population cross-section used for training data were eligible for sentence reclassification, and that realignment, by diverting the so called 'triple nons' from prison from October of 2011, would reduce the proportion of eligibles

[34] *The model produces probability scores; to create the smaller diversions we varied the cutpoint needed for a positive prediction. Diverting fewer property offenders leads to a larger proxy population, so the Proxy Low Adjustment group has a larger n than Proxy High Adjustment.*

in the population of November of 2014. For Property offenders however, the model predicted 27.7% of the offenders in the training data were actually eligible for sentence reclassification, which is substantially lower than the prediction for the 2011-12 cohort. This implies that over two years, realignment reduced the number of property offenders eligible for Proposition 47 reclassification by 29%, and realignment seems unlikely to have had such a large impact. Accordingly, we conducted a sensitivity analysis of removing different fractions of the offenders from the population. The results of the sensitivity analysis are shown in Table 6.17 and the results on AUCs in Table 6.19, following our review of the descriptive statistics for the proxy release cohorts. We decided to create two proxy cohorts, one based on the full diversion of Property and Drug offenders predicted by the model (Proxy High, i.e., diverting a high level of offenders), and a second based on a diversion of only 33% of Property and 36% of Drug offenders (Proxy Low).[34]

Table 6.18 Release and Proxy Cohorts Characteristics

	Cross-Section Nov 1 2014		*Cohort 2011-12*	*Drawn from Cohort 2011-12*	
	*Releases Months 1-7**	*Releases Months 8-14**	*Releases 2011-12*	*Proxy Low*	*Proxy High*
	N=24,174	N=14,735	N=56,860	N=43,881+	N=40,956+
Admission Age					
UNDER 18	0.4	0.5	0.4	0.5	0.5
18-24	21.9	25.0	24.2	27.8	27.7
25-34	34.8	34.4	34.9	35.7	35.6
35-44	22.4	21.9	23.4	21.4	21.4
45-54	15.6	13.5	13.9	11.7	11.8
55+	4.9	4.6	3.2	3.0	3.0
Mean (sd)	34 (11)	33 (11)	33 (11)	32(10)	32(10)
Sex					
F	6.7	6.0	8.9	7.5	7.3
Inmate Race					
American Indian/Alaskan	1.2	1.0	1.1	1.1	1.1
Asian or Pacific Islander	1.2	1.1	0.8	0.8	0.8
Black	25.5	25.7	25.2	25.3	25.4
Hispanic	41.3	41.6	40.5	42.0	42.1
Other	4.1	4.6	3.8	3.8	3.8
White	26.8	26.0	28.6	27.1	26.8
Status					
New Admission	79.2	80.1	52.7	54.7	55.0
PV ret w new term	20.8	19.9	23.7	22.0	21.6
PV ret to custody	0.0	0.0	22.4	22.2	22.3
Pending Revocation	0.0	0.0	1.2	1.1	1.1
Sentence Type					
2nd Striker	34.3	36.4	15.1	14.0	14.3
3rd Striker	0.3	0.3			
Determinate	63.0	59.5	84.3	85.3	85.0
Life	2.3	3.7	0.6	0.7	0.7
Life wo Parole	0.1	0.1	0.0	0.0	0.0
Death Row	0.0	0.0	0.0	0.0	0.0
Missing	—	—	—	—	—

** Months 1-7: Nov 2014 – May 2015. Months 8-14: Jun 2015 –Dec 2015*
+ 41 Missing data

[33] *These percentages used to set expectations are based on including the Other Release cases dropped from the modelling process and consequently Tables 6.10, 6.11, 6.14, and 6.15.*

Table 6.18 Release and Proxy Cohorts Characteristics (Cont)

	Cross-Section Nov 1 2014		Cohort 2011-12	Drawn from Cohort 2011-12	
	Releases Months 1-7*	Releases Months 8-14*	Releases 2011-12	Proxy Low	Proxy High
	N=24,174	N=14,735	N=56,860	N=43,881+	N=40,956+
Offense Category					
Persons	40.7	53.1	32.8	40.5	41.5
Property	27.2	22.6	30.9	25.5	24.1
Drugs	20.4	13.1	23.8	18.6	18.6
Other	11.8	11.1	12.5	15.5	15.9
Undetermined	—	—	—	—	—
Highest Serious/Violent TGID					
Neither	62.0	48.1	70.5	63.5	62.6
Serious	19.5	22.5	15.8	19.5	20.1
Violent	18.5	29.4	13.7	17.0	17.4
Number of Prior Offenses					
0	38.5	43.3	41.5	45.9	46.3
1	11.0	10.6	11.5	11.4	11.5
2	11.2	11.1	11.7	11.2	11.2
3	9.7	9.1	9.7	9.2	9.1
4-6	13.6	12.7	12.9	11.6	11.5
7-9	12.1	10.2	9.9	8.4	8.2
10-14	3.2	2.3	2.2	1.9	1.8
15+	0.6	0.6	0.5	0.4	0.4
Number of Prior Serious Offenses					
0	67.9	72.2	81.1	83.3	83.4
1	22.2	19.2	13.8	12.3	12.3
2	6.5	5.7	3.5	3.0	3.0
3	1.8	1.5	0.9	0.8	0.8
4-6	1.1	0.9	0.5	0.4	0.5
7+	0.6	0.5	0.2	0.2	0.2
Number of Prior Violent Offenses					
0	87.7	88.7	93.7	94.0	93.9
1	10.3	9.2	5.2	4.9	4.9
2	1.2	1.4	0.7	0.7	0.7
3	0.4	0.2	0.2	0.2	0.2
4-6	0.2	0.3	0.1	0.2	0.2
7+	0.1	0.2	0.1	0.1	0.1
PC290 Sex Offender Registration					
Yes	8.1	10.4	9.5	11.8	12.1
Proposition 47 Offense					
Yes	33.8	17.8	31.8	15.7	13.6
Proposition 47 Extended Offense					
Yes	46.8	34.4	41.1	27.2	25.4
Have an Excluding Offense					
Yes	9.7	13.8	8.2	10.1	10.4

** Months 1-7: Nov 2014 – May 2015. Months 8-14: Jun 2015 –Dec 2015*

+ 41 Missing data

Descriptive statistics for the two versions of the proxy release cohorts are given in Table 6.18, along with the columns of release cohorts from Table 6.7 to facilitate comparison. To recapitulate, we have divided releases from the November 1st Cross-section into two cohorts of early and later releases; these are the first two columns in Table 6.17. The third column is the full 2011-12 release cohort. The fourth column shows the results from using the "Low Diversion" proxy; the fifth column shows the results from using the "High Diversion" proxy.

Discussing Table 6.7, we noted that the 2011-12 release cohort more closely matched the earlier set of releases from the November 5 prison population in months 1 to 7, and anticipated that the proxy release cohorts would more closely resemble the later releases in months 8 to 14. We do in fact see a match, in the direction and generally the magnitude of shifts, between the early and later releases in 2014-15 and the between the full and proxy release cohorts of 2011-12. We see for example that more females were eligible and hence the percentage of women fell post-implementation. There are similar effects for having a serious or violent offense in the term and the percentage of required sex offense registrants. However, the prison population in 2011-2012 was sufficiently different from that of 2014 that achieving a complete match across all the listed characteristics would require more complex techniques. The exception regards the classification where we intervened directly, the proportion of offenders eligible for Proposition 47 remediation in the release cohorts (i.e. the Proposition 47 and Proposition 47 Extended Offense rows). Compared to the releases from the cross-sectional population, the proxy release cohorts have more offenders returned to custody with a new term, fewer second strikers, fewer with a controlling offense against persons or serious or violent offense in the term, and a lower percentage with prior serious offenses. Differences are only minor for age, sex, ethnicity, the number of prior and violent prior offenses, and sex offender registration. Four of the five classification categories which are over represented in the proxies have a positive association with recidivism while the fifth has a weak negative association; hence the recidivism rates in the proxies are likely higher than those that will be observed in post-Proposition 47 release cohorts.

6.3.5 The Effects of Proposition 47 on CSRA Performance

CSRA Predictive Ability

Table 6.19 Proxy Cohort Predictive Ability by Recidivism Offense

	Felony Recidivism Offense			
Adjustment	*Any*	*Drug*	*Property*	*Violent*
None	0.694	0.689	0.702	0.690
Prop47 Eligible	0.702	0.697	0.708	0.692
Extended Eligible	0.698	0.691	0.703	0.687
Drug 35	0.697	0.683	0.706	0.690
Property 30	0.698	0.682	0.707	0.690
Property 40	0.698	0.681	0.707	0.690
Property 49	0.698	0.697	0.705	0.689
Low: Drug w Prp30	0.698	0.698	0.705	0.688
High: Drug w Prp49	0.699	0.700	0.705	0.689

Table 6.19 details how proposition 47 affects the predictive ability of the CSRA.[35] Using the full 2011-12 release cohort, the AUC for prediction of any new felony conviction is 0.694; 0.689 for a new drug felony conviction; 0.702 for a new violent property felony conviction, and 0.690 for a new violent felony against persons. Removing everybody with an offense under a statute code covered by Proposition 47 (Prop 47 Eligible and Extended Eligible rows) would drop the greatest number of releasees from the proxies and hence have the maximum effect on the size of the proxy. The table shows small effects that in general increase the AUCs (+0.004 to +0.010) with the exception of the violent recidivism prediction, where the AUC decreases very slightly (-0.001 to -.004).

[35] *As this section investigates only the effect of changes in the CDCR population, and modifying the mapping as tested in section 2 above would induce other changes at the same time, here we use the standing mapping.*

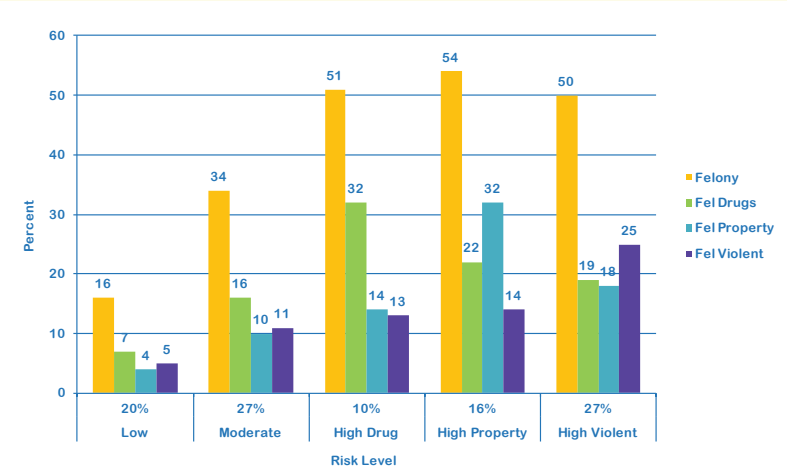
Looking at the effects of dropping those predicted as Proposition 47 eligible by the models, we see mostly minor effects on the AUCs, ranging from -0.007 to +.011. As the percentage of improvement over chance (an AUC of 0.5), the effects run from -4% (Drug recidivism in the Drug 38 adjustment) to +6% (Low or High diversion proxies for Any Felony recidivism.) Predictions for Any Felony and Property recidivism improve with increasing diversions as predicted by the models, while predictions for Violent felony recidivism decline, a loss in the AUC of -.005 or -3% in the Low and High proxies. Outside of Violent recidivism, Proposition 47 drug offense diversions are an exception to the general pattern; these cause the AUCs to decline by -3% to -4%, suggesting that the affected offenders are slightly more regular in their offender and hence more predictable than others. Ironically perhaps the slightly lower Violent recidivism AUCs suggest that the Proposition 47 affected population's behavior is somewhat more predictably non-violent than that of those who remain.

CSRA Risk Group Distribution and Recidivism Rates

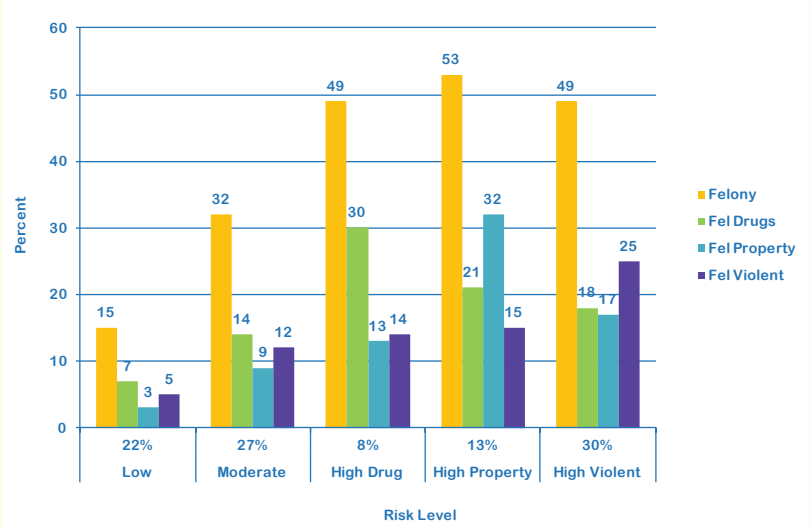
Diverting a subgroup of offenders from the prisons is likely to change the distribution of the population and releases across risk groups. It is less certain whether there will be an effect on recidivism rates and whether any changes in risk group size and recidivism rates are large enough to recommend a reconsideration of the cut points used to translate CSRA risk scores into risk group assignments. The charts of Figure 6.7 present our results. Panel A gives the baseline distribution and rates from the full 2011-12 release cohort. Panel B shows the results from using the "low adjustment" proxy; Panel C shows the results from using the "high adjustment" proxy.

FIGURE 6.7 RECIDIVISM RATES, 2011-12 RELEASE COHORT

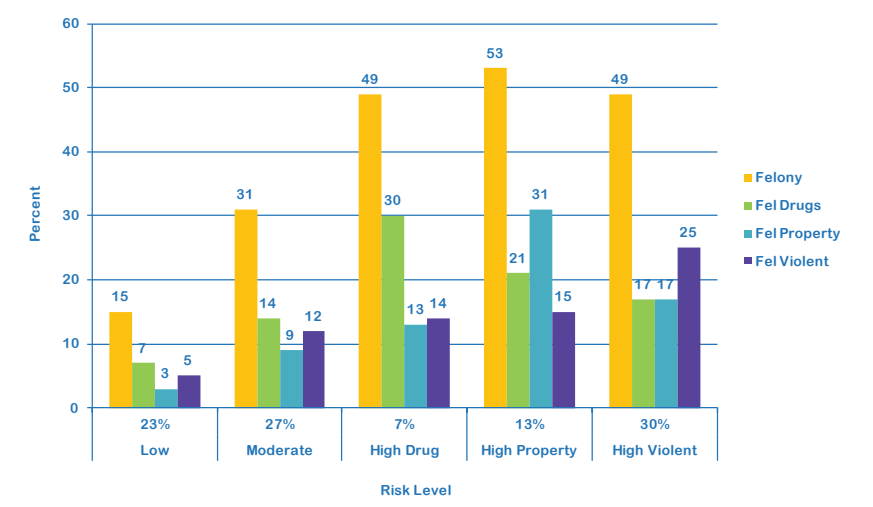
Panel A: Full Cohort without Proposition 47 Adjustments



Panel B: Proxy Cohort with Low Proposition 47 Adjustments



Panel C: High Adjustment Recidivism Rates by Risk Level and Offense Type



Regarding the distribution across risk groups, the impact of dropping the drug and property offenders is strongest in the High Drug and High Property risk groups, but as these low-level offenders are also found in other risk groups, these two don't absorb the full effects of the proxy population adjustment, and the impacts are more modest than one might expect. In both proxies, the size of the High Property risk group declines by 3 percentage points from 16% to 13%, a relative change of -19%. The High Drug risk group declines by 2 to 3 percentage points from 10%; with the low baseline this small decline is a relative change of -20 to -30%. Decreasing the proportion in these two risk groups leads to a rise in the proportion in the other risk groups. While the proportion in the Moderate risk group is unaffected, the High Violent risk group grows by 3 percentage points from 27% to 30%, a relative change of +11%, and the Low risk group also grows by 2 to 3 percentage points from a baseline of 20%; the relative change is +10 to +15%. Overall the shifts across the high risk categories somewhat balance out as the High Risk releases decline from roughly 53% to 50 or 51% of the total.

Turning to recidivism rates, overall these rates are generally unchanged or decline one to two percentage points in all risk groups with a few exceptions, one percentage point increases in Violent recidivism in the Moderate, High Drug and High Property groups. As relative changes averaged across risk groups (to ameliorate the exaggerations arising from low base rates), Property recidivism declines by -10 to 11%, Drug recidivism by -6 to -8%, and Any Felony by -4 to -5%.[35] The offenders diverted by Proposition 47 have somewhat above average drug and property recidivism rates; removing them from the population lowers these kinds of recidivism. In contrast, Violent recidivism rises by an average of 4% across all risk groups, or 8% if we drop the Low and High Violent risk groups where the recidivism rate remains unchanged and look only at the Moderate, High Drug, and High Felony risk groups. As noted in the discussion of changes in the AUCs, those diverted by Proposition 47 have below average rates of violent recidivism; removing them from the cohort raises the average rate of those remaining. Another way of looking at it is to suggest that those remaining may be less specialized offenders; as the High Drug and High Property groups are composed of relatively more of these, while the rate increases the overall number of violent recidivists declines.

[35] *Recidivism rate change averages, weighted by risk group size.*

Table 6.20 Discrimination of Recidivism Rates by Risk Groups, Proxies versus 2011-12 Baseline

Supervision	Recidivism Rate	Any Felony Conviction	Drug Felony Conviction	Property Felony Conviction	Violent Felony Conviction
2011-2012	Not High	25	16	12	11
	High	52	32	32	25
	Discrimination	2.07	2.00	2.78	2.33
Proxy Low	Not High	24	15	11	12
	High	50	30	32	25
	Discrimination	2.14	2.00	3.05	2.17
Ratio Proxy Low/Baseline		1.04	1.00	1.10	0.9
ProxyHigh	Not High	23	15	11	12
	High	50	30	31	25
	Discrimination	2.19	2.03	2.95	2.17
Ratio Proxy High/Baseline		1.06	1.02	1.06	0.93
Ratio Proxy High/Proxy Low		1.02	1.02	0.97	1.00

Here we turn again to the question raised in the discussion of Realignment impacts on the CSRA (Tables 3.10 and 3.11), how well do the offense-specific high risk groups differentiate between those likely to commit different kinds of recidivism? The Proposition 47 proxy cohorts hold up well in comparison with the 2011-12 release cohort, with values ranging from 2.0 for Drug recidivism to 3.05 for Property recidivism in the Low Adjustment proxy and 2.03 to 2.95 in the High Adjustment proxy. For Violent recidivism, consistent with the hypothesis that the remaining offenders in High Drug and High Property groups are less specialized and the finding of 7% to 8% rise in Violent recidivism rates in these groups (plus one percentage point), the measure of discrimination falls by 7%. Discrimination for Drug recidivism is essentially unchanged, and Property recidivism discrimination rises 6% to 10%.

Summarizing results across comparisons, CSRA predictions and classification hold up well for these proxies for the CDCR's post-Proposition 47 population. Predictive ability improves slightly. We find modest shifts in the population proportions from High Drug and High Property risk groups to Low, Moderate, and High Violent groups. We predict that recidivism rates will decline somewhat, and find slightly less differentiation between recidivism types in the High Drug and High Property risk groups.

7 Conclusions

We find that the CSRA continues to be a valid and useful risk assessment instrument for the changing population under CDCR supervision. Its predictive ability holds up well and the predictions as to recidivism outcomes are generally favorable. Collectively they do not signal, in and of themselves, a need for the CDCR to reallocate resources or strategies for managing its institutional and parole populations.

7.1 Recommendations for the CSRA

We find no substantial reasons to recommend any major changes in the CSRA beyond the periodic updating of the mapping tables to keep up with the addition of newly-defined offenses, and a modification of one of the ASP sections to improve recovery of charges recorded in a comments field. We recommend that we reassess the impact of Proposition 47 with a fiscal year 2015-2016 cohort in 2018 to confirm the results obtained here using population proxies on empirical data with two the three years of follow-up to allow sufficient time for the capture of recidivism.

Appendix A Random Forest Lessons

The Random Forest algorithm for regression, classification, and prediction has gained considerable attention in the fields of criminology and corrections in the past few years. As stated above, we used the implementation of the algorithm in the SAS Institute's JMP data analysis application. Here we include a sample of the output from an early run as an example of both its advantages and limitations

The tables and figures of Appendix A show the results of a run made before dropping the non-proposition 47 releases and splitting analysis into separate branches for drug and property offenders. No data pre-processing to collapse categories was used, and variable selection was employed only to drop fields with information on releases which indicated a release under Proposition 47. Of particular interest is that we did not use our indicators of eligibility for offense reclassification under Proposition 47.

The algorithm was able to cope with roughly 3000 statute codes in the offense fields and pick out the few dozen affected by the proposition from the others. The predictive ability, based on the results for the validation subset of the data, is very good: AUC = 0.934, accuracy ACC = 0.976, and explained variance (Entropy R2) = 0.578. These measures are good in part because the first cut is essentially differentiating property and drug offenses from crimes against persons and other offenses (note the high ranking of the OffenseCategory field which classifies offenses into these four groups). When property and drug offenders are broken out for separate analysis, these decline a few percent (AUC=0.902, ACC = .939, Entropy R2 = 0.500).

Since RF doesn't produce measures of the association of independent variables with the outcome, the variable importance plot rates them by showing how much performance is degraded by random permutations of the values of each variable in turn. The most important seven variables are either the statute code or classifications of classification of codes into groups. It shows that multicollinearity is not a problem; offense and statute code are actually the same thing measured at different levels of specificity. Yet this same feature shows that RF doesn't give any indication of redundancy or correlation between independent variables.

Inspecting a few of the trees produced in a run of RF showed that the same variable could not only get dichotomized at different and overlapping cut points but reverse the direction of association across different branches. One explanation advanced for this is that this reflects different 'mechanisms of action' in the real world generating the data. Another explanation is that the algorithm is opportunistic; it will seek among the randomly selected small subset of variables until it finds a way of dividing the branch's subpopulation into two more homogenous subgroups without regard for empirical or logical sense or consistency from one branch or one tree to another. Distinguishing true differences in the population from accidents of chance is difficult. Random processes also change the relative importance of variables from one run to another; it is initially unclear which are generally useful and which rise and fall by chance alone and/or may be in some sense substitutes for others – it is necessary to run replications on sets of variables and experiment with removing variables individually or in blocks and note if other variables are viable substitutes. In the end we made over 80 runs of the RF algorithm with different data and variable subsets and testing control parameters.

Presumably as a machine learning method, Random Forests allows autonomous construction of a highly accurate predictor, selecting useful variables out of a high-dimension dataset. In practice, there can be problems with this conception of RF as a tool. In fact, the exercise required considerable human intervention and investigator learning. However, for little initial effort, RF gave an indication of the amount of information about Proposition 47 eligibility in the data and provided a target for predictive accuracy to guide modeling efforts with conventional regression methods.

Appendix A Random Forest Table Specifications

Target Column

Prop47 Release	
Number of trees in the forest	100
Number of terms sampled per split	10
Training rows	95,867
Validation rows	41,100
Number of terms	40
Minimum Size Split	136

Measure	*Training*	*Validation*
Entropy RSquare	0.5949	0.5775
Generalized RSquare	0.6287	0.6125
Mean-Log p	0.0574	0.0612
RMSE	0.1302	0.1328
Mean Abs Dev	0.0361	0.0372
Misclassification Rate	0.0233	0.0241
N	95,867	41,100

Confusion Matrix

Training	*Actual*	*Predicted*
Prop47 Release	N	Y
N	92,054	745
Y	1489	1579

Validation	*Actual*	*Predicted*
Prop47 Release	N	Y
N	39,420	326
Y	664	690

Profit Matrix Maximization

Training	*Actual*	*Decision Rate*
Prop47 Release	N	Y
N	0.950	0.050
Y	0.090	0.910

Validation	*Actual*	*Decision Rate*
Prop47 Release	N	Y
N	0.948	0.052
Y	0.101	0.899

Predictive Ability

Set	*AUC*
Training	0.981
Validation	0.934

Column Contributions

Term	Number of Splits	G^2	Portion
Offense	350	3,499.07485	0.3502
StatuteCode	337	2,905.82641	0.2908
OffenseGroup	854	1, 093.26594	0.1094
OffenseCategory	516	677.573993	0.0678
HighestSeriousViolentTGID	606	602.360775	0.0603
Code_Type	323	194.703718	0.0195
Exclusion	245	184.900825	0.0185
PriorOffenseCount	775	140.222963	0.0140
SentenceType	772	103.124488	0.0103
PC290_Flag	195	85.0564647	0.0085
PriorSeriousCount	407	66.1699834	0.0066
AdmissionAge	945	58.5220364	0.0059
ISL_DSL	115	54.2452899	0.0054
InmateRace	813	44.7209927	0.0045
SenTyp	81	35.4274059	0.0035
ISL_Term	76	32.8230772	0.0033
PrisonTerm_t	345	31.0869136	0.0031
SCYC	838	29.3026006	0.0029
SentencingCounty	83	27.8569379	0.0028
JailTerm_t	512	22.6642346	0.0023
ProbationTerm_t	548	19.4816436	0.0019
FineAmount_t	339	11.2826937	0.0011
Trm_DVSS_t	644	10.8142717	0.0011
PriorViolentCount	148	9.20984266	0.0009
LastSTAT	416	9.20304006	0.0009
AdmissionMove	251	8.54768359	0.0009
Sex	157	8.34004991	0.0008
RestitutionAmount_t	266	6.00750127	0.0006
AdmissionReason	161	5.69481894	0.0006
Trm_DVSSX_t	177	4.13411664	0.0004
FN_SS_t	141	2.54171762	0.0003
ProbationTermX_t	47	1.54672899	0.0002
FN_SSX_t	58	1.39435157	0.0001
JailTermX_t	33	1.38117168	0.0001
UnkTerm_t	7	0.91726491	0.0001
FineAmountX_t	26	0.81610007	0.0001
RestitutionAmountX_t	32	0.72587515	0.0001
JuvTermX_t	38	0.61085781	0.0001
JuvTerm_t	19	0.39704854	0.0000
PrisonTermX_t	18	0.36496931	0.0000

Appendix B: Supplementary Tables

Figure B.1 Recidivism By Risk Group, 2005-2006 Cohort

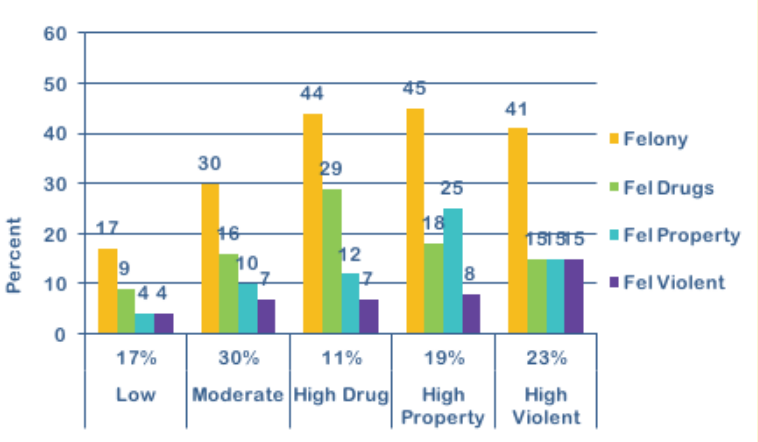


Figure B.2 Recidivism By Risk Group, 2007-2008 Cohort