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Evaluating the impact of Proposition 47 on property crimes in Los Angeles using causal inference methods

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Evaluating the impact of Proposition 47 on property crimes in Los Angeles using causal inference methods

A thesis submitted in partial satisfaction
of the requirements for the degree
Master of Applied Statistics and Data Science

by

Bryan Ding

2023

ABSTRACT OF THE THESIS

Evaluating the impact of Proposition 47
on property crimes in Los Angeles
using causal inference methods

by

Bryan Ding
Master of Applied Statistics and Data Science
University of California, Los Angeles, 2023
Professor Chad J. Hazlett, Chair

This thesis paper examines the causal effects of California Proposition 47, a criminal justice reform measure passed in 2014, on property crime rates in Los Angeles and other major cities in California. Proposition 47 aimed to reduce prison overcrowding by reclassifying certain nonviolent offenses as misdemeanors and reallocating resources to education, mental health, and drug treatment programs. Existing research on Proposition 47's impact on property crime rates has yielded mixed results, primarily due to limitations inherent in observational studies. To overcome these limitations, this study employs a causal inference approach, especially focusing on difference in difference and synthetic control methods. A general reweighting approach to causal inference with time-series cross-sectional (TSCS) data from Chad Hazlet and Yiqing Xu is used too, including methods such as mean-balancing and kernel-balancing. We analyzed data from the FBI crime database spanning 11 years and covering 23 cities, focusing on property crimes such as burglary, larceny-theft, and motor vehicle theft. The synthetic control method allows for the estimation of the policy intervention's effect by creating a synthetic control group that closely matches the characteristics of the treated group, addressing confounding factors. The study finds evidence that Proposition 47 increased property crime in Los Angeles and multiple major cities in California, supported by the average treatment effect on the treated (ATT) calculations and graphical representations. However, these conclusions rely on the assumptions made in the causal inference framework. Additionally, other studies indicate that Proposition 47 achieved decarceration and reduced racial prejudices within the judicial system, emphasizing the need to consider broader social impacts. The results of this study should be interpreted with caution, and further exploration of Proposition 47's long-term effects on the criminal justice system, communities, and individuals is necessary.

The thesis of Bryan Ding is approved.

Yingnian Wu

Frederic R. Paik Schoenberg

Chad J. Hazlett, Committee Chair

University of California, Los Angeles

2023

TABLE OF CONTENTS

1 Introduction **1**

2 Data **4**

3 Methodology and analysis **6**

3.1 Method background 6

3.2 Difference-in-difference (DID) 7

3.3 Mean balancing with synthetic control 11

3.4 Kernel balancing 16

3.5 DID with Synthetic control 20

3.6 Incorporating new treatment units 23

4 Conclusion **27**

References **29**

LIST OF FIGURES

2.1 Panel view of each observation with treatment status 5

3.1 Difference-in-difference model comparing crime rates in Los Angeles and Houston 1 year before and after Proposition 47 9

3.2 Difference-in-difference model comparing crime rates in Los Angeles and Houston 3 years before and after Proposition 47 9

3.3 Mean balancing weight distribution of non-treated units 14

3.4 Mean balancing estimated trends of counterfactuals versus actual trends from treated 15

3.5 Kernel balancing weight distribution of non-treated units 17

3.6 Kernel balancing estimated trends of counterfactuals versus actual trends from treated 18

3.7 Average treatment effect on the treated (ATT) over time 21

3.8 Difference in difference trends between Treatment and control groups 22

3.9 Panel view of each observation with treatment status including 3 major Californian cities 24

3.10 Mean balancing estimated trends of counterfactuals versus actual trends from treated, including 3 Californian cities 24

3.11 Kernel balancing estimated trends of counterfactuals versus actual trends from treated, including 3 Californian cities 25

3.12 DID estimated trends of counterfactuals versus actual trends from treated, including 3 Californian cities 25

LIST OF TABLES

2.1 First 6 rows of dataset 5

3.1 Output of mean balancing ATT calculations 13

3.2 Output of Kernel balancing ATT calculations 19

3.3 Output of DID ATT calculations 20

3.4 Output of mean balancing ATT calculations including 3 Californian cities 23

3.5 Output of kernel balancing ATT calculations including 3 Californian cities . . . 23

3.6 Output of DID ATT calculations including 3 Californian cities 26

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CHAPTER 1

Introduction

In November 2014, California Proposition 47, also known as the Safe Neighborhoods and Schools Act, was passed. This proposition served as a response to the state's issue with prison overcrowding. This landmark criminal justice reform measure aimed to reduce the state's prison population and redirect resources toward education, mental health, and drug treatment programs by reclassifying certain nonviolent offenses from felonies to misdemeanors. The reclassification under Proposition 47 included drug possession and property crimes valued at less than $950, which would now be misdemeanors instead of felonies, with the possibility of retroactive resentencing for individuals currently serving time for these offenses.

It's hard to overstate the issue of California's prison overcrowding. Poor health outcomes, high rates of violence, and high costs for taxpayers are just some of its main byproducts. This issue had led to court-ordered reductions in the state's inmate population [Gol11]. As such, it was no surprise that a new proposition was passed in California. However, Proposition 47's approval was met with both favor and criticism. Supporters contended that the proposal would reduce the state's prison population by shifting resources to more effective crime prevention initiatives and easing the load on taxpayers. They also claimed that the proposal will aid in the reduction of racial inequities in the criminal justice system, particularly with regard to drug charges, which have been demonstrated to disproportionately affect communities of color. Opponents contended that the proposal would increase crime, particularly property crime because people who would have been prosecuted with felonies for these actions would now face lesser punishments. They also claimed that the proposal would hinder law enforcement's ability to combat drug-related criminality, potentially leading to increased drug use and addiction [Geo14].

The question of whether Proposition 47 is a silver bullet for crime prevention and racial inequalities in the judicial system is complex and multifaceted and would require extensive research and data analysis to answer definitively. However, for the purposes of this paper, we will narrow our focus to a more specific question: whether Proposition 47 has had a measurable impact on property crime rates in Los Angeles and other large cities in California. By examining statistical data on crime rates in the years before and after the passage of Proposition 47 using methods to be outlined in the next chapter, we hope to determine whether there is a statistically significant increase in property crime that can be attributed to the measure. If such an increase is found, it could indicate a need for further investigation and research into the broader impact of Proposition 47 on public safety and criminal justice in California. Overall, this paper seeks to contribute to the ongoing discussion around criminal justice reform and the impacts of Proposition 47 specifically, by offering a data-driven analysis of its effects on property crime rates.

Now, it is important to note that some research adding to the debate already exists. A study conducted by the Public Policy Institute of California in 2018 found that Proposition 47 was associated with an increase in property crime rates in the state [MN18]. The study analyzed crime data from 2011 to 2016 and found that after the passage of Proposition 47, larceny thefts increased by 9.3 %, while motor vehicle thefts increased by 14.9 %. However, other studies have found mixed results regarding the impact of Proposition 47 on property crime rates. A study conducted by the University of California, Irvine, found that California's Proposition 47 didn't cause crime rise [Har18].

The main issue with the above reports is that they are very limited by the confines of observational studies. Observational studies are research studies that observe and analyze the behavior or outcomes of a population, without directly intervening or controlling variables. While observational studies can provide valuable insights into the relationships between variables, they also face a number of challenges that can limit the accuracy and reliability of their results, such as bias, confounding variables, and more. This study will take a causal inference approach that attempts to negate these shortcomings.

CHAPTER 2

Data

For this study, we utilized data obtained from the FBI crime database, which serves as an authoritative and comprehensive source of crime statistics in the United States [Inv23]. Our dataset encompasses a vast array of information spanning a period of 11 years and across 23 cities. In order to perform our analysis, we selected 22 of the largest cities within the US as our panel data. We exclusively focused on property crimes as defined by the FBI, which include offenses such as burglary, larceny-theft, and motor vehicle theft. Proposition 47 was implemented in November 2014, so we selected a timeframe that spans from 2008 to 2018. This approach offers an adequate reference frame before and after the policy's implementation, enabling us to observe trends and analyze patterns of criminal activity over time. By selecting this time span, we have ensured that our dataset is robust and representative, allowing us to draw insightful conclusions regarding the effects of Proposition 47 on property crime rates. The panel view in Figure 2.1 shows the treatment status of our data.

One of the strengths of using a comprehensive source like the FBI crime database issues such as missing variables are minimized, ensuring the accuracy and reliability of the data. However, the dataset presents unique challenges when it comes to conducting causal inference analysis due to the varying population sizes of the cities included in the study. If we were to base our analysis solely on net crime data, the results would be skewed and difficult to interpret since larger cities may naturally have higher levels of crime compared to smaller ones. To address this issue, we conducted a data transformation process to convert the crime data into a per capita basis. This involved dividing the total number of property crimes in each city by its corresponding population size and expressing the result as a rate per 100,000 people. This transformation allowed us to accurately compare crime rates between cities of different sizes, providing a more meaningful and comparable measure of crime incidence across the 22 cities in our panel data. After this transformation, we were left with a final clean and transformed dataframe that was perfectly suited for our causal inference models as seen in Table 2.1.

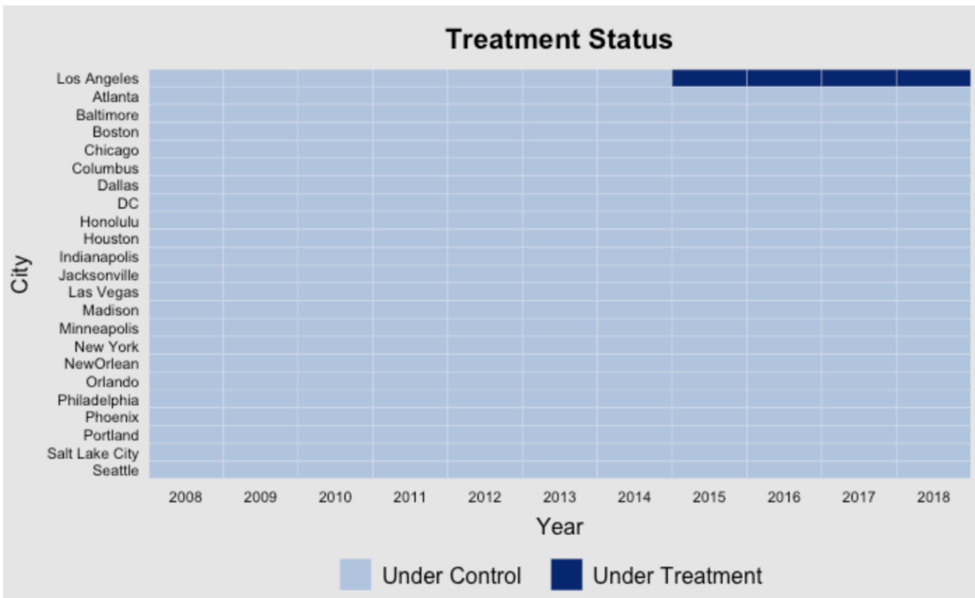

Figure 2.1: Panel view of each observation with treatment status

year <dbl>	city <chr>	propcrime <dbl>	treat <dbl>
2008	Los Angeles	2510.7957	0
2009	Los Angeles	2346.9057	0
2010	Los Angeles	2233.9435	0
2011	Los Angeles	2149.9191	0
2012	Los Angeles	2178.5083	0
2013	Los Angeles	2137.8160	0

Table 2.1: First 6 rows of dataset

CHAPTER 3

Methodology and analysis

3.1 Method background

Despite the significant debate surrounding Proposition 47, there has been limited research on its effects. One reason for this is that studies regarding crime policies face a large methodological challenge. While there are many statistical techniques to analyze the effects of a policy in an experimental study, crime policy data tend to only be observational. The main challenge here is that estimates of policy effects on crime rates may be biased due to many factors and confounders present in observational studies. As a way to combat this, our study will mainly focus on methods within the realm of causal inference. It is important to note that there are a handful of papers attempting to answer a similar question as the one posed here using methods in causal inference. For example, in [RB22] and [Jen21], synthetic control is indeed used to study Prop 47's effect on property crime, however, it is missing several key scopes such as studying multiple treatment cities. Also, the specific methodologies of said studies are brushed over and largely unexplained. This paper attempts to educate readers not just on Proposition 47, but also causal inference as a whole.

Using causal inference when examining the potential effects of a criminal justice policy is essential because it allows us to more accurately determine whether the policy caused the observed changes in crime rates. Without causal inference, policymakers may make decisions based on correlations or associations that do not indicate causality, leading to ineffective policies or even harmful outcomes. The goal of causal inference is to assess the causal effect of some potential cause (prop 47 in this case) on some outcome. The treatment that individual i actually does not receive is called counterfactual treatment. Likewise, the outcome under this treatment is referred to as counterfactual or potential outcome. This research will use counterfactuals to mimic crime rates if the policy change had not occurred. We will use longitudinal/panel data and comparison groups from outside the treated area to construct the counterfactuals. The main causal inference models at play here are Difference-in-difference, and Synthetic control.

3.2 Difference-in-difference (DID)

The Difference-in-Differences (DID) model is a statistical technique used in causal inference to estimate the causal effect of an intervention or treatment on an outcome of interest. It involves comparing changes in the outcome over time for a group that received the treatment with changes in the outcome over time for a group that did not receive the treatment. The basic idea behind the DID model is to compare the difference in the outcome before and after the intervention for the treatment group to the difference in the outcome before and after the intervention for the control group. The assumption underlying this approach is that any differences in the outcome between the two groups before the intervention are due to other factors that are constant over time and do not change in response to the intervention. By comparing the changes in the outcome for the treatment and control groups, the DID model seeks to isolate the effect of the intervention on the outcome from other factors that may be influencing it, arriving at the Average Treatment Effect on the Treated (ATT). This allows for a more accurate estimation of the causal effect of the intervention on the outcome of interest. The DID model has a number of advantages over other causal inference techniques, including its ability to control for time-invariant confounding variables, its flexibility in allowing for different types of interventions and outcomes, and its ability to handle missing data and other issues that can complicate causal inference [Cun21].

In a difference-in-differences model, the critical assumption is the parallel trends assumption, which posits that the effect of time on an outcome variable is identical between the treatment and control groups. This assumption is crucial because it enables us to isolate the effect of treatment on the outcome variable. However, it is challenging to validate the parallel trends assumption, as there are no foolproof statistical methods to do so. To assess the validity of the parallel trends assumption, a key falsification test involves examining data from prior periods to determine whether trends were parallel before the introduction of the treatment. This is typically done using an "eye-test" to visually inspect the data and identify any substantial deviations from parallel trends.

To perform this with Los Angeles as the treatment group, we also need to identify a control group that is similar to Los Angeles in terms of relevant characteristics, such as population size, demographics, and crime rates before the policy change. For this, we chose to use Houston, a city with similar demographics and crime rates as Los Angeles before Proposition 47. The figure below illustrates said parallel trend. Since there's no definitive estimate on which time frame illustrates the policy's effects most clearly, we chose two time periods of both 1 year and 3 years. This is illustrated in Figures 3.1 and 3.2

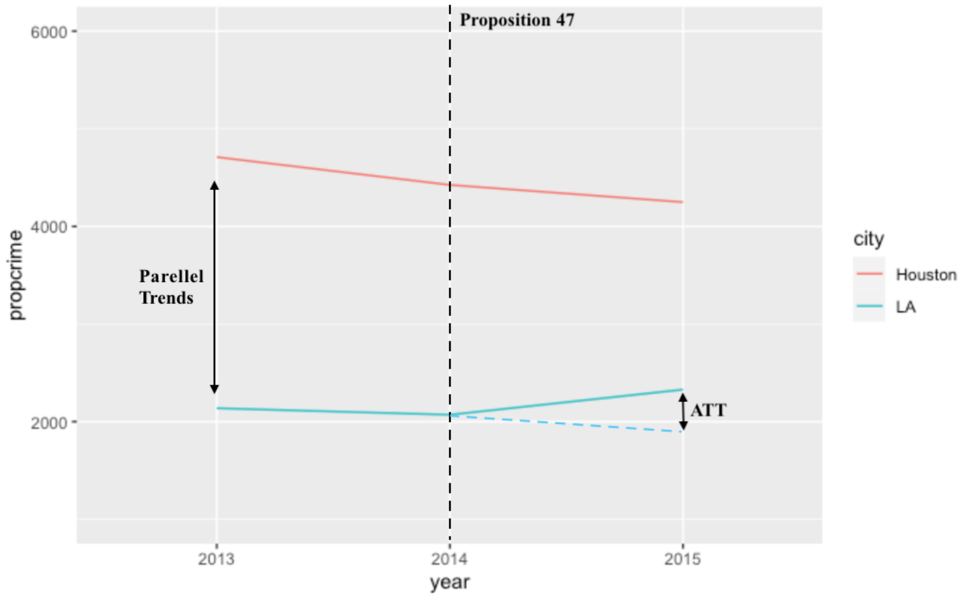

Figure 3.1: Difference-in-difference model comparing crime rates in Los Angeles and Houston 1 year before and after Proposition 47

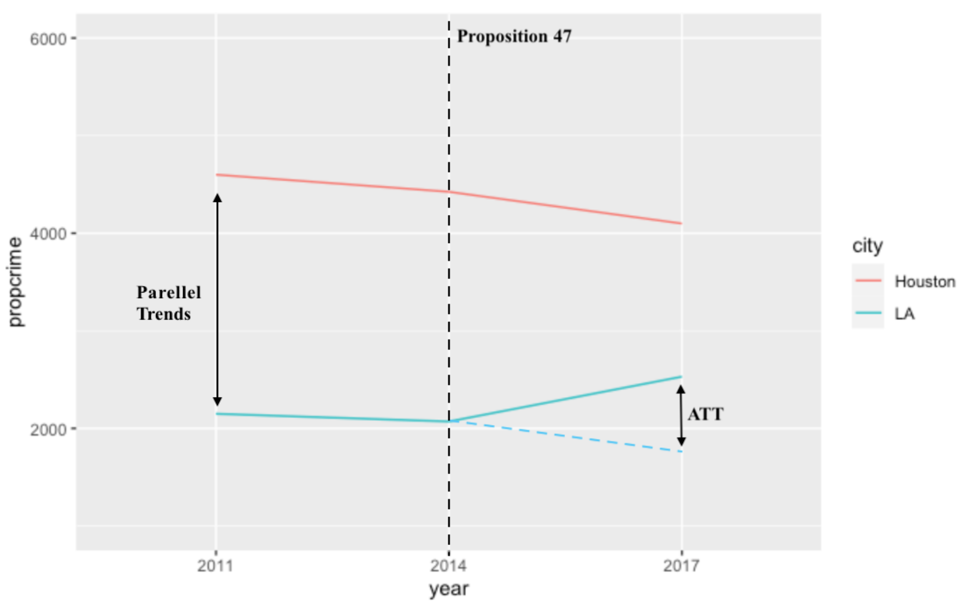

Figure 3.2: Difference-in-difference model comparing crime rates in Los Angeles and Houston 3 years before and after Proposition 47

We can now compare the changes in property crime rates in Los Angeles and Houston before and after the policy change. The average treatment effect on the treated (ATT) is an important concept in causal inference because it measures the causal impact of treatment on the group who actually received the treatment. This paper will outline multiple ways of estimating ATT, however we can estimate the ATT here by taking the difference in property crime rate changes between Los Angeles and Houston, as seen in the equations below.

1 year pre and post-treatment ATT:

$$\begin{aligned} ATT_{prop47} = [Crime^{LA}_{post} - Crime^{Houston}_{post}] \\ -[Crime^{LA}_{pre} - Crime^{Houston}_{pre}] \\ = [2328.55 - 4248.53] - [2070.45 - 4424.50] \\ = 434.07 \end{aligned}$$

3 year pre and post treatment ATT:

$$\begin{aligned} ATT_{prop47} = [Crime^{LA}_{post} - Crime^{Houston}_{post}] \\ -[Crime^{LA}_{pre} - Crime^{Houston}_{pre}] \\ = [2530.64 - 4099.02] - [2178.50 - 4572.31] \\ = 825.43 \end{aligned}$$

We can see that the parallel trends assumption looks to be satisfied, and the ATT is in fact present and significant. Beyond that, the ATT increases along with the timeframe, leading to speculations that the effects of Proposition 47 on property crime might be magnified with time. Now, one might certainly argue that the above equations are limited in that they only account for A: two groups, and B: two arbitrary time periods. This is of course a valid concern. Traditional DiD models serve as a great visualizer and a good first step. But for a more robust examination, we turn to more modern causal inference methods such as synthetic control.

3.3 Mean balancing with synthetic control

Synthetic control is a method of causal inference that allows researchers to estimate the effect of a policy intervention by creating a synthetic control group that closely matches the characteristics of the treated group. This method is particularly useful when there is no one perfect natural control group available, such as in our case. The synthetic control method begins by identifying a pool of control units that are similar to the treated unit based on observed characteristics, such as demographic and economic factors. Our panel data of the 22 large American cities serve as this pool. The weightings of these control units are then optimized to create a synthetic control group that closely matches the treated unit in the pre-intervention period. The effect of the policy intervention is then estimated by comparing the outcomes of the treated unit with the synthetic control group. By using the synthetic control group as a counterfactual, we can estimate the causal effect of the policy intervention, accounting for confounding factors that may have influenced the outcome variable.

Now, we have to select a method to perform synthetic control. Here, I used the excellent method developed by Chad Hazlet and Yiqing Xu. In [Cha18] the authors introduce a general reweighting approach to causal inference with time-series cross-sectional (TSCS) data. The authors introduce the mean balancing method that reweights the control units such that the averages of the pre-treatment outcomes and covariates are approximately equal between the treatment and (reweighted) control groups. The paper then relaxes the linearity assumption and proposes the kernel balancing method that seeks an approximate balance on a kernel-based feature expansion of the pre-treatment outcomes and covariates. The paper illustrates the method with simulations and two empirical examples and highlights that this approach is more feasible, stable, and reduces user discretion compared to existing approaches. Additionally, the method accommodates both short and long pre-treatment time periods with many or few treated units. It also achieves balance on the high-order "trajectory" of pre-treatment outcomes rather than their simple average at each time period.

Before we get started with the mean balancing method, it is important to note the key assumption of synthetic control. Assumptions are incredibly important to causal inference. If the assumptions are deemed more plausible and supported by evidence, there is generally higher confidence in the causal estimates produced by the chosen approach. However, it is also essential to acknowledge that no set of assumptions can be guaranteed to hold perfectly in every situation. The main assumption here is that the synthetic control group adequately represents the counterfactual trajectory of the treated unit, including the effects of time-varying factors that are shared across units. When constructing a synthetic control group, it is crucial to control for any time-varying factors that may affect the outcome variable of interest. These factors can include various city-specific characteristics, policies, economic conditions, or other time-dependent variables. By selecting appropriate control units and incorporating pre-treatment data, synthetic control attempts to capture the influence of these time-varying factors. As our control group consists of a large sample size of units that are similar to the treatment in characteristics, we are relatively confident this assumption holds.

As mentioned briefly above, The mean balancing method is a reweighting approach used in causal inference with time-series cross-sectional (TSCS) data, where one or more units are exposed to treatment at a given time, while a set of control units remain untreated throughout a time window of interest. The mean balancing method reweights the control units such that the averages of the pre-treatment outcomes and covariates are approximately equal between the treatment and (reweighted) control groups. This is achieved by computing a weight for each control unit that is proportional to the inverse of its distance to the treatment unit in terms of the pre-treatment outcomes and covariates. The goal of mean balancing is to achieve balance on the pre-treatment outcomes and covariates between the treatment and control groups, allowing for a more accurate estimation of the causal effect of the treatment. The mean balancing estimator for ATT is given by [Cha18]

$$\widehat{ATT}_t = \frac{1}{N_{tr}} \Sigma_{G_i=1} Y_{it} - \Sigma_{G_i=0} w_i Y_{it}$$

where the weight w_j are chosen s.t.

$$\frac{1}{N_{tr}} \Sigma_{G_i=1} Y_{it} = \Sigma_{G_i=0} w_i Y_{it}, \quad t = 1, 2, ..., T_0$$

and $\Sigma_{G_i=0} w_i = 1; w_i \geq 0$ for all i in the controls

So, we can see from our use of mean balancing, the weight distribution is carefully selected to give our synthetic control the best approximation (Figure 3.3). As opposed to DID, where the weight is distributed evenly among all non-treated groups.

We will now employ a reliable R package named "tjbal" [HX22]created by the authors mentioned in the section above to calculate the causal effect of Prop 47 using different methods within synthetic control. Upon analyzing the results of the mean balancing approach, it is evident that the ATT obtained from this method is considerably different from the one derived in section 3.2. The carefully selected weighting has resulted in an ATT of 472.2, as demonstrated in the output below. The corresponding Figure 3.4 illustrates how property crime in LA increased significantly following Proposition 47 as compared to the control group. Mean balancing did not result in a synthetic LA pre-treatment line to showcase the parallel trends assumption, for this, we will explore the next method of Kernel balancing.

```
Call:
tjbal.formula(formula = propcrime ~ treat, data = synth_data,
    index = c("city", "year"), demean = FALSE, estimator = "mean",
    vce = "jackknife")

   ~ by Period (including Pre-treatment Periods):
      2008       2009       2010       2011       2012       2013       2014       2015       2016       2017       2018
-2.293e-07 -2.122e-07 -2.249e-07 -2.470e-07 -2.442e-07 -2.435e-07 -2.688e-07  2.720e+02  4.549e+02  5.704e+02  5.915e+02

Average Treatment Effect on the Treated:
[1] 472.2
```

Table 3.1: Output of mean balancing ATT calculations

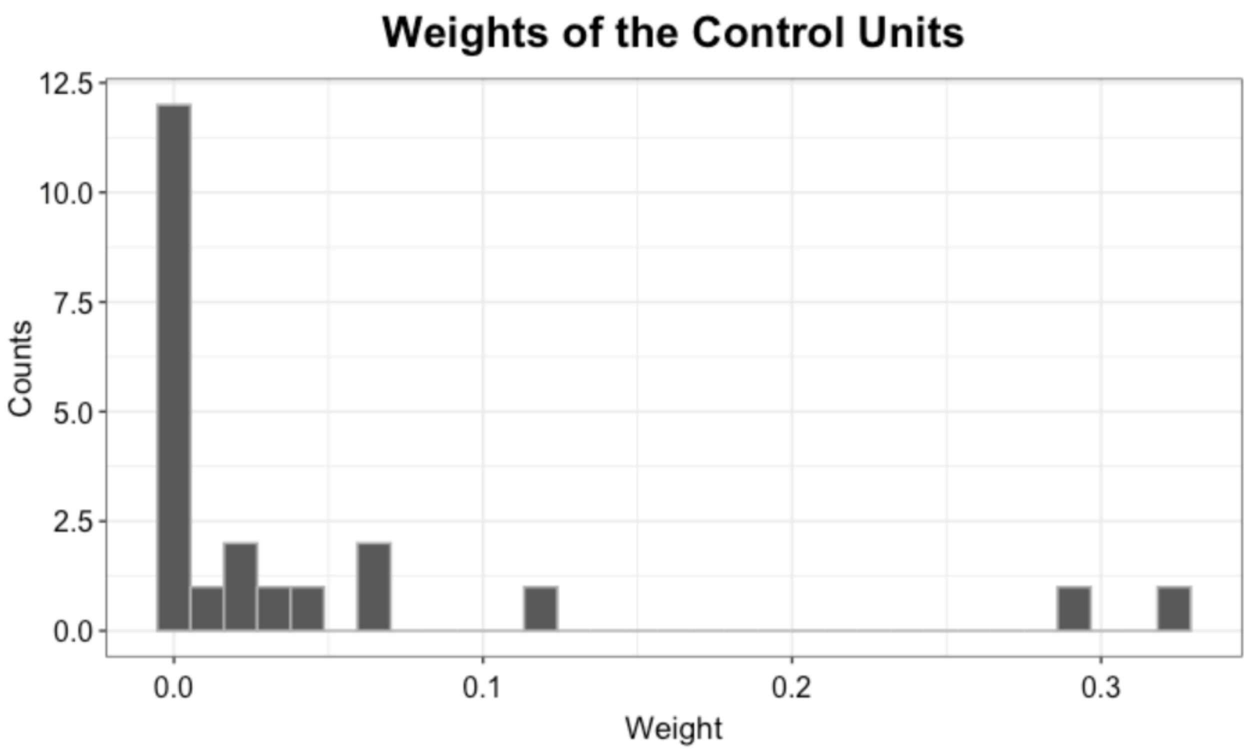

Figure 3.3: Mean balancing weight distribution of non-treated units

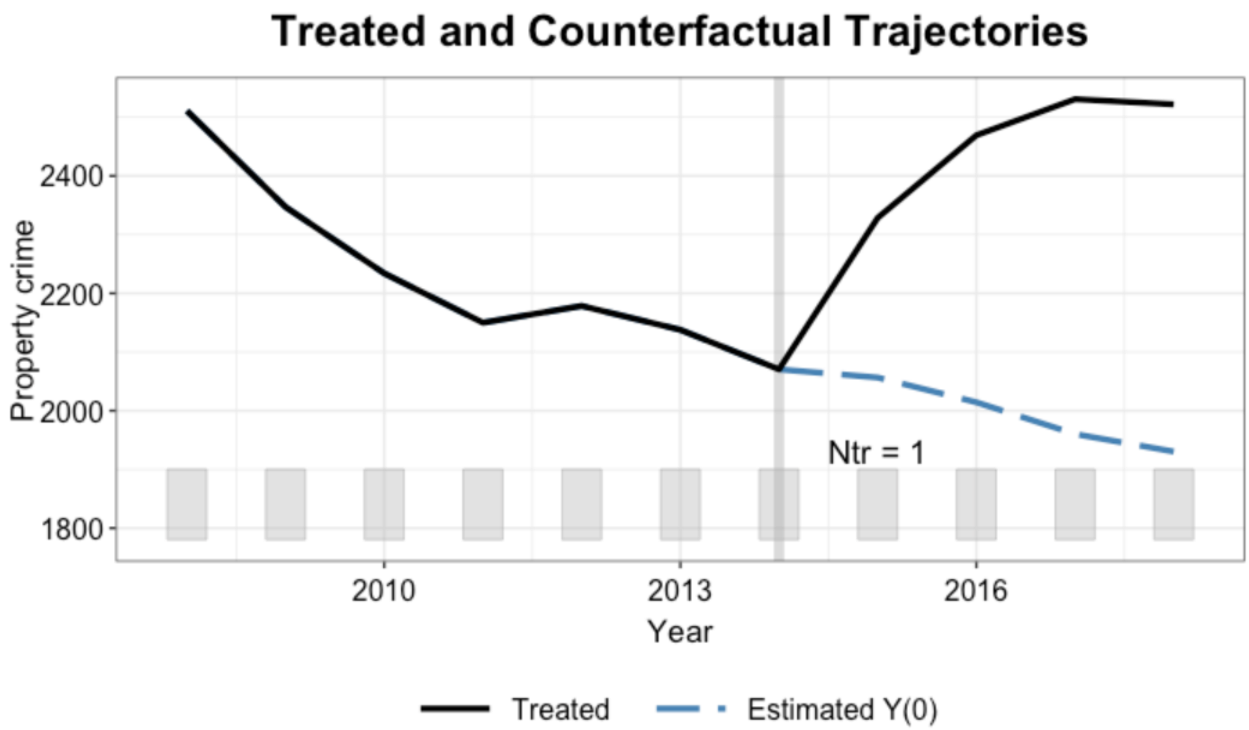

Figure 3.4: Mean balancing estimated trends of counterfactuals versus actual trends from treated

3.4 Kernel balancing

The kernel balancing method is a reweighting approach to causal inference with time-series cross-sectional data that relaxes the linearity assumption of the mean balancing method. The kernel balancing method seeks to balance the high-order "trajectory" of pre-treatment outcomes rather than their simple average at each time period. This method constructs a set of kernel-based features of pre-treatment outcomes and covariates, then seeks to balance the kernel features between the treatment and control groups. The kernel balancing method uses a kernel trick, which maps the input data into a higher-dimensional feature space, allowing for more flexible modeling of the relationship between pre-treatment outcomes and covariates. By using the kernel balancing method, it is possible to achieve an approximate balance on the high-order "trajectory" of pre-treatment outcomes and covariates, even in the presence of time-varying confounders. The resulting approach inherits the property of handling time-varying confounders as in synthetic control and latent factor models but has the advantages of accommodating both short and long pre-treatment time periods with many or few treated units and improving feasibility and stability with reduced user discretion compared to existing approaches. The Kernel balancing estimator for ATT is given by [Cha18]

$$\widehat{ATT}_t^k = \frac{1}{N_{tr}} \Sigma_{G_i=1} Y_{it} - \Sigma_{G_i=0} w_i Y_{it}$$

where the weight w_i are chosen s.t.

$$\frac{1}{N_{tr}} \Sigma_{G_i=1} \theta(Y_{i,pre}) = \Sigma_{G_i=0} w_i \theta(Y_{i,pre})$$

and $\Sigma_{G_i=0} w_i = 1; w_i > 0$ for all i in the controls

The weighting distribution chosen here is drastically different from the mean balancing method also, as seen in Figure 3.5. Through this kernel balancing estimator, we arrive at an ATT of 530.1, as demonstrated in the output below.

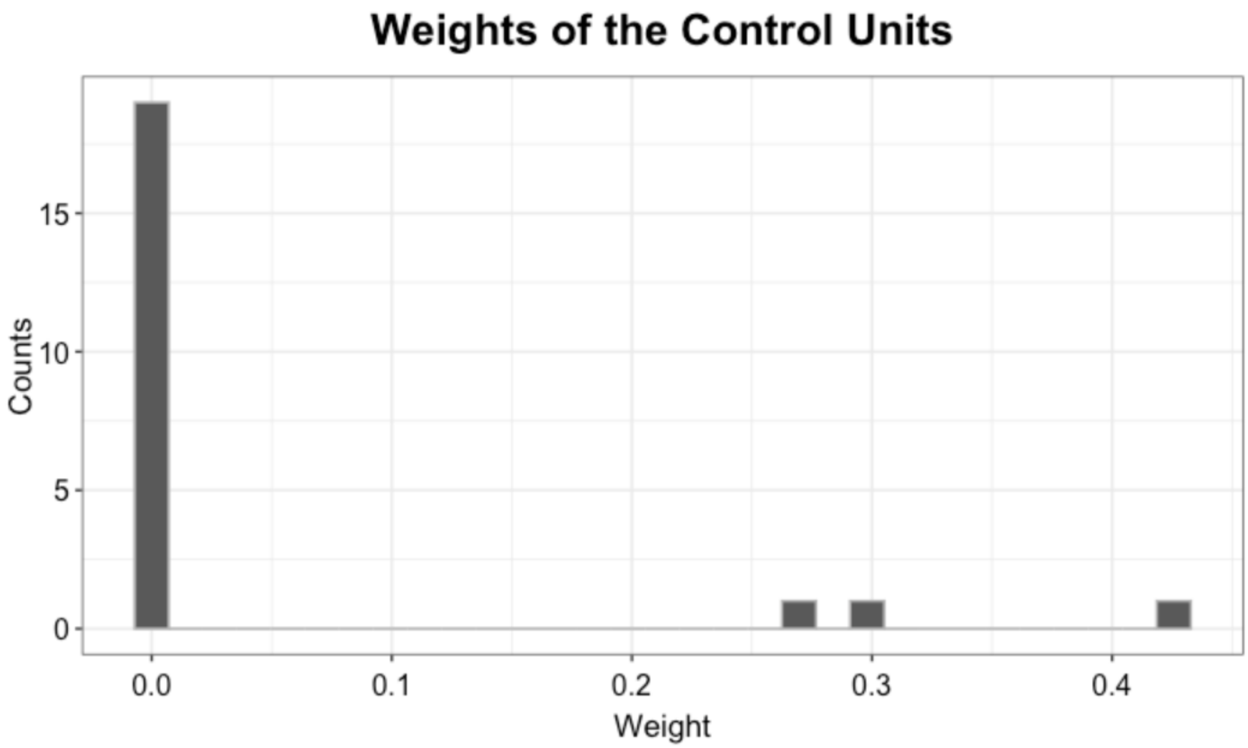

Figure 3.5: Kernel balancing weight distribution of non-treated units

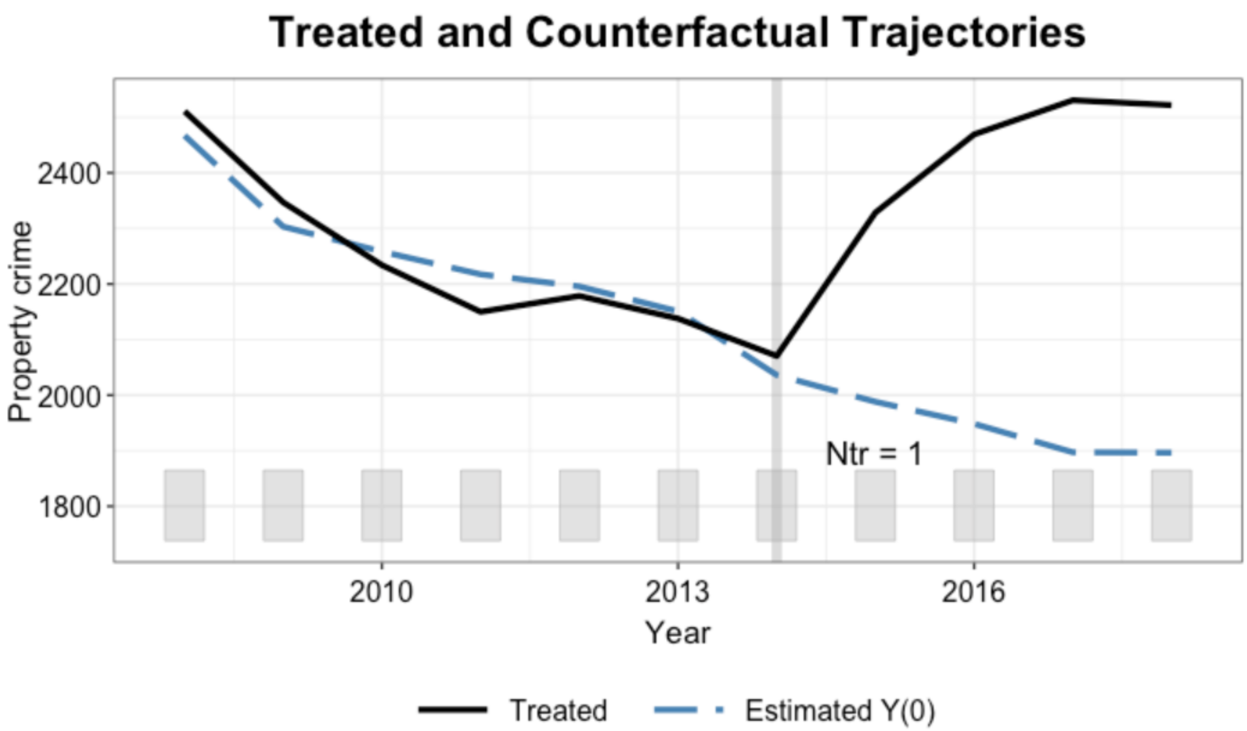

Figure 3.6: Kernel balancing estimated trends of counterfactuals versus actual trends from treated

```
Call:
tjbal.formula(formula = propcrime ~ treat, data = synth_data,
    index = c("city", "year"), demean = T, estimator = "kernel")

   ~ by Period (including Pre-treatment Periods):
  2008   2009   2010   2011   2012   2013   2014   2015   2016   2017   2018
 43.75  43.72 -24.32 -67.48 -17.08 -12.92  34.32 340.50 520.88 633.49 625.44

Average Treatment Effect on the Treated:
[1] 530.1
```

Table 3.2: Output of Kernel balancing ATT calculations

You can see from Figure 3.6 that Synthetic LA (dotted line), serves as an appropriate control group in this context. Throughout the pre-intervention period, LA and Synthetic LA exhibit similar trends, with minimal deviations from the overall trend. However, after the introduction of Proposition 47, it is observed that the property crime trends in LA experienced an upward trajectory while Synthetic LA remained relative stability declining. This observation implies that the increase in property crime in LA was likely caused by Proposition 47. It is important to note that while some minor deviations from the expected trends occurred during the pre-intervention period, they are inevitable as the control group of course deviates from LA in many factors such as demographics and population density. But the overall similarity in the trends between LA and Synthetic LA prior to Proposition 47's introduction strengthens the causal inference made using the kernel balancing methodology.

3.5 DID with Synthetic control

Calculating the ATT now with the difference-in-difference method using ”tjbal”, we arrive at a few conclusions. We can see that through DiD calculations, we obtain an ATT of 614.8 in Table 3.3. The weight we use in our synthetic control would be an average of all the cities used.

It is important to note that from the ATT graph in Figure 3.7, we see there was already an increasing trend pre-treatment in 2014. With that said, this is certainly a high ATT as it would imply Proposition 47 resulted in an extra 614.8 counts (per 100,000 people) of property crime in Los Angeles per year. This result is especially intriguing when combined with the traditional difference in difference graph seen in Figure 3.8, showing the change in crime between Los Angeles, and $Y(0)$ which here is the average count of the non-treated cities.

```
Call:
tjbal.formula(formula = propcrime ~ treat, data = synth_data,
    index = c("city", "year"), Y.match.npre = 0, demean = TRUE,
    vce = "boot", nsims = 200)

   ~ by Period (including Pre-treatment Periods):
   2008    2009    2010    2011    2012    2013    2014    2015    2016    2017    2018
-178.13  -23.21   21.23  -61.65   29.42  102.57  109.77  590.17  514.00  607.66  747.29

Average Treatment Effect on the Treated:
[1] 614.8
```

Table 3.3: Output of DID ATT calculations

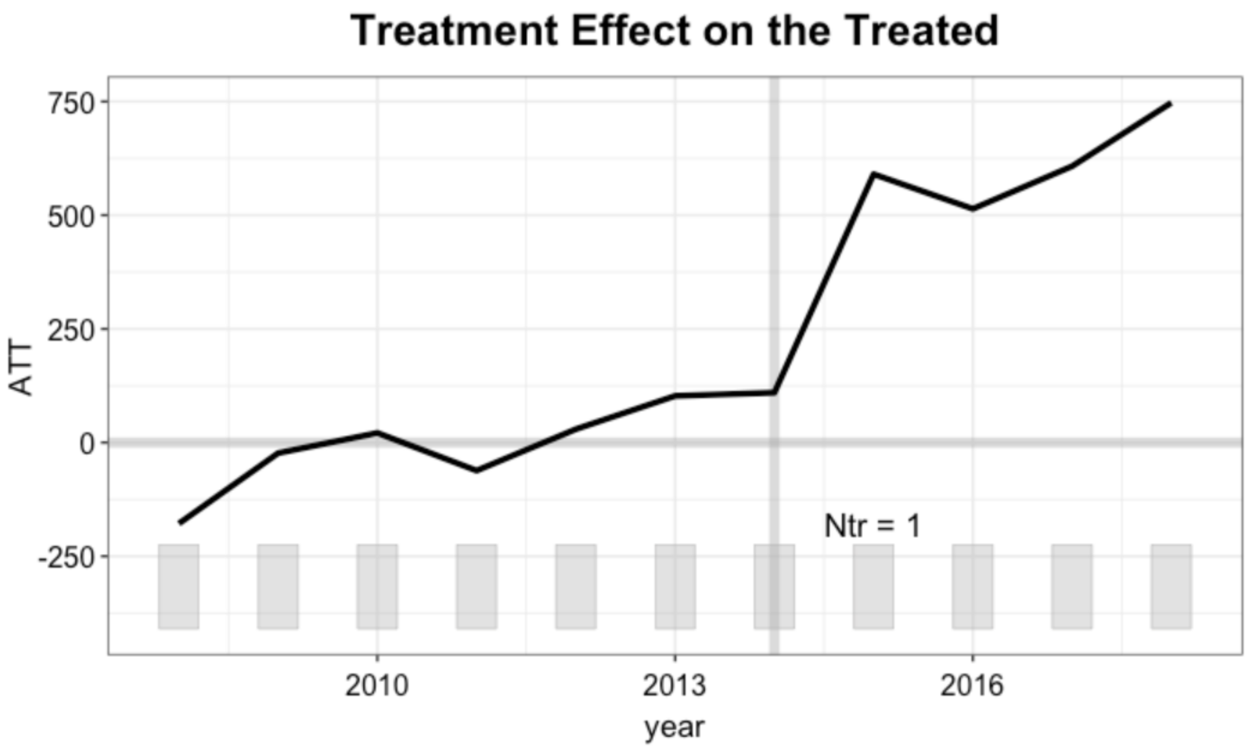

Figure 3.7: Average treatment effect on the treated (ATT) over time

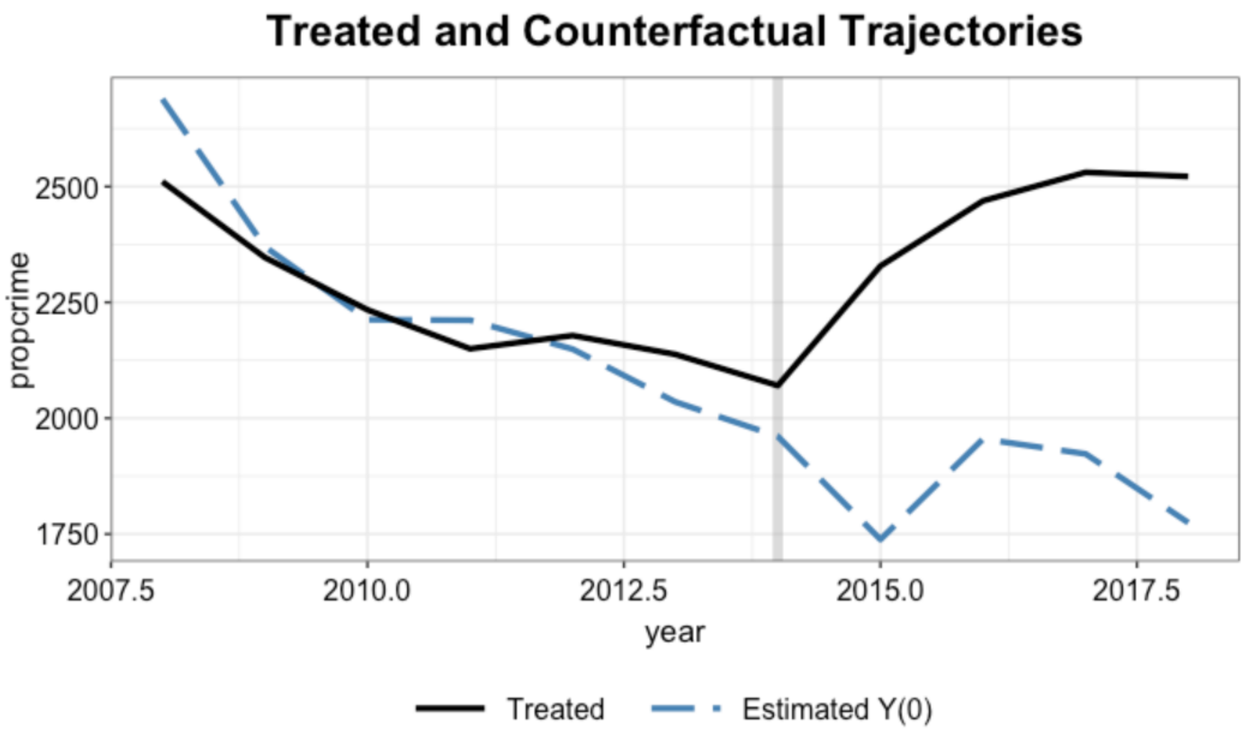

Figure 3.8: Difference in difference trends between Treatment and control groups

3.6 Incorporating new treatment units

A major commonality among studies done on Proposition 47, in the shortcoming department is that the findings of the study apply to a single city within an entire state experiencing a change in policy. Though this paper aimed to illustrate the methods above using only one treatment city for clarity's sake, attempting the above analysis with a larger treatment group would be beneficial for our results. We used the same FBI crime dataset to extract the property crime per capita of San Jose, San Diego, and San Francisco to add to the treatment group, as illustrated in the panel data view in Figure 3.9. We then repeated the synthetic control process from Mean Balancing (Table 3.4/Figure 3.10), Kernel balancing (Table 3.5/Figure 3.11), and DiD (Table 3.6/Figure 3.12). The results are firmly in line with what we learned about Los Angeles. There is a significant ATT calculated from all methods, (in fact, we see an increased ATT result here as compared to only Los Angeles as treatment) implying Proposition 47 affected property crime rates in other major cities in California too.

```
Call:
tjbal.formula(formula = propcrime ~ treat, data = synth_data1,
    index = c("city", "year"), demean = T, estimator = "kernel")

   ~ by Period (including Pre-treatment Periods):
   2008    2009    2010    2011    2012    2013    2014    2015    2016    2017    2018
-145.98  -18.91  -62.49 -128.66   77.55  422.55 -144.06  702.10  243.06  577.63  528.94

Average Treatment Effect on the Treated:
[1] 512.9
```

Table 3.4: Output of mean balancing ATT calculations including 3 Californian cities

```
Call:
tjbal.formula(formula = propcrime ~ treat, data = synth_data1,
    index = c("city", "year"), demean = FALSE, estimator = "mean",
    vce = "jackknife")

   ~ by Period (including Pre-treatment Periods):
   2008    2009    2010    2011    2012    2013    2014    2015    2016    2017    2018
-258.91 -282.83 -333.90 -330.46   83.41  720.67  540.10 1160.65  735.37 1101.28  890.41

Average Treatment Effect on the Treated:
[1] 971.9
```

Table 3.5: Output of kernel balancing ATT calculations including 3 Californian cities

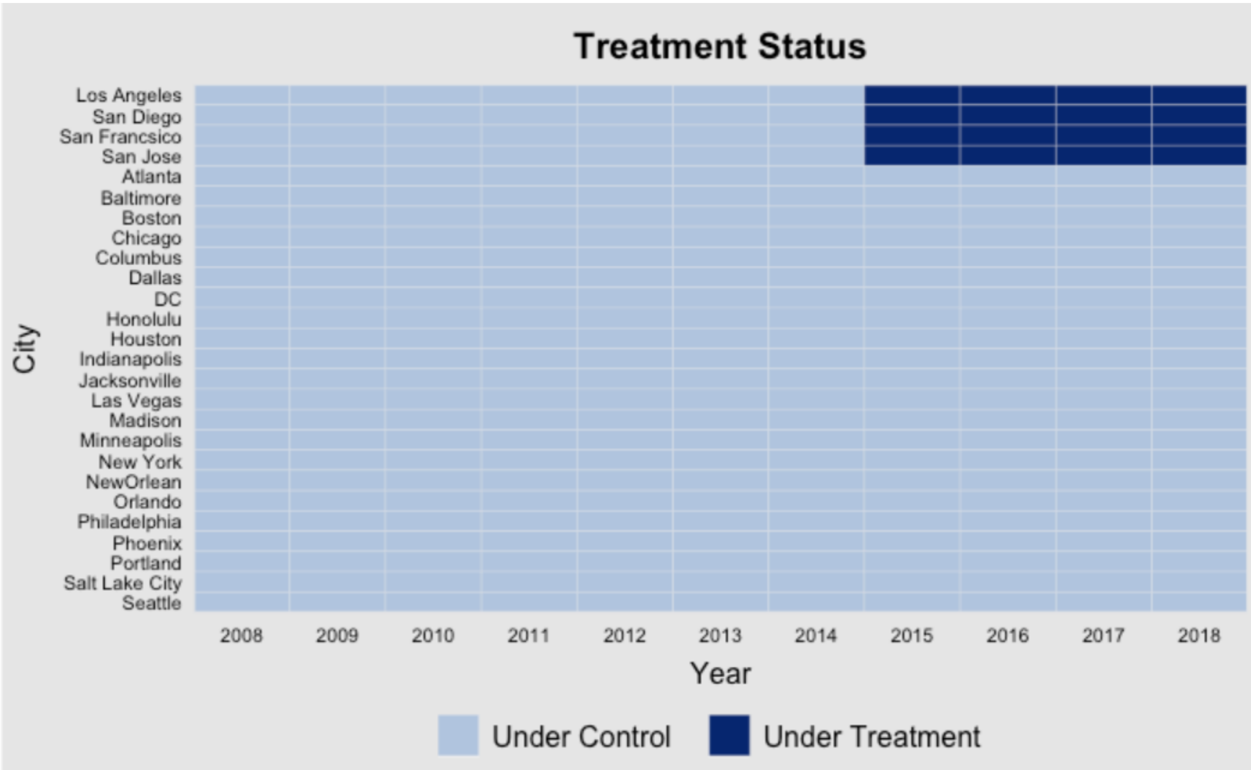

Figure 3.9: Panel view of each observation with treatment status including 3 major Californian cities

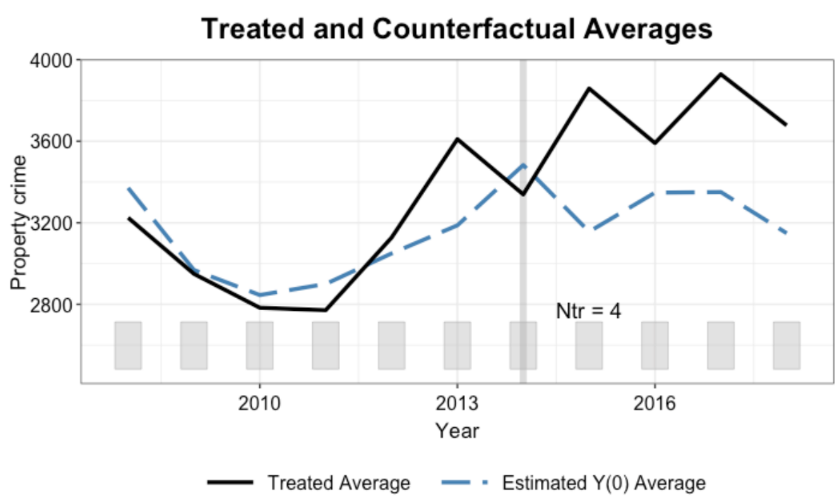

Figure 3.10: Mean balancing estimated trends of counterfactuals versus actual trends from treated, including 3 Californian cities

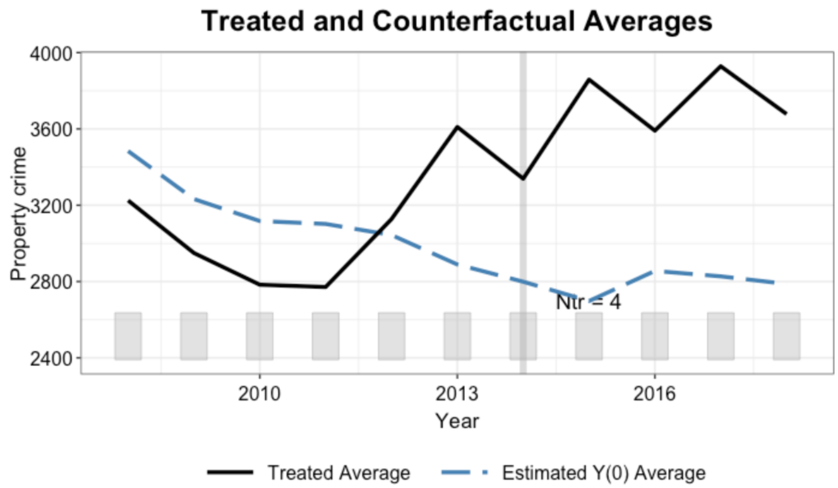

Figure 3.11: Kernel balancing estimated trends of counterfactuals versus actual trends from treated, including 3 Californian cities

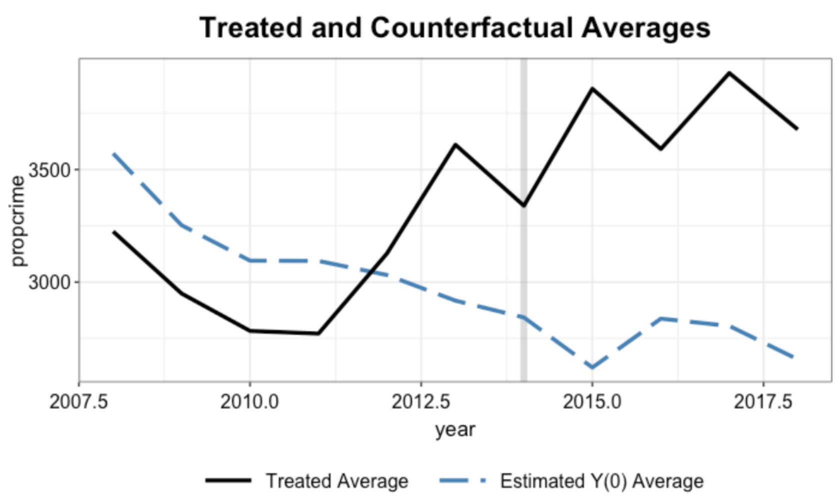

Figure 3.12: DID estimated trends of counterfactuals versus actual trends from treated, including 3 Californian cities

```
Call:
tjbal.formula(formula = propcrime ~ treat, data = synth_data1,
    index = c("city", "year"), Y.match.npre = 0, demean = TRUE,
    vce = "boot", nsims = 200)

   ~ by Period (including Pre-treatment Periods):
   2008    2009    2010    2011    2012    2013    2014    2015    2016    2017    2018
-346.45 -303.11 -311.89 -322.64   95.69  692.40  496.00 1237.70  753.26 1122.97 1020.75

Average Treatment Effect on the Treated:
[1] 1034
```

Table 3.6: Output of DID ATT calculations including 3 Californian cities

CHAPTER 4

Conclusion

All in all, this study took a walk across different methods in causal inference, from simple to complex, and in each stage was able to find some level of evidence that Proposition 47 did indeed increase property crime in Los Angeles. Beyond that, the policy showed signs of increasing property crime across multiple major cities in California. The resulting average treatment effect on the treated (ATT) calculated along with graphs illustrating the proposition's effects show a clear picture of Proposition 47 causing higher property crimes. Of course, only as long as our causal inference assumptions hold.

Regardless, this study had its fair share of limitations. First, there are methodological limitations to causal inference. The effectiveness of causal inference and synthetic control depends heavily on the assumptions made about the data. Violation of these assumptions can lead to biased estimates. The scope at hand was also limited in that it only considers the statistical implications of Proposition 47. When it comes to policies, especially ones relating to the judicial system, the human impact cannot be as easily assessed as taking a look at a number. While the numbers suggest the proposition increased crime, they do not shed any light onto to social impact of the policy. From findings in recent studies [MN16] [AC 18], it would appear that Prop 47 did indeed accomplish decarceration and reduced racial prejudices in the judicial system.

In light of these limitations, it is important to approach the results of this study with caution and not make any hasty conclusions. It is crucial to continue exploring the long-term effects of Proposition 47 on the criminal justice system, communities, and individuals affected by the policy. Moreover, future studies could consider incorporating more robust methods, such as natural experiments or randomized controlled trials, to complement the findings of this study and further strengthen the evidence.

In conclusion, this study aimed to provide valuable insights into the causal effects of Proposition 47 on property crime rates in Los Angeles and other major cities in California. The findings highlight the need for policymakers and advocates to consider the potential unintended consequences of a policy. However, statistical analysis alone may not capture the complete picture. A comprehensive approach that combines statistical analysis with robust public policy research would be incredibly helpful. By integrating these complementary methods, policymakers can gain a deeper understanding of the intricate social and economic dynamics at play and make well-informed decisions.

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