#### City University of New York (CUNY)

#### **CUNY Academic Works**

School of Arts & Sciences Theses

**Hunter College** 

Spring 5-5-2018

# Proposition 47 and Crime: A Difference in Differences Analysis of Incarceration Rates and Crime using border counties

Brian J. Fischer *CUNY Hunter College* 

# How does access to this work benefit you? Let us know!

More information about this work at: https://academicworks.cuny.edu/hc\_sas\_etds/308 Discover additional works at: https://academicworks.cuny.edu

This work is made publicly available by the City University of New York (CUNY). Contact: AcademicWorks@cuny.edu



## Proposition 47 and Crime: A Difference in Differences Analysis of Incarceration Rates And Crime Using Border Counties

by

#### Brian J. Fischer

Submitted in partial fulfillment of the requirements for the degree of Master of Arts in Economics Hunter College, City University of New York

2018

Thesis sponsor:

May 1, 2018
Date

Matthew Baker
First Reader

 $\frac{\text{May 1, 2018}}{\text{Date}} \qquad \qquad \frac{\text{Randall Filer}}{\text{Second Reader}}$ 



# Contents

1	Abstract	2
<b>2</b>	Proposition 47 and Incarceration	2
3	Controversy and Anecdotes	4
4	Empirical Studies	6
5	Data and Equation	10
6	Results	<b>12</b>
7	References	<b>17</b>
8	Tables	<b>25</b>
9	Figures	31



#### 1 Abstract

On November 4, 2014, the state of California passed a law that changed how the state punishes drug and theft offenses. The law is called Proposition 47, and this paper discusses it, its criticisms, and its immediate effects. I also add empirical evidence by statistically measuring the effect of the proposition on crime. I use a difference in differences model to compute the change in thefts with the change in jail inmate populations. I found an increase in crime after this law was passed, which disagrees with some other empirical studies. This evidence could shape incarceration policy in the future.

## 2 Proposition 47 and Incarceration

Proposition 47, otherwise known as the Safe Neighborhood and Schools Act, was passed with a 60% to 40% vote as a ballot initiative, which means a signed petition is sent to the legislature. The election officials then place the measure on the ballot to be voted on by the people. Prop 47 was enacted on November 5, 2017. This particular law affects the state of California only. It changes the penalties of non-serious, nonviolent, and nonsexual property and drug crimes (Bowen, 2014; Hughes 2016a; "Text of Proposed Laws," 2014).

The punishments for drug possession and property theft under \$950 were reclassified from felonies to misdemeanors. Theft charges that were changed included shoplifting, grand theft, receiving stolen property, forgery, fraud, and writing bad checks. This law also permits resentencing for these crimes. Those currently serving a prison sentence for a felony or who were previously convicted of a felony can have their crime reduced to a misdemeanor on their record. When the law was signed, 10,000 inmates in the state of California became eligible for resentencing or expunging past felony convictions. This estimate was expanded to 1 million inmates in January 2015. Resentencing and similar procedural changes are not easy processes. Each resentencing requires a thorough review of criminal history and a risk assessment. The law also created a fund into which the savings from decreased incarceration



rates are deposited. This fund will then be distributed to the Department of Education, the state and community corrections departments, and the victim and government compensations board (Culver, 2014; "Text of Proposed Laws," 2014; Ross, 2015).

The immediate effect of the proposition (and its goal) was to reduce the number of inmates. That number decreased so much that some of the sheriff departments in California closed parts of their jails. For example, Orange County closed a section their jail in response to the change (Gerber et al., 2015). In the first year, 4,700 inmates were released from incarceration (Hughes 2016a). This noticeable decrease can be used to measure the effect of crime after the law was enacted. However, more analysis can be conducted to separate the effect of more crime from less incarceration and more crime from weaker penalties (Lofstrom and Raphael, 2013).

Since 1970, there has been a steady increase in incarceration rates (Lofstrom and Raphael, 2013; Raphael et al., 2009). The incarcerated now make up a substantial percent of the United States population, in large part because of policy that has demonized drug use since the War on Drugs (Cole, 2011; Nguyen, 2015), a policy of underfunding and closing mental health facilities called deinstitutionalization (PBS, 2005; Harcourt, 2011), and public support for being tough on crime (Enns, 2014). Since housing prisoners is expensive, states are trying to save money after the budget crunches caused by the 2008 recession by changing criminal justice policies (Aviram, 2016). There has been a noteworthy policy shift from older policies to trying to tackle the problem of incarceration through more judicial attention and compassion toward prisoners (Aviram, 2016; John, 2014).

The overcrowding of jails and prisons has become an ethical problem, too. A recent major policy that attempted to solve this problem was the Public Safety Realignment of 2011. Realignment, or AB 109, was proposed in California after a court-mandated reduction of California's prison capacities from 200% to 137%, or 1994 capacity levels (Newman et al., 2012). The court ruled that these extremely high prison capacities were deemed cruel and unusual punishment and mentally harmful to prisoners. In reaction, to reduce prison



populations, California sent state prisoners to county jails or released prisoners for early parole. In 2014, Proposition 47 was passed. It was a continuation of the change in criminal justice that began in 2011. These two laws both reduced incarceration rates, as intended, to much lower than the courts required (Nguyen, 2016; Lofstrom and Raphael, 2013).

Policies like these have been trending in some states and at the federal level, aiming to reduce prison populations and prison costs. In recent years, incarceration rates have dropped and policies were passed ending mandatory minimums (Cole, 2011). These are noteworthy changes in criminal justice policies, but it is reasonable to question what will happen because of these laws. What will their effect be on crime rates?

## 3 Controversy and Anecdotes

Proposition 47 caused controversy even before it was enacted. For example, the people against Prop 47 argued that the lack of discussion during the ballot initiative process helped it pass without criticism. Instead, the proposition with the prime wording of the "Safe Neighborhoods and Schools Act" was voted into law. As one person stated, "Prop. 47 was a wolf in sheep's clothing" (Creasey et al., 2014). His argument is that this process changed California for the worst. Most criminals are released for misdemeanor offenses, and those resentenced for felony charges are released without probation or parole. Criminals are also able to calculate what they steal with a price barrier of \$950 and they argue the law increased the theft of items priced below this threshold. A storeowner said in a story about an increase in shoplifting post Prop 47, "They'll pick the \$800 unit and just grab it and run out the door" (Associated Press, 2016). The argument is that the law gives little to no punishment for low level criminals. Furthermore, the resentenced offenders are allowed to destroy their DNA samples on record as their felony is expunged, and this prevents law enforcement from potentially stopping future crime (Gatto, 2017; Hutchens, 2014; The Intermountain, 2014; Johnson, 2015).



Moreover, opponents say that the repercussions and consequences decrease from a felony to a misdemeanor penalty; therefore, there is less deterrence. Felonies are a way for judges to exude leverage over potential repeat offenders, forcing them to go into a drug rehabilitation facility (Gatto, 2017). The felony charge deters certain future crimes, for example, the theft of handguns valued under \$950. The theft of a weapon that might lead to murder would therefore be penalized as a misdemeanor under Proposition 47. Certain drugs, like the possession of date rape drugs, are punished as misdemeanors as well. Opponents argue that repeat offenses and crimes that may cause future offenses are increased with this law. These harsh penalties are used to prevent crime because they create a higher penalty if caught and make potential criminals think before committing a crime (Creasey et al., 2014; Gatto, 2017; The Intermountain, 2014; The Portola, 2014).

Finally, opponents argued against Prop 47 because of its economic effects, stating that the predicted increase in crime would cost retail and agriculture businesses money and should cause alarm. If there is a decrease in the penalty for theft, theft will increase, and the public will bear these costs, especially small businesses and farms that lose stolen property. Also, forging checks under \$950 would be considered a misdemeanor, making checking an insecure form of payment. It might cause many small business owners to stop using them completely. There are costs to decreasing penalties, and they argue, the voters needed to account for these costs to potential businesses and farms before the law was enacted (The Intermountain, 2014; The Portola, 2014).

People supporting the proposition celebrate the idea of forgiving criminals' mistakes. They say the problem with felony convictions is that they cause people to be passed over for work and education. Expunging past crimes allows rehabilitation to happen. If the country has Christian values, as argued, then it should treat its citizens in a forgiving way. When punishments are too harsh and permanent, they make forgiveness difficult (Hughes, 2016b).

Most supporters argued that the goal of ending overcrowding and mass incarceration was a good one (Creasey et al., 2014). They also said that blame should not be put on the law



when crime rates are still historically low and less money is now spent on deterring low level crimes. Others highlight that criminals still get punished, and they are only resentenced if the criminal does not have a history of violent crime or sex offenses. Law enforcement focuses on serious offenders and does not waste its time on non-serious, nonviolent, and nonsexual crimes. They also argue that concerns about theft of firearms and possession of date rape drugs are fear-mongering responses. The use of date rape drugs in coercion cases is a felony, as are most cases when thefts of firearms occur in conjunction with felony crimes (Arguments against Prop. 47 misleading., 2014; Johnson, 2015; Leyde, 2015).

Lastly, it is argued that after the passage of Proposition 47, the punishment did not fit the crime. Possession of small amounts of drugs warranted long sentences in prison before the law was enacted. One example is the 15 years that a convicted criminal received for the mandatory minimum-induced crime of narcotics possession. Proponents of criminal justice reform argue that penalties like these are the problem (Greene, 2015; Nguyen, 2015; Cole, 2011).

## 4 Empirical Studies

The reported studies on crime present mixed results. Some indicate that there is a direct increase in crime after passage of the law, and others say that changes in crime are unrelated. Most sources show an increase in violent crime and property crime in 2015. A report by the FBI compares the first half of 2015 to the first half of 2014. The reported homicides, shootings, aggravated assaults, property crimes, and overall violent crimes increased by double-digit percentage points (Kreins, 2016; Westly, 2016; Obernolte, 2016; Nichols, 2017; Debbaudt, 2016; Hanisee, 2016; Whiting, 2015). Other reports have looked at the entire year post passage, compared to crime in 2014. In 2015, there was an increase of 8.4% in violent crime and a 6.6% increase in property crime using FBI data. A paper on the unintended consequences of Prop 47 reports a percentage increase of 4% in overall crime,



9.9% in property crime, and a decrease of 28.9% in drug-related crime in the first year of enactment (Ee, 2017; Kreins, 2016).

However, some research institutions cite the opposite: that the effect of Prop 47 is unknown. Reports from the Center for Juvenile and Criminal Justice (CJCJ) state that burglary fell 4% across California, and Prop 47 has little impact on rising violent crime rates. They agree, however, that there is a 9% increase in violent crime with a 7% increase in property crime. Dr. Mike Males of the CJCJ acknowledges, "Overall crime rates have increased, not only in California, but across the nation" (Abram, 2016). The Public Policy Institute of California (PPIC) agrees that there has been an increase in crime but cautioned that the effects of Prop 47 are unknown, although it does point out that the higher property crime rate is unique to California. Further arguments say police are less practiced and historically less motivated to go after misdemeanor crimes, which would change the overall effect on crime rates. Police tactics and their effect on crime are documented in the literature, but it is difficult to ascertain that crime prevention strategies are ubiquitous across the state of California. Other reports from the CJCJ state that the decline in prison populations did not correlate with crime rates in 2015 (Males et al., 2016). They further report with the multiple changes in criminal justice reform property crime rates are declining (Hughes, 2015; Lofstrom et al., 2016; Males, 2017; Nichols, 2017).

One working paper states that there is no change in crime rates because of this law. The University of California at Irvine concludes through a synthetic controls model that there was no change in crime or this law was not responsible for the reported uptick in crime in California. This study was based on 2015 statewide data. The full paper is not yet published, but the study might have empirical evidence comparing California with "synthetic California." To see if this law changed crime rates, one would want to show that there was an increase in theft or a crime that has both misdemeanor and felony observations. One would need to look at misdemeanor offenses and see if they went up, but the variables are mostly felonies based on all previously mentioned studies (Krubin et al., 2018).



The theory of criminal deterrence is that incarceration decreases crime through deterrence or incapacitation. The decision to commit a crime is conceptualized as a gamble between two choices. The person receives utility from not committing a crime, committing a crime and not getting caught, or committing a crime and getting caught. Deterrence happens when the risk of penalty and income gained from crime is higher than the choice of not committing a crime. If one choice is rationally better than the other, a person may choose to commit a crime. If more people are in prison and the penalty is high, then the average person will have lower utility because of the risk of getting caught for that crime.

On the other hand, incapacitation reduces crime because the average criminal who commits a crime is likely to commit others. There is an assumption, in Economics, that criminals are risk loving. A choice for this criminal is not the choice of one particular crime; it is the choice of multiple types of crime. Deterrence and incapacitation can be difficult to differentiate. A drop in the number of jailed inmates would be an incapacitated effect, but the further change in penalty to a misdemeanor would affect deterrence. For these purposes, I look not only at the counts of crimes affected by the law, but also a range of crimes. I measure larceny, rape, murder, motor vehicle theft, total robbery, and strong arm robbery. These need to be analyzed to show that the change in penalty caused more theft or the release of prisoners caused an increase in crime rates (Becker, 1968; Chalfin and McCrary, 2014).

One study on incarceration and crime using a spline lag model found different elasticities. Liedka, Piehl, and Useem (2006) state that at different levels of incarceration, there are diminishing marginal returns to crime. Furthermore, Levitt states that there is a negative relationship when he used his instrumental variable regression (Chalfin and McCrary, 2014). For the state of California, Lofstrom et al. (2013) analyzed the effect of the realignment campaign or AB 109 in 2011. They identified the relationship using the synthetic controls model, which subtracts pre-post California as the treatment, with the pre-post "synthetic California" as the control. This showed that the reduction in inmates led to a significant



increase in auto theft, but there was no significant relationship with incarcerated populations and violent crime. Liedka et al. (2006), Johnson et al. (2012), and Levitt (1996) have also studied this relationship, providing a body of work with evidence of the negative relationship between incarceration and crime.

An examination of state prison incarceration rates reveals there was change due to the previous policy. The Public Safety Realignment, or AB109, was enacted in 2011. One study noted this change and created its model around the timeline. The study capped the timeline before October 2012 because that is when state prison populations stabilized (Lofstrom and Raphael, 2013). I conclude that the state prison incarceration rate can be used as a control variable because there is no overlap between the two policy changes.

I will use these control variables for the fixed effects regression, some of which are used to study their effects on crime. For example, the unemployment rate is a good proxy of crime. Normally, it has a positive relationship because it shows the legal options a person has to earn income. If there are fewer choices to earn income without crime, then the choice to commit crime would be rational. Raphael and Winter-Ebmer (2001) use a non-linear model to look at time trends of crime and unemployment. They found a strong link between property crime and the unemployment rate. This makes unemployment a great variable to use in my study because of the change in penalties for felony property crime in California.

I will also use a lagged police employment variable. The reason it is lagged is to avoid the simultaneity problem. As crime rises, more police are hired. As more are hired, more arrests are made. The literature points to one method that I use called Granger causality (Granger, 1969). This method points to the "temporal relationship rather than causality." Corman and Mocan (2000) use this theory by looking at when police are hired after crime happens. They found from monthly police employment variables that New York City had a reaction of six months after a crime occurred to hire new officers. The literature mentions the differences between where someone lives and reactionary hiring. Using a police employment variable of the year's previous employment will avoid the contemporaneous problems that



happens with police and crime (Levitt and Miles, 2006).

## 5 Data and Equation

Since the decline in incarceration rates happened in California after 2014, I study the difference between California and the surrounding states unaffected by the law. This becomes a natural experiment in which California counties are the treatment area, and Oregon, Nevada, and Arizona counties are the control areas. By looking at California border counties in relationship to the law, one can study the effect of the policy on crime. This is similar to a study based on minimum wage policy and unemployment rates, the policy of compulsory schooling laws and fertility, and policy with changes with industry (Card & Krueger, 1994; Holmes, 1998; Puerta, 2009) using a similar framework comparing rates at the state borders. The assumption of the comparison is they have similar demographic, social, and economic characteristics. The border of a state acts as a change in law where the areas' characteristics are the same.

Similar to Lofstrom and Raphael's 2013 study of Realignment and Puerta's border comparison studies, I use the difference in differences model to study the relationship discussed. The model can be shown in a theoretical way:

$$DiD = (\gamma_{\text{CaliforniaPOST}} - \gamma_{\text{CaliforniaPRE}}) - (\gamma_{\text{ControlStatesPOST}} - \gamma_{\text{ControlStatesPRE}})$$

The symbol  $\gamma$  describes the outcome of the regression for the county identified on the border of said state. The two time periods of Proposition 47 are January 2012 to October 2014 as the pre-period and November 2014 to December 2016 as the post-period. Using this identification strategy, I measure if Proposition 47 had an effect.

The California inmate populations will be given by the Board of State Community Corrections (BSCC). Their jail profile survey includes monthly average daily populations for

each California county. In-state counties will be compared to counties that are along the California border but not in California, including those in Oregon, Arizona, and Nevada. Data will be gathered by collecting information from each county jail facility.

I called each jail facility and spoke with the jail commander or the sheriff of that county to acquire average daily populations. If the average daily data were unavailable, then I requested an end-of-month headcount. Some jail facilities require a public information request. Ten of the 16 border counties emailed inmate information after my multiple attempts to gather 60 observations of jail population counts per county.

Looking at these two variables and accounting for county populations using US Census data, I analyze the results of this relationship. The final equation will look like this:

$$Larceny_{it} = \alpha + \zeta JailPop_{it} + \beta CA_i + \tau TimeEnacted_t + \gamma (CA \times TimeEnacted) + \mu_{it}$$

This equation accounts for the two time periods, pre-Prop 47 and post-Prop 47; the different counties i; and the different months t.  $\tau$  and  $\beta$  are the effects for each subgroup, month and county.  $\alpha$  is the constant term. The coefficients are  $\gamma$  and  $\zeta$ . This regression will include the relationship between California and its neighboring states, where  $\gamma$  is the effect of the enactment of Proposition 47.

The population weights that I will run in my regression were obtained from the annual county population of US Census estimates from April 2010 to July 2017 for border counties along the California border both in state and out of state. The jail populations will be given by their respective sources. All of California's counties are accounted for, whereas the counties in Arizona, Nevada, and Oregon are not. Counties without jail population headcounts or average daily populations include La Paz County in Arizona, Nye County, Mineral County, Esmeralda County, and Lyon County in Nevada, and Josephine County in Oregon. These counties either did not gather such information or were unable to send certain



data to me. Most were estimated over the phone as small county jails without long-term change; without the data, I do not know for sure. To account for this information and its effect on the pre-trends of the model, I use a fixed effects regression. Other variables are the police employment levels and unemployment rates for each county from the Bureau of Labor Statistics. The monthly observations of state prisoners were gathered by each state's department of corrections. All variables normalized to a rate per 10,000 people used the population weights mentioned earlier. Weights are used because the counts can be reflective of populations in California. Normalizing the variables to rates per 10,000 also puts these counts on the same scale. The Uniform Crime Reports' variables to be measured are the crimes in the Card 1 report. Card 1 is the found crime count in the dataset. Since all jail populations will be measured as adult males, Card 3, or juvenile crime counts, Card 0, which is unfounded, and Card 2, which is crime counts cleared by arrest, will not be used.

#### 6 Results

To check if there was a change in jail populations and larceny rates after the law was enacted, I created a table showing their means with pre, post, treated and control as follows. Using the difference in differences formula, I can get an average treatment effect. Looking at each variable individually with the same method, the average treatment effect of the larceny rate per 10,000 is 1.243146, and the average treatment effect of the jail incarceration rate per 10,000 is .507095. So individually, I can say there was an increase in crime and jail incarceration rate after this time in California.

Table 1: Larceny Rate Table

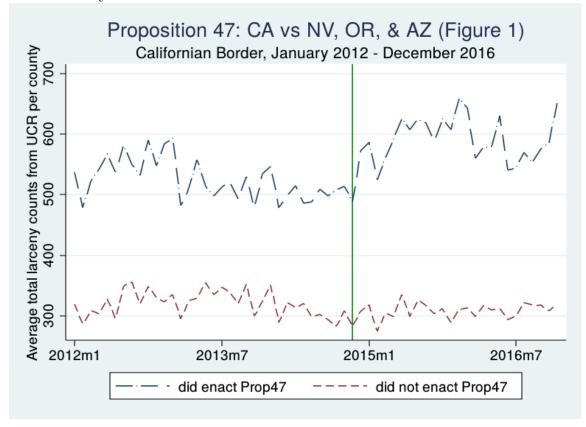
County is in California	Monthly O	bservation Occurs after October 2014
	0	1
0	12.397781	11.123095
1	10.21145	10.17991



Table 2: Incarceration Rate Table

County is in California	Monthly O	bservation Occurs after October 2014
	0	1
0	26.242997	24.960191
1	25.149745	24.374034

Figure 1 shows this data in graph form. It gives two trend lines for the control group and the treatment group. The y axis is the average larceny count, and the x axis is the timeline for this experiment. The month when the law was enacted is marked for both trends as a vertical line. The trends in the control states are steady, while the trends in the treatment state seem to show an increase after November 2014. This is further evidence that the crime counts for larceny were a direct effect of the law.



To see if there is a correlation between the two, the full regression equation was used. I



add lagged crime and lagged jail variables to that regression to see if the date of the count influenced the result in regressions. If the count was on the first of the month, does that represent crime that happened on the same day of the same month? For my purposes, the crime and jail rate variables will be lagged back for one month and lead forward for one month for a total of four variables. The regression is run, replacing these special variables in differing regressions as seen in Table 3, Table 4, and Table 5.

The results show a positive relationship in the treated area, meaning there was an increase in larceny in California after October 2014. The positive crime effect in these tables ranges from .87 to 1.13 crimes per 10,000 each month, or an increase from 317.6 to 391.9 counts of larceny per month. The counts are weighted to compare the effect of the normalized variables. The coefficients of the jail population variable are positive, and the interaction of the California dummy variable and the time of enactment dummy variable are also positive. Research states that the relationship between incarceration and crime should be negative, meaning that for every increase in jail population, larceny rates would decrease. Table 6 shows this result with a fixed effects regression. The coefficient for the jail population variable shows a negative relationship between larceny and incarceration. However, this is not for all crime. Other crimes in Table 6 are positive, which suggests that the enactment of decreasing penalties from Prop 47 caused this increase in crime. If the other relationships that are not larceny were also negative, then this would suggest the release of criminals caused more crime. This is not the case and shows that the penalty cost decreased for larceny and, therefore, economically, demand increased. The rates are significant at the 10% level or greater, and the counts are significant at the 5% percent level or greater.

Adding the fixed effects model would have the unobservable omitted variables removed and focus on the average treatment effect over time. Table 4 shows these results. The effect is negative on crime, meaning that there is a preventable effect resulting from Proposition 47. If there is an increase in jail population counts, then the number of larcenies would decrease. Adding more variables to the fixed effects model, a lagged police employment



rate, the unemployment rate, and the state prison incarceration per county percent of the population gives expected results except for the lagged police employment variable, which, according to research, would be negative. The relationship of unemployment is positive, the county share of state prison populations variable is positive because the crimes that changed were misdemeanor crimes, and lagged police employment is positive. It should be noted that unemployment and county share state prison populations are not significant in regression 3, but county share of prison populations is significant at the 10% level. More importantly, the counts of strong arm robbery, murder, total rape, total robbery, and motor vehicle theft are all positive. All are significant at the 1% level except motor vehicle theft. This suggests that these crimes are not preventable and are not affected by Proposition 47. This further suggests that the incapacitation effect does not apply in this case. Larceny was the only crime affected, bolstering the argument that the harsher penalty deterred criminals from stealing.

These results are in contrast to three institutions: the University of Irvine, the Public Policy Institute of California, and the Center on Juvenile and Criminal Justice. The working paper from the University of Irvine reports, using the synthetic controls model, that no increase in crime happened (Krubin et al., 2018). The problem with the synthetic controls is that the characters are not the same in the area of change. The use of other states to match California assumes that these states are similar. The border county comparison with difference in differences assumes that these demographics are the same by design; therefore, it is a better model. The PPIC said that the effects were unknown. They say that crime trends fluctuate frequently, and it is difficult to show a precise cause. This analysis was done in 2015. Two years of rates after the law was enacted shows an effect of increased larceny. The CJCJ reported no effect and followed with a report showing a decline in crime from 2010 to 2016. Its first report compared annually 2014 with 2015 while accounting for prison releases from November 2014 to December 2015. Comparing the two years does not consider the differences in those years' characteristics. There might be many reasons why 2014 had



less crime than 2015. Also the full effect is limited to only one year after Proposition 47 in this report. The second piece of analysis states that there was a decline since 2010 but there is an increase in property crime for 2015 from 2014.

It should be noted that by design of the model, most of California is not accounted for. The model only looks at the state's border counties. This effect is not definitive proof, and more studies are needed. The design uses the assumption of similar demographics to provide its results. It ignores the population-dense cities in California and other characteristics unique to the state. This still presents a fair argument about the effect on crime. If there is an effect with small populations, then crime increased, even if, using the entire state's population averages the results to be no effect. The cost of committing a crime decreased, and this model shows that crime could be prevented if the law was not enacted.

The enactment of Proposition 47 was a choice between the costs of housing inmates and risks of those inmates on society. When policy shifts to not be "tough on crime," we figure out how to better prevent crime instead of reacting with more facilities and police officers. Pushing other reform policies focusing on more opportunities for people more likely to commit crime might be a way to mitigate the effects of decreasing the deterrence of crime. It should be noted how small the effects found are. Enacting this law caused an increase of approximately 12 crimes per 10,000. This is quite small but this also does not include all of California. This is just for the border area. Showing that there was an increase can economically show the effect the law had and the rationality of criminal behavior.



#### 7 References

- [1] Abram, S. (2016, September 24 Saturday). "2 years later is Prop. 47 working?; The jury is still out on the impact and effect of reducing felonies to misdemeanors." Redlands Daily Facts (California). A,A; Pg. 1. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [2] "Arguments against Prop. 47 misleading." (2014, October 28 Tuesday). Legal Monitor Worldwide. 570 words. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [3] Associated Press, The May 2016). "Spike shoplifting blamed (14)in CBS on California Prop 47's reduced penalties." San Francisco. sanfrancisco.cbslocal.com/2016/05/14/shoplifting-california-prop-47-reducedpenalties/.
- [4] Aviram, H. (2016). The correctional hunger games: understanding realignment in the context of the great recession. The ANNALS of the American Academy of Political and Social Science, 664(1), 260-279.
- [5] Becker, G. S. (1968). Crime and punishment: An economic approach. In The economic dimensions of crime (pp. 13-68). Palgrave Macmillan, London.
- [6] Board of State and Community Corrections. 2017. "Jail Profile Survey." Retrieved 2

  December 2017 Available at www.bscc.ca.gov/s\_fsojailprofilesurvey.php
- [7] Bureau of Justice Statistics (BJS). 2017. "All terms and definitions." Retrieved 2 December 2017 www.bls.gov/cew
- [8] California General Election Official Voter Information Guide November 2014, "Text of Proposed Laws," accessed April 21, 2018 vig.cdn.sos.ca.gov/2014/general/pdf/text-ofproposed-laws1.pdf



- [9] Card, D., & Krueger, A. B. (1993). Minimum wages and employment: A case study of the fast food industry in New Jersey and Pennsylvania (No. w4509). National Bureau of Economic Research.
- [10] Carpizo, A. (2014, November 8 Saturday). "Butte, Glenn officials wary of Prop. 47 impacts." Chico Enterprise-Record (California). LOCAL. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [11] Chalfin, A., & McCrary, J. (2017). Criminal deterrence: A review of the literature. Journal of Economic Literature, 55(1), 5-48.
- [12] Cole, D. (2011). Turning the corner on mass incarceration. Ohio St. J. Crim. L., 9, 27.
- [13] Creasey, A; Vaughan, M. (2014, December 11 Thursday) "The pros and cons of Prop. 47." Appeal-Democrat (Marysville, California). State And Regional News. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [14] Culver, D. (2014, 27 June). "CA voters will decide on DA Gascon-backed plan to reduce sentences for low-level crimes." SF Appeal: San Francisco's Online Newspaper, Bay City News, sfappeal.com/2014/06/initiative-on-low-level-crimes-makes-november-ballot/.
- [15] Debbaudt, M. (2016, 18 March) "An explosion of California property crimes - due to Prop. 47." San Francisco Chronicle, Hearst Corporation, www.sfchronicle.com/opinion/openforum/article/An-explosion-of-California-propertycrimes-6922062.php.
- [16] Ee, Marilyn. Proposition 47: The Aftermath. Diss. California State University, Northridge, 2017.
- [17] Enns, P. (2014). The Public's Increasing Punitiveness and Its Influence on Mass Incarceration in the United States. American Journal of Political Science, 58(4), 857-872.
  Retrieved from http://www.jstor.org.proxy.wexler.hunter.cuny.edu/stable/24363530



- [18] Gatto, M. (2017, June 30) "Prop. 47 a tough lesson in initiatives' weakness." Chico Enterprise-Record (California). H,H; Pg. 9. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [19] Gerber, M., Sewell, A., & Chang, C. (2015, January 28). "Prop. 47 brings a shift to longer time spent behind bars" Los Angeles Times, Los Angeles Times, http://www.latimes.com/local/crime/la-me-early-release-20150128-story.html
- [20] Greene, R. (2015, 27 October). "California's Prop. 47 revolution: Do prosecutors really need a 'felony hammer' to deal with drug offenders?" Los Angeles Times, Los Angeles Times, www.latimes.com/opinion/opinion-la/la-ol-proposition-47-hammer-drug-felonies-20151026-story.html.
- [21] Hanisee M. (2016, October 7). "Crime rate as nation sees a decline." Association of Deputy District Attorneys, www.laadda.com/prop-47-fallout-continues-once-again-ca-suffers-a-rise-in-property-crime-rate-as-nation-sees-a-decline/.
- [22] Harcourt, B. E. (2011). An institutionalization effect: the impact of mental hospitalization and imprisonment on homicide in the United States, 19342001. The Journal of Legal Studies, 40(1), 39-83.
- [23] Holmes, T. J. (1998). The effect of state policies on the location of manufacturing: Evidence from state borders. Journal of political Economy, 106(4), 667-705.
- [24] Hughes, B. W., Jr. (2015, September 4 Friday). "Don't blame Prop. 47 for a rise in crime." Orange County Register (California). LOCAL; Pg. B. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [25] Hughes, B. W., Jr. (2016a, March 9 Wednesday). "Where's the missing savings from Prop. 47?" Orange County Register (California). LOCAL; Pg. B. LexisNexis Academic. Web. Date Accessed: 2018/01/27.



- [26] Hughes, B. W., Jr. (2016b, August 21, Sunday). "Prop. 47 giving men, women second chance." The Daily News of Los Angeles. A,A; Pg. 25. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [27] Hutchens, S. (2014, October 20 Monday). "Prop. 47 won't reduce crime, increase safety." Orange County Register (California). LOCAL; Pg. B. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [28] John, A. (2014, April 22). "A timeline of the rise and fall of 'tough on crime' drug sentencing." The Atlantic, Atlantic Media Company, www.theatlantic.com/politics/archive/2014/04/a-timeline-of-the-rise-and-fall-of-tough-on-crime-drug-sentencing/360983/.
- [29] Johnson, J. R. (2015, January 20 Tuesday). "County feels Prop. 47's impact." Corning Observer (California). State And Regional News. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [30] Johnson, R., & Raphael, S. (2012). How much crime reduction does the marginal prisoner buy?. The Journal of Law and Economics, 55(2), 275-310.
- [31] Kreins, M. (2016, March 2 Wednesday). "Is Prop. 47 working the way it was sold?." The Daily News of Los Angeles. A,A; Pg. 13. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [32] Krubin, C., & Bradley B. (2018, 7 March). "Proposition 47 not responsible for recent upticks in crime across California." UCI NEWS Criminology, Law and Society, University of California, Irvine, cls.soceco.uci.edu/news/proposition-47-not-responsible-recent-upticks-crime-across-california.
- [33] Lackey T. (2016, August 28 Sunday) "Rising crime numbers show faults in Prop. 47." The Daily News of Los Angeles. A,A; Pg. 21. LexisNexis Academic. Web. Date Accessed: 2018/01/27.



- [34] Lantigua-Williams, J. (2016, 7 June). "Crime is down, sort of." The Atlantic, Atlantic Media Company, www.theatlantic.com/politics/archive/2016/06/crime-imprisonment-rates/486014/.
- [35] Levitt, S. D., & Miles, T. J. (2006). Economic contributions to the understanding of crime. Annu. Rev. Law Soc. Sci., 2, 147-164.
- [36] Levitt, S. D. (1996). The effect of prison population size on crime rates: Evidence from prison overcrowding litigation. The quarterly journal of economics, 111(2), 319-351.
- [37] Leyde, T. (2015, November 16 Monday). "A fresh, new start; Groups mark one-year anniversary of Prop. 47." Monterey County Herald (California). A,A; Pg. 1. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [38] Liedka, R. V., Piehl, A. M., & Useem, B. (2006). The crime-control effect of incarceration: does scale matter?. Criminology & Public Policy, 5(2), 245-276.
- [39] Lofstrom, M., & Raphael, S. (2013). Impact of realignment on county jail populations.

  Public Policy Institute of California. Available at www.ppic.org/main/publication.asp.
- [40] Lofstrom, M., & Raphael, S. (2013). Incarceration and crime: evidence from Californias realignment sentencing reform. Working Paper.
- [41] Lofstrom, M., Bird, M., & Martin, B. (2016). California's Historic Corrections Reforms.

  San Francisco, CA: Public Policy Institute of California.
- [42] Males, M. & Webster, E. (2016, September). Proposition 47 And Crime In 2015: A County-Level Analysis. Center on Juvenile and Criminal Justice. Available at http://www.cjcj.org/news/10842.
- [43] Males, M. (2017, October 30). Most California Jurisdictions Show Declines in Property Crime During Justice Reform Era. Center on Juvenile and Criminal Justice. Available at http://www.cjcj.org/news/11799.



- [44] Newman, W. J., & Scott, C. L. (2012). Brown v. Plata: prison overcrowding in California. Journal of the American Academy of Psychiatry and the Law Online, 40(4), 547-552.
- [45] Nguyen, T. T. (2015). Downgrading Non-Violent Drug Crimes: An End to the Lock'Em and Leave'Em Mentality. Hamline J. Pub. L. & Pol'y, 36, v.
- [46] Nguyen, V. (2016). How Has Proposition 47 Affected Californias Jail Population?. Available at www.ppic.org/publication/how-has-proposition-47-affected-californias-jail-population.
- [47] Nichols, (2017,March 6:00am). "Has violent crime been on the Calif. since 2011?" Politifact California, Bay rise inTampa Times, www.politifact.com/california/statements/2017/mar/06/jeff-stone/has-violent-crimebeen-rise-california-2011-and-di/.
- [48] Nucum, J. (2016, April 30 Saturday). "Calif. criminal records purge help many; Filipinos missing out?." Philippines Daily Inquirer. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [49] PBS. (2005,10 May). "Deinstitutionalization: A psychiatric Titanic." PBS, Public Broadcasting Service, www.pbs.org/wgbh/pages/frontline/shows/asylums/special/excerpt.html.
- [50] Obernolte, J. (2016, July 31 Sunday). "It's time to fix rising crime problem caused by Prop. 47." Inland Valley Daily Bulletin (Ontario, CA). A,A; Pg. 20. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [51] Puerta, J. M. (2009). "The Fewer, the Merrier": Compulsory Schooling Laws, Human Capital, and Fertility in the United States. Job market paper.



- [52] Raphael, S., & Stoll, M. A. (2009). Why are so many Americans in prison?. Do prisons make us safer, 27-72.
- [53] Raphael, S., & Winter-Ebmer, R. (2001). Identifying the effect of unemployment on crime. The Journal of Law and Economics, 44(1), 259-283.
- [54] Ross, R. K. (2015, 15 January) "Four ways to make black, brown and all lives matter." Los Angeles Times, Los Angeles Times, www.latimes.com/nation/la-oe-0116-ross-california-reform-20150116-story.html.
- [55] staff, The Intermountain. (2014, October 8). "Prop. 47 adds to crime problems." The Intermountain News (Burney, California). LexisNexis Academic. Web. Date Accessed: 2018/04/21.
- [56] staff, The Portola. (2014, October 22). "Prop 47 threatens treatment programs, small businesses; WHERE I STAND." Portola Reporter (California). LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [57] "Statement of Vote November, 4 2014, General Election." 2014, October 20). California Secretary of State Debra Bowen Available at elections.cdn.sos.ca.gov/sov/2014-general/pdf/2014-complete-sov.pdf.
- [58] United States Census Bureau. 2017. "All terms and definitions." Retrieved April 2 2018. Available at https://www.census.gov/data/tables/2017/demo/popest/state-total.html.
- [59] Uniform Crime Reporting (UCR). Federal Bureau of Investigations. 2017. "RETA data from 2012 to 2016" Requested and recieved September 15 2017. https://ucr.fbi.gov.
- [60] Vaughan, M. (2016, March 8 Tuesday). "Sutter County prosecutors denounce Prop 47 in shoplifting case." Appeal-Democrat (Marysville, California). State And Regional News. LexisNexis Academic. Web. Date Accessed: 2018/01/27.



- [61] Westly, S. (2016, May 20 Friday). "What to do about California's crime surge?." Orange County Register (California). LOCAL; Pg. B. LexisNexis Academic. Web. Date Accessed: 2018/01/27.
- [62] Whiting, D. (2015, November 22 Sunday). "Beat officers: Prop. 47 boosts crime." Orange County Register (California). News; Pg. A. LexisNexis Academic. Web. Date Accessed: 2018/01/27.

# 8 Tables

Table 1: Larceny Rate Table

County is in California	Monthly O	bservation Occurs After October 2014
	0	1
0	12.397781	11.123095
1	10.21145	10.17991

Table 2: Incarceration Rate Table

County is in California	Monthly O	bservation Occurs After October 2014
	0	1
0	26.242997	24.960191
1	25.149745	24.374034

#### **Summary Statistics**

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
Datevar	1,719	653.3	17.28	624	683
Larc1	1,719	419.2	862.1	0	3,887
County	1,719	19,209	15,169	4,012	41,037
Jailpop	1,299	880.9	1,494	0	5,973
Population ipolated	1,719	311,736	644,266	782	2.402e+06
Population percent	1,719	0.0439	0.134	7.68e-05	0.734
Larceny rate	1,719	11.12	6.079	0	72.26
Jail incarceration rate	1,299	25.18	8.983	0	57.54
Strongarm robbery rate	1,719	0.206	0.372	0	10.31
Murder rate	1,719	0.0364	0.164	0	4.390
Rape rate	1,719	0.231	0.578	0	12.46
Total robbery rate	1,719	0.401	0.612	0	12.11
Total motor theft rate	1,719	1.823	1.707	0	24.18
County share of state Prison Populations	1,615	1,187	2,358	3.658	10,348

<sup>\*</sup>Datevar is the STATA formated date of month and year from 2012m1 to 2016m12, Larc1 is the UCR crime total larceny count card 1, county is the county state fips code. JailPop is the population count of inmates per county, Population ipolated is the monthly population per county gathered from annual US Census estimates, Population percent is the county ipolated population divided by the total state population for that state. All rates are their respective counts divided by the county ipolated population and multiplied by 10,000. County share of state Prison Populations is the total inmates at the state level variable multiplied by the Population Percent.



_
m
a
ਨ
a
s (Tabl
Total Larceny and Jail Populations with Lagged variables
0
œ
Ξ
3
~
ĕ
ρŏ
æ
ئــ
2
Ę
3
S
Ξ
∺
Ħ
=
₫
Ō
<u> </u>
፷
~
σ
⊆
מ
≥
ē
្ត
ā
ŭ
Б
Ħ
<b>≃</b>

וסנמו דמוכנווא מווכ	i Jaii ropulati	Total raicelly allo Jall Fobulations with ragged valiables (Table 3)		מטוב ט/						
	(1)	(2)	(3)	(4)	(2)	(9)	(7)	(8)	(6)	(10)
VARIABLES	larceny rate j	larceny rate jail incarceration rate larceny rate	larceny rate	larceny rate	larceny rate	lagcrime	leadcrime	leadcrime	lagcrime	lagcrime
jail incarceration rate			0.186***			0.186***	0.188***			
			(0.0138)			(0.0138)	(0.0140)			
leadjail				0.186***					0.188***	
				(0.0138)					(0.0138)	
lagjail					0.187***			0.188***		0.184***
					(0.0140)			(0.0142)		(0.0139)
CA	-2.186***	-1.093	-4.293***	-4.311***	-4.324***	-4.274***	-4.338***	-4.353***	-4.285***	-4.266***
	(0.385)	(0.667)	(0.331)	(0.329)	(0.337)	(0.334)	(0.332)	(0.338)	(0.332)	(0.335)
post	-1.275***	-1.283*	-0.926**	-0.921**	-0.962**	-0.886**	-0.904**	**426-0-	-0.796**	-0.919**
	(0.391)	(0.779)	(0.387)	(0.389)	(0.390)	(0.387)	(0.392)	(0.395)	(0.389)	(0.388)
interaction	1.243**	0.507	1.039**	1.034**	1.046**	*906.0	1.125**	1.133**	0.826	0.873*
	(0.591)	(1.021)	(0.506)	(0.510)	(0.511)	(0.507)	(0.514)	(0.518)	(0.509)	(0.508)
Constant	12.40***	26.24***	9.815***	9.823***	8.808**	9.827***	9.764***	9.812***	9.782***	9.892***
	(0.258)	(0.513)	(0.442)	(0.442)	(0.449)	(0.445)	(0.448)	(0.454)	(0.444)	(0.447)
Observations	1,719	1,299	1,299	1,277	1,277	1,277	1,277	1,255	1,255	1,277
R-squared	0.024	0.005	0.257	0.260	0.257	0.260	0.256	0.256	0.267	0.257
Adjusted R-squared	0.0224	0.00307	0.255	0.258	0.254	0.258	0.254	0.254	0.264	0.254
F test	14.15	2.335	112	112	109.8	111.8	109.7	107.5	113.7	109.8
Prob >F	4.14e-09	0.0723	0	0	0	0	0	0	0	0

Standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1
Rates are UCR total larceny counts card 1 (founded) and jail population data divided by the interpolated US census county population at that month times 10,000



<del>4</del>
ě
Tabl
Па
<u>ب</u>
es
虿
l variable
ē
<u></u>
h Lagged
88
Ē
_
₹
3
S
<u>ō</u>
at
Ë
ğ
2
=
/ and Ja
ਰ
a
E
ĕ
Larcen
=
ţ
2

	(1)	(2)	(3)	(4)	(2)	(9)	(7)	(8)	(6)	(10)
VARIABLES	larc1	jailpop	larc1	larc1	larc1	lagcrime count	lagcrime count leadcrime count leadcrime countlagcrime count lagcrime count	leadcrime count	lagcrime count	lagcrime count
ionlici			0 572***			~***U	O 532***			
202			(1.250-05)			(1.350-05)	(1.370-05)			
			(T-206-00)			(1.305-00)	(1.3/5-03)			
leadjailcount				0.523***					0.522***	
				(1.35e-05)					(1.35e-05)	
lagjailcount					0.523***			0.524***		0.523***
					(1.37e-05)			(1.38e-05)		(1.36e-05)
CA	640.5***	1,255***	-124.4***	-117.8**	-129.5***	-124.6***	-123.9***	-129.7***	-116.6***	-129.7***
	(0.136)	(0.203)	(0.0656)	(0.0651)	(0.0669)	(0.0665)	(0.0657)	(0.0674)	(0.0665)	(0.0668)
post	-39.22***	109.6***	-100.6***	-93.46***	-107.9***	-104.3***	-88.57***	-100.6***	-98.24**	-115.5***
	(0.161)	(0.229)	(0.0469)	(0.0468)	(0.0472)	(0.0469)	(0.0471)	(0.0478)	(0.0473)	(0.0473)
interaction	168.9***	-300.5***	330.2***	317.6***	335.8***	320.8***	335.7***	339.5***	319.8***	326.2***
	(0.204)	(0.303)	(0.101)	(0.101)	(0.101)	(0.100)	(0.102)	(0.102)	(0.101)	(0.101)
Constant	1,768***	2,717***	455.2***	447.8***	460.1***	454.4**	449.3***	457.4***	447.9***	462.4**
	(0.110)	(0.150)	(0.0531)	(0.0527)	(0.0540)	(0.0534)	(0.0533)	(0.0544)	(0.0535)	(0.0539)
Observations	535,875,545		523,138,472 523,138,472	514,141,545	514,141,545 514,643,947	514,643,947	514,141,545	505,647,020	505,647,020	514,643,947
R-squared	0.088	0.093	0.674	0.677	0.673	0.677	0.673	0.673	0.678	0.676
Adjusted R-squared	0.0884	0.0930	0.674	0.677	0.673	0.677	0.673	0.673	0.678	0.676
F test	1.690e+07	1.870e+07	3.830e+08	3.850e+08	3.730e+08	3.860e+08	3.770e+08	3.730e+08	3.810e+08	3.790e+08
Prob >F	0	0	0	0	0	0	0	0	0	0
Robust standard errors in parenthe	are in narenth	2020								

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Regressions are run with fweight that is the interpolated monthly county population from the US census

Variables are counts from jail population data and UCR card 1 (founded) total larceny

_	ı
5	
≝	ı
ā	ı
<u> </u>	ı
es	ı
0	ı
₽.	ı
igged variab	ı
2	ı
ĕ	ı
88	ı
Ē	ı
_	ı
₹	ı
3	ı
S	ı
ᅙ	ı
at	ı
<u>च</u>	ı
ĕ	ı
l Popu	ı
፹	ı
ceny and Jai	ı
ਠੁ	ı
ā	ı
>	ı
e	ı
5	ı
tal Lar	ı
ē	ı
ಕ	ı
_	1

lotal Larceny and Jall I	ı Jallı Popul	ations wit	n Lagged	Populations with Lagged Variables (Table 5,	l able 5)					
	(1)	(2)	(3)	(4)	(2)	(9)	(7)	(8)	(6)	(10)
VARIABLES	larc1	jailpop	larc1	larc1	larc1	lagcrime count l	leadcrime count	lagcrime count leadcrime count leadcrime count lagcrime count lagcrime count	lagcrime count	lagcrime count
200			***************************************			**	, , , , , , , , , , , , , , , , , , ,			
Jalipup			0.030			(0,000,0)	0.03T			
leadiailealn+			(10.0101)	*****		(06600.0)	(0.0101)		*****	
ieaujaiicouiit				(0.00997)					(0.0101)	
lagjailcount					0.651***			0.652***	•	0.650***
i					(0.00994)			(0.0102)		(0.0101)
S	474.9***	1,024***	-299.4***	-289.4**	-306.7***	-298.3***	-298.9***	-306.6**	-285.8***	-306.3***
	(124.4)	(182.2)	(102.8)	(102.3)	(104.7)	(104.0)	(103.7)	(106.4)	(104.3)	(104.4)
post	-48.51	115.6	-128.1***	-116.9***	-138.0***	-130.7***	-115.1***	-129.9***	-120.8***	-146.2***
	(149.4)	(202.3)	(44.86)	(44.50)	(44.54)	(44.48)	(44.43)	(45.39)	(45.90)	(45.20)
interaction	177.7	-306.2	381.3**	365.4**	388.8**	371.3**	386.2**	391.9**	366.9**	379.5**
	(187.3)	(271.0)	(150.7)	(150.8)	(151.9)	(150.3)	(152.0)	(153.3)	(151.4)	(150.7)
Constant	1,934***	2,948***	125.8***	117.7***	129.5***	125.0***	118.5***	128.0***	120.7***	134.3***
	(102.1)	(131.5)	(27.29)	(26.60)	(27.80)	(27.25)	(26.88)	(27.58)	(27.12)	(27.85)
-	1			,	,	,	,	, ,	, ,	7
Observations	1,719	1,299	1,299	1,2,1	1,2//	1,2//	1,2//	1,255	1,255	1,2//
R-squared	0.024	0.035	0.883	0.885	0.884	0.886	0.883	0.882	0.884	0.884
Adjusted R-squared	0.0225	0.0327	0.883	0.885	0.884	0.886	0.883	0.882	0.884	0.884
F test	12.14	14.78	1153	1163	1197	1170	1239	1273	1131	1130
Prob >F	7.35e-08	1.82e-09	0	0	0	0	0	0	0	0

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Regressions are run with pweight that is the interpolated monthly county population from the US census divided by total state population at that month Variables are counts from jail population data and UCR card 1 (founded) total larceny



9
Ð
豆
<u>ə</u> .
ᆫ
Ĕ
.ō
SS
ė
90
ē
œ
t
ပ္က
۳
Ш
Q
â
.≏

(1)  LES larc1  Julation -0.246***  Owment (0.0265)  oyment  share of state prison populations  oolice employment (4.620)  rt (23.75)  rtions (1,299  ed (0.066  of county (0.0491  d R-squared (5.0491)	Fixed Effects Regression (Table 6)								
lerc1 larc1 larc1 stro1 mrdr1 rapt1 -0.246***0.275*** 0.0162*** 0.00155*** 0.0115***  (0.0265)		(1)	(2)	(3)	(4)	(2)	(9)	(7)	(8)
-0.246***	VARIABLES	larc1	larc1	larc1	stro1	mrdr1	rapt1	robt1	mtvh1
(0.0265) (0.0274) (0.00299) (0.000527) (0.00219)  -1.73e-05  (0.0305) (0.0305) (0.0385  (0.0305) (0.0353)  yment  (0.0305) (0.0353)  4.901 5.551 5.094 2.025*** 0.296*** 3.994***  (4.620) (3.946) (5.217) (0.521) (0.0917) (0.381)  756.6*** 355.6*** 680.4*** 4.711* 0.0921 -1.589  (23.75) (35.94) (61.35) (2.677) (0.471) (1.957)  1,299 1,615 1,247 1,299 1,299 1,299  0.066 0.004 0.087 0.031 0.013 0.091  22 29 22 22  0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749  45 2.933 23.12 20.41 8.680 64.01	iei lation	***9700-		***5700-	.***	0.00155*	*****	0.03/3***	0.00512
(0.0255)	Jan Population	0.250		(12.0)	0.0102	0.00133	0.0000	0.000	0.00312
-1.73e-05  (0.000171)  (0.0305)  (0.0353)  (0.0358**  (0.0377)  4.901  5.551  5.094  2.025***  (0.0377)  756.6***  35.946)  (5.217)  (5.217)  (6.521)  (6.0917)  (6.381)  756.6***  355.6***  680.4***  4.711*  0.0921  -1.589  1,299  1,299  1,615  1,247  1,299  1,299  1,299  1,299  0.066  0.004  0.087  0.031  0.013  0.091  22  22  22  22  22  22  23  24  45  2.933  23.12  20.41  8.680  64.01		(0.0265)		(0.0274)	(0.00299)	(0.000527)	(0.00219)	(0.00548)	(0.0140)
(0.0305) (0.0353)  yyment (0.0377) 4.901 5.551 5.094 2.025*** 0.296*** 3.994*** 5 (4.620) (3.946) (5.217) (0.521) (0.0917) (0.381) 756.6*** 355.6*** 680.4*** 4.711* 0.0921 -1.589 1 (23.75) (35.94) (61.35) (2.677) (0.471) (1.957) 1,299 1,615 1,247 1,299 1,299 1,299 0.066 0.004 0.087 0.031 0.013 0.091 22 29 22 22 0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749 45 2.933 23.12 20.41 8.680 64.01	unemployment			-1.73e-05					
e prison populations 0.0508* 0.0385  (0.0305) (0.0353)  wyment 0.0858**  (0.0377)  4.901 5.551 5.094 2.025*** 0.296*** 3.994*** 5  (4.620) (3.946) (5.217) (0.521) (0.0917) (0.381)  756.6*** 355.6*** 680.4*** 4.711* 0.0921 -1.589 :  (23.75) (35.94) (61.35) (2.677) (0.471) (1.957)  1,299 1,615 1,247 1,299 1,299 1,299  0.066 0.004 0.087 0.031 0.013 0.091  22 29 22 22 22  0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749  45 2.933 23.12 20.41 8.680 64.01				(0.0001/1)					
vyment       (0.0305)       (0.0353)         0.0858**       (0.0377)         4.901       5.551       5.094       2.025***       0.296***       3.994***       5         (4.620)       (3.946)       (5.217)       (0.521)       (0.0917)       (0.381)         756.6***       35.94)       (61.35)       (2.677)       (0.471)       (1.957)         (23.75)       (35.94)       (61.35)       (2.677)       (0.471)       (1.957)         1,299       1,615       1,247       1,299       1,299       1,299         0.066       0.004       0.087       0.031       0.013       0.091         2       29       22       22       22       22         2       29       22       22       22       22         0.0491       -0.0152       0.0671       0.0135       -0.00436       0.0749         0       0       0       0       0       0       0			0.0508*	0.0385					
yment (0.0377) 4.901 5.551 5.094 2.025*** 0.296*** 3.994*** 5.94 (4.620) (3.946) (5.217) (0.521) (0.0917) (0.381) 756.6** 355.6** 680.4** 4.711* 0.0921 -1.589 1.299 (23.75) (35.94) (61.35) (2.677) (0.471) (1.957) 1,299 1,615 1,247 1,299 1,299 1,299 0.066 0.004 0.087 0.031 0.013 0.091 22 29 22 22 0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749 45 2.933 23.12 20.41 8.680 64.01 0 2.29-07 0 0 0 0			(0.0305)	(0.0353)					
(0.0377) 4.901 5.551 5.094 2.025*** 0.296*** 3.994*** 5 (4.620) (3.946) (5.217) (0.521) (0.0917) (0.381) 756.6** 355.6** 680.4** 4.711* 0.0921 -1.589 (23.75) (35.94) (61.35) (2.677) (0.471) (1.957) 1,299 1,615 1,247 1,299 1,299 1,299 0.066 0.004 0.087 0.031 0.013 0.091 22 29 22 22 29 22 22 22 0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749 45 2.933 23.12 20.41 8.680 64.01 0 2.296-07 0 0 0	lagged police employment			0.0858**					
4.901       5.551       5.094       2.025***       0.296***       3.994***       5         (4.620)       (3.946)       (5.217)       (0.521)       (0.0917)       (0.381)         756.6***       355.6***       680.4***       4.711*       0.0921       -1.589         (23.75)       (35.94)       (61.35)       (2.677)       (0.471)       (1.957)         1,299       1,615       1,247       1,299       1,299       1,299         0.066       0.004       0.087       0.031       0.013       0.091         22       29       22       22       22       22         20       29       22       22       22       22         0.0491       -0.0152       0.0671       0.0135       -0.00436       0.0749         45       2.29=.07       0       0       0       0       0				(0.0377)					
(4.620)     (3.946)     (5.217)     (0.521)     (0.0917)     (0.381)       756.6***     35.6***     680.4***     4.711*     0.0921     -1.589       (23.75)     (35.94)     (61.35)     (2.677)     (0.471)     (1.957)       1,299     1,615     1,247     1,299     1,299     1,299       0.066     0.004     0.087     0.031     0.013     0.091       22     29     22     22     22     22       0.0491     -0.0152     0.0671     0.0135     -0.00436     0.0749       45     2.933     23.12     20.41     8.680     64.01       0     2.29e-07     0     0     0     0	post	4.901	5.551	5.094	2.025***	0.296***	3.994***	5.823***	17.92***
756.6*** 355.6*** 680.4*** 4.711* 0.0921 -1.589 (23.75) (35.94) (61.35) (2.677) (0.471) (1.957) 1,299 1,615 1,247 1,299 1,299 1,299 0.066 0.004 0.087 0.031 0.013 0.091 22 29 22 22 22 0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749 45 2.933 23.12 20.41 8.680 64.01 0 2.29e-07 0 0 0 0		(4.620)	(3.946)	(5.217)	(0.521)	(0.0917)	(0.381)	(0.955)	(2.445)
(23.75)     (35.94)     (61.35)     (2.677)     (0.471)     (1.957)       1,299     1,615     1,247     1,299     1,299     1,299       0.066     0.004     0.087     0.031     0.013     0.091       22     29     22     22     22       0.0491     -0.0152     0.0671     0.0135     -0.00436     0.0749       45     2.933     23.12     20.41     8.680     64.01       0     2.29e-07     0     0     0     0	Constant	756.6***	355.6***	680.4***	4.711*	0.0921	-1.589	10.76**	124.6***
1,299     1,615     1,247     1,299     1,299     1,299       0.066     0.004     0.087     0.031     0.013     0.091       22     29     22     22     22       0.0491     -0.0152     0.0671     0.0135     -0.00436     0.0749       45     2.933     23.12     20.41     8.680     64.01       0     2.29e-07     0     0     0     0		(23.75)	(35.94)	(61.35)	(2.677)	(0.471)	(1.957)	(4.906)	(12.56)
0.066 0.004 0.087 0.031 0.013 0.091 22 29 22 22 22 0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749 ( 45 2.933 23.12 20.41 8.680 64.01 0 2.29e-07 0 0 0 0	Observations	1,299	1,615	1,247	1,299	1,299	1,299	1,299	1,299
22 22 22 22 22 22 22 22 22 22 0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749 (45 2.933 23.12 20.41 8.680 64.01 0 2.29e-07 0 0 0 0 0	R-squared	990.0	0.004	0.087	0.031	0.013	0.091	0.052	0.041
0.0491 -0.0152 0.0671 0.0135 -0.00436 0.0749 ( 45 2.933 23.12 20.41 8.680 64.01 0 2.29e-07 0 0 0	Number of county	22	29	22	22	22	22	22	22
45 2.933 23.12 20.41 8.680 64.01 F 0 2.29e-07 0 0 0 0	Adjusted R-squared	0.0491	-0.0152	0.0671	0.0135	-0.00436	0.0749	0.0347	0.0232
0 2.29e-07 0 0 0 0	F test	45	2.933	23.12	20.41	8.680	64.01	34.81	26.92
	Prob >F	0	2.29e-07	0	0	0	0	0	0
	7 O C !! ** ** **								

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Variables are UCR counts of card 1(founded): total larceny, strong arm robbery, murder, total rape, total robbery, motor vehicle theft These regressions are of counts and not rates per 10,000 in each respective county

# 9 Figures

