Criminal Decarceration Policies and the Effect on Community Safety

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Abstract

This paper examines the effect of re-sentencing policies as a means of decarceration on community well-being. In 2011 and 2014, California passed jail decarceration policies, *AB 109* and *Prop 47*, respectively. *AB 109* reallocated state prison inmates into local county jails. On the other hand, *Prop 47* reduced penalties for non-serious property crimes, thereby providing a second chance to offenders that committed specific non-violent crimes while lowering the burden on county jails by shifting offenders into local communities. My results indicate that *Prop 47* increased the homeless population and health-related governmental spending but did not reduce governmental spending on corrections. Furthermore, California jail disposition data show heterogeneous effects on recidivism. For example, *Prop 47* decreased recidivism rates for *Prop 47* charges (non-serious and non-violent charges) after *AB 109* increased the rates in county jails. However, *Prop 47* failed to lower recidivism rates for control group charges (more severe than *Prop 47* charges) after *AB 109* raised the rates in county jails. Finally, I find that *Prop 47* raised non-violent crime rates, utilizing Los Angeles crime data, especially among non-homeless offenders.

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1 Introduction

Decarceration policies have received bipartisan support in recent years as progressives have raised concerns regarding racial disparities and worsening welfare outcomes for inmates. At the same time, conservatives aim to reduce the financial burden of the criminal justice system on the government budget (Takei, 2017). The impact of reductions in the size of incarceration on community safety remains an open empirical research question. Given the political agreement, it is perhaps unsurprising that decarceration policies have been realized. Specifically, recent calls for reform in the criminal justice system have targeted reducing the incarcerated population and converting low-level, non-violent felony offenses into misdemeanors.

The question then arises as to whether mere re-sentencing is the appropriate means for decarceration when re-sentencing is not accompanied by resources to mitigate the cycle of individuals with a high risk for re-offending. For example, individuals released from jail could struggle with employment, finding housing, or addressing mental health issues. In this work, I examine Proposition 47 (Prop 47), which mirrors the calls for reform discussed nationwide in the United States. I will specifically investigate the effect of criminal re-sentencing policies on the homeless population, government spending, and criminal deterrence in California communities.

Historically, radical changes followed the United States Supreme Court ruling that the California prison system must reduce its population in 2011, *Brown v. Plata, 563 US 493 (2011).* Namely, California was required to reduce the prison population by 34,000 inmates by June 2013, approximately 20% of the prison population. To meet this goal, California enacted Assembly Bill 109 (AB 109) in 2011, which realigned the prison population, shifting many inmates to county jails, especially non-serious criminal offenders (Lofstrom et al., 2016). A shock to governmental fiscal stress was experienced during this event while not receiving attention from the public. As noted in Boylan and Mocan (2014), the court order to reduce the prison population led to a substitution effect in public spending that raised expenditures for prison reform, which was associated with a reduction in welfare expenditures. Three years later, the people of California passed Prop 47 in 2014 as another major reform to the criminal justice system.[1] Prop 47 aimed to remove racial disparities in the criminal justice system and decrease the burden of county jails, driven by the realignment in 2011, by reducing the penalty for non-serious property crimes so that those offenders did not have to be incarcerated in county jails. The jail population dropped by 9,000 inmates within two years after Prop 47,

[1] Prop 47 is not only supported by both political parties but also supported by the public. The people of California widely supported Prop 47. 59.6% of voters (4,238,156 in level) supported Prop 47, while 40.4% (2,871,943 in level) opposed it. The number of votes amounts to 40% among the total 17,803,823 registered voters (Debra Bowen, 2014, Statement of Vote, November 4, 2014 General Election, California State of State).

achieving pre-realignment levels for county jail populations (Lofstrom et al., 2016).

The major difference between these two pieces of legislation is that Prop 47 shifted offenders from incarceration to local communities. In contrast, AB 109 contained offenders within the carceral system, only moving the state prison population into county jails. Specifically, offenders with non-serious property crimes classified as misdemeanors under Prop 47 were likely to remain in local communities. County jails rarely admitted offenders found guilty of one of the charges outlined in Prop 47, which included drug possession, receiving stolen property, theft, shoplifting, writing bad checks, and check forgery.[2] Additionally, inmates who entered jails before Prop 47 for one of the Prop 47 charges could petition to be released early.

However, people with a high risk for re-offending are likely to become homeless without successful re-entry. It is not common for offenders to naturally return to society even after they are released; evidence shows that 70% of the unsheltered homeless in San Diego reported a history of incarceration in a 2018 survey conducted by the US Department of Housing and Urban Development.[3] Additionally, 15% of inmates reported a history of homelessness in a 2002 national survey conducted by the US Department of Justice (Greenberg and Rosenheck, 2008). Furthermore, not admitting offenders to county jails might stress alternative institutions to house the offender population since one of the stated functions of jails is to handle individuals with mental illness that have a high risk of committing crimes (Takei, 2017).

The homelessness issue is not mutually exclusive from the re-entry of offenders into communities and mental illness. In addition, evidence has accumulated regarding the difficulty in handling homelessness because the homeless population is more likely to be involved in substance abuse and criminal activities (Coldwell and Bender, 2007; Munthe-Kaas et al., 2018). Moreover, Prop 47 reduces the expected cost of committing Prop 47 crimes. Thus, in the current research, I empirically examine the effect that Prop 47 had on the size of the homeless population and changes in government welfare spending and criminal deterrence of non-serious property crimes more generally.

This research builds on the literature on the cost-benefit analysis of incarceration, incapacitation, and deterrence by explicitly discussing the effect of decarceration policies. Current evidence finds that the benefits of incarceration are minimal; the deterrence effect resulting from lengthy incarceration is relatively small

[2] The list of Penal Code sections for Prop 47 charges that qualify for re-sentencing is 459.5, 484, 487, 496, 470, 471, 472, 473, 474, 475, 476, and 476(a). The list of Health and Safety Code sections for Prop 47 charges that qualify for re-sentencing is 11350, 11357(a), and 11377. These charge code sections contain further subsections. Also, multiple charges occasionally get bundled; thus, the total number of charges containing any Prop 47 charges is 260 among the complete charge list provided by California county jails. I treat all the subsections and bundled multiple charges eligible for re-sentencing. Appendix Table A.3 displays examples of charge descriptions.

[3] *Criminal Justice System Involvement and Mental Illness among Unsheltered Homeless in California* (Policy Brief, November 2018).

(Abrams, 2012; Buonanno and Raphael, 2013; Lofstrom and Raphael, 2016). On the other hand, incarceration costs are sizable; a short period of pre-trial detention significantly and negatively impacts the welfare of detained potential offenders (Aizer and Doyle, 2015; Dobbie et al., 2018). Some evidence indicates mixed results; health risk increases among children who experienced family member imprisonment (Provencher and Conway, 2019), whereas Norris et al. (2021) found children benefited from parental/sibling imprisonment, lowering the likelihood of incarceration. Additionally, Barbarino and Mastrobuoni (2014) show that incapacitation causally decreased crime, presenting an Italian case where the social cost of releasing prisoners exceeds the cost of keeping them in prison. However, this evidence is less informative regarding US prison reform since Italian prison crowding is much lower than US prison crowding.

Regarding the cost-benefit analysis of decarceration, research on the benefits of decarceration centered on diversion programs research. However, research indicates offenders remained risky in terms of recidivism rates under traditional diversion programs (Steadman et al., 1995; Sung, 2011; DeMatteo et al., 2013; Tartaro, 2015; Wong et al., 2016). Thus, according to previous work, there is a call for further research on practical and responsible diversion programs. At the same time, specialized courts such as drug courts and mental health courts can help to mitigate recidivism (Pettus-Davis and Epperson, 2015). My research builds on this work by examining another decarceration cost, namely homelessness.

I start by analyzing the effect of re-sentencing, thus not admitting offenders to county jails, on the homeless population using Continuum of Care (CoC) level data, constructed and defined by the Department of Housing and Urban Development, from 2009 to 2019.[4] US Census State and Local Government Finance data provide welfare-related spending information (e.g., health and hospital expenditures) to test government finance concerns, whether Prop 47 stresses welfare-related county government spending. I then use county jail inmate disposition, admission, and discharge data provided by the California Department of Justice (CA DOJ) to test whether Prop 47 raised recidivism rates for offenders directly influenced by Prop 47. Finally, I refine my analysis to examine the effect of criminal behavior by homelessness status using Los Angeles crime data to see how non-serious property crimes changed after the passage of Prop 47 by offender homelessness status.

My results find a 26 percentage point increase in the homeless population relative to a set of propensity score matched CoC units outside California. Also, health spending per capita increases by 11 percentage points without reducing correctional or judicial costs. County jail disposition data provided by CA DOJ

[4] 51% of CoC units are comprised of several counties.

show that Prop 47 decreases county jail crowding, which resulted from shifting the state prison population into county jails. However, recidivism rates for control group charges remain high after both AB 109 and Prop 47, where the control group is a complementary set of Prop 47 charges sharing the same classification. In other words, Prop 47 offenders commit the control group charges that are still non-violent but more severe than Prop 47 charges, considering Prop 47 charges are regarded as non-violent and also non-serious charges. Within LA, both the Prop 47 charges and the control group charges increase among homeless offenders, while non-homeless offenders are the source of a large increase in control group charges.

Collectively, these findings indicate the failure of re-sentencing policies in solving racial disparities and reducing incarceration spending. While difficult to measure, the current research hints at the re-entry failure of re-sentencing that policymakers overlooked. Specifically, Prop 47 aimed to reduce the incarcerated population in county jails and decriminalize low-level, non-violent offenses. Ultimately, it appears to lead to increases in the unsheltered homeless population and health-related governmental spending without yielding savings from reduced correctional expenditures.

The remainder of this paper consists of five parts. The following section details the history of institutionalization and re-entry programs of offenders and the mentally ill. Section 3 provides a complete description of the data used in the analysis and the matching process employed to ensure that I find comparable locations. Section 4 describes the estimation strategy for the empirical analysis. Section 5 presents the regression results, and robustness specifications are presented in section 6. Finally, I conclude with a discussion of the empirical results and their implications for criminal justice reform.

2 History of Institutionalization of Offenders and the Mentally Ill, and Re-entry

Re-entry of offenders and the mentally ill is the key to successful decarceration policies if the fundamental objective of decarceration is to solve racial disparities and maximize public safety and well-being (Pettus-Davis and Epperson, 2015). Moreover, the ideal re-entry is offenders returning to the community rather than moving between different institutions (mental health facilities, prison, jail, etc.). In this regard, this section discusses the history of (de)institutionalization of offenders and the mentally ill, outlining research efforts on investigating and solving re-entry issues.

In the 1970s, the mentally ill were deinstitutionalized from mental health facilities by shortening the length of their stay in mental health facilities. Empirically, Raphael and Stoll (2013) found that "transinstitutionalziation" from mental health hospitals to jails or prisons from the 1980s to 2000s. In contrast, they did not find evidence of the deinstitutionalization effect of mental health facilities on the prison population from the 1950s to the 1980s. In this research, deinstitutionalization started with discharging the elderly and women and then moved towards discharging males. Considering the elderly and women are not representative prison inmates, this can explain why evidence identified a null effect of early deinstitutionalization from the 1950s to the 1980s of mental health facilities on the prison population, as young white and Black males primarily represent the prison population. Over the years, the mentally ill prevailed in today's jails and prisons, which requires a thorough investigation of proper treatment (Steadman et al., 2009; Torrey et al., 2010; Steadman, 2016).

Recent research examines re-entry programs with a magnified emphasis on targeted treatments for inmates after the prevalence of the mentally ill among prisoners (Vogel et al., 2007).[5] There are numerous studies on re-entry programs, according to the National Institute of Justice on their website.[6] Among about 600 studies, they evaluated 400 studies, including 280 randomized controlled trials. The programs included cognitive-behavioral treatment, education, employment, family-based programs, housing, mental and physical health, sex offender treatment, substance abuse, supervision and sanctions, and youth re-entry and aftercare programs. Overall results indicate both some partial successes and general failures of treatments.[7] In economics, there are two causally effective studies related to reintegration that concentrate on employment's effect on recidivism. Consistent with previous literature on the value of stable jobs, Schnepel (2018) found that areas with job opportunities for manufacturing and construction had lower recidivism rates than areas with fewer job openings in the manufacturing and construction areas. Also, Bhuller et al. (2020) found rehabilitative training programs enhanced employment and reduced recidivism among inmates. These re-entry studies focus on the success rate of specific re-entry programs. My paper addresses the process of offenders failing

[5]Past research primarily focused on offenders who participated in restorative justice programs rather than directly handled re-entry issues (Visher et al., 2005; Latimer et al., 2005; Ndrecka, 2014; Mitchell et al., 2016; Berghuis, 2018; Lipsey, 2019). Visher et al. (2005) examined eight studies from the 1970s and the 1980s and they found the community-based employment interventions did not statistically lower the rate of recidivism. And this is likely to be a failure of intervention instruments as stable employment itself is the crucial factor in reducing recidivism. On the other hand, twenty-two studies did show a statistically significant effect of employment interventions on recidivism, and studies drew a large proportion of effect sizes from journals without a peer review (less suffering from publication bias). This body of works did not rule out self-selection bias due to the voluntary nature of the restorative justice program (Latimer et al., 2005). On the contrary, a more recent meta-analysis found no significant difference between voluntary and mandatory attendance (Ndrecka, 2014). The most recent meta-analysis hints at the importance of quality treatments; targeted intervention design is effective with the involvement of evaluators and with a focus on cognitive skill, group work, mentoring, and mental health treatment (Lipsey, 2019).

[6]https://crimesolutions.ojp.gov

[7]Nevertheless, two programs are evaluated to substantially affect - cognitive-behavioral treatment and targeted treatment for the mentally ill. In England, several cognitive-behavioral therapies effectively enhanced thinking patterns and cognitive skills of offenders during twenty sessions for two hours each. There is one effective Washington-based study in the US, targeting mentally ill offenders and deploying random assignment designs.

to be back to legal society by examining homelessness.

3 Data

In this section, I outline the data sources that I use to analyze the effects of AB 109 and Prop 47 on community safety and well-being. I start with discussing the US Department of Housing and Urban Development homelessness data, which collected information from the Continuum of Care units across the entire US. Governmental expenditure information by categories comes from State and Local Government Finances data by the US Census Bureau. In addition, I discuss control variables sourced from the National Cancer Institute, Bureau of Economic Analysis, and US Census Bureau, utilized to find a suitable comparison group. I also discuss charge disposition and jail admission/discharge data with codified inmate identifiers from the entire county jails within California. I then provide a discussion of charge data that are specific to Los Angeles, including offender information by homelessness status.

3.1 Nation-Wide Data Sources

US Department of Housing and Urban Development Homeless Data

US Department of Housing and Urban Development (HUD) data are utilized, which provide measures of homeless populations from Point-in-Time (PIT) surveys, and measures of homelessness resources from the Housing Inventory Count (HIC) survey. These measures are relatively consistent from 2007 to 2019, collected in the middle of January each year. The unit of measures is the Continuum of Care level (CoC), which comprises 386 entities across the United States, geographically smaller than states but more aggregated than counties. Figure 1 shows that the average number of the unsheltered homeless population is trending upward in the CoC units in California. On the other hand, other CoC units outside of California do not exhibit an upward trend, on average. In the analysis, the treatment group includes every CoC in California, and the pool of control locations has every CoC outside of California.

[Figure 1 Here]

State and Local Government Finances

Government spending data, which will be incorporated as an outcome variable, are sourced from State and Local Government Finances published annually by the US Census Bureau. I use a database compiled by Pierson et al. (2015), which generates a measure of coherence for detailed expenditure categories over time. I select seven variables the analysis - health, policing, correctional, judicial, hospital, welfare, and community development expenditures per capita (in current dollars). One shortcoming of the data is it is only available for a set of representative counties. Nevertheless, US Census collects information from more than half the total counties in the US.[8] After combining data sets based on a crosswalk between CoC units and counties (Byrne et al., 2013), more than 80 percent of available data points among counties were mapped into CoC units (Figure 2).[9]

[Figure 2 Here]

Covariates

Covariates for matching are obtained from the Surveillance, Epidemiology, and End Results Program (SEER) data provided by National Cancer Institute, Personal Income and Employment by Major Component (CAINC4) data from the Bureau of Economic Analysis, and the American Community Survey 5-Year Estimates (ACS5) from the US Census Bureau. Specifically, SEER data contains population demographics such as the percent female, white, and Black population by age groups (5-year breaks from 10 to 64). CAINC4 data includes averages of farm/non-farm income, proprietors' income, total income, wage, employer/employee contributions for pension and insurance funds, full-time and part-time employment, and proprietors' employment in each county. ACS5 contains geographic mobility by race (White, Black, and Asian), poverty status by race, population by occupation, and sex by race. Additionally, I use information from the unsheltered homeless population and the number of temporary shelter beds from HUD.

Generating an Appropriate Control Group

I conduct a matching procedure using a random forest method and optimal matching using data from before the treatment period (2009 to 2014) to avoid contamination from covariates after treatment has occurred. Note that the homeless population should not be influenced by AB 109 because inmates are still housed within carceral facilities. AB 109 transfers them from the state prison to county jails.[10] The random forest method utilizes a non-parametric procedure, which reduces the collinearity problem of including too many variables for matching. 111 CoC units are selected as a control group for the 40 treated CoC units.[11] After

[8] US Census collects information from the entire 3,006 counties in a 5-year cycle. For example, the data contain the universe of the entire counties in 2012 and 2018. In 2009, 2010, 2011, 2013, 2014, 2015, 2016, and 2017 (except for 2012 and 2018), the data have information for around 1,600 counties.

[9] Some large counties (e.g., Los Angeles County) were distributed into several CoC units. In these instances, I weight counties' governmental spending and socioeconomic values by the number of CoC units. The implicit assumption is that several CoC units evenly share the burden of homelessness.

[10] At best, county correctional expenditures could be impacted by AB 109. However, there is no evidence county jail staffing drastically increased, which is consistent with the trend of average correctional costs presented in Figure 9 in Section 4.

[11] Appendix Table A.1 displays the list of CoC units utilized in the analysis.

matching, several variables are aggregated and included in the regression analysis as a set of covariates, including the share of populations by race and sex, employment per capita, and personal income per capita (Table 1). The differences between groups are not economically meaningful but statistically significant;[12] thus, I control for these aggregated covariates in the final regressions.

[Table 1 Here]

3.2 California State-Wide Data Source

Two more data sources are included to further delve into the detailed impact of Prop 47 on local communities. First, the California Department of Justice (CA DOJ) data provide daily charge disposition information with codified individual identifiers. The data enable me to examine the effect of decarceration policies on the jail populations, the number of offenders in jails. Importantly, this data set allows me to calculate the recidivism of discharged offenders.[13] I utilize data for the period January 2005 - December 2018. The analysis then compares charges eligible for Prop 47 with similar charges but not impacted by Prop 47. Specifically, nine charge groups out of forty-two (defined by CA DOJ) contain at least one charge eligible for Prop 47 (bold text in Table 2). The control group is a complementary set of Prop 47 charges within each charge group.[14]

[Table 2 Here]

Table 3 presents a summary of offender information with treatment and control groups. The Prop 47 charge descriptions include drug possession, receiving stolen property, theft, shoplifting, writing bad checks, and check forgery. The control charges are a complementary set of Prop 47 charges sharing the same charge group classification defined by the CA DOJ. Appendix Table A.3 details how different charges are classified into each charge group and which specific charges are part of the Prop 47 group, which are in the control group. Additionally, the "Violent" charge group includes burglary, robbery, and assault (charge group code 22, 12, and 13 respectively in Table 2). "Other" charge group contains all other charges excluding the charges described above.

3.3 Los Angeles City-Wide Data Source

Next, I linked Los Angeles Police Department daily charge data to the homelessness status of offenders, provided by the New York Times. The data include race/sex information for individual offenders and

[12] A group of crucial variables likely determine the propensity score among 185 variables deployed in the propensity score matching, thus leaving space for several socioeconomic control variables to remain different at an aggregate level.

[13] I focus on recidivism within one year to avoid data censoring in later years.

[14] Two hundred sixty charges from the treatment group and 1,600 charges from the control group account for approximately 25% of the total charges. Appendix Table A.3 presents the example charges.

misdemeanor complaints about charges from 2012 to 2016. These data make it possible to test which population between homeless and non-homeless offenders drives potential increases in non-serious property crimes. Finally, I aggregated the data to the monthly level.

I further subset the data to focus on relevant observations for the analysis. With a similar logic in the California DOJ data, I use Prop 47 charges as a treatment group and focus on the charge groups that contain at least one Prop 47 charge. Six charge groups include Prop 47 charges (bold text in Table 5), "Forgery/Counterfeit," "Fraud/Embezzlement," "Larceny," "Narcotic Drug Laws," "Receive Stolen Property," and "Vehicle Theft" charge groups. The control group is a complementary set of Prop 47 charges within each charge group.

[Table 5 Here]

To determine the plausibility of the Prop 47 treatment and control groupings, I examine the share of misdemeanor complaints per charge across time. Prop 47 converted felony charges into misdemeanors; thus, the treatment group is associated with the increased percentage of misdemeanor complaints. The treatment group (Prop 47 charges) displays an increase in the ratio of misdemeanor complaints from 0.3 to 0.6 in the left panel of Figure 5. On the contrary, the control group did not show a similar increase (right panel of Figure 5).

[Figure 5 Here]

Location information contains an address unit obscuring to the "nearest hundred block" level[15] and 21 policing area units. I use the 21 policing areas as the unit of analysis. The graphical representation of the average number of charges by the policing areas in Figure 7 mirrors the total number of charges from the raw data in Figure 6.[16] The homeless offenders are predominantly older, Black and white citizens, and more prevalent in the Central and Hollywood policing areas (Table 6).

[Table 6 Here]

The left panel of Figure 7 shows crime trends among homeless offenders. Prop 47 impacted the number of Prop 47 charges and the number of control charges, a potential violation of $SUTVA$.[17] Graphically, the number of Prop 47 charges decreased, and the control charges exhibited upward trends. The right panel of

[15] For example, if the true address was 216 Main Street, my data would simply state 200 Main Street.

[16] The trends by the "nearest hundred block" address unit in Figure 8 do not mirror the raw data, likely due to the widely unbalanced data structure. Specifically, among the entire 182,000 daily observations from 2012 to 2016, there are 23,000 unique "nearest hundred block" address units. On average, 23,000/182,000 = 8 incidents per address unit occurred across the entire time. The variance is substantial, as the most frequent address unit appeared 1,300 times. Since the OLS regression is central to the Difference-in-Differences strategy, the unbalanced data structure is likely to result in biased and inconsistent estimates. Although not reported, checking the regression results with the "nearest hundred block" address unit reveals the direction of coefficients remains the same regardless of the unit of analysis. Also, the treatment effect remains statistically significant among non-homeless offenders with a smaller coefficient magnitude compared to the regression result reported in Section 5.

[17] This means we need to exercise caution in interpreting the regression coefficients due to spillover effects.

Figure 7 shows charge trends among non-homeless offenders. The effect is more drastic because Prop 47 charges abruptly decreased, whereas the control charges show a smooth upward trend.

[Figure 7 Here] [Figure 6 Here] [Figure 8 Here]

4 Empirical Strategy

4.1 Nation-Wide Data

I examine the effect of Prop 47 on the homeless population and government spending using a differences-in-differences (DiD) strategy (Equation 1):

$$Log(Y_{it}) = \alpha_0 + \alpha_1 Prop47_i \times Post_t + X'r + CoC_i + Year_t + e_{it}, \tag{1}$$

where Y_{it} is the outcome of interest to measure homelessness and governmental spending. $Prop47_i$ is indicating CoC units impacted by Prop 47. $Post_t$ is an indicator variable for the period after Prop 47 was enacted on November 5^{th}, 2014. CoC_i and $Year_t$ are individual CoC and year fixed effects, respectively. X is a set of socioeconomic control variables including the percentage of the population with aged 10 to 64 by female, white, Black, and Asian populations, the average income per capita, and employment per capita to absorb variation at the CoC level over time. Robust standard errors are clustered in CoC unit.

The crucial identifying assumption to apply Difference-in-Differences identification strategy is that in the absence of Prop 47, adopting counties would have experienced changes in outcome variables similar to non-adopting counties in comparable locations. The homeless and government spending data make it possible for me to support the parallel trend assumption by presenting visual evidence that the outcomes of the two groups are parallel in the years prior to adoption (Figure 1). Regarding governmental expenditures, Figure 9 reveals that parallel pre-trends hold in the unsheltered homeless population, health, and correctional spending.

[Figure 1 Here] [Figure 9 Here]

In addition, the history of homeless policies in Los Angeles supports the assumption of no anticipation effects corresponding to Prop 47 on the homeless population.[18] Sheeley et al. (2021) organized a detailed history of homelessness within Los Angeles, where both homeless and resources for the homeless are prevalent.

[18]This does not mean California did not put any effort into handling the homelessness issue by itself. Historically, California counties' awareness about homelessness goes back to the 1980s, and some stylized facts emphasize education, employment, and affordable housing (Quigley et al., 2001; United States Interagency Council on Homelessness, 2015).

They note that the most relevant policy, before Prop 47, was *not* to pursue a plan of replacing part of a Men's Central Jail facility into an integrated mental illness treatment center in 2013. The second most recent policy occurred in 2007, a permanent supportive housing program targeting the most vulnerable population launched by the Board of Supervisors in Los Angeles. After that, the Los Angeles County Board of Supervisors established a grand plan to solve the homelessness issue collaboratively with other counties, cities, and community partners in 2015 (Los Angeles County Chief Executive Office, 2016), which indicates LA county initiated homeless policies and programs after Prop 47 in 2014.

4.2 California State-Wide Data

Second, I examine the the effect of AB 109 and Prop 47 on county jail population within California using a differences-in-differences (DiD) strategy (Equation 2):

$$\begin{aligned} Log(Y_{it}) = \alpha_0 + \alpha_1 Prop47_i \times Post1_t + \alpha_2 Prop47_i \times Post2_t \\ + County_i \times YearMonth_t + County_i \times Prop47_i + e_{it}, \end{aligned} \tag{2}$$

where Y includes the number of offenders and recidivism. $Prop47_i$ is an indicator variable whether Prop 47 charge group or control charge group. $Post1$ is an indicator for the period October, 2011 to October (AB 109 period), 2014. $Post2$ is an indicator for the period November, 2014 to December, 2018 (Prop 47 period). $County_i$ are county fixed effects. $YearMonth_t$ is month by year fixed effects. Different from Equation 1, the current equation includes county by Prop 47 status fixed effects because geographical location is not the main variable to separate treatment and control groups (the treatment group is classified by specific charges). Thus, county by month by year fixed effects are included to absorb geographical variations across time regardless of treatment status. Robust standard errors are clustered according to county by Prop 47 status.

The identifying assumption is that offenders with offenses impacted by AB 109 and Prop 47 would have behaved similarly to those with comparable offense charges which were not affected by Prop 47. CA DOJ data make it possible for me to support the parallel trend assumption by presenting visual evidence that the jail population trends between two groups are parallel in the years prior to the adoption of AB 109 (Figure 3 and Figure 4).[19] Thus I set the periods before AB 109 as pre-treatment periods for the Difference-in-

[19] For graphical representation, I dropped observations six months before December 2007, 2011, and 2015 due to massive reductions in the numbers, consistent between groups and charges. Since a Difference-in-Differences strategy is used, the parallel trend between groups and charges cancels out in the final regression outcomes; although not reported, the regression

Differences strategy.

[Figure 3 Here] [Figure 4 Here]

4.3 Los Angeles City-Wide Data

Lastly, I examine the the effect of Prop 47 on homeless and non-homeless crime rates within Los Angeles using a differences-in-differences (DiD) strategy (Equation 3):

$$\begin{aligned} Log(Charge_{it}) = \alpha_0 + \alpha_1 Prop47_i \times Post_t + Area_i \times YearMonth_t \\ + Area_i \times Charge_i \times Prop47_i + e_{it}, \end{aligned} \tag{3}$$

where $Prop47_i$ is 1 if a charge is Prop 47 charges and 0 if a charge is the complementary set of Prop 47 charges. $Area_i$, $Charge_i$, and $YearMonth_t$ are indicator variables for the 21 policing area units, charge group, and month in year fixed effects, respectively. Different from Equation 1, the current equation includes policing area by charge group by Prop 47 status fixed effects because geographical location and charge group are not the main variables to separate treatment and control groups (the treatment group is classified by specific charges). Thus, policing area by month by year fixed effects are controlled for absorbing geographical variations across time regardless of treatment status. Robust standard errors are clustered in policing area by charge group by Prop 47 status.

The identifying assumption is that offenders with offenses impacted by Prop 47 would have behaved similarly to those with comparable offense charges which were not affected by Prop 47. LA crime data make it possible for me to support the parallel trend assumption by presenting visual evidence that the outcomes of the two groups are parallel in the years prior to the adoption of Prop 47 (Figure 7).

5 Results

5.1 Nation-Wide Data

Table 4 displays the regression results from Equation 1. Columns (1), (3), and (5) show the estimates from the DiD specification on the unsheltered homeless population, health expenditures, and policing expenditures. Columns (2), (4), and (6) include DiD estimates for each year, which are also plotted in Figure 10. The coefficient in Column (1) means Prop 47 leads to a 26.7 percentage point increase in the unsheltered

results remain the same before and after dropping these observations.

homeless population. Similarly, health and policing expenditures increased (however, policing expenditures are accompanied by changes in pre-trend). The 11 percentage point increase in health spending in Column (3) indicates governmental financial stress on health expenditures. Since the outcome variable is health spending per capita, the results imply individual California residents bear an 11 percentage point larger burden than residents in the control group, CoC units outside California. The even-numbered Columns indicate the treatment effects each year. Column (2) reveals that the effects come from 2015 and 2016, and homelessness' most considerable impact from 2019. Column (4) shows a more consistent effect across time in health spending. Still, the effect sizes are more prominent in later years. This phenomenon could be due to the accumulation of homeless and ex-convict populations. In other words, without successful reentry, those populations could keep rising, stressing government spending more over time.
[Table 4 Here] [Figure 10 Here]

5.2 California State-Wide Data

Table 7 presents the regression results for Equation 2. The jail population (Column 1), discharged population (Column 2), and recidivism within one year (Column 3) showed statistically significant increases during the AB109 period and also increased during Prop 47 periods compared to periods before AB109. However, the Prop 47 effects are statistically smaller than the AB 109 effect. Combined with the graphical trends in Figure 3, this implies Prop 47 is likely to absorb the jail crowding shock from the 2011 realignment, consistent with the purpose of Prop 47. The difference between AB 109 and Prop 47 effects is approximately 0.10 across outcomes in Columns (1), (2), (3), and (6). In other words, Prop 47 decreases the amount of each outcome increased from AB 109 by ten percentage points, which translates into around 43 offenders based on the average number of offenders in Column (1). Similarly, the results translate into about nine discharges based on the average number of discharges in Column (2), around eight recidivism based on the average number of recidivism in Column (3), and approximately 13 recidivism of violent crimes in Column (6).
I observe heterogeneous effects among different types of recidivism behaviors. Column (4) in Table 7 estimates the Prop 47 effect on recidivism within one year, specifically Prop 47 charges. The difference between the AB109 and Prop 47 effect is 0.16 (0.315 - 0.156) for Prop 47 charge recidivism in Column (4), which means that Prop 47 decreases the amount of each outcome increased from AB 109 by 16 percentage points (greater than ten percentage points in Columns (1), (2), (3), and (6)). However, in Column (5), Prop 47 fails to absorb the shock from AB 109 for recidivism behavior for control group charges (a complementary set of Prop 47 charges). The coefficient in Column (5) indicates that the Prop 47 charge offenders re-offend control

group charges 39 percentage points more, on average than control group charge offenders re-offending control group charges. Considering control charges are a complementary set of Prop 47 charges (which are non-serious and non-violent charges according to policymakers), this indicates a spillover effect from non-serious charges to charges that are still non-violent but more serious than Prop 47 charges.

[Table 7 Here]

5.3 Los Angeles City-Wide Data

The violation of SUTVA makes it hard to interpret the regression results. I still present the regression results for Equation 3 in Table 8 for transparency.[20] Column (1) shows Prop 47 reduced the number of charges by 40.8 percentage points, on average. The mean of the dependent variable (in levels) is 11.4 charges; thus, the effect of Prop 47 is 4.7 fewer charges, on average, compared to the control group. This effect is smaller among homeless offenders in Column (2) than the effect from non-homeless offenders in Column (3).

[Table 8]

Meanwhile, the narcotic drug law charges can be the driving charge group of the results considering they are 62% of the data used in the analysis (113,000 out of 183,000 daily charges used for the analysis from 2012 to 2016 shown in Table 5). Thus, I present the graphs of average trends (Figure 11) and the regression results (Table 9) based on data excluding the narcotic drug law charges. Figure 11 reveals the spillover effect is driving the results (the control group contributes to the statistically significant treatment effect) and is especially visible among charges involved with non-homeless offenders (the right panel of Figure 11). The trends of Prop 47 charges are stable regardless of offender homelessness status before and after the passage of Prop 47. Thus, instead of interpreting the negative coefficient in Table 9 as decreases in Prop 47 charges, it should be construed as increases in the number of charges in the control group. Since Prop 47 charges are non-serious and non-violent, this phenomenon implies an increase in more severe charges than Prop 47 charges, considering the control group is a complementary set of non-serious Prop 47. Column (3) indicates that Prop 47 raises the number of control charges by 57 percentage points. The mean of the dependent variable in level is 7.4, implying a 4.2 charge increase compared to the treatment group.

Combined, the number of drug offenses eligible for Prop 47 decreased. A possible explanation is that the policing behaviors changed due to Prop 47, resulting in fewer arrests being made due to non-prosecution, especially for drug offenders (Garner, 2020). On the contrary, other property offenses such as larceny and

[20] Covariates are excluded due to concerns of contamination since they are directly related to the jail population and composition (thus Prop 47). Although not reported, the magnitude of Prop 47 $\times$ Post coefficients is smaller after controlling for covariates.

vehicle theft ineligible for Prop 47 increased and the effect is more significant among the non-homeless offenders. This phenomenon can be related to two possible explanations. First, since Prop 47 reduced the penalty for non-violent crimes, offenders began committing more non-violent crimes, spilling over more severe non-violent crimes. Second, prosecutors and police officers changed their behaviors, focusing on non-Prop 47 charges.

[Figure 11 Here] [Table 9 Here]

6 Robustness

The core of DiD estimates is to find the right control group. Instead of deploying the matching method to find the control group, we can also see the distribution of DiD estimates with different control groups by randomly matching the control group. By doing so, we can see if the main results are plausible compared to the distribution of possible coefficients. To perform this analysis, I use a strongly balanced panel of 40 consistent (across years) CoC units in California as a treatment group and then randomly find 160 CoC units from other states as a control group. Figure 12 shows the distribution of coefficients from 5,000 repetitions. The coefficient from the main regression after propensity score matching (0.27) is located in the middle of the distribution; the main regression results present a viable DiD estimate compared to the distribution of possible DiD estimates.

[Figure 12 Here]

7 Conclusion and Discussion

In this analysis, I examine the impact of decarceration policies on the homeless population, county governmental spending, crimes, and recidivism. Specifically, the study implements a nationwide data analysis on the homeless population and governmental spending, a California state-wide data analysis on county jail population and recidivism, and a Los Angeles city-wide data analysis on the number of charges by offender homelessness status.

This investigation is vital because re-sentencing is one of the significant decarceration policies and the recent Criminal Justice Reform, and receives attention from national policymakers. Also, the current analysis complements the cost-benefit analysis of incarceration and decarceration policies.

I find that Prop 47 raised the unsheltered homeless population by 26 percentage points and health spending by 11 percentage points in nationwide data analysis. In California state-wide data analysis, AB 109 raised the county jail population by 18.5 percentage points and recidivism by 37.5 percentage points. The Prop 47 effect mitigates the AB 109 effect by ten percentage points, implying Prop 47 absorbed the county jail crowding pressure stemming from AB 109. However, Prop 47 fails to decrease the recidivism rate among Prop 47 offenders who commit control group charges. Los Angeles city-wide data analysis observes Prop 47 raises overall non-violent crime rates.

Several important questions remain for future research. Fundamentally, the role of decarceration is about distributing central government function as a social control into local communities (Chan and Erickson, 1981). However, re-sentencing and reduced penalties imply the offenders essentially become under supervision such as probation and parole. Then communities with a lack of resources are likely to rely on private companies, reallocating the inmate population managed by governmental correctional facilities into private supervision companies. For instance, private prisons multiplied, housing around 7,000 prisoners in 1990, to more than 126,000 in 2015 across the United States when state prisons were under crowding pressures (Takei, 2017). Furthermore, private prisons do not yield a cost-efficient outcome (Pratt and Maahs, 1999). Additional research ought to tackle these concerns to aid policymakers.

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Table 1: Descriptive Statistics Comparing Groups

	Total	Treat	Control
Unsheltered Homeless	530.17***	1915.10	646.41
	(1752.82)	(4219.96)	(1319.54)
Percent White Male 10-64	0.31***	0.31	0.33
	(0.05)	(0.04)	(0.05)
Percent White Female 10-64	0.31***	0.31	0.33
	(0.05)	(0.04)	(0.05)
Percent Black Male 10-64	0.05***	0.02	0.03
	(0.04)	(0.01)	(0.03)
Percent Black Female 10-64	0.05***	0.02	0.03
	(0.05)	(0.02)	(0.04)
Percent Asian Male 10-64	0.02***	0.05	0.02
	(0.03)	(0.03)	(0.04)
Percent Asian Female 10-64	0.02***	0.05	0.02
	(0.03)	(0.04)	(0.04)
Employment per capita	0.58***	0.54	0.59
	(0.12)	(0.12)	(0.11)
Personal Income per Capita	47.06***	50.68	47.58
	(13.79)	(18.94)	(12.84)
Observations	4101	400	1060

*** $p<0.01$, ** $p<0.05$, * $p<0.10$ for indicating statistical difference between groups.
Standard deviations are in parenthesis.

Table 2: CA DOJ Classification of 42 Charge Groups

Group Code	Description
01	SOVEREIGNTY
02	MILITARY
03	IMMIGRATION
04	FEDERAL OFFENSE
08	JUVENILE OFFENSE
09	HOMICIDE/MANSLAUGHTER
10	KIDNAPPING
11	SEXUAL ASSAULT
12	ROBBERY
13	ASSAULT
14	ABORTION
16	TERRORIST THREATS
20	ARSON
21	EXTORTION
22	BURGLARY
23	**LARCENY**
24	STOLEN VEHICLE
25	**FORGERY**
26	**FRAUD**
27	**EMBEZZLEMENT**
28	**STOLEN PROPERTY**
23	PROPERTY DAMAGE
30	**CREDIT CARD/ACCESS CARD OFFENSE**
31	**IMPROPER BUSINESS PRACTICE**
32	TRESPASS
33	SCHOOL DISTURBANCE/TRESPASS
34	INHUMANE TREATMENT OF ANIMALS
35	**DANGEROUS DRUGS/NARCOTICS**
36	SEX OFFENSE
37	OBSCENE MATTER
38	FAMILY OFFENSE
39	GAMBLING
40	COMMERCIAL SEX
41	LIQUOR OFFENSE
42	DRIVING UNDER INFLUENCE
43	CONTRIBUTE DELINQUENCY OF MINOR
44	IMPERSONATION
45	LIBEL/SLANDER
46	ACCESSORY/CONSPIRACY
47	PUBLIC JUSTICE
48	OBSTRUCT PUBLIC OFFICER
49	FLIGHT/ESCAPE

Table 3: Comparison of Before and After Prop 47 among Different Charge Groups

	Total	Before AB109	AB109	Prop47
Control 47 Offender	379.29	429.51	330.18	333.57
	(663.91)	(752.28)	(534.40)	(586.08)
Control 47 Charge	994.90	1123.99	874.20	873.23
	(1597.48)	(1808.54)	(1294.29)	(1405.45)
Control 47 Discharge	66.37	79.21	60.56	48.78
	(128.13)	(150.32)	(101.93)	(99.23)
Control 47 Repeat Any	55.81	67.24	50.75	40.07
	(108.13)	(127.79)	(84.49)	(82.18)
Control 47 Repeat Prop 47	13.06	14.43	12.78	10.93
	(25.62)	(28.25)	(21.94)	(23.25)
Control 47 Repeat Control 47	29.17	34.97	26.22	21.48
	(53.89)	(63.31)	(41.89)	(42.11)
Control 47 Repeat Violent	7.58	8.87	7.57	5.38
	(14.19)	(16.32)	(12.21)	(11.07)
Control 47 Release	7.14	8.37	6.73	5.33
	(22.74)	(27.36)	(17.47)	(16.63)
Prop 47 Offender	492.42	525.05	504.82	429.91
	(960.99)	(1057.66)	(974.99)	(761.31)
Prop 47 Charge	1680.05	1744.63	1738.03	1531.46
	(2762.47)	(2975.92)	(2790.55)	(2342.87)
Prop 47 Discharge	123.44	131.24	142.28	95.70
	(247.50)	(268.40)	(276.57)	(173.69)
Prop 47 Repeat Any	104.82	110.42	122.59	81.61
	(207.61)	(223.46)	(232.64)	(149.09)
Prop 47 Repeat Prop 47	53.62	53.89	66.13	43.47
	(104.59)	(109.30)	(122.21)	(77.01)
Prop 47 Repeat Control 47	38.11	38.54	43.12	33.50
	(64.96)	(67.39)	(68.67)	(57.04)
Prop 47 Repeat Violent	17.67	18.31	21.84	13.35
	(33.35)	(35.19)	(38.99)	(23.48)
Prop 47 Release	9.08	9.66	11.08	6.55
	(30.94)	(35.16)	(34.93)	(16.53)
Observations	9621	4658	2116	2847

Standard deviations are in parenthesis.
Notes: "Before AB109" columns shows the averages of observations from January, 2005 to September, 2011. "AB109" column shows the averages of observations from October, 2011 to October, 2014. "Prop47" column shows the averages of observations from November, 2014 to December, 2018.
Notes: "Prop 47" charges include drug possession, receiving stolen property, theft, shoplifting, writing bad checks, and check forgery, which were impacted by Proposition 47. "Control 47" charges share the same upper categories with "Prop 47". "Violent" charges include burglary, robbery, and assault. "Other" charges are all other charges excluding "Prop 47", "Control 47", and "Violent".

Table 4: The Effects of Prop 47 on Homelessness and Government Finance

	Log(Homeless)		Log(Health)		Log(Police)	
	(1)	(2)	(3)	(4)	(5)	(6)
	DiD	Annual	DiD	Annual	DiD	Annual
Prop47 × Post	0.267**		0.117**		0.135***	
	(0.118)		(0.053)		(0.035)	
Prop47 × 2015		0.251**		0.073		0.106***
		(0.109)		(0.049)		(0.026)
Prop47 × 2016		0.255**		0.132**		0.160***
		(0.123)		(0.051)		(0.028)
Prop47 × 2017		0.225		0.089		0.087**
		(0.137)		(0.062)		(0.042)
Prop47 × 2018		0.156		0.182**		0.197***
		(0.140)		(0.082)		(0.073)
Prop47 × 2019		0.466***				
		(0.155)				
Observations	1620	1620	1368	1368	1392	1392
Mean of Dept. Var. (Level)	1516		146		118	
F stat	5.03					
R^2	0.935	0.935	0.933	0.933	0.944	0.944
CoC and Year FEs	X	X	X	X	X	X
Covariates	X	X	X	X	X	X

Robust standard error clustered in CoC level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 5: List of Charge Groups and Total Number of Incidents

Charge Group	Count	Percent
Against Family/Child	4,576	0.77
Aggravated Assault	50,423	8.53
Burglary	14,564	2.46
Disorderly Conduct	2,174	0.37
Disturbing the Peace	466	0.08
Driving Under Influence	73,560	12.44
Drunkeness	2,776	0.47
Federal Offenses	119	0.02
Forgery/Counterfeit	4,786	0.81
Fraud/Embezzlement	5,860	0.99
Gambling	212	0.04
Homicide	1,350	0.23
Larceny	39,322	6.65
Liquor Laws	792	0.13
Miscellaneous Other Violations	116,707	19.74
Moving Traffic Violations	45,533	7.7
Narcotic Drug Laws	112,991	19.11
Non-Criminal Detention	9	0
Other Assaults	34,310	5.8
Pre-Delinquency	9	0
Prostitution/Allied	21,794	3.69
Rape	1,595	0.27
Receive Stolen Property	4,730	0.8
Robbery	13,338	2.26
Sex (except rape/prst)	6,142	1.04
Vehicle Theft	15,160	2.56
Weapon (carry/poss)	17,918	3.03

Note: charge groups in bold text qualify for Proposition 47.

Table 6: Summary between Homeless Offenders and Non-homeless Offenders

	Total	Homeless	Non-Homeless
Male	0.79***	0.82	0.79
Age	34.48***	39.33	33.61
Felony	0.45***	0.43	0.45
Misdemeanor	0.52***	0.51	0.52
Other	0.03***	0.06	0.03
Black	0.32***	0.39	0.31
Hispanic	0.44***	0.28	0.47
Other	0.05***	0.03	0.06
White	0.18***	0.30	0.16
77th Street	0.07***	0.03	0.08
Central	0.09***	0.22	0.07
Devonshire	0.03***	0.02	0.03
Foothill	0.04***	0.03	0.05
Harbor	0.04***	0.03	0.04
Hollenbeck	0.03***	0.02	0.03
Hollywood	0.08***	0.13	0.07
Mission	0.05***	0.04	0.06
N Hollywood	0.05	0.05	0.05
Newton	0.05***	0.04	0.05
Northeast	0.03	0.04	0.03
Olympic	0.04***	0.03	0.04
Pacific	0.05***	0.08	0.05
Rampart	0.04***	0.05	0.04
Southeast	0.05***	0.02	0.05
Southwest	0.06***	0.03	0.07
Topanga	0.04***	0.03	0.04
Van Nuys	0.06***	0.05	0.06
West LA	0.02***	0.03	0.02
West Valley	0.04***	0.03	0.04
Wilshire	0.03**	0.03	0.03
Observations	591216	90743	500473

*** p<0.01, ** p<0.05, * p<0.1 for indicating statistical difference between groups

Table 7: DiD Estimates of the Effects of AB 109 and Prop 47 on Number of Offenders, Discharges, and Recidivism within California

	(1) Log(Offender)	(2) Log(Discharge)	(3) Log(Total Repeat)	(4) Log(Prop47 Repeat)	(5) Log(Control Repeat)	(6) Log(Violent Repeat)
Treat × Post1 (AB 109)	0.185***	0.336***	0.375***	0.315***	0.362***	0.328***
	(0.023)	(0.030)	(0.033)	(0.032)	(0.037)	(0.038)
Treat × Post2 (Prop 47)	0.097***	0.226***	0.278***	0.156***	0.390***	0.249***
	(0.035)	(0.043)	(0.045)	(0.053)	(0.042)	(0.050)
Observations	18932	17444	17048	14052	15100	12440
Mean of Dept. Var (Level)	436	95	81	34	34	13
Linear Combination	p<0.01	p<0.01	p<0.01	p<0.01	p>0.1	p<0.10
R^2	0.992	0.980	0.979	0.967	0.968	0.945
County by Year-Month FEs	X	X	X	X	X	X
County by Prop 47 FEs	X	X	X	X	X	X

Robust standard error clustered in county by Prop 47 status
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10
Control group is the offenders with a complementary set of Proposition 47 charges within the same category.
"Linear Combination" row indicates the p-values from testing whether the AB 109 effect is statistically different from the Prop 47 effect.

Table 8: DiD Estimates between Homeless and Non-Homeless for the Effects of Prop 47 on Crime within LA

	(1) Total	(2) Homeless	(3) Non-Homeless
Prop 47 × Post	-0.408***	-0.343***	-0.584***
	(0.048)	(0.058)	(0.066)
Observations	16037	5387	10608
Mean of Dept. Var. (Level)	11.4	6.2	14
R^2	0.516	0.734	0.797
Year-Month by Area FEs	X	X	X
Area by Charge by Prop47 FEs	X	X	X

Robust standard error clustered in area by charge group by Prop 47 status
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 9: DiD Estimates between Homeless and Non-Homeless for the Effects of Prop 47 on Crime within LA Excluding Narcotic Drug Laws Charges

	(1) Total	(2) Homeless	(3) Non-Homeless
Prop 47 × Post	-0.378***	-0.212***	-0.565***
	(0.057)	(0.065)	(0.074)
Observations	11315	2938	8090
Mean of Dept. Var. (Level)	6.2	3.2	7.4
R^2	0.404	0.645	0.664
Year-Month by Area FEs	X	X	X
Area by Charge by Prop47 FEs	X	X	X

Robust standard error clustered in area by charge group by Prop 47 status
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

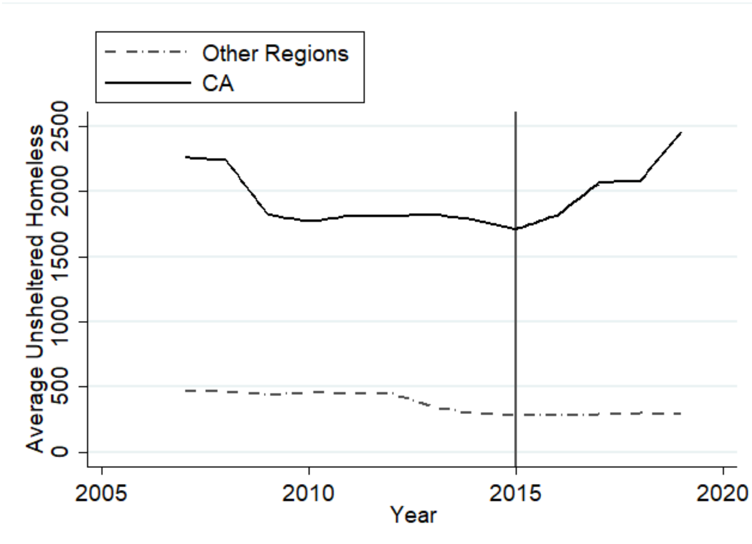

Figure 1: Unsheltered Homeless Population

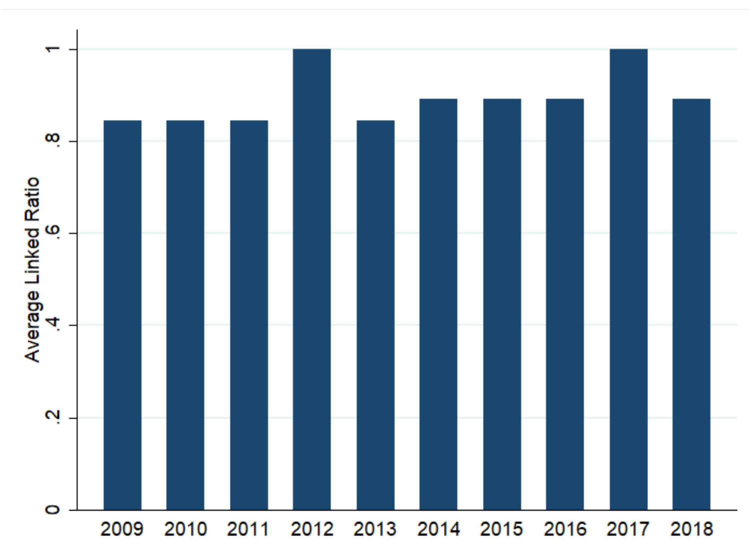

Figure 2: Linked Ratio of Counties to CoC Units

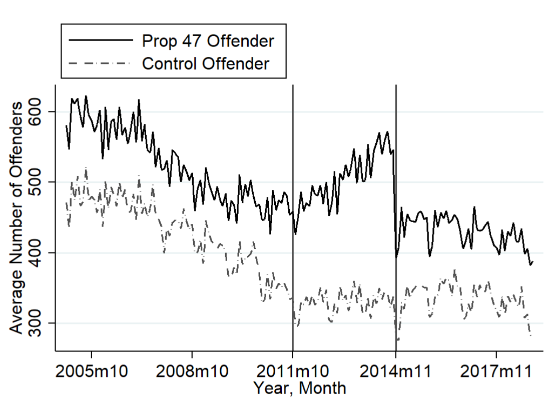

Figure 3: Number of Prop 47 Charges and Control Charges

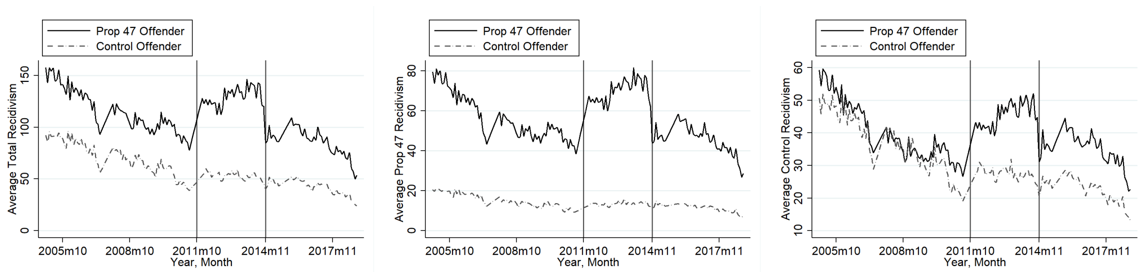

Figure 4: Recidivism for All Charges Vs. Prop 47 Charges Vs. Control Charges

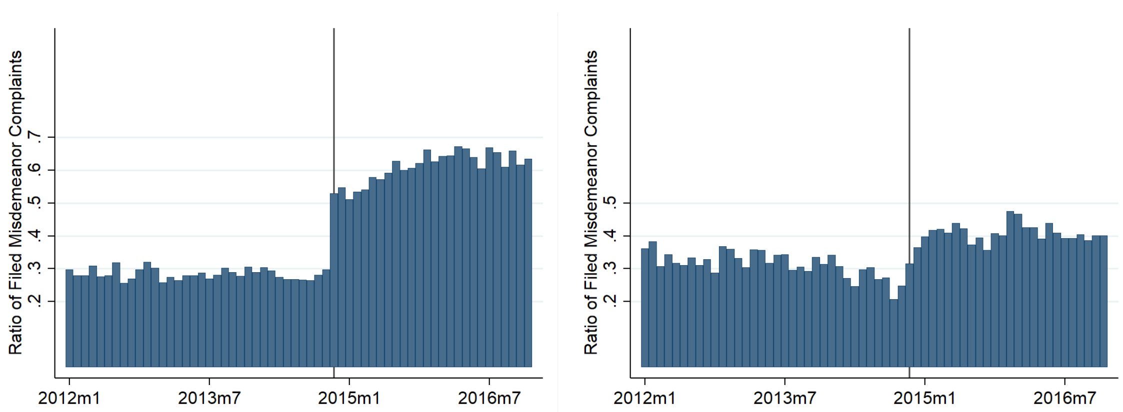

Figure 5: Share of Misdemeanor Complaints per Charge - Treatment Group Vs. Control Group

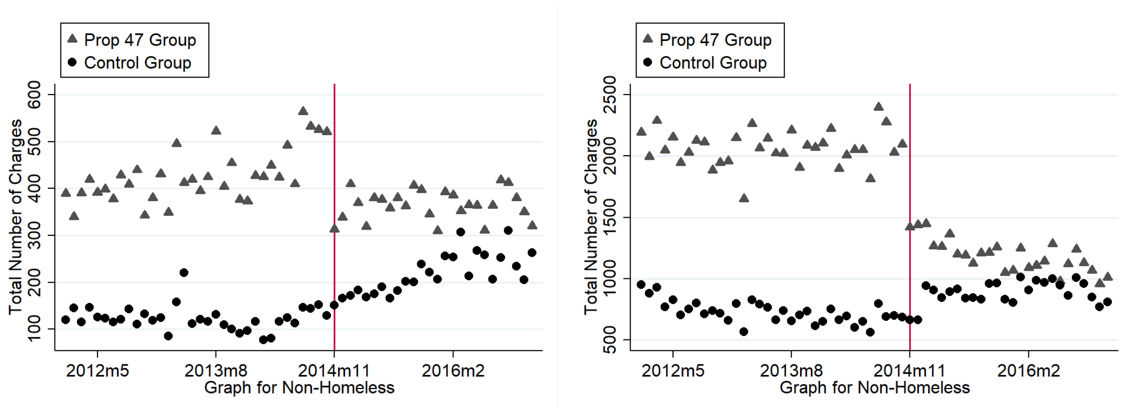

Figure 6: Comparing Total LA Crime Trends between Groups by Offender Homelessness Status Based on Raw Data

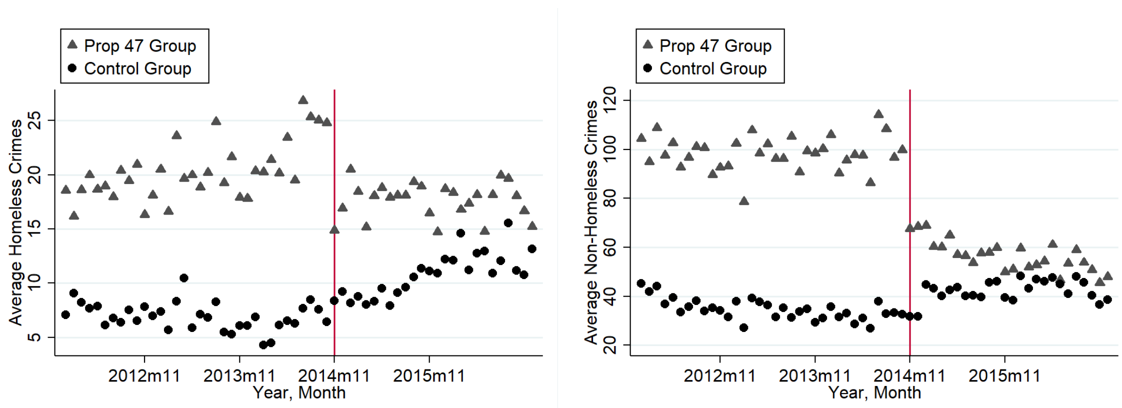

Figure 7: Comparing Average LA Crime Trends between Groups by Offender Homelessness Status Based on 21 Policing Area Unit

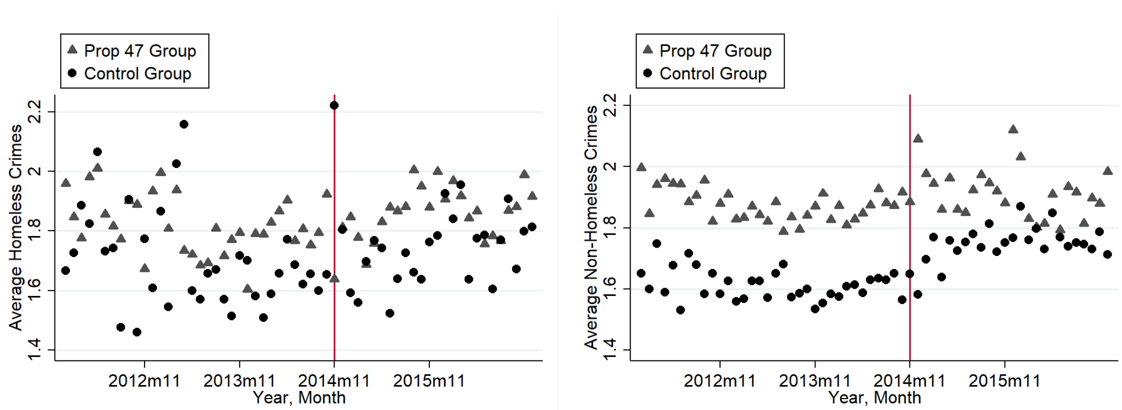

Figure 8: Comparing Average LA Crime Trends between Groups by Offender Homelessness Status Based on Address Unit

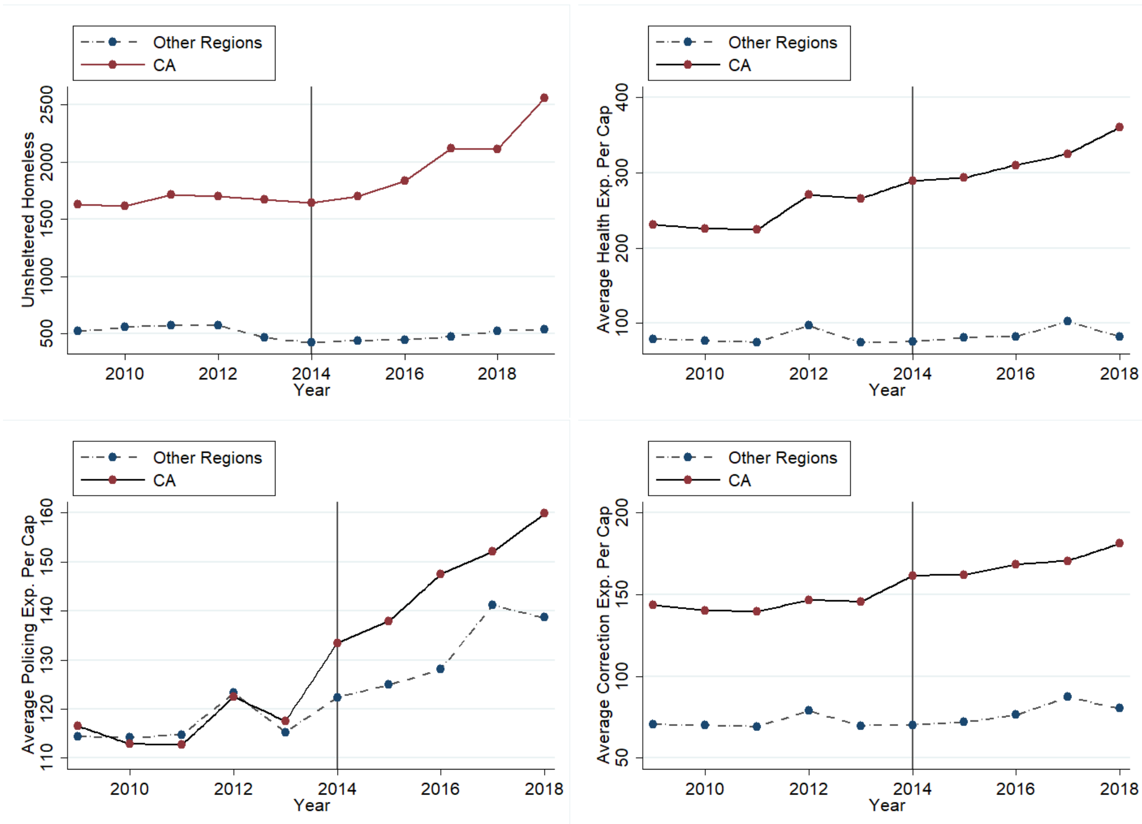

Figure 9: Comparison of Homeless Population and Governmental Expenditure between Treatment and Control Groups after Matching - Unsheltered Homeless, and Health, Policing, and Correctional Expenditures

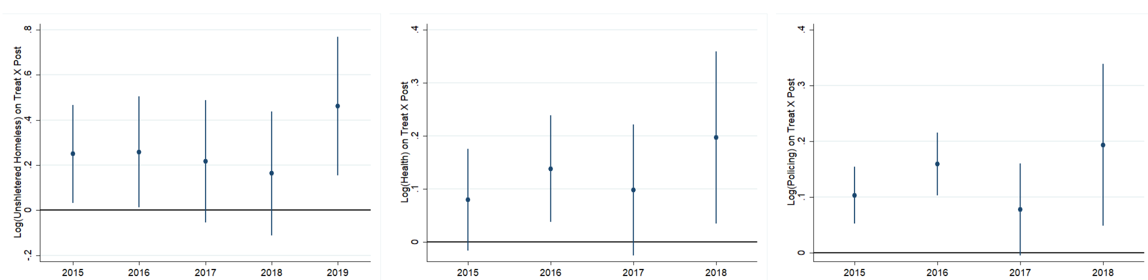

Figure 10: Coefficients Plot for DiD Estimates Each Year - Unsheltered Homeless, Health, Policing Expenditures

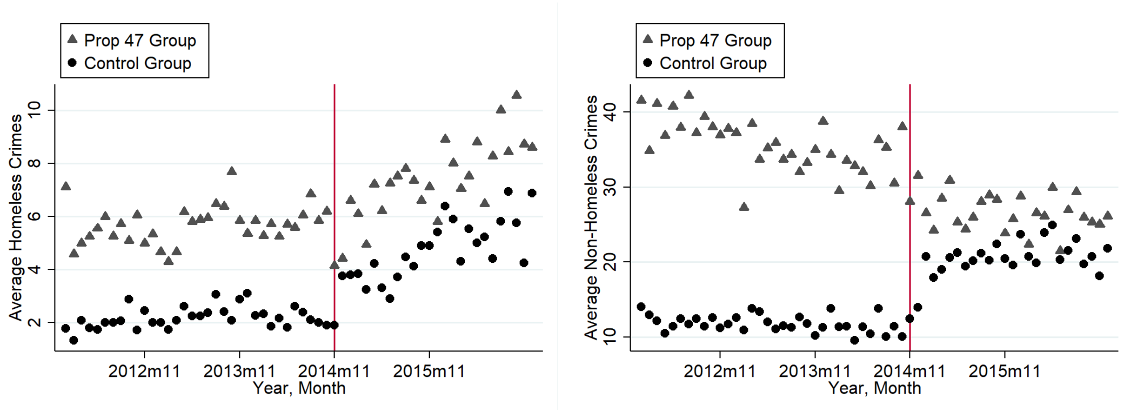

Figure 11: Comparing LA Crime Trends between Homeless and Non-Homeless Excluding Narcotic Drug Laws Charges

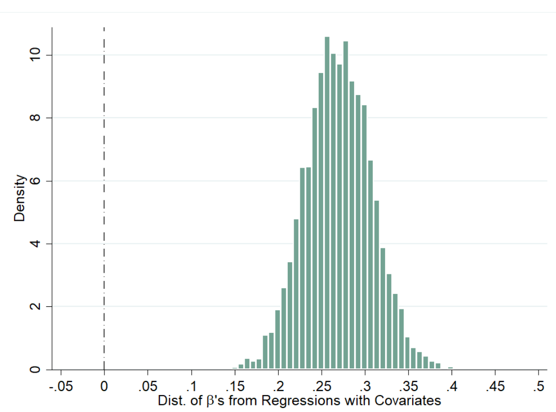

Figure 12: Coefficients from Randomly Matched Control Groups

A Appendix

A.1 Sheltered Homeless Vs. Unsheltered Homeless

The sheltered homeless population is less likely to be the representative prison population since the male and the Black dominate in the state prison and county jails. On the other hand, CoC units prioritize to house the most vulnerable, women and children, thus out of the scope of the current analysis. Nonetheless, one might point out sheltered homeless population exhibits a continuously decreasing trend regardless of treatment status (left panel of Figure A.1). However, this seems to reflect a homeless housing regime change from temporary housing to permanent housing. According to the HUD's definition, the permanently housed population is not classified as the homeless. In other words, a portion of the sheltered homeless population is constantly being re-defined as the permanently housed population, thus lowering the count of the sheltered homeless population. The accompanying Housing Inventory Count (HIC) data supports this argument (Figure A.1). The middle panel in Figure A.1 indicates the temporary housing stocks, and the right panel displays the total housing stocks, including permanent housing. The center panel exhibits precisely the same trend as the sheltered homeless population. The right panel shows that the total amount of housing stock is irrelevant to the policy change.

A.2 Total Effect Vs. Indirect Effect

The absence of statistical significance in total effect does not necessarily mean the variable of interest does not have meanings, as total effects could overshadow the mechanism. As a trial for unpacking the mechanism, we might separate the total impact and the indirect impact of Prop 47 through the homeless population. In this case, I can utilize a mediation analysis, a method designed to examine the mechanism by separating indirect effect from total effect through the linear projection of treatment effect on the indirect effect of interest. I conduct a mediation analysis of the impact of Prop 47 on the outcome of interest in Equation A.1.

$$Log(Y_{it}) = \gamma_0 + \gamma_1 Prop47_i \times Post_t + \gamma_2 Log(\widehat{Homeless_{it}}) + X'r + CoC_i + Year_t + e_{it}, \tag{A.1}$$

where $Log(\widehat{Homeless_{it}})$ is the indirect of Prop 47 through the homelessness population and obtained from Equation 1. γ_2 is the coefficient measuring the indirect effect of the unsheltered homeless population and γ_1 is total effect of Prop 47 excluding the indirect effect.

Lastly, we can investigate fiscal stress largely involved with the homeless population (Equation A.2). According to State and Local Government Finance data documentation, community development, and housing expenditures include activities on "urban renewal and slum clearance; redevelopment and rehabilitation of substandard or deteriorated facilities and areas; rural redevelopment; and revitalization of commercial." Thus, community housing and development expenditures are relevant in dealing with chronic homeless populations, not offender-related expenses. Therefore, I implement an instrumental variable strategy, see Equation A.2, with Prop 47 being instrumented for the unsheltered homeless.

$$Log(Development)_{it} = \delta_0 + \delta_1 Log(\widehat{Homeless})_{it} + X'r + CoC_i + Year_t + e_{it} \tag{A.2}$$

where $Log(\widehat{Homeless_{it}})$ is the causal effect of the unsheltered homeless population on the governmental spending.

Table A.2 shows the regression results from Equation A.1 and Equation A.2. One of the aims of Prop 47 was to reduce correctional expenditure by decreasing the jail population. As seen in column (1) of Table A.2, there is no statistically significant reduction in correctional spending due to Prop 47. However, the signs of coefficients imply a potential mechanism. While the coefficient from $Treat \times Post$ is the total effect of Prop 47, the coefficient from $Log(\widehat{Homeless})$ is the indirect effect of Prop 47 through the homeless population. The negative sign of the indirect effect coefficient means the increased homelessness from Prop 47 is pushing the correctional expenditures to decrease. The indirect channel of homelessness raised hospital expenditures in Column (2). Since the homeless population grew by 26.6 percentage points, the coefficient 0.932 implies a 26.6 $\times$ 0.932 = 24.79 percentage point increase in hospital expenditure. Community development expenditures in Column (3) did not show a statistically significant increase, but the sign indicates the predicted direction. Ultimately, Prop 47 was planned to save correctional funds but does not seem to save funds stressing other governmental expenditures.

A.3 California Mental Health Capacity

Table A.4 displays whether there was an overall change in county capacity to deal with potential inmates with mental illness. Some averages show quite a bit of increase (e.g., Psy Patient Days, Psy Discharge, Psy Bed Days, etc.), likely to be driven by outliers rather than a statistical manner except for the increases in days of patients using psychiatric beds.

Table A.1: List of CoC Units in Analysis

CoC Name	State	CoC Name	State
Amador, Calaveras, Mariposa, Tuolumne Counties CoC	CA	Grand Traverse, Antrim, Leelanau Counties CoC	MI
Bakersfield/Kern County CoC	CA	Holland/Ottawa County CoC	MI
Chico, Paradise/Butte County CoC	CA	Lenawee County CoC	MI
Colusa, Glenn, Trinity Counties CoC	CA	Livingston County CoC	MI
Daly/San Mateo County CoC	CA	Marquette, Alger Counties CoC	MI
Davis, Woodland/Yolo County CoC	CA	Monroe City & County CoC	MI
El Dorado County CoC	CA	Duluth/St.Louis County CoC	MN
Fresno City & County/Madera County CoC	CA	Minneapolis/Hennepin County CoC	MN
Glendale CoC	CA	Moorhead/West Central Minnesota CoC	MN
Humboldt County CoC	CA	Northeast Minnesota CoC	MN
Imperial County CoC	CA	Northwest Minnesota CoC	MN
Long Beach CoC	CA	Rochester/Southeast Minnesota CoC	MN
Los Angeles City & County CoC	CA	Southwest Minnesota CoC	MN
Marin County CoC	CA	Joplin/Jasper, Newton Counties CoC	MO
Mendocino County CoC	CA	Montana Statewide CoC	MT
Merced City & County CoC	CA	Chapel Hill/Orange County CoC	NC
Napa City & County CoC	CA	Northwest North Carolina CoC	NC
Oakland, Berkeley/Alameda County CoC	CA	Lincoln CoC	NE
Oxnard, San Buenaventura/Ventura County CoC	CA	Nebraska Balance of State CoC	NE
Pasadena CoC	CA	New Hampshire Balance of State CoC	NH
Redding/Shasta, Siskiyou, Lassen, Plumas, Del Norte, Modoc, Sierra Counties CoC	CA	Bergen County CoC	NJ
Richmond/Contra Costa County CoC	CA	Jersey City, Bayonne/Hudson County CoC	NJ
Riverside City & County CoC	CA	Morris County CoC	NJ
Roseville, Rocklin/Placer County CoC	CA	New Brunswick/Middlesex County CoC	NJ
Sacramento City & County CoC	CA	Warren, Sussex, Hunterdon Counties CoC	NJ
Salinas/Monterey, San Benito Counties CoC	CA	Albuquerque CoC	NM
San Bernardino City & County CoC	CA	Las Vegas/Clark County CoC	NV
San Diego City and County CoC	CA	Nevada Balance of State CoC	NV
San Francisco CoC	CA	Reno, Sparks/Washoe County CoC	NV
San Jose/Santa Clara City & County CoC	CA	Cattaragus County CoC	NY
San Luis Obispo County CoC	CA	Clinton County CoC	NY
Santa Ana, Anaheim/Orange County CoC	CA	Columbia, Greene Counties CoC	NY
Santa Maria/Santa Barbara County CoC	CA	Elmira/Steuben, Allegany, Livingston, Chemung, Schuyler Counties CoC	NY
Santa Rosa, Petaluma/Sonoma County CoC	CA	Franklin, Essex Counties CoC	NY
Stockton/San Joaquin County CoC	CA	Glens Falls, Saratoga Springs/Saratoga, Washington, Warren, Hamilton Counties Co	NY
Turlock, Modesto/Stanislaus County CoC	CA	Ithaca/Tompkins County CoC	NY
Vallejo/Solano County CoC	CA	Jamestown, Dunkirk/Chautauqua County CoC	NY
Visalia/Kings, Tulare Counties CoC	CA	Jefferson, Lewis, St. Lawrence Counties CoC	NY
Watsonville/Santa Cruz City & County CoC	CA	Nassau, Suffolk Counties CoC	NY
Yuba City & County/Sutter County CoC	CA	New York City CoC	NY
Alaska Balance of State CoC	AK	Sullivan County CoC	NY
Anchorage CoC	AK	Norman/Cleveland County CoC	OK
Fayetteville/Northwest Arkansas CoC	AR	Central Oregon CoC	OR
Phoenix, Mesa/Maricopa County CoC	AZ	Clackamas County CoC	OR
Colorado Balance of State CoC	CO	Eugene, Springfield/Lane County CoC	OR
Metropolitan Denver CoC	CO	Hillsboro, Beaverton/Washington County CoC	OR
Columbia, Hamilton, Lafayette, Suwannee Counties CoC	FL	Medford, Ashland/Jackson County CoC	OR
Hendry, Hardee, Highlands Counties CoC	FL	Oregon Balance of State CoC	OR
Miami-Dade County CoC	FL	Portland, Gresham/Multnomah County CoC	OR
Monroe County CoC	FL	Philadelphia CoC	PA
Naples/Collier County CoC	FL	South Dakota Statewide CoC	SD
Orlando/Orange, Osceola, Seminole Counties CoC	FL	Austin/Travis County CoC	TX
Punta Gorda/Charlotte County CoC	FL	Dallas City & County, Irving CoC	TX
St. Johns County CoC	FL	El Paso City & County CoC	TX
Tampa/Hillsborough County CoC	FL	Houston, Pasadena, Conroe/Harris, Ft. Bend, Montgomery, Counties CoC	TX
West Palm Beach/Palm Beach County CoC	FL	San Antonio/Bexar County CoC	TX
Georgia Balance of State CoC	GA	Texas Balance of State CoC	TX
Hawaii Balance of State CoC	HI	Provo/Mountainland CoC	UT
Honolulu City and County CoC	HI	Salt Lake City & County CoC	UT
Iowa Balance of State CoC	IA	Arlington County CoC	VA
Sioux City/Dakota, Woodbury Counties CoC	IA	Harrisburg, Winchester/Western Virginia CoC	VA
Boise/Ada County CoC	ID	Loudoun County CoC	VA
Idaho Balance of State CoC	ID	Burlington/Chittenden County CoC	VT
Aurora, Elgin/Kane County CoC	IL	Vermont Balance of State CoC	VT
Chicago CoC	IL	Everett/Snohomish County CoC	WA
McHenry County CoC	IL	Seattle/King County CoC	WA
South Central Illinois CoC	IL	Spokane City & County CoC	WA
Waukegan, North Chicago/Lake County CoC	IL	Vancouver/Clark County CoC	WA
West Central Illinois CoC	IL	Washington Balance of State CoC	WA
Cape Cod Islands CoC	MA	Wisconsin Balance of State CoC	WI
Massachusetts Balance of State CoC	MA	Huntington/Cabell, Wayne Counties CoC	WV
Pittsfield/Berkshire, Franklin, Hampshire Counties CoC	MA	Wheeling, Weirton Area CoC	WV
Carroll County CoC	MD	Wyoming Statewide CoC	WY
Cumberland/Allegany County CoC	MD		
Garrett County CoC	MD		
Howard County CoC	MD		
Montgomery County CoC	MD		
Prince George's County CoC	MD		

Table A.2: Disentangling the Effect of Prop 47 on Homelessness and Government Finance

	A. Mediation Analysis		B. 2SLS
	(1) Log(Correction)	(2) Log(Hospital)	(3) Log(Develop)
Prop47 × Post	0.084	-0.237	
	(0.072)	(0.213)	
$Log(\widehat{Homeless})$	-0.312	0.970*	1.765
	(0.214)	(0.504)	(1.079)
Observations	1362	538	1008
Mean of Dept. Var. (Level)	97	286	24
R^2	0.919	0.927	0.769
CoC and Year FEs	X	X	X
Total Revenue	X	X	X

Robust standard error clustered in CoC level
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10
Columns (1) and (2) represent regression results from a mediation analysis. The coefficients from $Log(\widehat{Homeless})$ indicate the indirect effects of Prop 47.

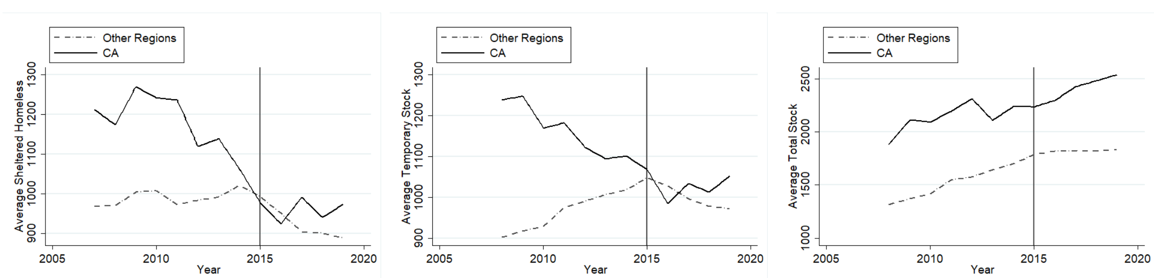

Figure A.1: Sheltered Homeless Vs. Temporary Shelter Beds Vs. Total Shelter Beds

Table A.3: CA DOJ Example List of Charges Classified into Prop 47 and Control 47 Charges

Charge Description	Charge Group	Type	Disqualification
LARCENY	23		
602 WI-JUVENILE/LARCENY	23	Control47	0
182 PC-CONSPIRACY/LARCENY	23	Control47	0
664 PC-ATTEMPT CRIME/LARCENY	23	Control47	0
220 PC-ASSAULT TO COMMIT GRAND LARCENY	23	Control47	1
337.4 PC-OBTAIN OVER $200 BY TOUTING	23	Control47	0
355 PC-DESTROY EVIDENCE OF OWNERSHIP	23	Control47	0
356 PC-DESTROY OWNER'S ID MARK ON LUMBER	23	Control47	0
484 PC-THEFT	23	Prop47	0
484(A) PC-THEFT OF PERSONAL PROPERTY	23	Prop47	0
484(B) PC-THEFT:NONRETURN OF RENTAL PROPERTY	23	Prop47	0
484H(B) PC-FAIL TO GIVE GOODS AS STATED	23	Prop47	0
485 PC-APPROPRIATE LOST PROPERTY	23	Control47	0
487 PC-GRAND THEFT	23	Prop47	0
487.1 PC-GRAND THEFT:PROPERTY	23	Prop47	0
487.2 PC-GRAND THEFT FROM PERSON	23	Prop47	0
487.3 PC-GRAND THEFT:MISCELLANEOUS	23	Prop47	0
487A PC-GRAND THEFT:ANIMAL CARCASS	23	Prop47	0
487B PC-GRAND THEFT:CONVERT REAL PROPERTY	23	Prop47	0
STOLEN VEHICLE	24		
602 WI-JUVENILE/STOLEN VEHICLE	24	Control47	0
182 PC-CONSPIRACY/STOLEN VEHICLE	24	Control47	0
664 PC-ATTEMPT CRIME/STOLEN VEHICLE	24	Control47	0
487.3 PC-GRAND THEFT:AUTO	24	Prop47	0
499B PC-TAKE VEHICLE FOR TEMPORARY USE	24	Control47	0
499D PC-TAKE AIRCRAFT W/O OWNER'S CONSENT	24	Control47	0
18 2312 US-INTERSTATE TRANSPORT STOLEN VEHICLE	24	Control47	0
AUTO THEFT	24	Control47	0
503 VC-TAKE CAR W/OUT OWNERS CONSENT	24	Control47	0
FORGERY	25		
602 WI-JUVENILE/FORGERY	25	Control47	0
182 PC-CONSPIRACY/FORGERY	25	Control47	0
664 PC-ATTEMPT CRIME/FORGERY	25	Control47	0
115 PC-OFFER/ETC FALSE/FORGED INSTRMNT TO FILE	25	Control47	0
366 PC-COUNTERFEIT QUICKSILVER STAMPS	25	Control47	0
470 PC-FORGERY	25	Prop47	0
471 PC-MAKE FALSE ENTRIES IN RECORDS	25	Prop47	0
472 PC-FORGE OFFICIAL SEAL	25	Prop47	0
473 PC-FORGERY	25	Prop47	0
474 PC-SEND FORGED TEL/TEL MESSAGE TO DEFRAUD	25	Prop47	0
475 PC-POSS/ETC FORGED NOTES/ETC	25	Prop47	0
475A PC-POSSESS BAD CHECK/MONEY ORDER	25	Prop47	0
476 PC-MAKE/PASS FICTITIOUS CHECK	25	Prop47	0
477 PC-COUNTERFEITING	25	Control47	0
478 PC-COUNTERFEITING	25	Control47	0
479 PC-POSSESS/RECEIVE COUNTERFEIT COIN/ETC	25	Control47	0

Note: disqualification column indicates a previous record of the marked charge that disqualifies offenders from being qualified for Prop 47 classification.

Table A.4: Hospital Utilization

	Total	Pre	Post
EMS Station	135.70	130.23	147.06
GAC Bed	1328.12	1320.35	1339.91
GAC Patient Days	262276.51	259852.77	265994.37
GAC Discharge	56959.45	56766.58	57255.30
GAC Bed Days	482757.21	479352.76	487924.68
Psy Bed	212.60	194.00	262.65
Psy Patient Days	52484.93	47430.43	66397.82
Psy Discharge	5409.07	4881.15	6862.22
Psy Locked Patient Days	133.29*	110.07	198.22
Psy Bed Days	77645.57	70931.39	95706.74
Psy Open Patient Days	25.89*	22.34	43.88
Rehab Bed	64.29	58.14	75.42
Rehab Patient Days	12912.23	11700.79	15098.10
Rehab Discharge	936.79	843.46	1105.17
Rehab Bed Days	23138.52	21119.57	26810.67
Facility Count	8.17	8.32	7.94
Observations	564	340	224

*** $p<0.01$, ** $p<0.05$, * $p<0.10$ for indicating statistical difference between groups.
"EMS Station" is the total number of Emergency Medical Treatment Stations. "Facility Count" is the number of facilities within a county
"GAC" is stocks that are assigned for general acute care patients.
"Psy" is stocks that are assigned for acute psychiatric patients.
"Rehab" is stocks for rehabilitation care patients.
"Bed" is the number of licensed beds. "Patient Days" indicates the number of days of patients using each licensed bed.
"Discharge" is the number of discharges from hospitals. "Bed Days" is the dates of licensure during the reporting period.