PUBLIC POLICY INSTITUTE OF CALIFORNIA

# Is Public Safety Realignment Reducing Recidivism in California?

# Technical Appendix

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## Statistical adjustment of recidivism trends

The statistically adjusted recidivism trends are generated by estimating a series of multiple regression models that hold constant the effects of these variables on recidivism and graphically displaying the remaining time trends that are effectively adjusted for such changes in composition. Specifically, we estimate regression models where the dependent variable is a recidivism outcome and the explanatory variables include all of the variables listed in Table 1, a complete set of county-of-commitment fixed effects, along with a series of time dummies marking each monthly cohort in our analysis period. Evaluating the regression model at the means for all explanatory variables for each monthly cohort then provides us with a statistically-adjusted time-trend that effectively holds constant the composition of prison releases.

## Estimating pre- and post-realignment differences in recidivism outcomes

In this appendix we present estimates of the effects of changes in policy and practice ushered in by realignment on several arrest and conviction outcomes. To do so, we exclude from the analysis all offenders released between October 1, 2010 and September 30, 2011 since they left prison before realignment, but nonetheless had some indirect exposure to it during the one-year post-release period we examine. Furthermore, we define a pre-realignment nine-month cohort to include all those released between October 1, 2009 and June 30, 2011. The post-realignment nine-month cohort consists of all offenders released between October 1, 2011 and June 30, 2012. These restrictions and definitions on the analysis sample ensure that those inmates designated as in the pre-realignment period are followed up for an entire year under the old system of parole supervision and that inmates under the new realignment regime are also followed up for a year.

Our basic strategy is to present the estimated changes in various recidivism outcomes after statistically adjusting for observable differences in characteristics between those released before realignment and those released after realignment. We incorporate the same characteristics, including county fixed effects, as we do in our trend analysis.

To provide insights into the factors that contribute to the observed changes in recidivism outcomes, we estimate model specifications that differ in the controls included. For each recidivism outcome, we present an estimate of the pre- and post-realignment change in recidivism that (1) does not adjust for any observable factors; (2) makes statistical adjustments for the county of release (the column titled "county fixed effects"); (3) statistically adjusts for differences in individual characteristics; and (4) makes statistical adjustments for differences in both county of commitment and individual characteristics. We expected that adjusting for the re-released inmates would have the largest impact on our estimates, and this was indeed the case. The estimated models are of the general form:

$$recidivism_{ijt} = \alpha_j + \boldsymbol{X}_i\boldsymbol{\beta} + \gamma Post_i + \varepsilon_{ijt}$$

where $recidivism_{ijt}$ is an indicator variable equal to one if offender $i$ released to county $j$ at time $t$ is observed recidivating during the one-year follow-up period and equal to zero if no recidivating event is observed. County fixed effects are represented by $\alpha_j$ and the individual covariates are represented by matrix $\boldsymbol{X}_i$. The latter includes a broad set of individual-level variables such as offender demographic characteristics, criminal history, last term served, mental health status, and indicator variables for each of the California Static Risk Assessment score categories. Pre- and post-realignment means of the individual level covariates are shown in Table 1. The models are linear probability models where $\alpha j$, $\beta$, and $\gamma$ are parameters estimated by ordinary least square and $\varepsilon ijt$ is a mean-zero normally distributed error term. The parameter of particular interest is $\gamma$, which represents the pre- and post-realignment change in recidivism, holding observable characteristics constant. In the models used to generate the statistically adjusted trends, the specifications include monthly release cohort dummies instead of the Post dummy variable.

We begin our analysis by examining arrest outcomes. Specifically, we focus on the arrest rate, the arrest rate adjusted for returns to custody (RTC), arrests by type, whether the individual is arrested multiple times over the course of the year, and number of arrests.

The arrest rate is not statistically different between the two release cohorts when no controls are included in the model. However, once we control for compositional changes, the estimated post-realignment arrest rate is a statistically significant 2.6 percentage points higher. But this measure has a built-in bias against post-realignment releases since a non-trivial share of arrests in the pre-realignment era were made by parole officers. In our data, these are observed as arrests adjusted for RTC.

Although arrest rates adjusted for RTC are lower for post-realignment released offenders, two-thirds of the decline is due to compositional changes. The overall unadjusted arrest rate declined by a substantial 6.1 percentage points after implementation of realignment. Controlling for difference in county of release does not affect the estimate. On the other hand, statistically controlling for differences in offender characteristics greatly diminishes the estimated decline. Accounting for the change in released offender composition, we find a 1.9 percentage point decline in arrest rates. When we include county fixed effects, thereby holding constant time-invariant county-of-arrest factors, we arrive at a final estimate of a statistically significant 2 percentage point post-realignment decline.

There is a statistically significant decline in arrests for supervision violations. Adjusting for observable covariates and county of release only slightly reduces the estimated decline from 5.1 percentage points with no adjustments to 3.7 percentage points including all available control variables. There is also a 2.4 percentage point decline in misdemeanor arrests in the models with no controls. Again, the observed decline is largely driven by more favorable characteristics of post-realignment releases in terms of risk of re-offending. Our estimate drops to 1.2 percentage points in the model controlling for all available variables. Offsetting these declines is an increase in offenders arrested for a felony. This increase is small and not statistically significant in the models without controls. When all available factors are controlled for, the felony arrest rate increases by a statistically significant 2.1 percentage points.

The finding regarding the increase in the felony arrest rate merits further discussions. It must be that some of this increase reflects the rise in the proportion of arrests officially recorded with a booking. In fact, the increase in felony arrests is smaller in magnitude than the decrease in the proportion of offenders directly returned to custody by a parole officer without an official arrest. To the extent that this change in procedures, or recording of data, drives the increase in the felony arrest rate, then there is no real pre-realignment, post-realignment change in felony offending behavior. Combined with the overall arrest rates decline, we believe that these changes, which are not due to changes in offender criminal behavior, plausibly explains this pattern.

One of the most striking changes is the increase in multiple arrests among post-realignment released offenders. We find a statistically significant increase in the proportion of offenders arrested multiple times over the year. In the model without controls, the increase is roughly 4.1 percentage points. When we statistically control for county of release and individual characteristics, the estimate of the effect of realignment on multiple arrests increases to 7.4 percentage points. Similarly, average number of arrests increase by about one-third of an arrest.

**TABLE A1**
**Estimates of the pre- and post-realignment change in one-year arrest outcomes with and without regression adjustment for observable covariates**

| | Model Specification | | | |
|---|---|---|---|---|
| **Recidivism outcome** | **No controls** | **County fixed effects** | **Individual covariates** | **County fixed effects and individual covariates** |
| Arrested | -0.011<br>(0.013) | -0.013<br>(0.012) | 0.028**<br>(0.012) | 0.026**<br>(0.012) |
| Arrested (includes parole arrests) | -0.061***<br>(0.010) | -0.061***<br>(0.010) | -0.019**<br>(0.008) | -0.020**<br>(0.008) |
| Arrest for parole violation | -0.051***<br>(0.010) | -0.052***<br>(0.010) | -0.034***<br>(0.011) | -0.037***<br>(0.011) |
| Felony arrest | 0.007<br>(0.007) | 0.008<br>(0.007) | 0.020***<br>(0.007) | 0.021***<br>(0.007) |
| Misdemeanor arrest | -0.024***<br>(0.006) | -0.024***<br>(0.005) | -0.012**<br>(0.005) | -0.012**<br>(0.005) |
| Arrested for unknown reason | 0.007*<br>(0.004) | 0.007*<br>(0.004) | 0.007*<br>(0.004) | 0.007*<br>(0.004) |
| Multiple arrests | 0.041***<br>(0.011) | 0.042***<br>(0.011) | 0.075***<br>(0.011) | 0.074***<br>(0.011) |
| Times arrested | 0.215***<br>(0.060) | 0.217***<br>(0.056) | 0.335***<br>(0.062) | 0.331***<br>(0.062) |

SOURCE: Authors' estimates based on CDCR individual administrative data.

NOTE: Clustered standard errors are in parentheses. Figures in the table are the coefficient on a post-realignment dummy variable from a regression of each recidivism outcome for the sample restricted to releases occurring before October 2010 and after September 2011. The first column model specification includes only the post-realignment dummy. The second column model specification adds a complete set of county fixed effects. The third column model specification includes all of the individual characteristics listed in table 1. The final column includes all individual characteristics as well as county dummy variables. The figures in the table are interpreted as the pre- and post-realignment change in the recidivism outcome, holding constant the other factors included in the model specification.

* Statistically significant at the 10 percent level of confidence

** Statistically significant at the 5 percent level of confidence.

***Statistically significant at the one percent level of confidence

Controlling for compositional changes in the released offender population reveals increases in one-year conviction rates. We present our estimates of the effect of realignment on conviction and return-to-custody outcomes in Table 3. Here we see that statistical adjustment changes the sign and significance level of the proportion convicted of a new crime. In the model without controls, there is a slight insignificant decline in this proportion. Accounting for the changing composition of released offenders yields a statistically significant 1.2 percentage point increase in the conviction rate. When we analyze convictions separately by type of offense, we see that nearly all of this is driven by an increase in convictions for new felony offenses.

**TABLE A2**
**Estimates of the pre- and post-realignment change in one-year conviction and return-to-custody outcomes with and without regression adjustment for observable covariates**

| | Model Specification | | | |
|---|---|---|---|---|
| Recidivism outcome | No controls | County fixed effects | Individual covariates | County fixed effects and individual covariates |
| Convicted of a new crime | -0.009<br>(0.006) | -0.009*<br>(0.006) | 0.011*<br>(0.006) | 0.012**<br>(0.006) |
| Convicted of a felony | -0.0002<br>(0.004) | -0.001<br>(0.004) | 0.010**<br>(0.004) | 0.010**<br>(0.004) |
| Convicted of a misdemeanor | -0.009***<br>(0.003) | -0.008***<br>(0.003) | 0.002<br>(0.003) | 0.002<br>(0.003) |
| Convicted conditional on arrest | 0.025**<br>(0.012) | 0.023**<br>(0.011) | 0.030**<br>(0.012) | 0.031***<br>(0.011) |
| Multiple convictions | 0.001<br>(0.001) | 0.001<br>(0.001) | 0.004***<br>(0.001) | 0.004***<br>(0.001) |
| Times convicted | -0.007<br>(0.007) | -0.007<br>(0.006) | 0.017**<br>(0.007) | 0.018**<br>(0.007) |
| Returned to prison | -0.354***<br>(0.043) | -0.351***<br>(0.045) | -0.329***<br>(0.045) | -0.331***<br>(0.045) |

SOURCE: Authors' estimates based on CDCR individual administrative data.

NOTE: Clustered standard errors are in parentheses. Figures in the table are the coefficient on a post-realignment dummy variable from a regression of each recidivism outcome for the sample restricted to releases occurring before October 2010 and after September 2011. The first column model specification includes only the post-realignment dummy. The second column model specification adds a complete set of county fixed effects. The third column model specification includes all of the individual characteristics listed in table 1. The final column includes all individual characteristics as well as county dummy variables. The figures in the table are interpreted as the pre- and post-realignment change in the recidivism outcome, holding constant the other factors included in the model specification.

* Statistically significant at the 10 percent level of confidence

** Statistically significant at the 5 percent level of confidence.

***Statistically significant at the one percent level of confidence

In this report's introduction, we noted that realignment effectively eliminated the ability to quickly send an offender back to prison via the Board of Parole Hearings. In the pre-realignment period, it was likely that some individuals who could have been tried and convicted for new felonies were instead returned to custody via parole revocation. These two factors suggest we might expect local district attorneys to try a greater proportion of arrests and consequently increase conviction rates. Moreover, we would expect this to be especially the case for an individual arrested on more serious felony charges. To test this conjecture, we estimate the effect of realignment on the likelihood of being convicted conditional on an arrest. In other words, we restrict the sample to those individuals arrested within one-year of release and assess whether the likelihood of being convicted for a new crime has increased. Without controlling for compositional changes, we find a statistically significant 2.5 percentage points increase in the probability of conviction conditional on arrest. Holding constant all factors yields an estimate of 3.1 percentage points.

When combined with our arrest results, this finding suggests that much of the increase in conviction rates is likely driven by a greater propensity among local authorities to try and convict felony offenders in the post-realignment period. To be specific, when changes in released offender composition are held constant, we find that arrest rate adjusted for RTC went down somewhat, but roughly held steady at approximately 60 percent of released offenders. A 3.1 percentage point increase in the likelihood of being convicted conditional on arrest suggests that the overall conviction rate should increase by 1.86 percentage points (0.6x0.031x100). As our actual estimate of the increase in conviction rates is 1.2 percentage points, it is unlikely that the higher conviction rate reflects an increase in the probability of committing a felony among those released.

Once compositional changes are accounted for, our estimates show a modest but statistically significant increase in multiple convictions. In models that do not adjust for compositional changes, we observe no measurable difference in the proportion convicted more than once or in the average number of convictions. Holding constant observable variables yields statistically significant, though very small, increases in conviction conditional on arrest and multiple convictions. For example, the fully adjusted models show an increase in the proportion with multiple convictions of 0.4 percentage point and an increase in the average number of convictions of 0.018 incidents.

Lastly, controlling for observable variables does not qualitatively alter our estimate of the change in the proportion returned to CDCR custody. Holding constant all factors yields an estimate of a decline of 33 percentage points.

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