PUBLIC POLICY INSTITUTE OF CALIFORNIA

The Impact of Proposition 47 on Crime and Recidivism

Technical Appendices

CONTENTS

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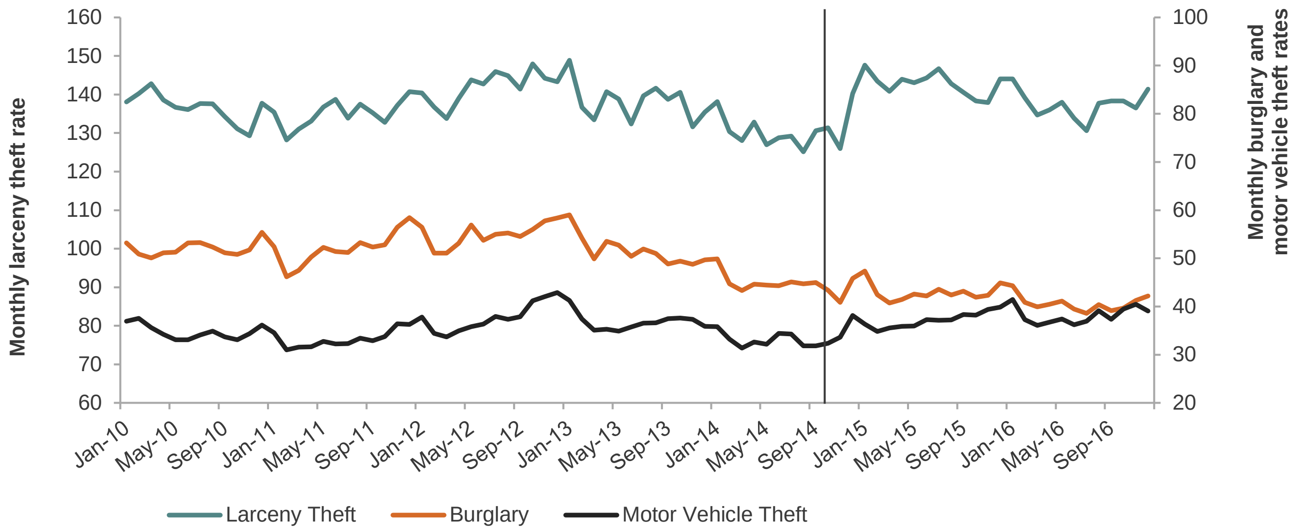
Appendix A. Crime Analysis

For the crime analysis, we use data provided by the California Department of Justice's Criminal Justice Statistics Center, within the Office of the California State Attorney General. Crime totals for part 1 offenses are reported by month and police agency. The data include county identifiers that permit summing total offenses by county and month. We also use state-level Uniform Crime Report data provided by the FBI.

FIGURE A1

The increase in larceny thefts drives the post-Proposition 47 increase in the monthly property crime rate

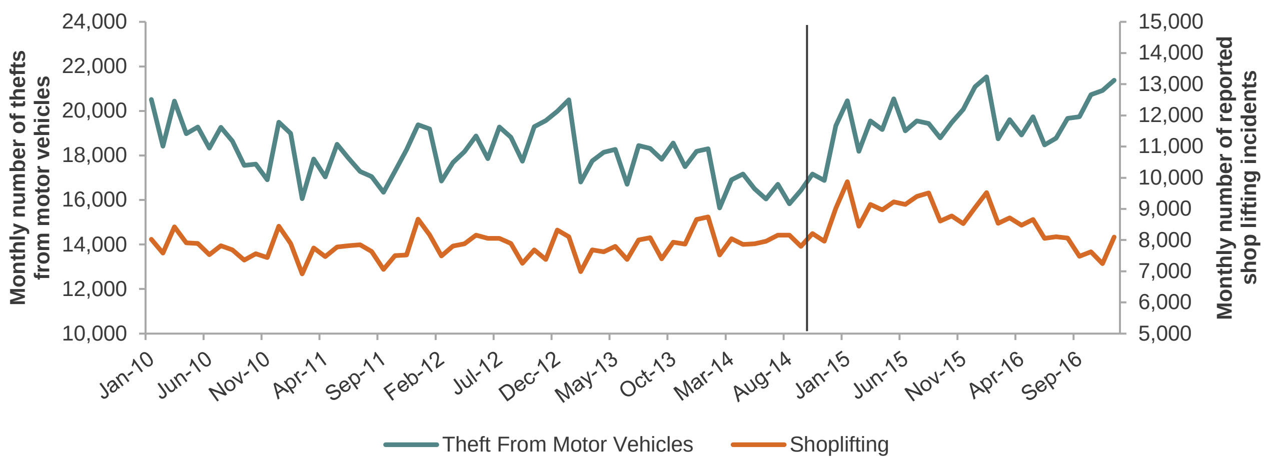


SOURCE: Author calculation based on California Department of Justice's Criminal Justice Statistics Center, California Crimes and Clearances Monthly Files, 2010–2016.

NOTES: Since number of days in a month varies, the monthly numbers are adjusted accordingly. For example, February numbers in non-leap years are multiplied by a factor of 31/28.

FIGURE A2

Both shoplifting and thefts from motor vehicles jumped up in the wake of Proposition 47, but shoplifting declined to pre-reforms levels in 2016



SOURCE: Author calculation based on California Department of Justice's Criminal Justice Statistics Center, California Crimes and Clearances Monthly Files, 2010–2016.

Difference-in-Difference Estimates from Synthetic Cohort Analysis

We use annual state-level crime data from the Federal Bureau of Investigation's Uniform Crime Report for the period 2000-2016. We employ the synthetic control approach of Abadie, Diamond and Hainmueller (2010) to identify a convex combination of states with pre-intervention crime trends that closely match those of California. We then use this synthetic comparison group to chart out the counterfactual path for California, using this as a benchmark against which actual California crime trends can be compared. Given the amount of policy activity in California since 2011 (realignment in 2011, proposition 36 in 2012), we use the period from 2000 to 2010 to identify the synthetic comparison states. We measure the effect of Proposition 47 by assessing the degree to which the difference in crime rates relative to the synthetic comparison cohort widens in the latter years of our panel above and beyond differences that emerge in the immediate pre-Proposition 47 period due to earlier reforms.

To be specific, let the index j =(0,1,…,J) denote states. The value j=0 corresponds to California and j=(1,…,J) correspond to each of the other J states that are candidate contributors to the control group (or in the language of Abadie et. al, the donor pool). Define F_0 as a 11x1 vector with elements equal to the offense specific crime rates in California in years 2000 through 2010 (the 11 years we use here as our pre-intervention period). Similarly, define the 11xJ matrix F_1 as the collection of comparable time series for each of the 49 states in the donor pool (with each column corresponding to a separate state-level time series for the period 2000 through 2010).

The synthetic control method identifies a convex combination of the J states in the donor pool that best approximates the pre-intervention time series for the treated state. Define the Jx1 weighting vector $W=(w_1,w_2,\ldots,w_J)'$ such that $\sum_{j=1}^{J} w_j = 1$, and $w_j \geq 0$ for j=(1,…,J). The product F_1W then gives a weighted average of the pre-intervention time series for all states omitting California, with the difference between California and this average given by $F_0 - F_1W$. The synthetic control method essentially chooses a value for the weighting vector, W, that yields a synthetic comparison group (consisting of an average of some subset of donor states) that best approximates the pre-intervention path for California. Specifically, the weighting vector is chosen by solving the constrained quadratic minimization problem

$$\begin{aligned} &W^* = \arg\min_W (F_0 - F_1W)'V(F_0 - F_1W) \\ &s.t. \\ &W'i = 1, w_j \geq 0, j = (1,\ldots J) \end{aligned} \quad (1)$$

where V is a 11x11, diagonal positive-definite matrix with diagonal elements providing the relative weights for the contribution of the square of the elements in the vector $F_0 - F_1W$ to the objective function being minimized. Once an optimal weighting vector W^* is chosen, both the pre-intervention path as well as the post-intervention values for the dependent variable in "synthetic California" can be tabulated by calculating the corresponding weighted average for each year using the donor states with positive weights. The post-intervention values for the synthetic control group serve as our counterfactual outcomes for California.

Our principal estimate of the impacts of Proposition 47 on crime uses the synthetic control group to generate a series of difference-in-difference estimate. Specifically, define $Outcome_{2009-2010}^{CA}$ as the average value of the outcome of interest for California for the pre-intervention years 2009 and 2010, $Outcome_{2012-2014}^{CA}$ as the average value of the outcome during the post-realignment/pre-47 period, and $Outcome_{2015-2016}^{CA}$ as the average value for the outcome in the post-47 period. Similarly, define $Outcome_{2009-2010}^{Synth}$, $Outcome_{2012-2014}^{Synth}$, and

$Outcome^{Synth}_{2015-2016}$ as the comparable averages for the synthetic control group. With these averages, we define and estimate the following three alternative difference-in-difference estimates:

(2)

$$\Delta^2_{realignment} = \left[Outcome^{CA}_{2012-2014} - Outcome^{Synth}_{2012-2014}\right] - \left[Outcome^{CA}_{2009-2010} - Outcome^{Synth}_{2009-2010}\right]$$

$$\Delta^2_{real.+prop47} = \left[Outcome^{CA}_{2015-2016} - Outcome^{Synth}_{2015-2016}\right] - \left[Outcome^{CA}_{2009-2010} - Outcome^{Synth}_{2009-2010}\right]$$

$$\Delta^2_{proposition\ 47} = \left[Outcome^{CA}_{2015-2016} - Outcome^{Synth}_{2015-2016}\right] - \left[Outcome^{CA}_{2012-2014} - Outcome^{Synth}_{2012-2014}\right]$$

The first difference-in-difference estimator identifies the effect of the realignment reforms on crime rates. The second measures the cumulative effects of realignment and Proposition 47. The final estimator measured the differential effect of Proposition 47 above and beyond the lasting effects the realignment reforms.

To formally test the significance of any observed relative increase in California's crime rates, we apply the permutation test suggested by Abadie et. al. (2010) to the difference-in-difference estimator discussed above.[1] Specifically, for each state in the donor pool, we identify synthetic comparison groups based on the solution to the quadratic minimization problem. We then estimate the three difference-in-difference estimators for each state as if we were testing for comparable policy impacts in these states. The distribution of these "placebo" difference-in-difference estimates then provides the equivalent of a sampling distribution for the estimates of $\Delta^2_{realignment}$, $\Delta^2_{real.+prop\ 47}$, and $\Delta^2_{proposition\ 47}$. For example, if the cumulative empirical density function of the complete set of estimates of $\Delta^2_{proposition\ 47}$ is given by F(.) the p-value from a one-tailed test of the hypothesis that $\Delta^2_{proposition\ 47} > 0$ is given by 1-F($\Delta^2_{proposition\ 47}$).

Our principal synthetic cohort analysis uses state-level crime rate data for the period 2000 through 2016 tabulated by the FBI from agency-level data reported through the Uniform Crime Reports program. The main benefit of using the FBI tabulations of state-level crime rates rather than tabulating them directly from agency level data provided in the annual Offenses Known and Cleared by Arrests computer files concerns the handling of rape. On January 1, 2013, the FBI changed the official definition of rape towards a more inclusive definition that mechanically increased the reported rate for this particular crime. The FBI still collects information on the legacy definition in addition to crime totals using the new definition and reports crime rates by state using both measures. However, the data in the Offenses Known and Cleared by Arrests files are based on the legacy definition prior to adoption of the new definition by each agency and the new definition thereafter. The California Department of Justice officially adopted the new rape definition in 2014, though many police agencies throughout the state including large agencies such as the Los Angeles Police Department (LAPD) did not adopt the new definition until 2015. To avoid a mechanical increase in this crime in 2015 and 2016, we use the state level rates as tabulated by the FBI where rape is consistently measured with the legacy definition and the total violent crime rate (which includes rape as a component crime) is not impacted by the definitional change.

We also present a parallel series of synthetic control results where we tabulate California crime rates omitting crime reported by LAPD and the population covered by LAPD from crime and population totals for the state.

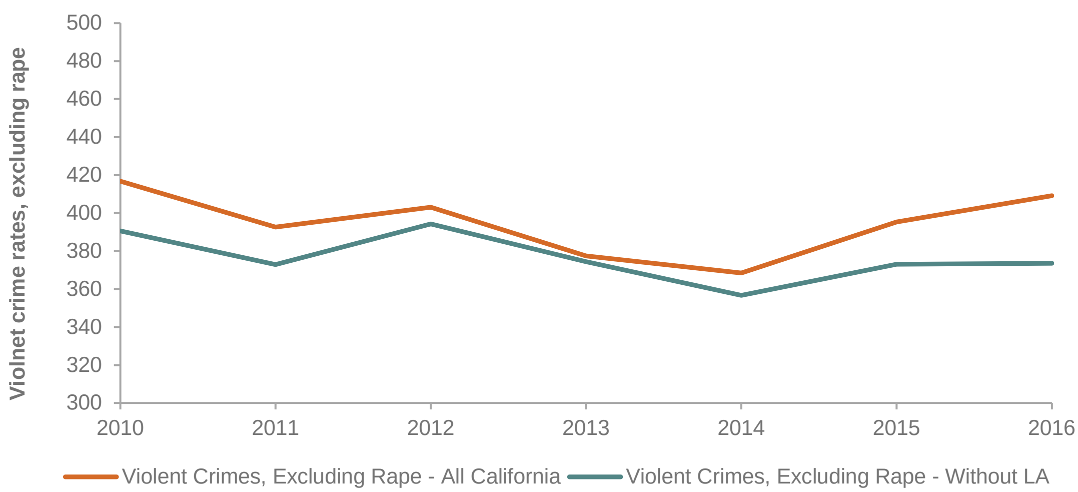
[1] Buchmueller, DiNardo and Valletta (2009) use a similar permutation test to that described here to test for an impact of Hawaii's employer-mandate to provide health insurance benefits to employees on benefits coverage, health care costs, wages and employment.

LAPD came under press scrutiny in 2014 for under-reporting aggravated assaults.[2] Aggravated assaults account for nearly 60 percent of all violent crimes and is the largest contributor to the violent crime index, followed by robbery (33 percent of the total). A subsequent audit of crime report narratives and arrest charges by the LAPD Office of the Inspector General revealed that between 2008 and 2014 aggravated assaults were underreported by between 30 and 39 percent in each year, with many aggravated assaults involving brandishing a weapon and domestic violence being incorrectly recorded as simple assault (a part II crime not included in official crime rate totals). To address this issue the LAPD created a data integrity unit in November 2014 (the exact month when Proposition 47 went into effect) that closely monitors crime reporting, performs targeted audits, and conducts widespread training on crime recording. The data reveal a near 40 percent increase in reported aggravated assaults in Los Angeles between 2014 and 2016.[3] The LAPD has jurisdiction over roughly 10 percent of the state's population. Given the size of the area policed by this agency, the fact that the observed increase in aggravated assaults is likely due to changes in how aggravated assaults are being classified, and the compositional importance of assaults as a contributor to total violent crime, it is important to assess whether results are sensitivity to the inclusion of Los Angeles. While the data integrity unit appears to have concentrated their efforts on increasing the accuracy of aggravated assault totals, we adjust all other crimes as well in the event that the enhanced training and monitoring impact the degree of under-reporting of other part I offenses.

To estimate the alternative crime rates for California, we tabulate total crimes in the state using the Offenses Known and Cleared by Arrests files for the years 2000 through 2016 excluding crimes report by LAPD from the numerator and the population policed by LAPD from the denominator. Doing so creates the new issue of the change in the rape definition and the fact that these agency-level data do not include totals for the legacy definition once an agency switches over. Hence, our synthetic cohort estimates using the "LA-adjusted" California time series omits a separate estimate for rape.[4]

FIGURE A3

Adjusting for definitional changes in rape and excluding Los Angeles reveal noticeably lower post-Proposition 47 violent crime rates



SOURCE: Author calculation based on California Department of Justice's Criminal Justice Statistics Center, California Crimes and Clearances Monthly Files, 2010–2016.

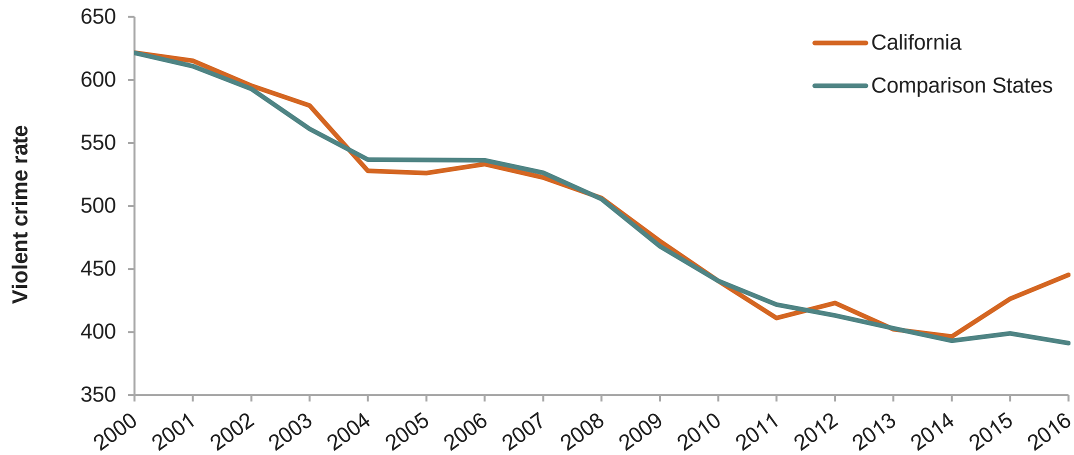
[2] See Poston, Ben and Joel Rubin "LAPD Misclassified Nearly 1,200 Violent Crimes as Minor Offenses," *Los Angeles Times*, August 9, 2014.

[3] For 2010 through 2016, the number of aggravated assaults reported by LAPD are 9,344, 8,843, 8,329, 7,624, 9,836, 13,713, and 15,874, respectively.

[4] We do however present an estimate for overall violent crime which is inclusive of rape. As the California rape rate for some agencies in 2014 and most if not all agencies in 2015 and 2016 will be based on the new more inclusive definition, the estimate of proposition 47 on violent crime will be upwardly biased. This bias, however is likely to be negligible as rape accounts for only 6 percent of violent crime in California.

FIGURE A4

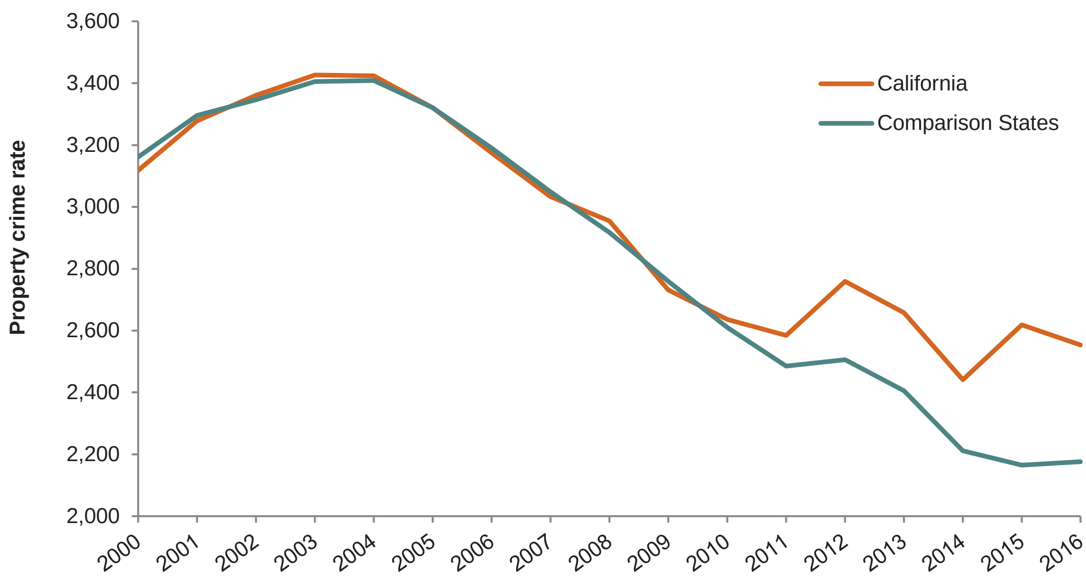
The recent increase in California's violent crime rate deviates from comparison states but is not statistically significant



SOURCE: Authors' estimates based on annual state level data from the FBI's Uniform Crime Reports, 2000–2016.

FIGURE A5

The gap between California's property crime rate and comparison states further widened after Prop 47



SOURCE: Authors' estimates based on annual state level data from the FBI's Uniform Crime Reports, 2000–2016.

NOTE: The matched comparison states (with estimated weights in parentheses) are Colorado (0.033), Georgia (0.001), Kentucky (0.133), Massachusetts (0.032), Nevada (0.163), Tennessee (0.075), West Virginia (0.041), and Wyoming (0.522).

TABLE A1

Difference-in-difference estimates of the effects of the estimates of sentencing reforms on violent crime rates along with statistical inference from the distribution of placebo estimates

	Diff-in-diff, 2012-2014 minus 2009-2010		Diff-in-diff, 2015-2016 mins 2009-2010		Diff-in-diff, 2015-2016 minus 2012-2014	
	Δ^2	Rank ($P[\Delta^2 > \Delta^2_{CA}]$)	Δ^2	Rank ($P[\Delta^2 > \Delta^2_{CA}]$)	Δ^2	Rank ($P[\Delta^2 > \Delta^2_{CA}]$)
With LA						
Violent	5.97	34/50 (0.32)	43.05	44/50 (0.12)	37.09	44/50 (0.12)
Murder	0.02	30/50 (0.40)	-0.96	10/50 (0.80)	-0.98	4/50 (0.92)
Rape	-0.78	23/50 (0.54)	1.74	36/50 (0.28)	2.53	43/50 (0.14)
Robbery	-1.35	25/50 (0.50)	2.08	31/50 (0.38)	3.44	32/50 (0.36)
Assault	6.07	37/50 (0.26)	31.11	44/50 (0.12)	25.05	42/50 (0.16)
Without LA						
Violent	-2.37	33/50 (0.34)	-7.66	26/50 (0.48)	-5.92	23/50 (0.54)
Murder	-0.10	27/50 (0.46)	-0.82	10/50 (0.80)	-0.72	8/50 (0.84)
Rape[a]	-	-	-	-	-	-
Robbery	3.02	33/50 (0.34)	2.50	32/50 (0.36)	-0.51	27/50 (0.46)
Assault	7.17	37/50 (0.26)	10.02	34/50 (0.32)	2.84	33/50 (0.34)

Notes: Δ^2 statistics present the difference-in-difference between California and synthetic California in the given crime rate for the two noted time periods. The rank indicates where California's estimate sits within the distribution of placebo estimates for all 50 states. The probability value estimate provides the empirical probability that a placebo difference-in-difference crime rate effect exceeds the estimate for California. We interpret this figure as the p-value from a one-tailed test of the significance of the California crime effect.

Furthermore, we omit tabulations for rape without Los Angeles due to the fact that the FBI UCR agency level data do not include rape tabulation for recent years using the legacy definition. Our state level panel data set produced by the FBI uses the legacy definition for rape through 2016. Tabulating the rate of rape per 100,000 for California from agency level data yields a mechanical increase in rape in 2015 and 2016 due to the adoption of the new rape definition in several large agencies in California.

TABLE A2

Difference-in-difference estimates of the effects of the estimates of sentencing reforms on property crime rates along with statistical inference from the distribution of placebo estimates

	Diff-in-diff, 2012-2014 minus 2009-2010		Diff-in-diff, 2015-2016 mins 2009-2010		Diff-in-diff, 2015-2016 minus 2012-2014	
	Δ^2	Rank ($P[\Delta^2 > \Delta^2_{CA}]$)	Δ^2	Rank ($P[\Delta^2 > \Delta^2_{CA}]$)	Δ^2	Rank ($P[\Delta^2 > \Delta^2_{CA}]$)
With LA						
Property	233.79	46/50 (0.08)	427.63	46/50 (0.08)	193.85	42/50 (0.16)
Burglary	39.75	37/50 (0.26)	40.49	36/50 (0.28)	0.74	28/50 (0.44)
Larceny	7.86	29/50 (0.42)	144.62	38/50 (0.24)	136.76	45/50 (0.10)
MVT	64.43	49/50 (0.02)	51.45	40/50 (0.20)	-12.98	20/50 (0.60)
Without LA						
Property	256.46	47/50 (0.06)	399.60	45/50 (0.10)	134.13	41/50 (0.18)
Burglary	51.65	42/50 (0.16)	46.98	36/50 (0.28)	-4.67	26/50 (0.48)
Larceny	28.18	33/50 (0.34)	153.16	38/50 (0.24)	124.98	43/50 (0.14)
MVT	59.76	48/50 (0.04)	41.28	38/50 (0.24)	-18.48	18/50 (0.64)

Notes: Δ^2 statistics present the difference-in-difference between California and synthetic California in the given crime rate for the two noted time periods. The rank indicates where California's estimate sits within the distribution of placebo estimates for all 50 states. The probability value estimate provides the empirical probability that a placebo difference-in-difference crime rate effect exceeds the estimate for California. We interpret this figure as the p-value from a one-tailed test of the significance of the California crime effect.

Projecting a Counterfactual Based on Higher-Frequency California Data

Our second strategy involves a univariate analysis of the monthly crime rate time series for California. We focus on the 24 months preceding November 2014 and the first 24 post-proposition months inclusive of November 2014. Figures 3 and 4 reveal relatively stable prison and jail populations for the 24 months preceding November 2014, while Figure 7 shows relatively stable arrest rates. Moreover, the beginning of the period 24 months prior to November 2014 (November 2012) is one full year following the implementation of realignment. Hence, one would expect little effect of realignment on crime rates by that time and little impact of the earlier reform on crime trends during this specified pre-period.

We conduct a univariate analysis of violent and property crime rates overall and for the component part 1 offenses that comprise the aggregate crime indices. Define t as an index measuring month relative to November 2014 (-1 in October 2014, 0 in November 2014, 1 in December 2014, and so on). For each crime rate we estimate the following model,

(3)

$$Crime_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \beta_0 After_t + \beta_1 After_t.t + \beta_2 After_t.t^2 + \varepsilon_t,$$

where Aftert is a dummy variable indicating t>-1, εt is an error term, and α_0, α_1, α_2, β_0, β_1, and β_2 are parameters to be estimated. Equation (3) effectively fits a quadratic trend to the 24 pre-intervention months and separate quadratic trend to the 24 post intervention months with a discontinuous break at t=0. The equation is comparable to the model used in Buonanno and Raphael (2013) to test for a discontinuous effect of the Italian Collective Clemency on Italian crime rates. Equation (3) can be used to project the counterfactual crime rate based on the estimated pre-intervention quadratic trend and to then measure the difference between the crime predicted by the full equation and the counterfactual. Specifically, for any t>-1, the difference in the crime rate predicted by equation (3) and the counterfactual crime rate predicted by the pre-intervention trends is given by

(4)

$$Diff\ relative\ to\ cf_t = \beta_0 After_t + \beta_1 After_t.t + \beta_2 After_t.t^2 + \varepsilon_t,$$

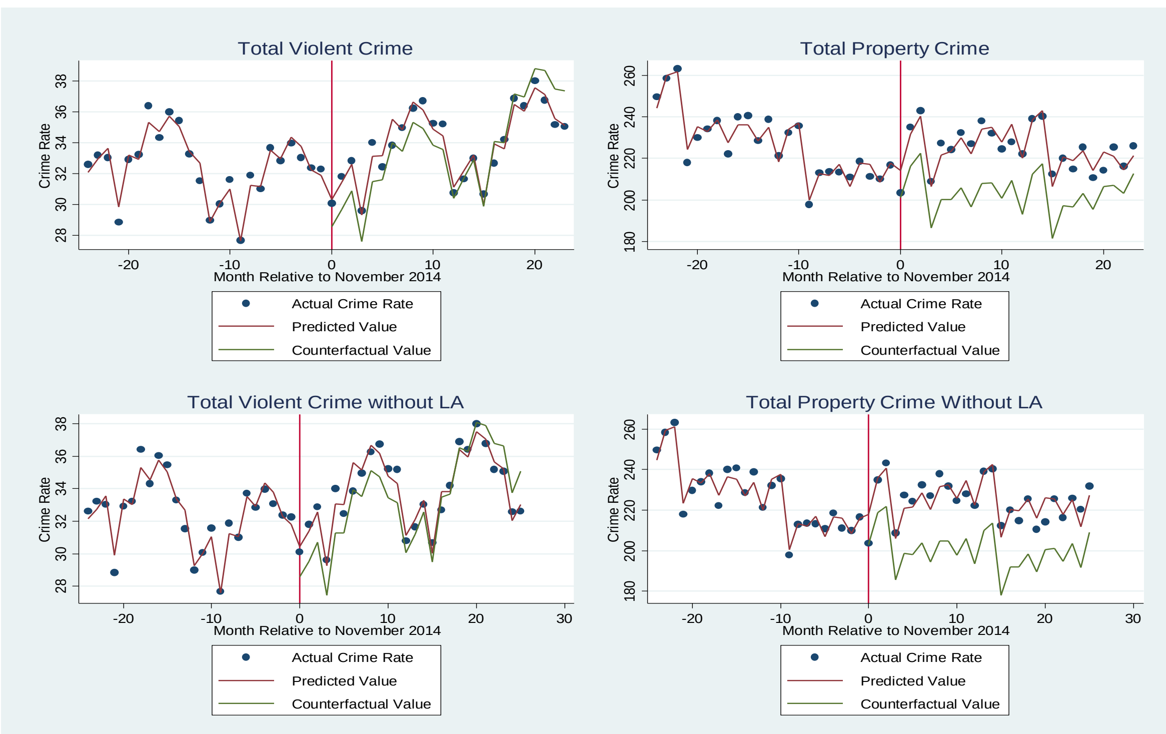
with the difference in the first post-intervention month simply equal to the coefficient on the variable $After_t$. We use equation (4) to generate several alternative estimates of the annualized effect of Proposition 47 on specific crime rates. First, following Buonanno and Raphael (2013), we simply use twelve times the estimate of the discontinuity at November 2014 as an annualized crime effect estimate. Second, we tabulated the difference in equation (4) for each of the first twelve post-intervention months and then sum these estimates. The first estimate is based on the most precise definition of the counterfactual yet may miss impacts of the proposition that occur beyond the first month. On the other hand, the second estimate will be overly sensitive to over-projection of what may be a temporary downward trend in crime during the pre-intervention period, to the extent that property crime levels in California in 2014 were outliers.

We apply the model in equation (3) to the individual part 1 offenses using monthly data tabulated by the California Department of Justice (DOJ). For the major part 1 offenses, again we present analysis with and without crimes reported by LAPD. We pull monthly crime totals from the Offenses Known and Cleared by Arrests file for LAPD and subtract them from the monthly crime totals provided by the California DOJ. We should also note that the monthly data provided by the California DOJ records rape totals based on the definition in use at the time of reporting and does not report a consistent total for the legacy definition.

Figure A6 graphically depicts the estimation procedure we deploy to use within-state time trends to project counterfactual crime rates. Specifically, for 24 pre-47 and 24 post-47 months, we fit a simple regression model of crime rates on time measured relative to November 2014, time squared, an indicator variable for time>-1, and interactions between the quadratic function and the indicator variable (equation (3) above). The models allow for first-order serial correlation in the residuals. Figure B5 plots the actual monthly crime rate against time (denoted with dots), the fitted values from the interacted quadratic function in time, and the projected counterfactual values for the post-period (the predicted value less the post-period differential given by equation (4) above). Our estimates of the effect of the proposition are based on either twelve times the discontinuous break in the crime rate time series in November 2011 or the difference between the predicted value and the counterfactual value over the first post-Proposition 47 year. While we are also able to generate estimates for the second post-Proposition 47 year, these estimates are quite imprecise (with standard errors larger than the point estimates in each case) and thus we focus on various estimates of the annualized crime effect over the first year.

FIGURE A6

Actual and projected monthly violent and property crime rates for the two pre-47 years and two post-47 year, rates tabulated with and without Los Angeles County



For violent crime, the predicted and counterfactual values are visibly similar regardless of whether crime reported by LAPD is included in the state monthly crime totals. For property crime however, there is a visible difference between the projected counterfactual and predicted crime rate, with the pre-intervention trends predicting substantial subsequent declines in crime in 2015 and 2016. In fact, the difference between the two series increases with time. The average monthly counterfactual crime rate declines by approximately 6 percent when comparing the first twelve post-proposition months to the 12 preceding months and declines by another two percent between the first and second post-proposition years. Similar to the results for violent crime, these estimates are not sensitive to the exclusion of offenses reported by LAPD.

Table A3 presents annualized estimates for total violent crime, total property crime, and for each part 1 offense making up the violent and property crime indices. For each crime rate we present estimates including and excluding crime reported by LAPD in the aggregate crime series. Within each of these groups we first present annualized estimated based on the discontinuity and then an annual estimate based on the sum of the estimated treatment effects over the first post-proposition year. The patterns roughly conform to the findings from the state synthetic cohort analysis, with a few key differences. First, while we find no significant effect on violent crime overall in three of the four specifications, we do find a significant coefficient based on the predicted discontinuity when we omit crime reported by LAPD. For all four specifications we find statistically significant increases in robbery amounting to roughly 10 percent of base levels in 2012 through 2014. We should note that the robbery rate in 2014 was particularly low and the decline in robbery from 2013 to 2014 unusually large both relative to past changes for California as well as relative to the changes observed for synthetic comparison matches discussed in the previous section. To the extent that our method is over-projecting the counterfactual decline based on an unusual year, this estimate may be unreliable.

TABLE A3

Estimates of the effect of proposition 47 on crime rates based on the discontinuous change in crime as well as the difference between the model predicted value and the counterfactual values over the first post-47 year

	Including LAPD crime reports		Excluding LAPD crime reports	
	Annualized estimates based on discontinuous break at t=0	Difference between prediction and counterfactual over first twelve months	Annualized estimates based on discontinuous break at t=0	Difference between prediction and counterfactual over first twelve months
Violent	19.81 (13.70)	11.01 (22.94)	21.07[c] (10.88)	17.43 (17.69)
Murder	0.24 (0.57)	0.34 (0.79)	0.15 (0.40)	0.43 (0.50)
Rape	0.07 (1.48)	-2.81 (3.49)	0.05 (1.31)	-2.84 (2.64)
Robbery	14.29[a] (2.77)	14.79[a] (4.14)	14.74[a] (2.60)	17.14[a] (3.64)
Assault	6.05 (12.12)	-0.62 (20.75)	7.89 (10.86)	4.48 (16.33)
Property	152.14[a] (56.72)	266.43[b] (104.75)	155.41[a] (61.18)	267.23[b] (113.55)
Burglary	-9.30 (10.08)	-1.27 (18.28)	-10.79 (9.92)	6.88 (17.09)
Larceny	128.94[a] (43.27)	193.85[b] (66.84)	129.33[a] (46.43)	186.44[b] (86.90)
Motor Vehicle Theft	24.86[c] (13.13)	63.10[a] (23.30)	21.78 (14.35)	61.99[b] (25.34)

Standard errors are in parentheses. Estimates are based on estimation of equations (3) and (4) from the main text. Regression models allow for an AR(1) error structure.

a. Statistically significant at the one percent level of confidence.**b.** Statistically significant at the five percent level of confidence.
c. Statistically significant at the ten percent level of confidence.

Regarding property crime, we again find significant effects for property crime overall as well as for larceny. Here, however, we also find a significant effect on motor vehicle theft in three of the four model estimates. These motor vehicle theft results contrast sharply with the results from the synthetic comparison group analysis, and thus we should identify the source of the contrast in results. Our time series projections generate a counterfactual decrease in motor vehicle theft between the last pre-proposition year and the first post-proposition year of 7.4 percent and a further decrease of 2.9 percent between the first and second post years. Moreover, the predicted value from the full model projects an 8.5 percent increase in motor vehicle theft which, when combined with the decline in the counterfactual crime rate, generates the statistically significant relative increases in motor vehicle theft presented in the table. The difference here relative to the synthetic comparison analysis is due entirely to the behavior of the counterfactual crime rate from these two estimators. For our synthetic comparison states for California, motor vehicle theft increases by 9 percent between 2014 and 2015 (an increase larger than the 8.5 percent predicted absolute increase for this period generated by our full time series model), and increases by another 10 percent between 2015 and 2016. Hence, the difference in results is due in its entirety to the different counterfactual predictions generated by the two estimators.

More generally, when we estimate based on the discontinuity the magnitudes better align with the results from the synthetic cohort analysis. For example, the estimated effects on overall property crime from the synthetic cohort analysis was an increase in property crimes per 100,000 of between 134 to 193 incidents. The results based on the discontinuous change in property crime are increases of 152 to 155, lying within the range of these estimates. Similarly, the synthetic cohort analysis yielded estimated increases in the larceny theft rate of between 124 and136 incidents per 100,000. The annualized estimates based on the discontinuous change are comparable (roughly 129 whether or not LAPD crimes are included). In contrast, when we estimate the effect based on the sum of the first twelve treatment effects, the effect size grow considerably, with the overall property crime effect 72 percent larger and the overall larceny effect roughly 50 percent larger. This disparity is driven by the fact that the pre-existing trends predict continuous declines in crime over the subsequent two years largely due to the very low property crime rate in 2014.

Testing Whether Cross-County Heterogeneity in the Proposition 47 Dose Predicts Cross-County Heterogeneity in Crime Trends

Our final strategy exploits cross-county variation in the impact of Proposition 47 on local incarceration, resentencing and reclassification activity, and arrest rates on local crime rates. Specifically, we calculate the change in average monthly crime rates by county and regress these changes on the change in local jail incarceration rates, the amount of resentencing and case reclassification per capita in the county, and changes in arrests rates for property and drug offenses. Monthly data on local jail populations comes from the Jail Profile Survey maintained by the California Board of State and Community Corrections. Data on resentencing and reclassification totals by counties comes from a survey administered to counties by the Judicial Council of California. Finally, we tabulated average changes in arrest activity by county using data from the California Monthly Arrest and Citation Register files.

Table A4 presents the results from county-level regressions of changes in monthly crime rates on changes in the jail average daily population per 100,000, the number of resentencing/reclassification petitions per 100,000, and the change in drug and property arrests per 100,000. Each row corresponds to a separate regression model. For each crime we present separate estimates for unweighted models and regression models that are weighted by county-level population. We interpret a significant negative coefficient on the change in jail incarceration rates, a significant positive coefficient on petition rates, and a significant negative coefficient on the change in arrest rates as evidence of an adverse effect of the Proposition 47 shock to these variables on crime rates. The models in Table A4 are based on changes for the 24 months preceding and following the passage of Proposition 47. In appendix Table A5 we present comparable model estimates where the changes are calculated using the 12 months preceding and 12 months following the passage of the proposition.

TABLE A4

Regression pre-post changes in average county-level monthly crime rates on corresponding changes in average jail DP per 100,000, average arrests for drug and property offenses per 100,000, and the number of Prop. 47 resentencing and reclassification petitions per 100,000 using 26 pre and post-Prop. 47 months

	Change in jail ADP rate	Resentencing/reclassification petitions per 100,000	Change in drug and property arrests per 100,000
Violent			
Unweighted	0.005 (0.034)	-0.001 (0.002)	0.027 (0.076)
Weighted	0.051[c] (0.030)	-0.003[a] (0.001)	-0.030 (0.038)
Murder			
Unweighted	0.002 (0.002)	0.0000 (0.0001)	0.0005 (0.003)
Weighted	-0.002 (0.002)	-0.0000 (0.0001)	0.004[b] (0.002)
Rape			
Unweighted	0.009 (0.007)	-0.0002 (0.0004)	0.026[c] (0.015)
Weighted	0.008 (0.006)	-0.0004[b] (0.0002)	0.008 (0.007)
Robbery			
Unweighted	0.006 (0.008)	-0.0005 (0.0006)	-0.023 (0.018)
Weighted	0.009 (0.011)	-0.0009[b] (0.0003)	-0.030[b] (0.025)
Assault			
Unweighted	-0.011 (0.032)	0.000 (0.002)	0.023 (0.072)
Weighted	0.036 (0.025)	-0.001[c] (0.0007)	-0.009 (0.032)
Property			
Unweighted	0.032 (0.093)	-0.005 (0.006)	0.015 (0.211)
Weighted	-0.284 (0.172)	-0.011 (0.004)	-0.015 (0.221)
Burglary			
Unweighted	-0.003 (0.035)	-0.003 (0.002)	0.083 (0.079)
Weighted	0.012 (0.045)	-0.002[c] (0.001)	-0.090 (0.059)
Larceny			
Unweighted	0.051 (0.069)	-0.003 (0.005)	-0.183 (0.154)
Weighted	-0.194[c] (0.119)	-0.005 (0.003)	-0.061 (0.143)
Motor Veh. Theft			
Unweighted	-0.015 (0.024)	0.001 (0.002)	0.115 (0.055)[b]
Weighted	-0.102[c] (0.053)	-0.003[b] (0.001)	0.136[c] (0.068)

Standard errors are in parentheses. Each row presents the results from a separate regression of the change in monthly crime rates pre-post Proposition 47 on the change in the jail incarceration rate, the quantity of resentencing/reclassification petitions filed per capita, and the change in property and drug crime arrests per 100,000. Each regression has 56 observations. We omit observations for Alpine and Sierras counties since they do not operate independent jail systems for the entire period analyzed.
a. Statistically significant at the one percent level of confidence. **b.** Statistically significant at the five percent level of confidence.
c. Statistically significant at the ten percent level of confidence.

Beginning with the results for violent crime rates, we find no evidence of a relative increase in violent crime overall or on any of the individual violent crime rates of prop-47 induced changes in jail incarceration, resentencing/reclassification petitions, or changes in arrests activity. All of the coefficient estimates on the change in the jail population are all small and statistically insignificant and often the wrong sign. We do see significant negative coefficients in several models on the number of resentencing/reclassification petitions per 100,000 residents. However, the estimates suggest that crime fell by more in counties with more petition activity, suggestive of a crime-abating effect of the proposition. Regarding the estimates for change in arrest activity on violent crime, there is one significant negative coefficient on robbery when the model is weighted by county populations. Statewide the arrest rate declined by roughly 16 per 100,000. Taking the one significant coefficient estimate for robbery at face value (-0.03) suggests an annualized effect of the decline in arrest activity of 5.76 incidents per 100,000 (0.03x16x12). When we estimate these models using the year-over-year changes in crime to construct the dependent variable for the regression rather than the average change over two pre and two post years (presented in table A5), again we find little evidence of any effects on violent crime. The negative effect of the change in arrests on robbery does not appear in these models.

TABLE A5

Regression pre-post changes in average county-level monthly crime rates on corresponding changes in average jail DP per 100,000, average arrests for drug and property offenses per 100,000, and the number of Prop. 47 resentencing and reclassification petitions per 100,000 using 12 pre and post-Prop. 47 months

	Change in jail ADP rate	Resentencing/reclassification petitions per 100,000	Change in drug and property arrests per 100,000
Violent			
Unweighted	-0.020 (0.031)	-0.001 (0.002)	0.066 (0.070)
Weighted	0.041 (0.036)	-0.003[a] (0.001)	0.082[b] (0.036)
Murder			
Unweighted	0.003[c] (0.001)	0.0000 (0.0001)	0.002 (0.004)
Weighted	-0.001 (0.003)	-0.00002 (0.00006)	0.005[c] (0.003)
Rape			
Unweighted	0.008 (0.006)	-0.0004 (0.0004)	0.024 (0.014)
Weighted	0.008 (0.007)	-0.004[b] (0.002)	0.009 (0.007)
Robbery			
Unweighted	0.013 (0.009)	-0.001 (0.001)	-0.013 (0.020)
Weighted	0.014 (0.015)	-0.001[a] (0.0003)	-0.0007 (0.015)
Assault			
Unweighted	-0.044 (0.030)	0.0003 (0.002)	0.054 (0.067)
Weighted	0.019 (0.031)	-0.001[b] (0.0007)	0.069[b] (0.031)
Property			
Unweighted	0.042 (0.085)	-0.006 (0.006)	0.120 (0.188)
Weighted	-0.158 (0.181)	-0.014[a] (0.005)	0.133 (0.182)
Burglary			
Unweighted	0.010 (0.036)	-0.003 (0.002)	0.139[c] (0.081)
Weighted	0.019 (0.052)	-0.003[b] (0.001)	-0.077 (0.052)
Larceny			
Unweighted	0.036 (0.061)	-0.003 (0.004)	-0.195 (0.137)
Weighted	-0.143 (0.123)	-0.007[b] (0.003)	0.021 (0.125)
Motor Veh. Theft			
Unweighted	-0.005 (0.025)	0.0002 (0.002)	0.175[a] (0.056)
Weighted	-0.034 (0.065)	-0.004[a] (0.001)	0.189[a] (0.065)

Standard errors are in parentheses. Each row presents the results from a separate regression of the change in monthly crime rates pre-post Proposition 47 on the change in the jail incarceration rate, the quantity of resentencing/reclassification petitions filed per capita, and the change in property and drug crime arrests per 100,000. Each regression has 56 observations. We omit observations for Alpine and Sierras counties since they do not operate independent jail systems for the entire period analyzed.

a. Statistically significant at the one percent level of confidence. **b.** Statistically significant at the five percent level of confidence.
c. Statistically significant at the ten percent level of confidence.

Turning to the results for property crime, there are notable differences between the models that weight the regressions by county population and those that do not. None of the unweighted models yield evidence of a Proposition 47 effect on property crime overall or the individual property crime rates. In the weighted models however, we find a nearly significant negative coefficient on the change in jail incarceration rates for property crime overall (with a p-value of 0.105) and marginally significant coefficients on the jail incarceration rate for larceny and motor vehicle theft. The coefficient estimate for property crime overall in the weighted model is consistent with an annualized effect of 71.6 additional property crimes per 100,000 (calculated by the multiplying the coefficient estimate (0.284), by the statewide decline in the jail incarceration rate (21), by the number of months in a year). The comparable implied annualized estimates for larceny theft and motor vehicle theft are 48.9 and 25.7, respectively. These estimates are considerably smaller than the results from the within-state time series analysis as well as the results from the synthetic cohort analysis. These estimates suggest a 2.8 percent increase in property crime rates overall, a 3.1 percent increase in larceny theft and a 7 percent increase in auto theft. We find no evidence of an effect of resentencing/reclassification petitions activity nor of the change in arrest rates in any of the models.

The results for property crime using year-over-year changes presented in appendix Table A5 are roughly consistent with the findings in Table A4, though the point estimates on the change in the jail incarceration rate imply much smaller effects on property crime overall and larceny theft and little effect on motor vehicle theft. None of the coefficient on the change in the jail incarceration rate are statistically significant in these models.

To summarize the results in this section, we find very little evidence that cross-county variation in the effect of Proposition 47 on jail populations, resentencing and reclassification petitions, and on arrest activity predicts inter-county variation in the pre-post 47 change in violent crime rates in a manner consistent with an adverse effect of the proposition. There is some evidence of an impact on property crime overall and on larceny and motor vehicle theft, though the estimates are sensitive to whether the models are weighted by population and by the time periods used to calculate the changes in crime and jail incarceration rates. Moreover, the largest estimates from this analysis imply property crime effects that are smaller than those implied by the synthetic cohort analysis and the within-state time series results.

Lastly, we note that we have not at this time been able to incorporate data on a key relevant population for the possible impact of Prop 47 on crime rates: the changes in the prison population as result of the reform. We hope to obtain monthly county level data that allows us to examine whether this channel had any impacts on public safety.

The Relative Strengths and Weaknesses of These Three Approaches

Each method applied here has its strength and weaknesses. We discuss those briefly here. The synthetic cohort analysis matches on the years 2000 through 2010. Given the size and scope of realignment reforms, the states that match California from these earlier time periods may no longer be an appropriate gauge of counterfactual crime paths. Our higher-frequency analysis based on monthly data may be overfitting pre-existing trends to an unusual year. The property crime rate in California recorded in 2014 is literally the lowest rate on record since 1960 and notably lower than the immediately preceding years. Hence, estimates based solely on pre-existing trends run the risk of over-projecting the counterfactual crime decline. The cross county analysis estimates the effects of the proposition based on heterogeneity across counties in the differential impact of the proposition on arrests and jail populations. Any general deterrence effect that impacts state crime levels overall washes out in the analysis.

Nonetheless, the relative strengths of these strategies complement one another. The synthetic cohort and time series strategy will capture statewide general deterrent effects that the cross-county analysis may miss. The clear differences in dose across county permit analysis of the proposition’s effect that does not depend on a potentially problematic pre-proposition year. Moreover, whether the projected counterfactuals from the within state analysis reflect over-fitting to an outlier pre-intervention year can be verified by comparison to other states from the synthetic cohort estimator. Our strategy is to present estimation result from all three approaches and to interpret overlapping results that accord with one another as evidence of an effect of the proposition.

Appendix B. Recidivism Analysis

We draw on data collected through the BSCC–PPIC Multi-County Study (MCS) to analyze the effects of California's Proposition 47 on recidivism outcomes for lower-level drug and property offenders. To identify the effects of Prop 47 on recidivism, we leverage the swift passage and implementation of this natural policy experiment. Drawing on a rich set of individual-level characteristics, including demographics and criminal histories, we use propensity score matching to construct a pre-Prop 47 control group with similar characteristics to the post-Prop 47 treatment group. We then use a regression model to estimate the effects of Prop 47 on rearrest and reconviction rates, adjusting for any remaining differences in characteristics between the control and treatment groups.

Data

Our analysis relies primarily on data from the BSCC–PPIC Multi-County Study (MCS), a collaborative effort between the California Board of State and Community Corrections (BSCC) and PPIC. The MCS was established in the wake of public safety realignment with the goal of bringing together the data needed to rigorously evaluate the effects of statewide policy reforms and to identify the most effective recidivism-reduction interventions at the local level. To achieve these goals, we identified a group of counties representative of the state as a whole and partnered with these counties to examine how individuals move through local jail and probation systems after realignment.

FIGURE B1

The 12 counties participating in the MCS represent California's geographic diversity

Figure B1 shows the 12 counties participating in the study: Alameda, Contra Costa, Fresno, Humboldt, Kern, Los Angeles, Orange, Sacramento, San Bernardino, San Francisco, Shasta, and Stanislaus. Taken together, these counties comprise 60 percent of California's population and represent the state's geographic diversity, as well as its overall demographic and economic characteristics. Table B1 summarizes the characteristics of the MCS counties relative to the statewide population. While quite similar, the MCS counties tend to be more urban (as measured by population density) and have higher shares of African Americans, Asian Americans, and Latinos. In addition, the poverty and unemployment rates are slightly higher among the MCS counties.

TABLE B1

MCS counties are similar to the state overall in demographic and economic characteristics

	California	MCS counties
Demographic characteristics		
Male	49.7%	49.4%
African American	6.5%	8.0%
Asian American	14.8%	16.2%
Latino	38.6%	40.6%
Native American	1.7%	1.5%
White	73.3%	70.8%
Two or more	3.7%	3.6%
Under 20	26.4%	26.2%
Age 20–39	28.9%	29.5%
Age 40–59	26.5%	26.8%
Age 60+	18.2%	17.5%
Population density (population per square mile)	244.6	454.7
Economic characteristics		
Unemployment rate	9.1%	9.2%
Poverty rate	16.5%	17.6%
Total population	*38,335,203*	*22,847,093*

SOURCES: Demographic and population density characteristics are from the US Census. Poverty rates are from the Small Area Income and Poverty Estimates (SAIPE) program within the Census Bureau. Unemployment rates are from the Bureau of Labor Statistics.

NOTES: Characteristics for the MCS county group are population-weighted for the year 2013.

In addition to the data provided by the counties, the California Department of Justice (DOJ) and the California Department of Corrections and Rehabilitation (CDCR) provided essential data to fill out the state-local picture. Altogether, the newly available data used in this analysis includes demographic characteristics, criminal history, and recidivism outcomes. The participation of the MCS counties allows us to expand on previous research by assessing outcomes for individuals sentenced to serve time in county correctional agencies, who, because they pass through local systems, are not tracked at the state level.

Identifying Prop 47 Offenders

This analysis focuses on the recidivism outcomes of individuals who were convicted of Prop 47 offenses and sentenced to jail, probation, or prison. We use the current conviction charges and prior criminal history factors to identify Prop 47 offenders. We first exclude individuals from the analysis who have disqualifying past convictions for violent offenses that carry a maximum sanction of life in prison or death, offenses that require sex offender registration, sex crimes pursuant to PC 667.61, and crimes pursuant to PC 667.7 or PC 667.71.[5] We also exclude those with prior or co-occurring property offenses that exclude offenders from eligibility under Prop 47.[6] For individuals convicted of PC 473, the analysis excludes any offender with a co-occurring PC 530.5 conviction. For individuals convicted of PC 476, the analysis excludes any offender with 3 or more violations of PC 470, PC 475, or PC 476. For individuals convicted of petty theft with priors (PC 666), individuals with three or more prior specified property offenses or a prior serious or violent conviction that is not covered under PC 667(e)(2)(C)(iv)(ii) or PC 290(c) are retained in the pre-period while individuals convicted of PC 666 are dropped in the post-period. Because individuals in the pre-period likely would have been eligible for Prop 47 sentencing in the post-period, they are retained in the analysis. In the case of one specific offense – shoplifting – a new penal code (Section 459.5(a)) was created for this offense in the post-Prop 47 period. Prior to this period, shoplifting was charged as second degree burglary (Section 459). Including individuals convicted of second degree burglary in the pre period and excluding them in the post period could systematically bias our estimates. Therefore, we include individuals convicted of second degree burglaries and/or shoplifting in both periods.

One limitation of the data is the lack of information on the property value involved associated with a potentially qualifying Prop 47 property offense. If the property offense qualifies under Prop 47, the property value is less than or equal to $950, and the individual does not have a disqualifying history, then they should be included as Prop 47 offenders. However, it is not possible to determine property value in the data and, therefore, we elect to include all qualifying individuals convicted of Prop 47 offenses. As a result of this limitation, the analysis is over-inclusive when identifying Prop 47 offenders.

Methodology and Findings

The pre-Prop 47 group includes individuals released from custody or convicted out of custody between November 5, 2011 and October 31, 2012, allowing for a two-year recidivism window before the passage of Prop 47. The post-Prop 47 group includes individuals released from custody or convicted out of custody between November 5, 2014 and October 31, 2015 and followed for two years after release. Given that the characteristics of individuals in the post-Prop 47 group differ from those of their counterparts released prior to Prop 47, we have a two-stage approach to addressing selection on observables.

First, we use propensity score matching to identify those individuals from the pre-Prop 47 group that are most similar, in terms of their likelihood of treatment given their characteristics, to those in the post-Prop 47 group.[7] Table B2 summarizes the characteristics of the pre-Prop 47 and post-Prop 47 groups.

[5] See penal code Section 677(e)(2)(C)(iv)(VIII) and Section 290(c). See also: Appendix A of "Impact of Proposition 47 on Los Angeles County Operations and Budget", authored by Sarah B. Hunter, Lois M. Davis, Rosanna Smart, Susan Turner, June 2017. https://www.rand.org/pubs/research_reports/RR1754.html

[6] See exclusions detailed in Appendix III of "Proposition 47: The Safe Neighborhoods and Schools Act," authored by Judge J. Richard Couzens and Judge Tricia A. Bigelow, May 2017. http://www.courts.ca.gov/documents/Prop-47-Information.pdf.

[7] The mean p-score of the treatment group is 0.416. Prior to matching, the full pre-Prop 47 group had a mean p-score of 0.374; after matching, the refined pre-Prop 47 control group has a mean p-score of 0.416, equivalent to that of the treatment groups.

TABLE B2
Pre-post mean demographic and criminal history characteristics for control and treatment groups

	Pre-Prop 47, full group	Pre-Prop 47, matched comparison group	Post-Prop 47, treatment group
Age	34.5	34.9	35.1
Male	72.8%	75.8%	76.6%
White	32.6%	34.7%	34.9%
African American	23.9%	23.0%	23.1%
Hispanic/Latino	37.9%	36.9%	36.8%
Asian American	2.1%	2.1%	2.0%
American Indian	0.4%	0.4%	0.4%
Other race	3.0%	2.9%	2.7%
Jail	54.0%	53.9%	56.3%
Prison	21.5%	24.9%	19.8%
Length of stay	122.2	141.6	176.3
Second Degree Burglary (including shoplifting)	15.8%	20.5%	22.4%
Theft	27.8%	20.1%	18.6%
Writing bad checks	2.9%	2.8%	2.8%
Embezzlement	0.2%	0.3%	0.5%
Receiving stolen property	7.3%	7.6%	7.2%
Controlled substance	44.9%	47.4%	47.1%
Marijuana	1.1%	1.4%	1.42%
Number of previous violent convictions	0.05	0.1	0.1
Number of previous serious convictions	0.06	0.1	0.1
Age at first arrest	21.4	20.8	20.6
Number of previous arrests	15.0	16.8	17.6
Number of previous felony arrests	8.4	9.4	9.8
Number of previous persons offense arrests	2.0	2.3	2.4
Number of previous property offense arrests	4.6	5.0	5.2
Number of previous drug offense arrests	4.9	5.4	5.6
Age at first conviction	24.8	24.2	24.1
Number of previous convictions	5.4	5.9	6.2
Number of previous felony convictions	2.4	2.5	2.6
Number of previous persons offense convictions	0.5	0.6	0.6
Number of previous property offense convictions	1.9	2.0	2.1
Number of previous drug offense convictions	1.8	2.0	2.0
Number of observations	44,985	20,029	28,484

SOURCES: BSCC-PPIC Multi-County Study.

The matching process allows us to narrow the pre-Prop 47 group to those individuals who are most similar to the post-Prop 47 treatment group. After matching, we then use a linear probability model to estimate treatment effects, addressing any remaining differences in characteristics between the post-Prop 47 treatment group and pre-Prop 47 comparison group. This strategy improves on the traditional approach by reducing reliance on the regression model to adjust for differences in observable characteristics. While we leverage the Prop 47 policy experiment and draw on a rich set of individual-level characteristics, it is possible that there are unobserved differences between the post- and pre-Prop 47 groups and that these differences could play a role in the estimated differences in recidivism outcomes.

Table B3 presents unadjusted recidivism rates for the pre- and post-Prop 47 groups. The post-Prop 47 group has lower recidivism rates across all measures, with the exception of the two-year Prop 47 property offense rearrest rate.

TABLE B3

Unadjusted recidivism rates

	Pre-Prop 47	Post-Prop 47
Two-year arrest rate	72.5%	70.6%
Two-year Prop 47 arrest rate	44.7%	35.3%
Two-year Prop 47 property offense arrest rate	19.2%	19.8%
Two-year Prop 47 drug offense arrest rate	32.0%	21.2%
Two-year Prop 47 conviction rate	25.2%	14.2%
Two-year Prop 47 property offense conviction rate	11.7%	7.8%
Two-year Prop 47 drug offense conviction rate	15.4%	7.5%
Number of observations	20,029	28,484

SOURCES: BSCC-PPIC Multi-County Study.

Regression models include the demographic and criminal history characteristics shown in Table B2 and are consistent in their structure across analyses. We estimate the effects of Prop 47 on rearrest and reconviction rates over two-year recidivism windows. We estimate similar treatment effects with and without county fixed effects; the estimates without county fixed effects are presented below and used to construct the point estimates presented in the main body of the report. Rearrest findings are presented in Table B4 and reconviction findings are presented in Table B5. Given the relative size of Los Angeles County, we estimate effects with and without individuals from Los Angeles.

TABLE B4

Coefficient estimates of effect of Prop 47 on two-year rearrest rates for individuals released to MCS counties

	Any offense	Prop 47 offense	Prop 47 property offense	Prop 47 drug offense
All MCS counties	-1.8***	-10.2***	0.4	-11.3***
MCS counties, excluding Los Angeles	-2.6***	-11.0***	-0.6	-11.3***

SOURCES: BSCC-PPIC Multi-County Study.

NOTES: Each cell represents the coefficient estimate of the difference in rearrest outcomes for the referenced post-Prop 47 treatment group when compared with the pre-Prop 47 matched control group. In each case, we use a regression model to adjust for remaining, post-matching differences in the demographic and criminal history characteristics. Coefficient estimates should be interpreted as percentage point differences between the treatment and control group. ***p<.01, **p<.05, *p<.10.

TABLE B5

Coefficient estimates of effect of Prop 47 on two-year reconviction rates for individuals released to MCS counties

	Any	Prop 47 offense	Prop 47 property offense	Prop 47 drug offense
MCS counties	-3.1***	-11.3***	-4.2***	-7.9***
MCS counties, excluding Los Angeles	-4.3***	-9.2***	-4.3***	-5.5***

SOURCES: BSCC-PPIC Multi-County Study.

NOTES: Each cell represents the coefficient estimate of the difference in reconviction outcomes for the referenced post-Prop 47 treatment group when compared with the pre-Prop 47 matched control group. In each case, we use a regression model to adjust for remaining, post-matching differences in the demographic and criminal history characteristics. Coefficient estimates should be interpreted as percentage point differences between the treatment and control group. ***p<.01, **p<.05, *p<.10.

Appendix C. Additional Proposition 47 Funding Information

Proposition 47 Savings

TABLE C1

Proposition 47 allocations (in $ millions)

Department	2016-17	2016-17 Supplemental	2017-18	2018-19
Board of State and Community Corrections	25.6	10	29.4	41.6
Department of Education	9.9	18	11.3	16
Victim Compensation and Government Claims Board	3.9	0	4.5	6.4
Total	39.4	28	45.2	64

SOURCES: California Department of Finance, Enacted Budget Summaries for 2016-17 and 2017-18, and Governor's Budget Proposal for 2018-19.

NOTES: The legislature decided to include a supplemental funding for the transfer that occurred during the 2016-17 budget year.

Board of State and Community Corrections

TABLE C2

First round of awards from BSCC

County	Lead Agency	Amount ($)
Alameda	Health Care Services	6,000,000
Contra Costa	Health Services	5,984,047
Los Angeles	City Attorney's Office	6,000,000
Los Angeles	El Rancho USD	997,436
Los Angeles	Health Services	20,000,000
Los Angeles	Mayor's Office	5,998,383
Los Angeles	Pasadena Police Department	2,511,537
Marin	Health and Human Services	998,504
Merced	Probation	960,667
Monterey	Health Department	6,000,000
Orange	Health Care	6,000,000
Placer	Health and Human Services	990,000
Plumas	District Attorney	1,000,000
Riverside	Riverside University Health System	6,000,000
San Bernardino	City of Railto	996,975
San Bernardino	Public Health	1,246,936
San Diego	County (with District Attorney)	6,000,000
San Diego	Oceanside USD	998,300
San Francisco	Public Health	6,000,000
San Joaquin	Behavioral Health Services	6,000,000
Solano	Health and Human Services	6,000,000
Tehama	City of Corning	1,000,000
Yolo	Health and Human Services	5,968,215

SOURCES: Board of State and Community Corrections

NOTES: The County of San Bernardino is the only applicant that received a partial award. The county is only receiving $1.25 million of the $6 million it requested.

California Department of Education

The California Department of Education (CDE) receives 25 percent of the state savings from Proposition 47. The funds CDE receives are dispersed through a competitive grant program, Learning Communities for School Success Program (LCSSP), to support evidence-based, non-punitive programs to help vulnerable students stay in school and out of the criminal justice system. CDE has given out the first round of funding for a three year grant program running from 2017-18 fiscal year to 2019-20 (referred to as Cohort 1), totaling $37 million in funding. Grants selected for funding receive $50 per year per student enrolled, with the minimum grant being $15,000 and the max grant being $2 million. Thirty-four districts received funding as part of cohort 1 (see Appendix Table C2 below). CDE will award an additional $10 million for cohort 2, running from 2018-19 fiscal year to 2020-21 in May 2018.

TABLE C3

First Round of Awards from CDE

County	Local Educational Agency	Amount ($)
Alameda	Alameda COE	1,759,400
Alameda	Hayward USD	1,759,400
Alameda	Leadership Public Schools Oakland R&D	192,628
Alameda	San Leandro USD	1,139,563
Colusa	Pierce Joint USD	195,293
Contra Costa	West Contra Costa USD	1,759,400
Del Norte	Del Norte COE	542,335
Imperial	Brawley ESD	526,764
Imperial	Brawley Union HSD	243,589
Imperial	Central Union HSD	543,443
Kern	Kernville Union ESD	116,252
Kern	McFarland USD	327,239
Kings	Reef Sunset USD	349,681
Los Angeles	Bellflower USD	1,045,955
Los Angeles	El Rancho USD	1,155,134
Los Angeles	Los Angeles USD	1,753,418
Los Angeles	Pomona USD	1,759,400
Madera	Madera USD	1,759,400
Mendocino	Ukiah USD	782,625
Riverside	Banning USD	562,128
Riverside	Coachella Valley USD	1,544,723
Riverside	Desert Sands USD	1,174,751
Riverside	Hemet USD	954,914
Sacramento	Sacramento City USD	1,707,854
Sacramento	San Juan USD	1,365,998
San Benito	Hollister USD	533,494
San Benito	San Benito COE	555,122
San Bernardino	San Bernardino USD	1,759,400
San Joaquin	Lodi USD	1,701,032
Shasta	Shasta COE	940,707
Sonoma	Santa Rosa HSD	1,076,615

County	Local Educational Agency	Amount ($)
Stanislaus	Stanislaus COE	1,758,168
Tehama	Red Bluff Joint Union HSD	214,559
Tulare	Visalia USD	1,759,400

SOURCES: California Department of Education

NOTES: COE = County Office of Education; ESD = Elementary School District; HSD: High School District; USD = Unified School District.

California Victim Compensation and Government Claims Board

Since 2013 the California Victim Compensation and Government Claims Board (CVCGCB) has been required (CA Government Code Sec. 13963.1) to administer a competitive grant program to provide up to $2 million (appropriated by the Legislature from the state's Restitution Fund) to trauma recovery centers. With the passage of Proposition 47, the CVCGCB also now receives 10 percent of state savings from the measure for grants to trauma recovery centers, in addition to the funding from the Restitution Fund. The table below list all of the grants awarded to trauma recovery centers that are funded with Proposition 47 savings.

TABLE C4

Awards from the CVCGCB to TRCs using Prop 47 Savings

Region	Trauma recovery center	Amount ($)	Award start date	Funding timeframe (months)
Los Angeles	California State University at Long Beach	1,005,525	Sept 2016	15
Los Angeles	St. Francis Medical Center	766,484	Sept 2016	22
Sacramento	The Grace Network	733,333	Sept 2016	22
San Francisco	San Francisco Trauma Recovery Center	880,949 (*)	Sept 2016	11
Los Angeles	Downtown Women's Center	468,453	Mar 2017	16
San Diego	Chadwick Center for Children and Families	1,058,306	Jul 2017	24
Solano	Solano Courage Center	612,010	Jul 2017	24
Los Angeles	Special Service for Groups	1,389,946	Jul 2017	24
Los Angeles	Strength United/California State University at Northridge	514,922	Jul 2017	24
San Joaquin	Fathers and Families of San Joaquin	332,572 (*)	Jul 2017	24

SOURCES: Board Agenda Items, California Victim Compensation and Government Claim Board, 2015-2017.

NOTES: (*) = are proposals that received funding from both the Prop 47 savings and the Restitution Fund. The amount listed is only the amount of funded provided from Prop 47 savings for the specific grant start date and period.

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