The Impact of Execution Moratoriums on Homicide Rates

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Abstract

I examine the impact of moratoriums on executions on homicide rates. I employ the Synthetic Control Method to construct a synthetic version each of the four states that implemented a moratorium on executions. The results indicate no significant deterrent effect on homicide rates in these states. Robustness checks and supplementary analyses were conducted to ensure the validity of the primary SCM results. Furthermore, additional analyses incorporating control variables, such as population, race, income, and unemployment rate, were performed using a two-way fixed effects (TWFE) difference-in-differences (DiD) model. The findings consistently show no statistically significant effect of the policy on homicide rates.

JEL Codes:
Keywords: Crime; Death Penalty; Capital Punishment; Deterrence; Homicide; Synthetic Control Method

Introduction

One of the basic core principles in the field of economics is that humans respond to incentives, whether they are positive or negative. This principle is based on the assumption that rational human beings will attempt to avoid endeavors that cause them aches and pains (disutility) and instead engage in activities that bring them joy and happiness (utility). In the context of criminal justice policy, negative incentives are commonly referred to as deterrence. Deterrence theory posits that threats of punishment, and more importantly, the

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actual implementation of punishment, can dissuade individuals from engaging in certain actions. Deterrence is generally more effective when the actor believes that the probability of facing the threat is real and outweighs the potential benefits they would gain from such behavior.

Our entire criminal justice system is built on the idea of deterrence: commit a crime, such as theft or assault, and face the associated punishment. Depending on the offense, this could involve a monetary fine and/or some form of incarceration. In more extreme cases, such as capital punishment, the convicted individual may face death as their punishment. The assumption behind capital punishment is that not only are human beings rational actors capable of weighing the costs and benefits of their actions, but also that the potential consequences defined in criminal justice laws are common knowledge. Deterrence has three key components: severity, certainty, and speed. The severity of the punishment, the likelihood of being caught and punished, and the speed of the punishment's execution all play a role. In the case of capital punishment, deterrence largely relies on the severity component, which is rarely imposed and often prolonged over several years before being carried out.

Capital punishment has been extensively studied over the past five decades. The literature on the deterrent effect of capital punishment is inconclusive at best. Recently, several states have implemented moratoriums on executions. These moratoriums involve the governors of these states halting capital punishment, although under the moratorium, a defendant can still be tried and sentenced to death. However, the execution will not be carried out as long as the moratorium remains in effect.

Capital punishment as a deterrent has been studied in various settings using different methods. Currently, there are five states with such moratoriums: Oregon (since 2011), Colorado (since 2013; the death penalty was abolished in 2020), Washington (since 2014; the death penalty was abolished in 2018), Pennsylvania (since 2015), and California (since 2019).

These recent moratoriums have various underlying reasons. One is the financial burden imposed on taxpayers due to the extensive costs associated with repeated court proceedings. Another significant factor is the perceived discrimination against mentally ill or black defendants, as well as individuals unable to afford high-priced legal representation. Moreover, the irreversibility of capital punishment raises concerns, as there is no way to undo an execution once it has been carried out. Additionally, the notable number of death penalty sentences being reversed raises questions about whether true justice is being served through capital punishment.

In this paper, my research objective is to evaluate the impact of state-level moratorium, on homicide rates. To accomplish this, I employ the Synthetic Control Method (SCM) developed by [Abadie and Gardeazabal, 2003]. After conducting the analysis, I find no statistically significant impact on homicide rates.

Literature Review

Capital punishment, also known as the death penalty, has been extensively examined through an economic lens in numerous studies published. One influential work by Becker [1968] presents an economic model that suggests the death penalty can act as a deterrent to crime. In this seminal work, Becker presents an economic model that considers the deterrence effect of capital punishment on potential offenders. He argues that individuals weigh the costs and benefits of committing a crime, including the risk of punishment. Becker suggests that the death penalty can act as a deterrent to crime.

Research on the deterrent impact of capital punishment has yielded mixed results, with several factors contributing to this variability. These factors include methods adopted, time periods examined, observational units, and the nature of the dataset (such as time-series or cross-sectional). Additionally, the selection and treatment of variables play a crucial role. For instance, researchers must decide whether to transform variables (e.g., using logarithmic or square root functions), handle outliers, or employ order differences instead of absolute values. These methodological differences make it challenging to reach a consensus on the deterrent effect of capital punishment [Yang and Lester, 2008].

Some early studies found a deterrent effect, while others failed to find such an effect. Studies that reported a deterrent effect likely played a role in the reinstatement of capital punishment in 1976 after it was deemed unconstitutional by the Supreme Court in 1972. One notable study by Ehrlich [1975] examines the relationship between capital punishment and its potential deterrent effect on crime rates. Using time-series analysis covering the period from 1933 to 1969, the study supports the deterrence hypothesis. Specifically, Ehrlich's findings suggested that one execution could potentially prevent 7-8 murders per year during the examined time period.

However, Passell and Taylor [1977] revisited Ehrlich's data, focusing on the years 1935 to 1964, and found that Ehrlich's results were highly sensitive to the choice of independent variables and model specifications. When using alternative models, Ehrlich's original findings failed to generate a deterrent effect for executions. In response to these criticisms, Ehrlich [1977] expands on his previous work, this time using a cross-sectional analysis for 1940 and 1950, refining his models, and incorporating updated data. The paper presents additional analysis and evidence supporting the deterrence hypothesis, suggesting that an increase in the probability of execution is associated with a decrease in homicide rates.

Cloninger [1977] examines the relationship between the death penalty and crime deterrence using a cross-sectional analysis, focusing solely on year 1960. By analyzing data from multiple states, the study finds significant evidence to support the deterrence hypothesis. Layson [1985] reevaluates the evidence on the relationship between homicide rates and deterrence in the United States, with a specific focus on the potential impact of capital punishment. Using time-series data, Layson employs a variety of specifications, including varying lengths of examined time periods, different sets of independent variables, and alternative functional forms. Overall, the findings indicate that there is evidence to support the claim that capital punishment serves as a deterrent to homicide.

Shepherd [2005] investigates the heterogeneity in the effects of capital punishment across different states in the United States. Using a data-set composed of U.S. counties from 1977 to 1996, the study examines whether capital punishment has a differing impact on murder rates among states. The analysis reveals that while some states experience a deterrent effect, others exhibit a brutalization effect, wherein executions lead to an increase in homicide rates. Mocan and Gittings [2003] contribute to the discussion by demonstrating that commutations to life imprisonment, rather than executions, have a significant deterrent effect. Their research explores the idea that the possibility of being removed from death row may weaken the perceived severity of the punishment, potentially diminishing the deterrent effect. The findings indicate that commuted sentences have a substantial impact on reducing future homicides, highlighting the role of the fear of execution in reducing violent crime rates. Using panel data, Dezhbakhsh et al. [2003] analyze the impact of capital punishment on murder rates. Their results indicate that capital punishment has a deterrent effect, particularly in states with a high execution rate. The authors suggest that a well-designed and consistently implemented death penalty system can contribute to reducing homicides.

On the other side of the debate, there is a growing body of literature suggesting that capital punishment does not have a deterrent effect. Cheatwood [1993], using a matching process, identified 293 pairs of counties in the U.S. that share 45% or more of their borders across a state line. The study used data from the 1988 *County and City Data Book* to examine the difference in the violent crime rate in each pair. By comparing counties within the same state that differ in their application of the death penalty, the study finds no significant influence of capital punishment on violent crime rates. Grogger [1990] takes a unique approach by analyzing daily time-series data in California from 1960 to 1963 to examine the immediate and short-term effects of capital punishment on homicide rates. Using two-week and four-week windows surrounding the dates on which an execution was carried out, he examines for potential deterrent effects. The study does not find significant evidence to support the deterrence hypothesis in the short term.

Furthermore, Donohue and Wolfers [2006] conducted an investigation into the empirical evidence concerning the impact of the deterrent effect of capital punishment. Their analysis concludes that studies supporting the deterrence hypothesis often rely on flawed methodologies, leading to an overstatement of the deterrent effect. Additionally, in another study, Donohue III and Wolfers [2009] examined panel data from all 50 U.S. states and found no evidence to support the notion that the death penalty has a significant deterrent effect on murder rates.

Similarly, Zimmerman [2004] examined the relationship between state executions and homicide rates to assess the potential deterrent effect of capital punishment. The study did not find any evidence to suggest that executions have a significant negative impact on murder rates. Another example is the study by Kovandzic et al. [2009], which evaluated panel data from 1977 to 2006. Their results provided no empirical support for the argument that the death penalty has a deterrent effect. Parker [2021], using the SCM, examines seven states that abolished capital punishment between 1995 and 2018 and its impact on deterring murders. The findings of the study suggest that the presence of capital punishment on the books in a state is not sufficient to deter murders. Overall, Parker's research challenges the belief that the mere presence of capital punishment legislation is effective in deterring murders.

The present study shares similarities with Oliphant [2022] research as both studies examines recent moratoriums on executions. However, there are some distinctions between the papers. For instance, I study the following states: Oregon, Washington, Colorado, and Pennsylvania whereas Oliphant studies Illinois, New Jersey, Washington, and Pennsylvania. Additionally, in my study, all untreated states serve as units in the donor pool, in contrast to Oliphant's approach of including only states that currently have the death penalty in the donor pool. I also use a TWFE DiD model to estimate the impact of this policy on homicide rates.

The current findings align closely with those of Oliphant [2022], as both studies fail to observe a deterrent effect of the death penalty. These findings suggest that recent moratoriums on executions have not resulted in a significant impact on reducing homicide rates.

Data

Data Source

I constructed a state-by-year panel using data collected from various sources, including the Federal Bureau of Investigation's (FBI) Uniform Crime Reporting (UCR) database, the Center for Disease Control and Prevention (CDC), the Bureau of Economic Analysis (BEA), and the Bureau of Labor Statistics (BLS). Homicide rates were collected from the FBI's UCR database for the years 2000 to 2020. Suicide rate data was obtained from the CDC, available from 2000 to 2019. Additionally, total property crime data was collected from the FBI's UCR database for the years 2000 to 2020. Homicide rates, suicide rates, and property crime rates are measured per 100,000 people.

Based on their previous inclusion in death penalty studies, twelve variables were included in this study [Kovandzic et al., 2009, Oliphant, 2022]. These variables are at the state-level. The following variables were used in the present study: population data, gender data (male and female), and race/ethnicity data provided by the CDC for the period spanning 2000 to 2020. Income data was extracted from the BEA, specifically the median household annual income, covering the years 2000 to 2020. Seasonally adjusted annual state-level unemployment rate data was collected from the BLS for the same time frame. I selected the unemployment rate from the first month (January) of each year for each state and used it as the rate for the entire year.

Education attainment variables, such as high school attainment and college attainment, were obtained from Mark W. Frank's website[1] and cover the years 2000 to 2015. These education variables are expressed as percentages by dividing the total number of graduates

[1] Accessed at https://www.shsu.edu/eco_mwf/inequality.html

by the total state population. Prison population data, measured per 100,000 adults, was acquired from Jacob Kaplan's website[2] and encompasses the years 2000 to 2016.

Table 1 below presents the summary statistics of the dataset used in this project. The panel dataset includes data from all fifty states spanning a twenty-one-year period, from 2000 to 2020.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Homicide Rate (per 100,000)	1,050	4.672	2.402	0.60	15.80
Suicide Rate (per 100,000)	1,000	14.153	4.174	1.50	29.70
Property Crime Rate	1,050	2,900.81	846.84	1,053.20	5,849.80
Prison Population Black Male	850	3,449	1,396	1,030	19,208
Prison Population White Male	850	516	197	136	1,060
Population	1,050	6,138,838	6,809,090	494,300	39,512,223
Male (gender ratio)	1,050	0.498	0.137	0.480	0.762
White (proportion of population)	1,050	0.827	0.264	0.296	0.978
Black (proportion of population)	1,050	0.113	0.102	0.004	0.385
Median Household Income	1,050	41,387.96	10,341.43	21,640	78,609
Unemployment Rate	1,050	5.398	2.009	2.00	13.70
High School Attainment	800	0.646	0.039	0.526	0.748
College Attainment	800	0.195	0.042	0.107	0.306

Suicide rate data runs from 2000 to 2019. The prison population variables run from 2000 to 2016 and is measured per 100,000 adults. The male variable measures the ratio among males and females. The race variables measure the proportion of population. The educational attainment variables run from 2000 to 2015.

Policy Implementation

Currently, there are five states that have implemented a moratorium on executions: Oregon in 2011, Colorado in 2013, Washington in 2014, Pennsylvania in 2015, and California in 2019. Currently, in the United States, there are 27 states that have the death penalty and 23 states that do not.

The reason behind these moratoriums is the claim that capital punishment has resulted in discrimination against mentally ill, black and brown defendants, or individuals who cannot

[2] Assessed at https://jacobdkaplan.com/index.html

afford expensive legal representation [Center, n.d.]. Additionally, it has been argued and debated that capital punishment provides no public safety benefits or value as a deterrent and has wasted billions of taxpayer dollars.[3] Pennsylvania Governor Tom Wolf, in 2015, stated that the decision for a moratorium was based on a flawed system characterized by endless court proceedings, inefficiency, injustice, and high costs [Center, n.d.]. Oregon Governor John Kitzhaber, in 2011, expressed his belief that executions did not contribute to public safety nor did they elevate our society morally. He further stated that the death penalty, as implemented in Oregon, lacked fairness and justice, and lacked the attributes of swiftness, certainty, and equal application for all individuals involved. Similarly, Washington Governor Jay Inslee, in 2014, expressed concerns about flaws within the system, emphasizing that when the ultimate decision is death, the stakes are too high to accept an imperfect process. He also noted that the majority of death penalty sentences lead to reversals, raising doubts about the entire system [Center, n.d.].

Method

I empirically test whether the implementation of moratorium policies has had an impact on homicide rates using the SCM approach developed by [Abadie and Gardeazabal, 2003]. The logic behind the SCM involves selecting a group of comparison units from the pool of untreated units, known as the donor pool. These comparison units are assigned weights in a way that ensures the synthetic control closely resembles the treated unit before the implementation of the treatment. Typically many untreated units receive a weight of zero, resulting in the synthetic control being a weighted average of only a subset of the donor pool.

To formalize this model, let's suppose there are S control units available, which have not implemented the moratorium on executions, forming what is referred to as the "donor pool." Let T_0 be the final time period before the policy's implementation. Thus, the periods before the treatment are denoted as $t = 1, ..., T_0$, while the treated periods are represented

[3] California Governor Gavin Newsom March 13, 2019 Center [n.d.]

by $t = T_0 + 1, ..., \overline{T}$.

Let $\mathbf{W} = (w_1, w_2, ..., w_S)$ be a $S \times 1$ vector, where each w_s is a non-negative weight assigned to an individual control unit from the donor pool of S units. The weights in the vector sum up to one. There are K predictor variables. Define $\mathbf{X}_1$ as a $K \times 1$ vector that contains the values of these predictor variables for the treated unit. Similarly, $\mathbf{X}_0$ is the $K \times S$ matrix that contains the same predictor variables for the S control units. The optimal counterfactual is determined by the vector of weights, $\mathbf{W}^*$, which minimizes the distance between $||\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}||$. Where $||\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}|| = \sqrt{(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})'V(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})}$ with V being a diagonal matrix. Let X_{sm} be the value of the mth covariates for unit s. Then the synthetic control weights minimize:

$$\sum_{m=1}^{K} v_m \left(X_{1m} - \sum_{s=1}^{S} w_s X_{sm} \right)^2$$

where v_m is a weight that represents the relative importance assigned to the mth variable [Cunningham, 2021]. The goal of constructing the synthetic control is to estimate the counterfactual time path of the outcome variable for the treated unit in the absence of the policy adoption.

I apply the SCM independently to Colorado, Oregon, Washington, and Pennsylvania, which currently have these policies, while using the remaining 45 states as the donor pool.[4] When applying the SCM to a single treated state, the other treated states are excluded from the donor pool because they implemented the policy at a later stage. The post-treated period for each state is initiated in the year when the moratorium on executions was implemented.

Predictor variables used in this project include the outcome variable (homicide rates) as well as suicide rates, property crime, prison population (separately for black males and white males), total population, gender (male-to-female ratio), race (percentage of white and black

[4] One reason for including states that do not have capital punishment is to have a larger pool of potential comparison units. This is particularly important because, with the synthetic control method, it is possible for states in the donor pool to receive a weight of zero. I also run synthetics where the donor pool is restricted to states that have the death penalty. Those results can be found in the Supplemental Appendix.

populations), median household income, unemployment rate, and educational attainment (separately for high school and college degree). Following Abadie et al. [2015], in addition to optimizing over the donor pool, I also optimize the weights of the predictor variables.

The purpose of the synthetic controls is to provide the best possible representation of what the homicide rates would have been in the treated states if the moratorium on executions had not been implemented. Any differences observed between the actual homicide rates in Oregon, Colorado, Washington, and Pennsylvania after 2011, 2013, 2014, and 2015, respectively, and the synthetic counterparts can be attributed to the respective moratoriums that were put in place.

Results

Using the techniques described in the previous section, I create a synthetic control for each treated unit (Oregon, Colorado, Washington, and Pennsylvania).[5]

Table 2 below presents the weights assigned to the donor states that make up each synthetic control.

[5]I have also generated synthetics where the predictor variables are given equal weights. The results of these analyses can be found in the supplemental appendix.

Table 2: State Weights in each Synthetic

States	Weight	States	Weight
Oregon		*Colorado*	
Alaska	0.135	Alaska	0.158
Hawaii	0.008	Maryland	0.173
Idaho	0.040	New Hampshire	0.397
Maine	.671	New Mexico	0.042
Rhode Island	0.135	Vermont	0.229
Utah	0.050		
Washington		*Pennsylvania*	
Hawaii	0.157	Maryland	0.067
Maine	0.056	Michigan	0.418
Minnesota	0.273	Missouri	0.098
Ohio	0.322	New Jersey	0.117
Rhode Island	0.118	New York	0.058
Utah	0.074	South Dakota	0.169
		Virginia	0.047
		Wyoming	0.023

All other states in the donor pool obtain zero weights for each synthetic. In each case the synthetic state weights sum to one.

Table 3 presents the predictor variables values for each treated state and its corresponding synthetic. This allows us to evaluate the quality of the synthetic by comparing the predictor variables between the actual treated states (Oregon, Colorado, Washington, and Pennsylvania) and their respective synthetics. Essentially, the table compares the pre-treatment characteristics of the treated states with those of the created synthetics. Table 7 in the Appendix presents the predictor variable weights. For example, the four most important predictors for synthetic Colorado (in order from highest to lowest weight) are homicide rate (.442), college attainment (.199), suicide rate (.103), and male population (.069).

Table 3: Homicide Rate Predictor Means

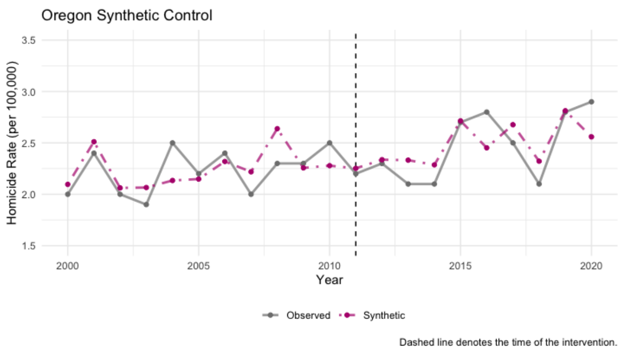
State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.33	2.36	3.54	3.59	2.92	3.02	5.50	5.38
Suicide Rate	16.5	15.6	18.4	15.5	14.4	12.4	12.9	12.5
Property Crime	3,530	2,407	3,082	2,427	3,893	2,975	2,121	2,459
Prison Pop. Black Male	3,909	2,590	4,038	3,606	2,796	2,967	3,804	3,399
Prison Pop. White Male	647	375	490	477	407	405	333	472
Total Population	3,833,168	1,277,607	5,057,360	1,856,077	6,474,998	5,776,368	12,620,622	7,798,563
Male Population	0.495	0.493	0.502	0.496	0.499	0.493	0.488	0.512
White Population	0.907	0.912	0.90	0.858	0.843	0.787	0.846	0.838
Black Population	0.025	0.028	0.048	0.070	0.046	0.074	0.131	0.142
Median HH Income	39,094	40,589	45,198	46,804	46,450	41,506	43,650	42,763
Unemployment Rate	6.56	5.42	5.03	4.65	6.02	5.21	5.67	5.67
High School Attainment	0.675	0.675	0.659	0.682	0.665	0.663	0.671	0.661
College Attainment	0.206	0.201	0.266	0.238	0.209	0.201	0.199	0.199

The key observation in Table 3 is that the states comprising the respective synthetics closely track the treated states in terms of the outcome variable, which in this case is homicide rates. Across all four synthetics, the outcome variable shows a strong similarity. In most cases, the synthetics closely match the values observed in the treated states. Therefore, the SCM does a commendable job of replicating the treated states' conditions prior to the policy implementation.

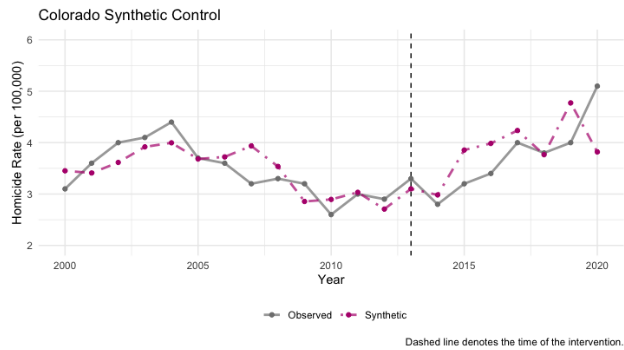
Treatment Effect

Figure 1 visually represents the two time series for each of the four synthetics. The dashed vertical lines indicate when the treated state implemented its moratorium on executions.

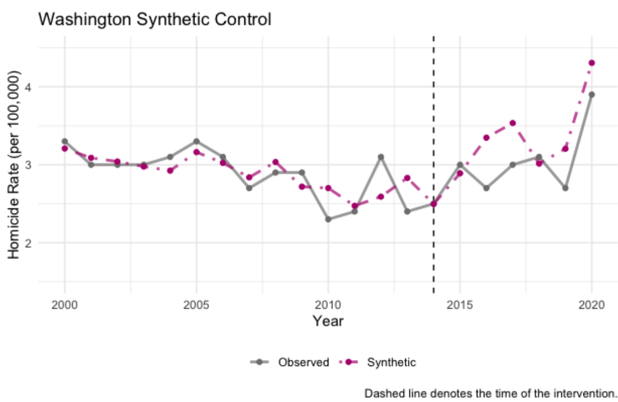
Figure 1: Synthetic Control Plots



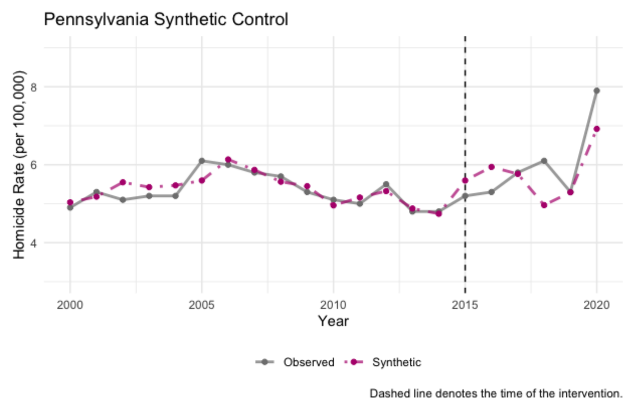
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates



(c) Actual & Synthetic WA Homicide Rates



(d) Actual & Synthetic PA Homicide Rates

Panel (a) of Figure 1 displays the results for Oregon, with the synthetic control represented by the dashed line and the observed data represented by the solid line. The post-treatment period shows no outstanding divergence between the synthetic and observed time series, suggesting that the policy had no discernible effect.

Panel (b) of Figure 1 illustrates the results for Colorado. The pre-treatment fit demonstrates a reasonably close match between the synthetic Colorado and the actual observed data. Similarly, in the post-treatment period, the synthetic Colorado and observed data remain relatively close to each other, indicating that the policy implementation did not have a noticeable impact on homicide rates.

Panel (c) of Figure 1 presents the results for Washington. The pre-treatment match shows a fairly good alignment between the synthetic Washington and the actual observed data. Although there is a slight divergence between the two series around 2016/2017, they converge again in 2018, suggesting no substantial impact of the policy on homicide rates.

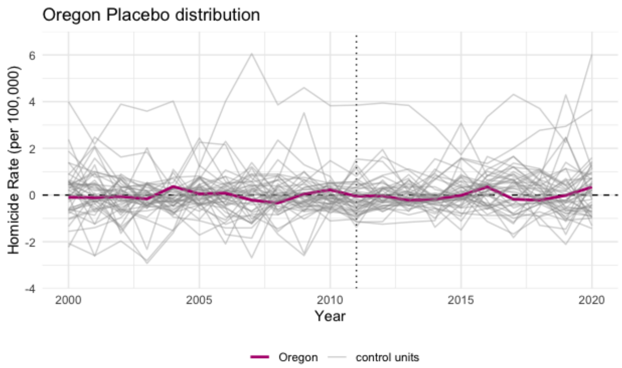
Panel (d) of Figure 1 illustrates the results for Pennsylvania. The pre-treatment fit appears to be quite accurate. Furthermore, there is no noticeable difference in homicide rates between the synthetic Pennsylvania and the actual Pennsylvania after the treatment is implemented.

Hypothesis Testing

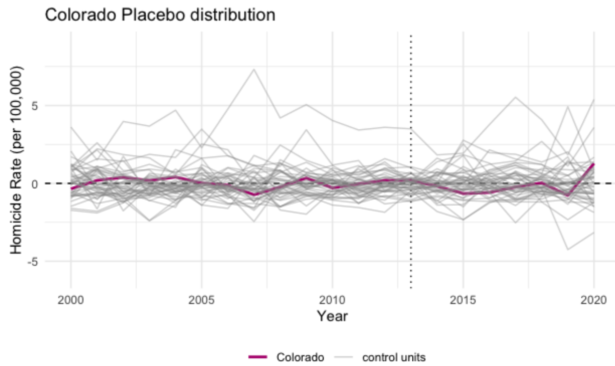
The most common approach to conducting statistical inference with synthetic control is to perform multiple placebo tests, following the methodology outlined in [Abadie et al., 2010]. In these placebo tests, each unit in the donor pool is treated as if it had adopted or received the policy in the same year it was actually implemented for the treated state. For each state in the donor pool, I assume that it had the treatment in the same year as the treated states (2011, 2013, 2014, and 2015). Consequently, a synthetic control is constructed, and the divergence observed with this "counterfeit" treatment date is calculated.

By comparing the computed divergence for each treated state (Oregon, Colorado, Washington, and Pennsylvania) to the distribution of divergences, I can draw conclusions about the impact of the policy treatment (moratorium on executions). If the computed divergence for a state falls within the middle of the distribution, it suggests that the policy had little impact. Conversely, if only a few states show significant divergence, it indicates a non-zero treatment effect.

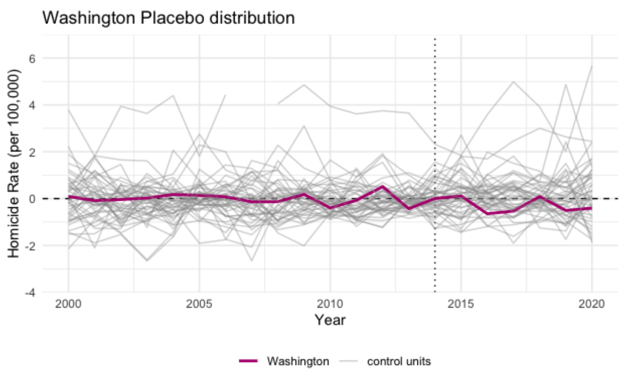
Figure 2: Placebo Tests



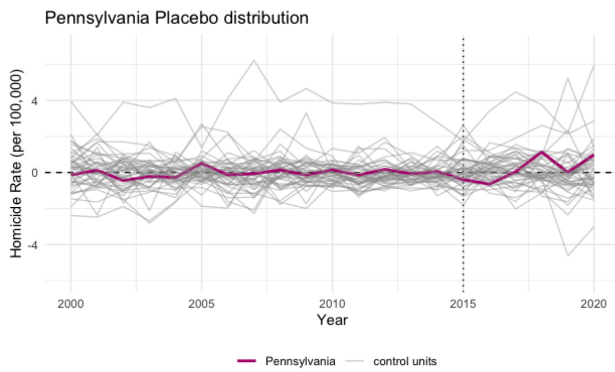
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

Rather than using the traditional approach of hypothesis testing, which involves examining the ratio of pre-MSPE and post-MSPE, I chose to employ a one-tailed test for the post-treatment periods. This decision was made to consider the direction and actual difference between the synthetic and treated time series, rather than solely looking at the squared distance. In the one-tailed test, I analyzed the distribution of placebo homicide rates in the post-treatment periods that were greater than or equal to the homicide rates of the treated units.

To conduct this test, I subtracted the synthetic homicide rate from the actual treated state homicide rate for each year in the post-treatment period, as well as for each placebo case. Then, I calculated the average of these differences to create a distribution. The same procedure was applied to all placebo cases, resulting in a distribution of average differences.

This entire process was separately repeated for each treated state. Table 4 below presents the results from the one-tailed test.

Table 4: Post-treatment P-value

State	P-value
Oregon	0.44
Colorado	0.54
Washington	0.74
Pennsylvania	0.20

In the one-tailed test for the post-treatment period, it was observed that 20 states had a greater or equal average post-treatment value compared to Oregon's, $(\frac{20}{46}) = 0.4348$. For Colorado, 25 states had a greater or equal average post-treatment value, $(\frac{25}{46}) = 0.5434$. For Washington, 34 states had a greater or equal average post-treatment value, $(\frac{34}{46}) = 0.7391$. For Pennsylvania, 9 states had a greater or equal average post-treatment value, $(\frac{9}{46}) = 0.1956$.

Based on the p-values presented in Table 4, these findings suggest that the policy did not have a statistically significant effect on homicide rates.

Robustness Checks

While the SCM is currently considered the most transparent method and does not require parallel trends for casual identification, for the sake of providing a more widely understood approach, I also chose to investigate this policy using the difference-in-differences (DiD) method. This also allows me to test the null results using a different method and see if they change when employing DiD.

Difference-in-Differences

In addition to examining the impact of the moratoriums on executions on homicide rates using the SCM, I employ a two-way fixed effects (TWFE) DiD model to further evaluate their effect on homicide rates:

$$Y_{st} = \alpha Intervention_{st} + \beta X_{st} + \sigma_s + \tau_t + \epsilon_{st}. \tag{1}$$

The variable Y_{st} represents an outcome for state s and year t. I will use homicide rate as the dependent variables. The model includes state fixed effects, notated by σ, year fixed effects, τ, and an error term, ϵ. I also include time-varying state level controls, which is notated by X. The coefficient of primary interest is α which is the DiD estimate of the effect of Moratorium on Executions on homicide rates in states that have passed this policy. DiD attempts to identify a causal effect by comparing the changes in outcomes over time between a group that has received the treatment/adopted a policy to a group that did not receive the treatment/adopt the policy.

Table 5 below displays the results on the impact of a moratorium on executions on homicide rates. In addition to the original four states (Oregon, Colorado, Washington, and Pennsylvania), this specification includes California as a treated state since it implemented a moratorium on executions in 2019. Consequently, there are a total of five treated states considered in the DiD analysis.

Table 5: DiD Homicide Rate Results

Dependent Variable:	Homicide Rate	
Model:	(A)	(B)
Variables		
Intervention	-0.0736	0.0657
	(0.1847)	(0.1688)
Property Crime		0.0007***
		(0.0002)
Population		-0.0386**
		(0.01635)
Male		-29.64
		(24.72)
White		15.64
		(12.16)
Black		11.51
		(19.46)
Income		-0.8192
		(1.1738)
Unemployment		-0.1606***
		(0.0452)
Fixed-effects		
States	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	1,050	1,050
R^2	0.89872	0.91220

These are DiD regression coefficients. Homicide Rate data is at the state level on an annual basis. All data included in the models are at the state level. Both models include both state and year fixed effects. The coefficients and standard errors for Income and Population have been re-scaled to be in the thousands. Standard errors are clustered at the state level in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Model (A) in Table 5 shows the results of the TWFE DiD analysis without control variables. The coefficient of interest, representing the moratorium on executions, is negative but not statistically significant. Model (B) includes control variables, and the coefficient of interest reverses, suggesting that the removal of capital punishment is associated with an increase in homicide rates. However, this coefficient is also not statistically significant. These findings align with previous DiD and synthetic control estimates, indicating no statistically significant impact of the policy on homicide rates, regardless of the inclusion of control variables.

Following McCannon [2022], I pooled the data from the four treated states with the four synthetics to calculate the average treatment effects. This pooling resulted in a panel data set with 168 observations (8 observational units $\times$ 21 years = 168 observations). Using this dataset, I estimate a DiD specification:

$$Y_{sty} = \delta Synthetic_t + \gamma Intervention_{sy} + \omega Synthetic_t \times Intervention_{sy} + \epsilon_{sty}. \quad (2)$$

The dummy variable $Synthetic_t$ is equal to one if the observation comes from a synthetically created observation, and zero if it represents the actual state's value. The dummy variable $Intervention_{sy}$ equals one if the observation occurs in a year, y, after state s has implemented its moratorium on executions. The final term represents the DiD component as it identifies whether the gap between the synthetic and actual treated state widens or narrows in the years following the moratorium on executions.

Table 6: Average Treatment Effects

Dependent Variable:	Homicide Rate
Model:	(C)
Variables	
Synthetic × Intervention	0.0244
	(0.2811)
Synthetic	0.0175
	(0.2415)
Intervention	-0.0077
	(0.2811)
Fit statistics	
Observations	168
R^2	0.00019

These are the DiD regression coefficients from the four treated states along with the four synthetics. Standard errors are presented in parentheses. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results presented in Table 6 above indicate that the implementation of moratoriums on executions does not yield statistically significant effects on homicide rates. These findings reinforce the previous conclusions drawn from the synthetic control method along with the TWFE DiD, which also demonstrated statistically insignificant results.

Conclusion

In conclusion, I investigate the impact of moratoriums on executions on homicide rates. The SCM is employed to construct synthetic control groups for each of the four states that implemented the moratorium. Overall, the results presented in this study indicate that for the states who have a moratorium on executions there is no statistically significant deterrent effect on homicide rates. To ensure the validity of the primary method, the study conducted robustness checks and supplementary analyses.

However, I would be remiss if I did not also raise the point that this paper's findings suggest no clear evidence that homicide rates increased due to moratoriums on executions.

Given that the death penalty is final and cannot be reversed, and its significant implications, policymakers should carefully consider the evidence regarding its deterrent effect, while also considering other factors such as fairness, justice, and equity in their decision-making process regarding capital punishment policy.

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Appendix

Table 7: Variable Weights in each Synthetic

Variables	Oregon	Colorado	Washington	Pennsylvania
Homicide Rate	.861	.442	.747	.453
Suicide Rate	.01	.103	0	.074
Property Crime	.001	.044	.017	.046
Prison Population Black Male	.005	.07	.024	.004
Prison Population White Male	.087	.002	.065	.001
Total Population	.005	.035	.018	0
Male Population	.017	.069	.01	0
White Population	.014	0	.019	.114
Black Population	.023	0	.001	0
Median HH Income	.002	0	.002	.044
Unemployment Rate	.004	.016	.019	.1
High School Attainment	.048	0	.072	.008
College Attainment	.014	.199	.001	.153

Supplemental Appendix

Synthetics with Equal Predictor Variable Weights

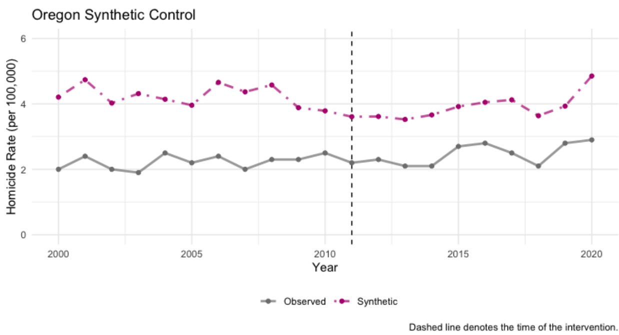
Table 8: State Weights in each Synthetic

States	Weight	States	Weight
Oregon		*Colorado*	
Alaska	.064	Alaska	.133
Arizona	.235	Arizona	.015
Florida	.089	Florida	.08
Hawaii	.003	Massachusetts	.198
Montana	.278	Missouri	.021
Rhode Island	.248	New Hampshire	.059
		New Mexico	.203
		Vermont	.289
Washington		*Pennsylvania*	
Alaska	.128	Illinois	.067
Arizona	.161	Michigan	.255
Florida	.077	Montana	.134
Hawaii	.053	New York	.357
Massachusetts	.071	North Dakota	.004
New Mexico	.048	Vermont	.18
Ohio	.079	Wisconsin	.159
		Wyoming	.006

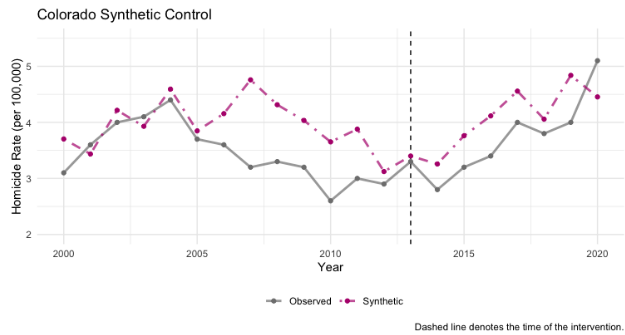
Table 9: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.33	4.08	3.54	4	2.92	4.02	5.50	4.46
Suicide Rate	16.5	16.8	18.4	16	14.4	14.4	12.9	12.1
Property Crime	3,530	3,004	3,082	2,743	3,893	3,107	2,121	2,326
Prison Pop. Black Male	3,909	3,974	4,038	3,991	2,796	3,015	3,804	3,702
Prison Pop. White Male	647	571	490	481	407	460	333	385
Total Population	3,833,168	3,885,702	5,057,360	3,807,396	6,749,998	6,165,769	12,620,622	11,342,472
Male Population	.0495	.495	.502	.499	.499	.498	.488	.491
White Population	.907	.871	.90	.875	.843	.812	.846	.811
Black Population	.025	.053	.048	.051	.046	.068	.131	.126
Median HH Income	39,094	39,533	45,198	43,934	46,450	43,198	43,650	43,810
Unemployment Rate	6.56	5.71	5.03	5.10	6.02	5.35	5.67	6.83
High School Attainment	.675	.652	.659	.664	.665	.665	.671	.664
College Attainment	.206	.199	.266	.225	.209	.210	.199	.205

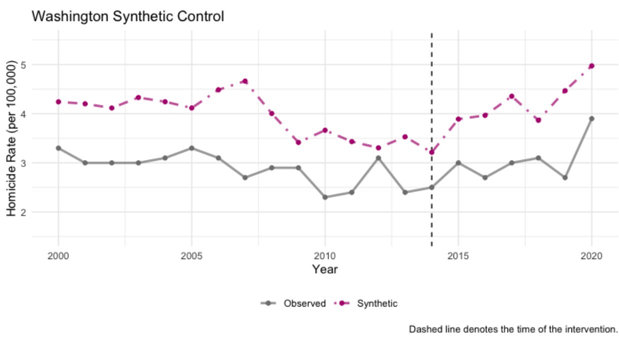
Figure 3: Synthetic Control Plots



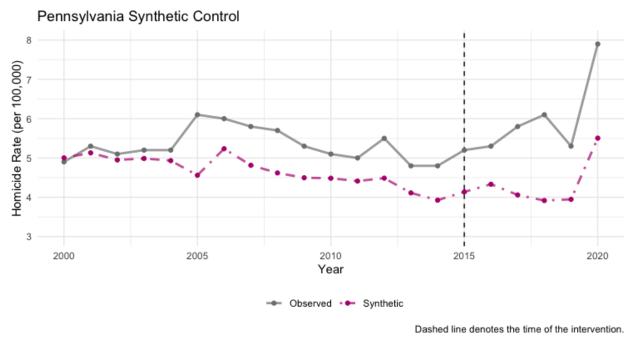
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates

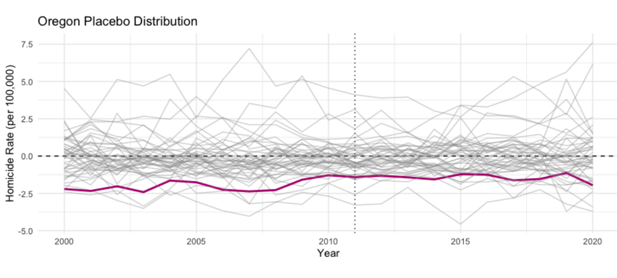


(c) Actual & Synthetic WA Homicide Rates

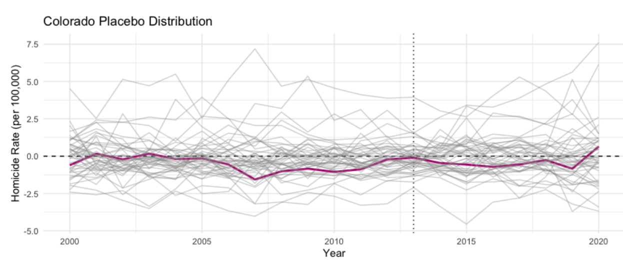


(d) Actual & Synthetic PA Homicide Rates

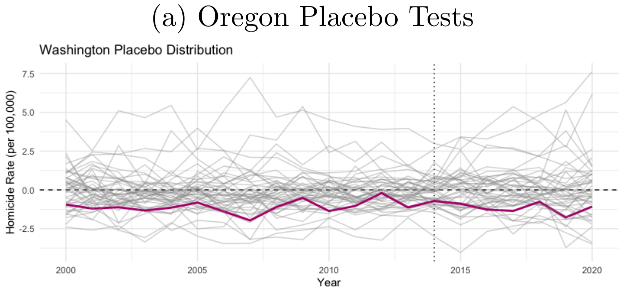
Figure 4: Placebo Tests



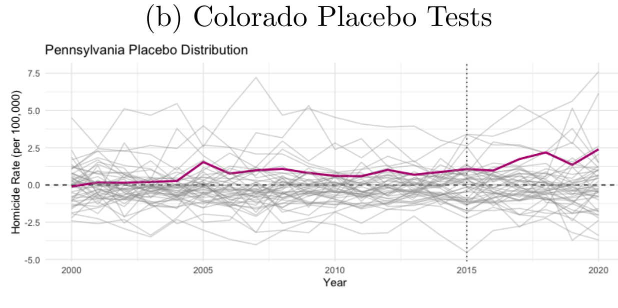
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

3-Year Moving Average Homicide Rate

This section presents the result when using a 3-year moving average for homicide rates with all predictor variables employed in this project.

Table 10: State Weights in each Synthetic

States	**Weight**	**States**	**Weight**
Oregon		*Colorado*	
Hawaii	.067	Alaska	.354
Maine	0.282	Hawaii	.083
Montana	.197	Kansas	.187
Ohio	.059	New Hampshire	.129
Rhode Island	.046	New Mexico	.037
Utah	.151	Vermont	.210
Vermont	.193		
Washington		*Pennsylvania*	
Alaska	.073	Maryland	.134
Connecticut	.063	Michigan	.438
Hawaii	.151	New Jersey	.171
Kansas	.201	New York	.024
Minnesota	.294	South Dakota	.233
Missouri	.046		
Utah	.165		

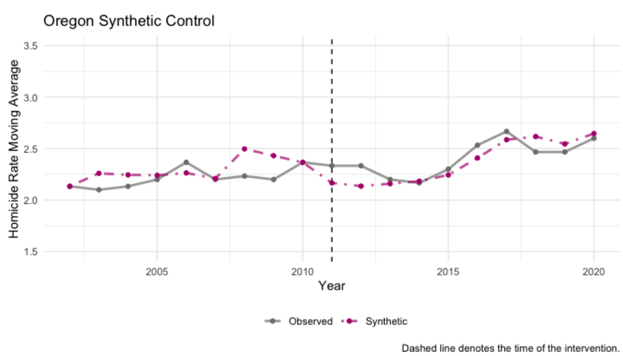
Table 11: Variable Weights in each Synthetic

Variables	Oregon	Colorado	Washington	Pennsylvania
Homicide Rate	.77	.256	.532	.389
Suicide Rate	.055	.167	.061	.054
Property Crime	.003	.102	.045	.074
Prison Population Black Male	.015	.072	.016	.019
Prison Population White Male	.001	0	0	.037
Total Population	0	.002	.007	0
Male Population	.009	.001	0	0
White Population	.029	.002	.093	.142
Black Population	.042	.025	.146	.034
Median HH Income	.020	.206	.058	.082
Unemployment Rate	.001	.024	.007	.074
High School Attainment	.054	.112	.022	.018
College Attainment	0	.031	.012	.076

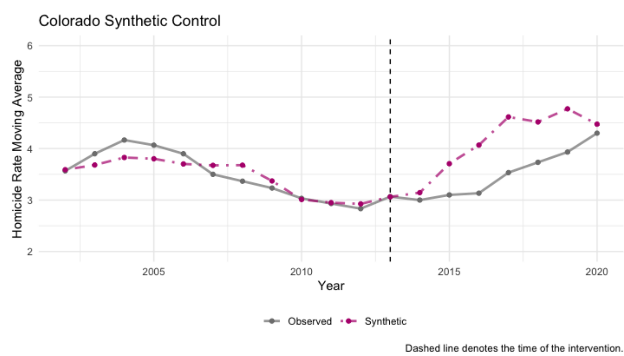
Table 12: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.31	2.33	3.49	3.71	2.88	3	5.44	5.29
Suicide Rate	16.7	16.8	18.7	18.1	14.6	14.4	13.1	12.2
Property Crime	3,415	2,549	3,012	2,809	3,801	3,016	2,075	2,296
Prison Pop. Black Male	3,797	3,763	3,986	3,963	2,708	2,946	3,792	3,279
Prison Pop. White Male	658	450	495	612	413	431	345	441
Total Population	3,873,625	1,973,843	5,129,051	1,259,948	6,834,407	3,338,134	12,655,259	7,298,032
Male Population	.495	.496	.502	.507	.499	.513	.446	.492
White Population	.905	.895	.898	.804	.839	.810	.771	.789
Black Population	.025	.025	.049	.038	.048	.058	.121	.142
Median HH Income	40,177	40,314	46,314	46,127	47,856	44,516	44,985	44,743
Unemployment Rate	6.70	4.82	5.27	5.25	6.12	4.85	5.82	5.83
High School Attainment	.679	.679	.663	.664	.669	.657	.676	.667
College Attainment	.208	.206	.270	.214	.214	.212	.202	.207

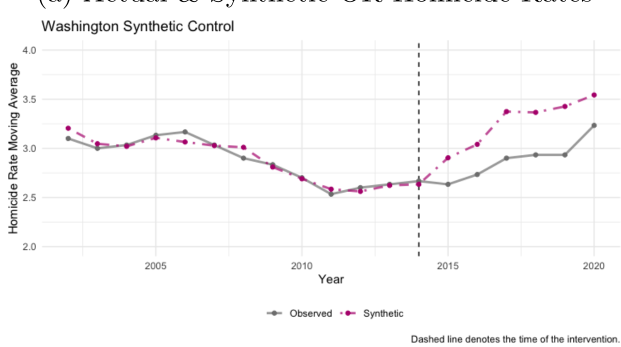
Figure 5: Synthetic Control Plots



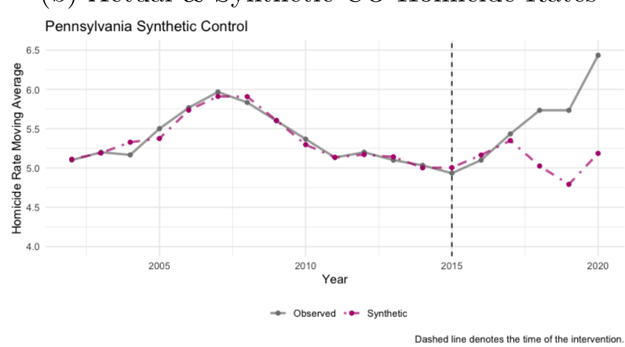
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates



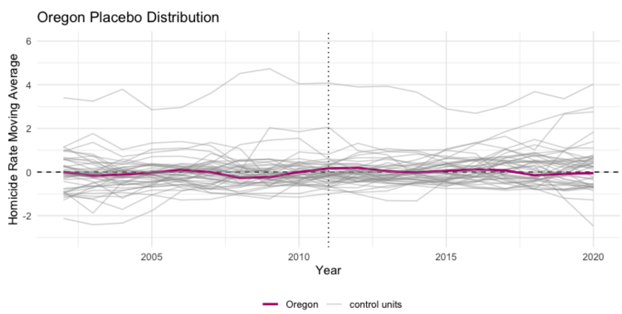
(c) Actual & Synthetic WA Homicide Rates



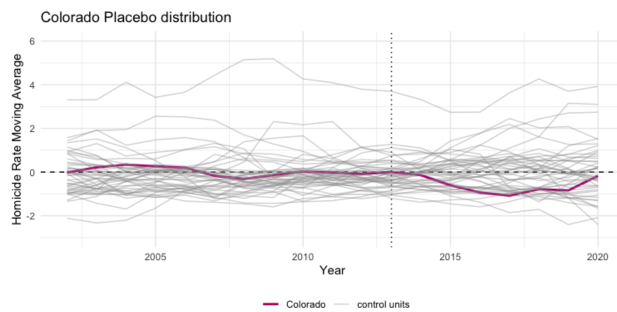
(d) Actual & Synthetic PA Homicide Rates

The plots above uses a three-year moving average for homicide rate to reduce some of the noise as the dependent variable as well as a predictor variable along with all the predictor variables involved with this project, unequal predictor variable weights. The moving average starts in 2002 and is the average homicide rate for the 2000, 2001, and 2002 for each individual state. That process is carried out for each year through 2020. So, the 2020 moving average homicide rate is a combination of 2018, 2019, and 2020.

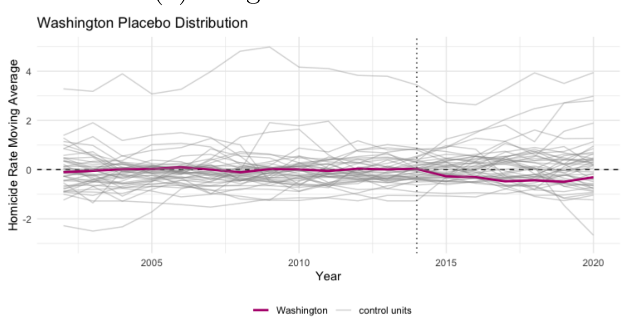
Figure 6: Placebo Tests



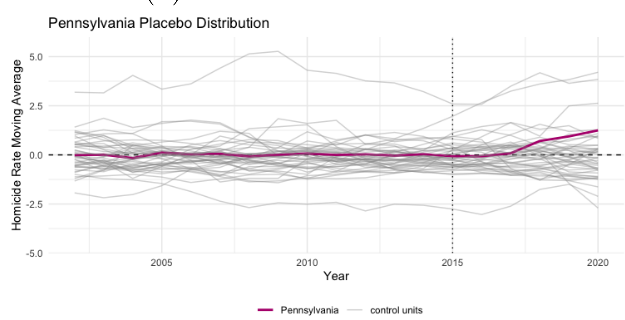
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

Homicide Rate as sole predictor variable

Table 13: State Weights in each Synthetic

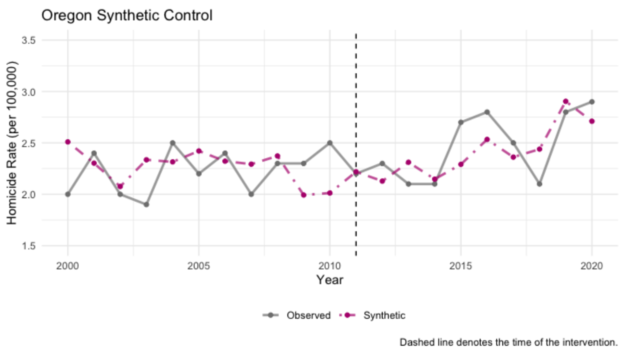
States	Weight	States	Weight
Oregon		*Colorado*	
Iowa	.032	Hawaii	.034
Maine	.051	Idaho	.034
New Hampshire	.471	Iowa	.035
Vermont	.033	Maine	.049
		Massachusetts	.030
		Minnesota	.034
		New Hampshire	.112
		North Dakota	.033
		Utah	.034
		Vermont	.040
Washington		*Pennsylvania*	
Hawaii	.033	Louisiana	.075
Idaho	.034	Maryland	.030
Iowa	.042		
Maine	.060		
Minnesota	.032		
New Hampshire	.249		
North Dakota	.032		
Utah	.033		
Vermont	.043		

All states that contributed less than 3% to the synthetic were omitted from this table. For Oregon's Synthetic there were 15 states that received a weight greater than 1% but strictly less than 2% $(1 < w < 3)$, where w is the weight associated with a particular state. For Colorado's Synthetic there were 32 states that received a weight greater than 1% but strictly less than 3%. For Washington's Synthetic there were 19 states that received a weight greater than 1% but strictly less than 3%. For Pennsylvania's Synthetic there were 43 states that received a weight greater than 1% but strictly less than 3%.

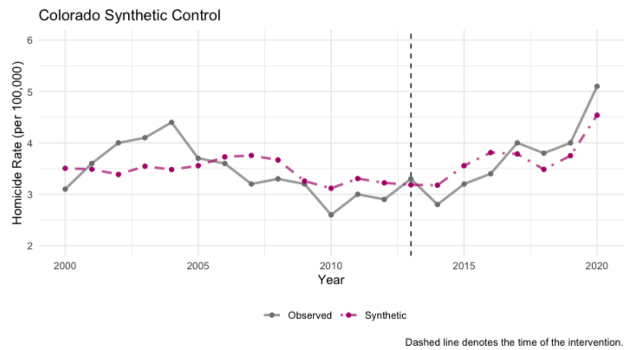
Table 14: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.33	2.33	3.54	3.54	2.92	2.92	5.50	5.50

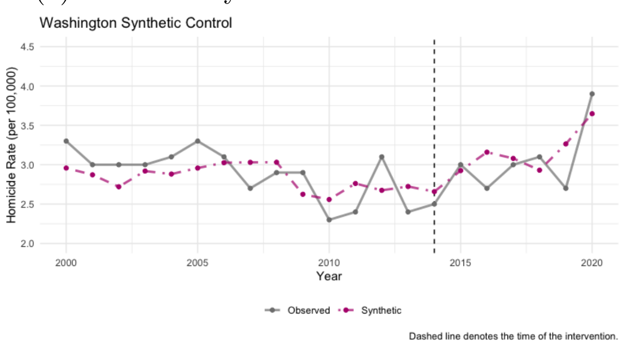
Figure 7: Synthetic Control Plots



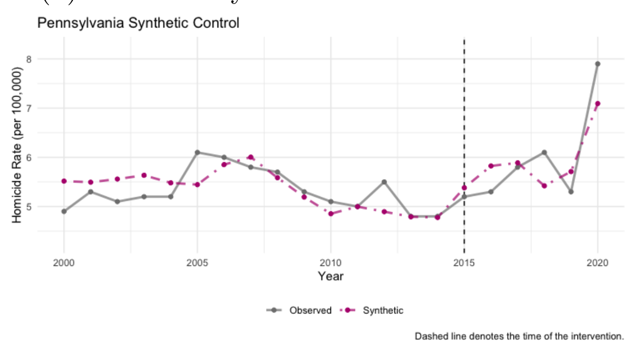
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates



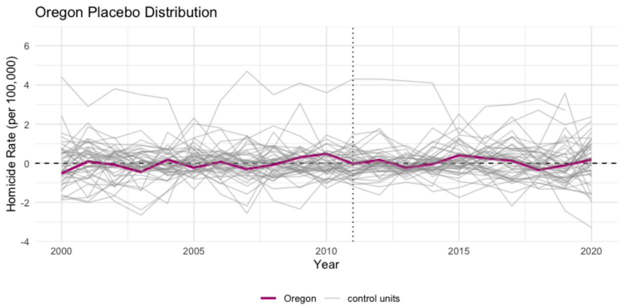
(c) Actual & Synthetic WA Homicide Rates



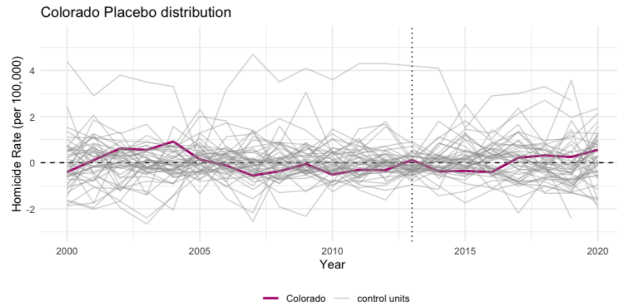
(d) Actual & Synthetic PA Homicide Rates

The plots above only uses the annual homicide rate as the sole predictor variable.

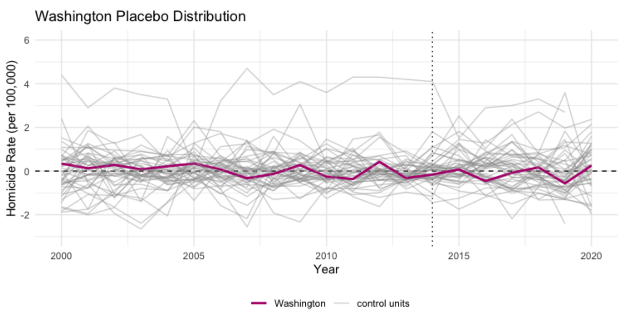
Figure 8: Placebo Tests



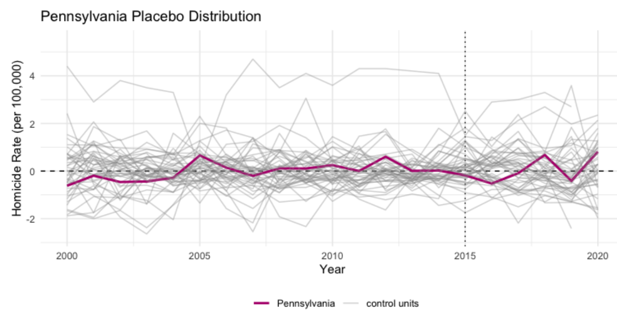
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

3-Year Moving Average Homicide Rate as sole predictor variable

Table 15: State Weights in each Synthetic

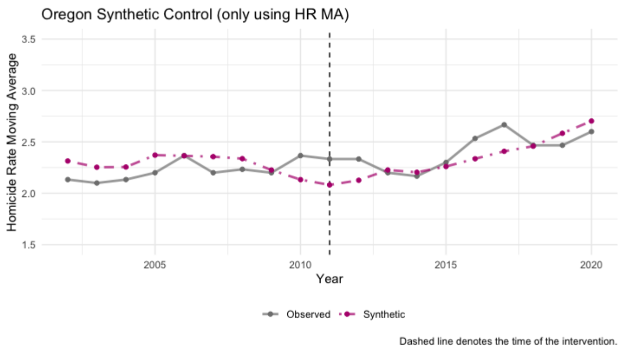
States	Weight	States	Weight
Oregon		*Colorado*	
Hawaii	.026	Connecticut	.024
Idaho	.024	Hawaii	.036
Iowa	.033	Idaho	.034
Maine	.045	Iowa	.041
Minnesota	.025	Maine	.048
New Hampshire	.473	Massachusetts	.029
North Dakota	.023	Minnesota	.035
Utah	.025	Montana	.023
Vermont	.031	Nebraska	.025
		New Hampshire	.116
		North Dakota	.033
		Rhode Island	.027
		South Dakota	.027
		Utah	.035
		Vermont	.039
		Wisconsin	.023
		Wyoming	.027
Washington		*Pennsylvania*	
Hawaii	.035	Alabama	.03
Idaho	.032	Louisiana	.075
Iowa	.043	Maryland	.03
Maine	.055	Mississippi	.03
Massachusetts	.026	South Carolina	.03
Minnesota	.034		
Nebraska	.021		
New Hampshire	.257		
North Dakota	.031		
Rhode Island	.024		
South Dakota	.023		
Utah	.034		
Vermont	.041		
Wyoming	.024		

All states that contributed less than 2% to the synthetic were omitted from this table. For Oregon's Synthetic there were ten states that received a weight greater than 1% but strictly less than 2% ($1 < w < 2$), where w is the weight associated with a particular state. For Colorado's Synthetic there were 25 states that received a weight greater than 1% but strictly less than 2%. For Washington's Synthetic there were 14 states that received a weight greater than 1% but strictly less than 2%.

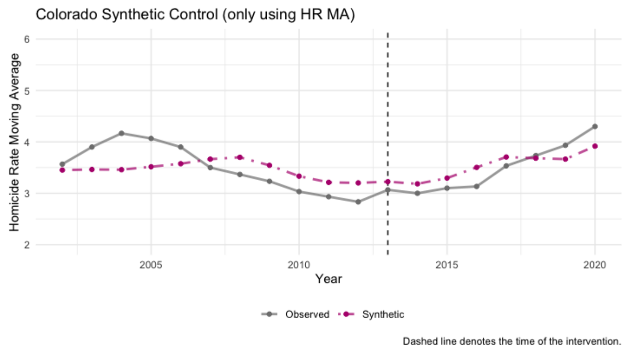
Table 16: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.32	2.32	3.49	3.49	2.88	2.88	5.44	5.44

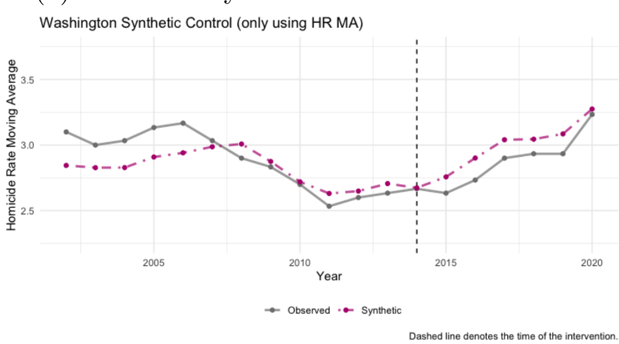
Figure 9: Synthetic Control Plots



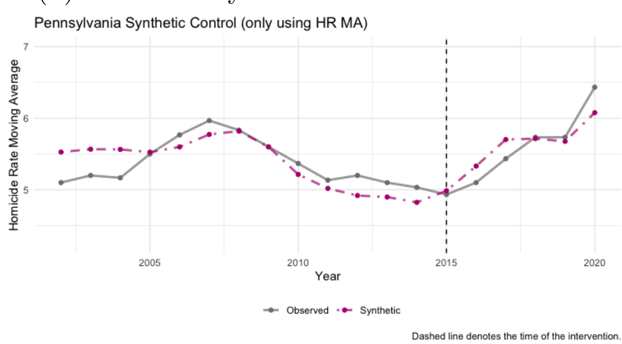
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates



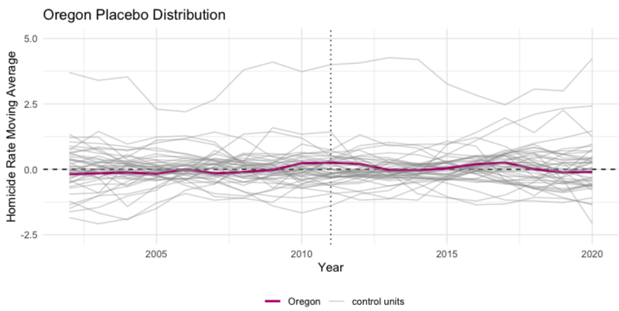
(c) Actual & Synthetic WA Homicide Rates



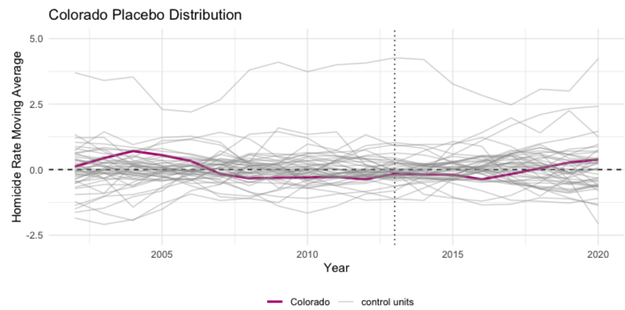
(d) Actual & Synthetic PA Homicide Rates

The plots above uses a three-year moving average for homicide rate as the sole predictor variable and for the dependent variable.

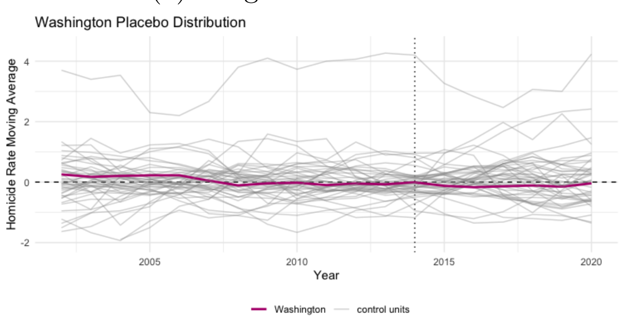
Figure 10: Placebo Tests



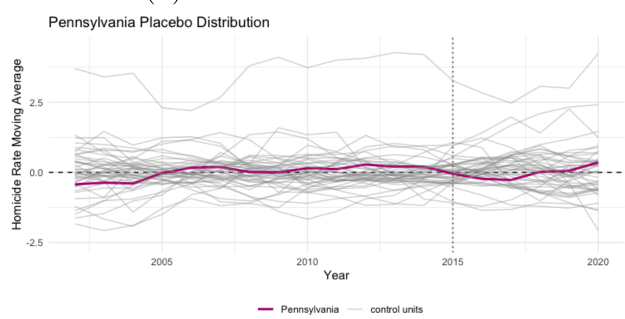
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

Synthetic Control using only states with capital punishment

Unequal Predictor Variable Weights

Table 17: State Weights in each Synthetic

States	Weight	States	Weight
Oregon		*Colorado*	
Montana	.269	Arizona	.043
Nebraska	.054	Kansas	.083
Utah	.677	Montana	.231
		Ohio	.169
		Texas	.071
		Utah	.125
		Wyoming	.268
Washington		*Pennsylvania*	
Idaho	.065	Florida	.093
Kansas	.184	Georgia	.054
Ohio	.184	Louisiana	.064
Utah	.543	Ohio	.613
		Oklahoma	.175

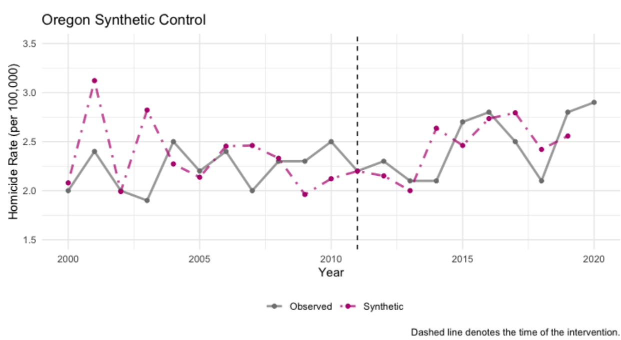
Table 18: Variable Weights in each Synthetic

Variables	Oregon	Colorado	Washington	Pennsylvania
Homicide Rate	.815	.540	.762	.165
Suicide Rate	0	.102	.002	.077
Property Crime	.031	.011	0	0
Prison Population Black Male	.005	.017	0	.307
Prison Population White Male	0	0	.024	.002
Total Population	0	.093	.003	.001
Male Population	.040	.008	.070	.086
White Population	.026	.112	.027	.164
Black Population	.073	.086	.094	.045
Median HH Income	0	.001	0	0
Unemployment Rate	0	.024	.013	.132
High School Attainment	.009	0	0	.021
College Attainment	0	0	.006	0

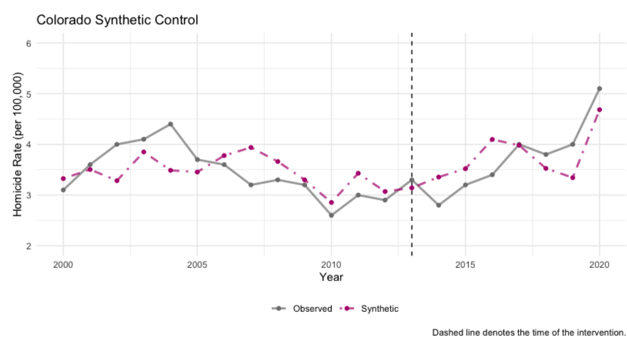
Table 19: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.33	2.44	3.54	3.55	2.92	3.03	5.50	5.56
Suicide Rate	16.5	18.3	18.4	18.3	14.4	15.8	12.9	13.4
Property Crime	3,530	3,126	3,082	2,968	3,893	3,180	2,121	3,277
Prison Pop. Black Male	3,909	3,816	4,038	3,941	2,796	3,600	3,804	3,777
Prison Pop. White Male	647	415	490	552	407	422	333	611
Total Population	3,833,168	2,228,681	5,057,360	5,057,755	6,749,998	4,449,433	12,620,622	10,305,582
Male Population	.495	.502	.502	.501	.499	.501	.447	.489
White Population	.907	.927	.900	.903	.843	.910	.773	.808
Black Population	.025	.015	.049	.049	.047	.051	.120	.149
Median HH Income	39,094	36,008	45,198	40,226	46,450	36,891	43,650	38,469
Unemployment Rate	6.56	4.38	5.03	4.95	6.02	4.81	5.67	5.73
High School Attainment	.675	.626	.659	.649	.665	.621	.671	.647
College Attainment	.206	.175	.266	.171	.209	.177	.199	.171

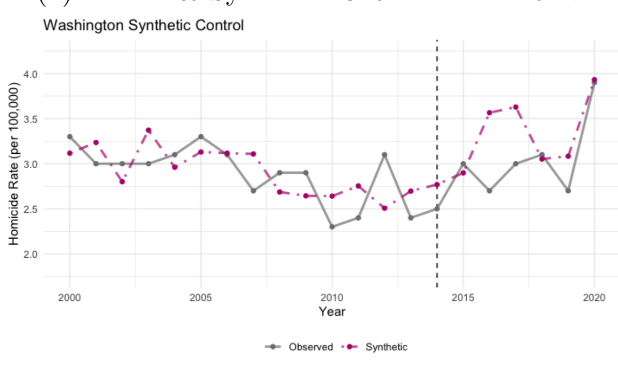
Figure 11: Synthetic Control Plots



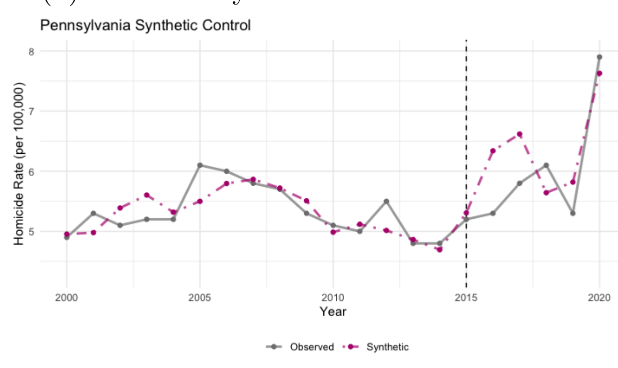
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates

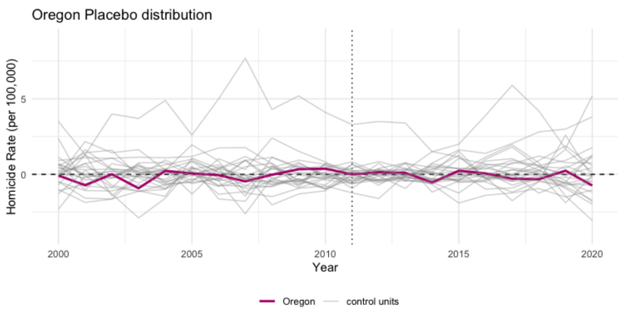


(c) Actual & Synthetic WA Homicide Rates

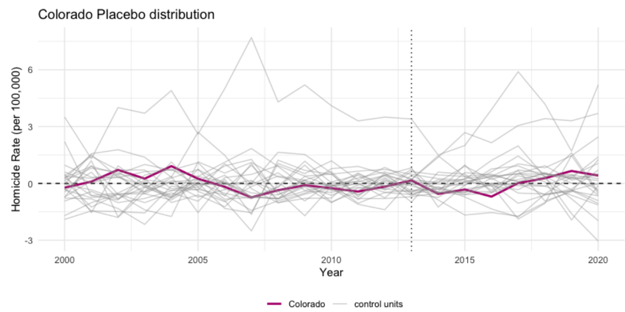


(d) Actual & Synthetic PA Homicide Rates

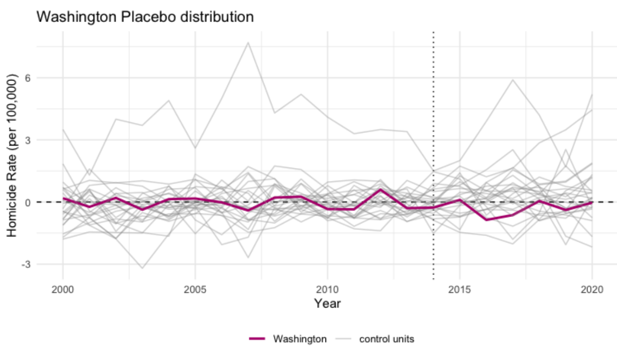
Figure 12: Placebo Tests



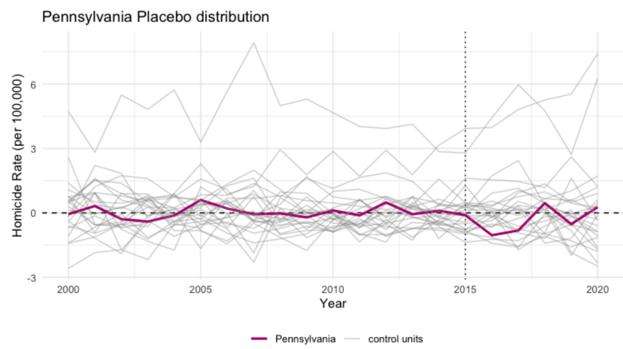
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

Equal Predictor Variable Weights

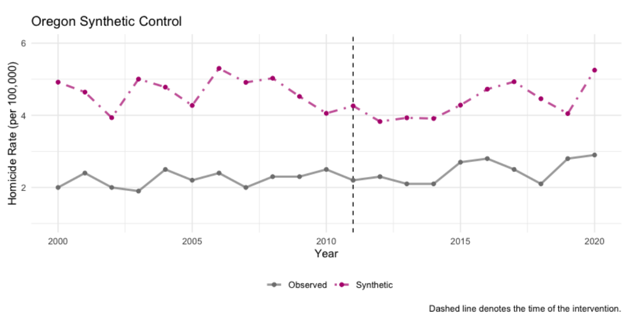
Table 20: State Weights in each Synthetic

States	**Weight**	**States**	**Weight**
Oregon		*Colorado*	
Arizona	.207	Florida	.032
Florida	.113	Kansas	.853
Kansas	.287	Montana	.115
Montana	.285		
Ohio	.108		
Washington		*Pennsylvania*	
Florida	.207	Florida	.150
Kansas	.551	Kansas	.014
Nebraska	.073	Nebraska	.187
North Carolina	.142	Ohio	.546
Wyoming	.027	South Dakota	.104

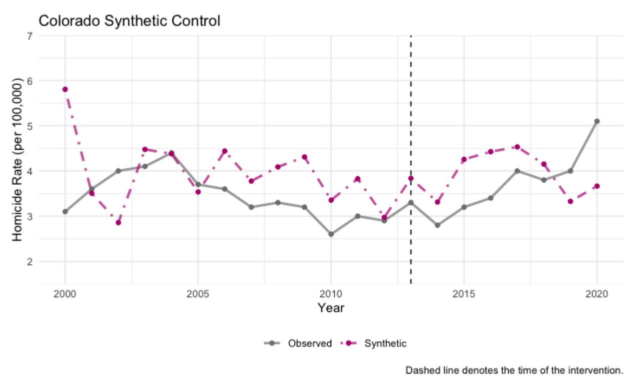
Table 21: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.33	4.52	3.54	3.94	2.92	4.46	5.50	4.29
Suicide Rate	16.5	17.2	18.4	15.6	14.4	14.4	12.9	13.1
Property Crime	3,530	3,261	3,082	3,195	3,893	3,284	2,121	3,006
Prison Pop. Black Male	3,909	3,965	4,038	3,775	2,796	3,365	3,804	3,392
Prison Pop. White Male	647	569	490	449	407	472	333	492
Total Population	3,833,168	5,773,445	5,057,360	3,097,473	6,749,998	6,934,441	12,620,622	9,609,400
Male Population	.495	.500	.502	.507	.499	.501	.447	.492
White Population	.907	.882	.900	.909	.843	.865	.773	.855
Black Population	.025	.065	.049	.066	.047	.109	.120	.109
Median HH Income	39,094	38,358	45,198	40,332	46,450	40,494	43,650	39,943
Unemployment Rate	6.56	5.25	5.03	4.78	6.02	5.02	5.67	5.21
High School Attainment	.675	.653	.659	.653	.665	.647	.671	.658
College Attainment	.206	.194	.266	.211	.209	.203	.199	.180

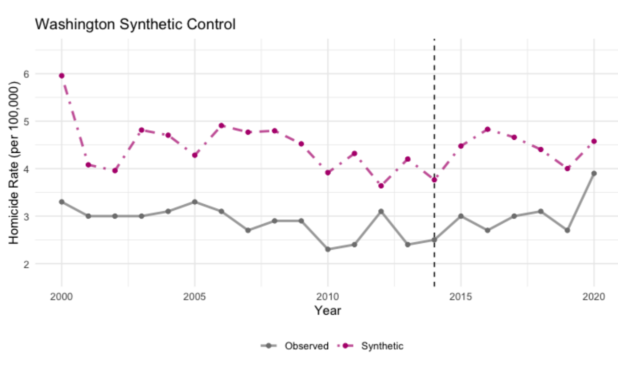
Figure 13: Synthetic Control Plots



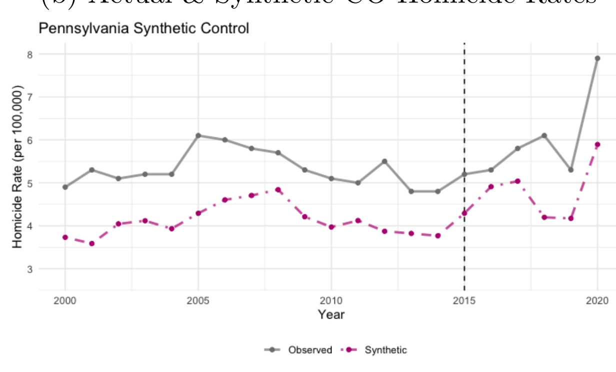
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates

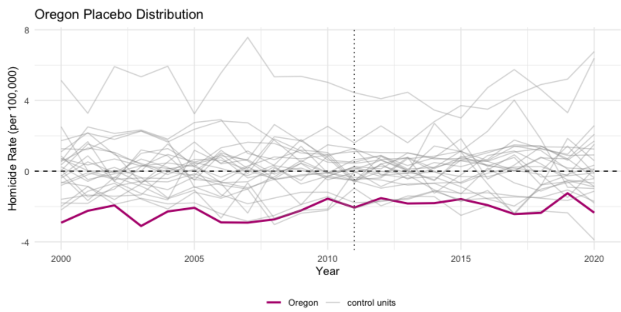


(c) Actual & Synthetic WA Homicide Rates

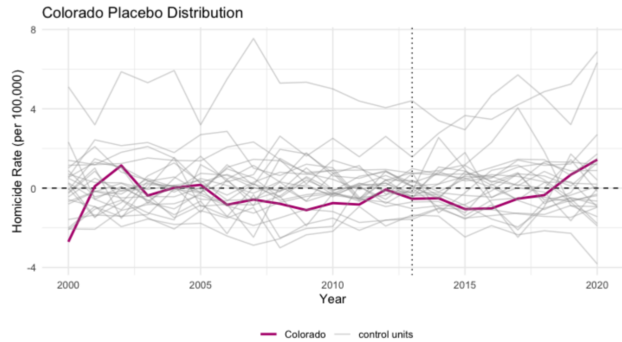


(d) Actual & Synthetic PA Homicide Rates

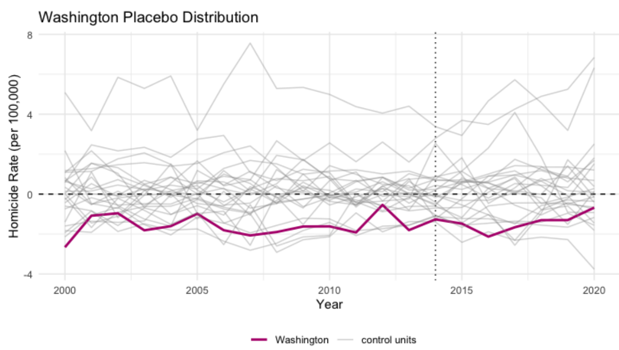
Figure 14: Placebo Tests



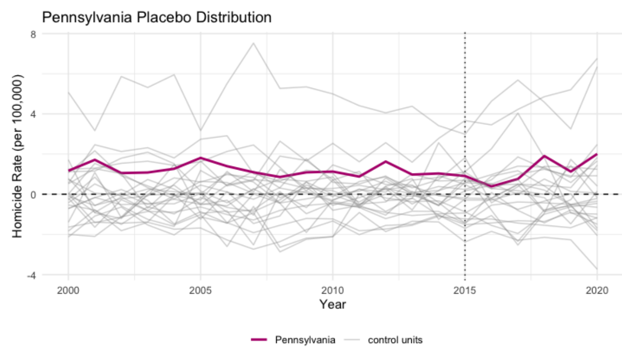
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

3-Year Moving Average Homicide Rate

Table 22: State Weights in each Synthetic

States	**Weight**	**States**	**Weight**
Oregon		*Colorado*	
Montana	.307	Kansas	.462
Utah	.693	Ohio	.011
		Texas	.109
		Utah	.096
		Wyoming	.321
Washington		*Pennsylvania*	
Kansas	.262	Alabama	.102
Ohio	.147	Florida	.315
Utah	.581	Louisiana	.024
		Ohio	.496
		Oklahoma	.064

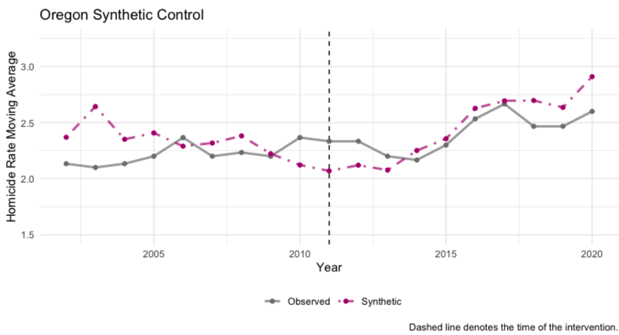
Table 23: Variable Weights in each Synthetic

Variables	Oregon	Colorado	Washington	Pennsylvania
Homicide Rate	.891	.719	.839	.749
Suicide Rate	.002	.005	.011	.017
Property Crime	.017	.034	.009	.001
Prison Population Black Male	.005	.007	.013	.008
Prison Population White Male	.003	.032	.012	0
Total Population	0	.035	.002	.049
Male Population	.008	.033	.003	.074
White Population	.018	.048	.003	.056
Black Population	.051	.083	.085	.021
Median HH Income	0	.004	0	0
Unemployment Rate	0	0	.012	.020
High School Attainment	.004	0	.005	.004
College Attainment	0	0	.006	0

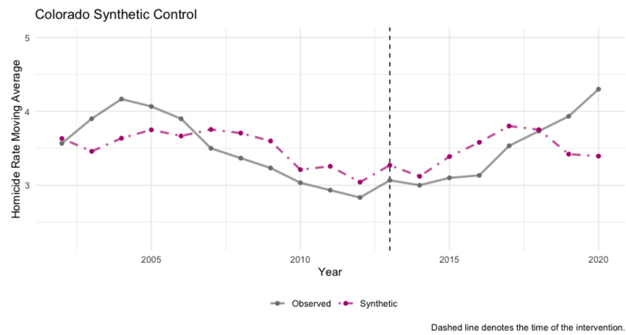
Table 24: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.32	2.40	3.49	3.50	2.88	2.99	5.44	5.44
Suicide Rate	16.8	19.2	18.7	17.4	14.6	16.1	13.1	13.8
Property Crime	3,415	3,045	3,012	2,968	3,801	3,176	2,075	3,224
Prison Pop. Black Male	3,798	3,397	3,986	3,647	2,708	3,190	3,792	3,496
Prison Pop. White Male	658	424	495	527	413	398	345	621
Total Population	3,873,625	2,241,494	5,129,051	4,646,781	6,834,407	4,143,552	12,655,259	12,614,753
Male Population	.495	.502	.502	.507	.499	.502	.446	.489
White Population	.905	.927	.898	.915	.839	.913	.771	.807
Black Population	.025	.013	.049	.054	.048	.049	.121	.159
Median HH Income	40,177	36,884	46,314	43,612	47,856	38,359	44,985	39,748
Unemployment Rate	6.71	4.50	5.27	4.77	6.12	4.82	5.82	5.95
High School Attainment	.680	.630	.663	.642	.669	.624	.676	.656
College Attainment	.209	.177	.270	.184	.214	.184	.202	.180

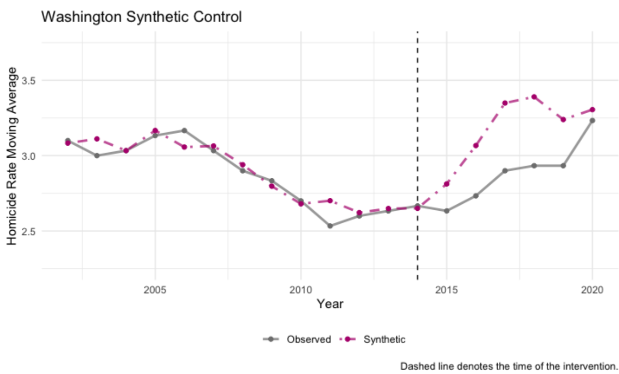
Figure 15: Synthetic Control Plots



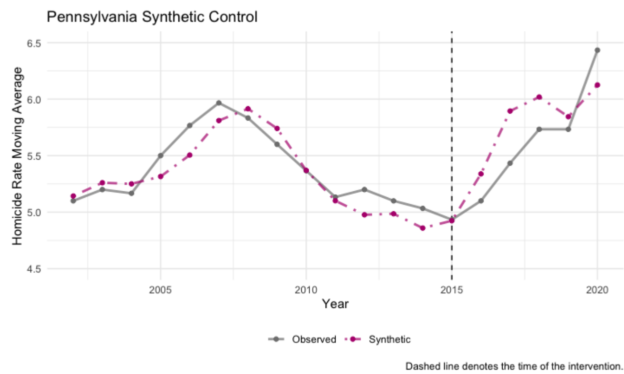
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates

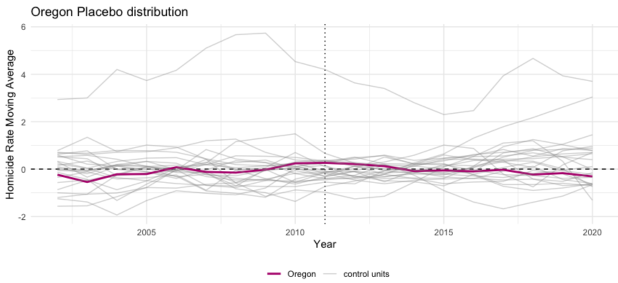


(c) Actual & Synthetic WA Homicide Rates

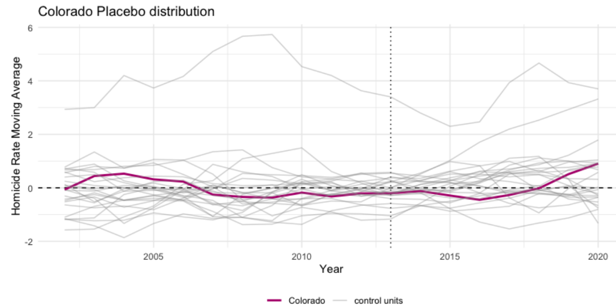


(d) Actual & Synthetic PA Homicide Rates

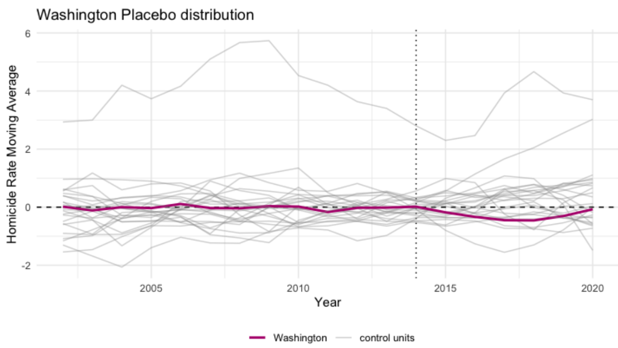
Figure 16: Placebo Tests



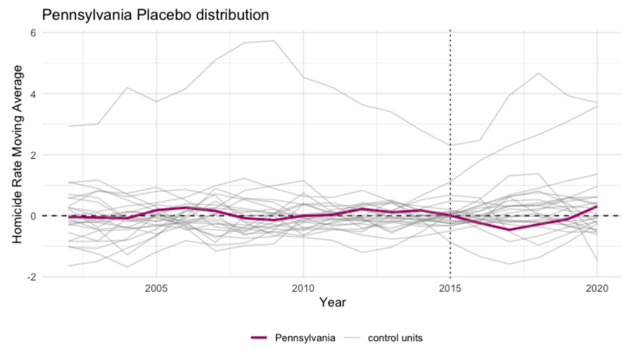
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

Homicide Rate as sole predictor variable

Table 25: State Weights in each Synthetic

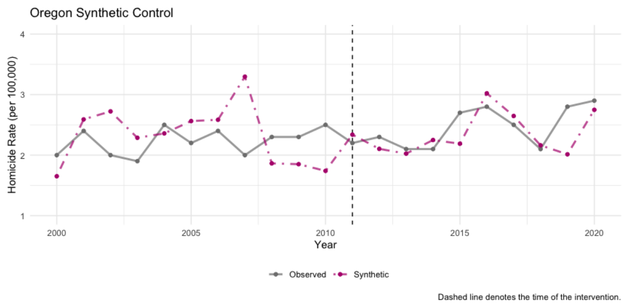
States	Weight	States	Weight
Oregon		*Colorado*	
Idaho	.714	Idaho	.247
Nebraska	.012	Kansas	.033
South Dakota	.017	Montana	.047
Utah	.174	Nebraska	.053
Wyoming	.019	South Dakota	.065
		Utah	.195
		Wyoming	.067
Washington		*Pennsylvania*	
Idaho	.398		
Kansas	.021		
Montana	.031		
Nebraska	.037		
South Dakota	.047		
Utah	.252		
Wyoming	.050		

For Pennsylvania, all 24 states that currently still have capital punishment, receive a weight between 3.91% and 4.29% ($3.91 \leq w \leq 4.29$).

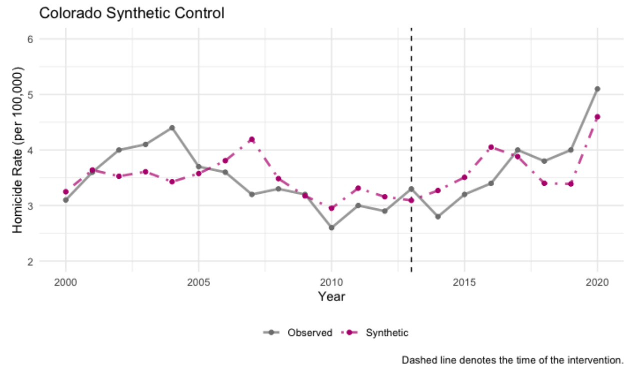
Table 26: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.33	2.33	3.54	3.54	2.92	2.92	5.50	5.50

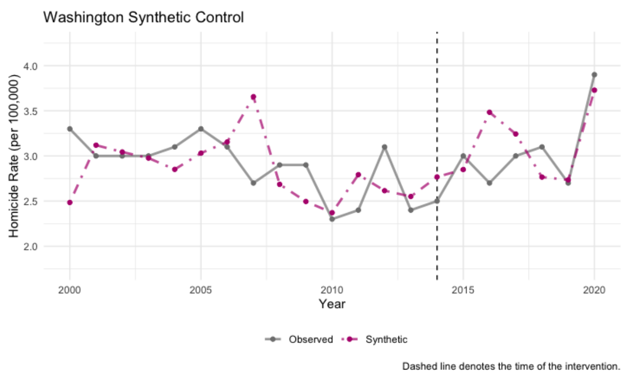
Figure 17: Synthetic Control Plots



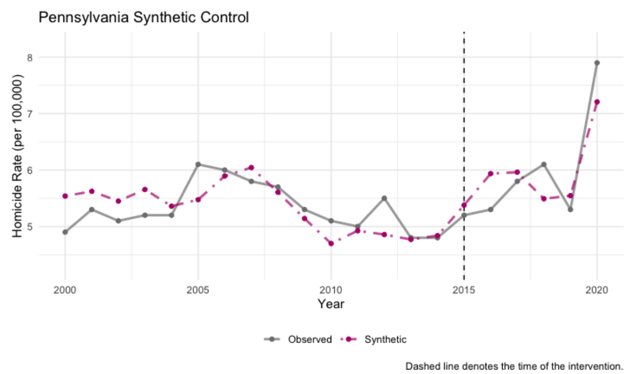
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates

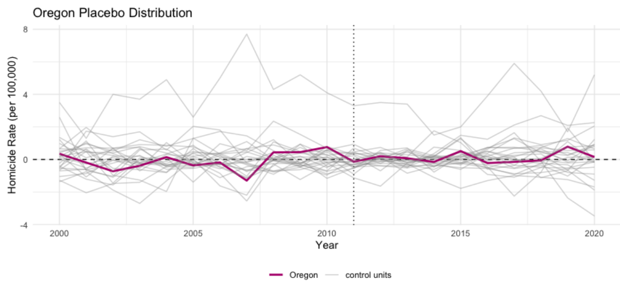


(c) Actual & Synthetic WA Homicide Rates

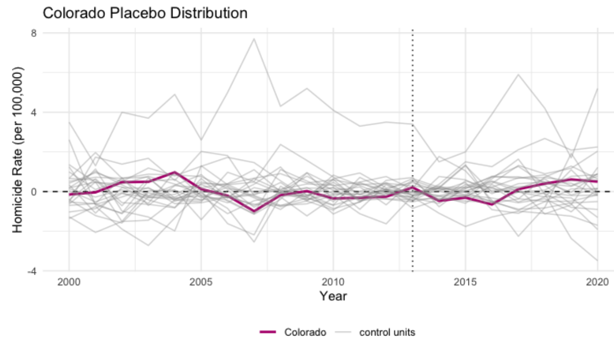


(d) Actual & Synthetic PA Homicide Rates

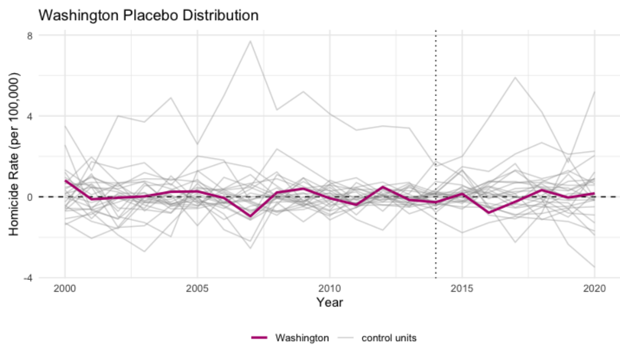
Figure 18: Placebo Tests



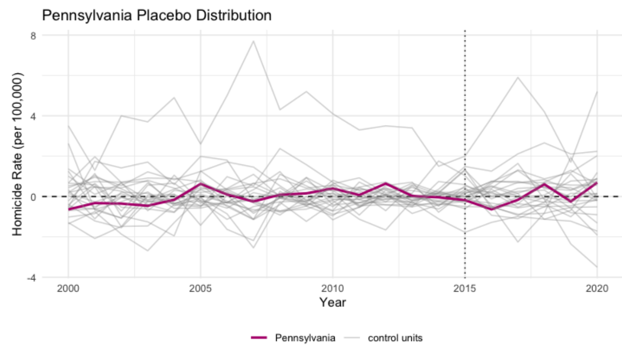
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests

3-Year Moving Average Homicide Rate as sole predictor variable

Table 27: State Weights in each Synthetic

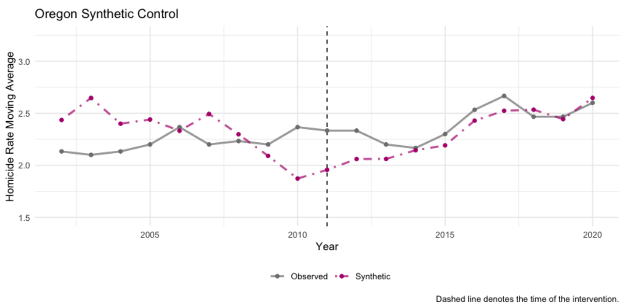
States	Weight	States	Weight
Oregon		*Colorado*	
Idaho	.150	Idaho	.181
Montana	.010	Kansas	.033
Nebraska	.013	Montana	.047
South Dakota	.017	Nebraska	.054
Utah	.739	South Dakota	.062
Wyoming	.019	Utah	.269
		Wyoming	.066
Washington		*Pennsylvania*	
Idaho	.213		
Montana	.031		
South Dakota	.044		
Utah	.448		
Wyoming	.048		

For Pennsylvania, all 24 states that currently still have capital punishment, receive a weight between 3.96% and 4.26% ($3.96 \leq w \leq 4.26$).

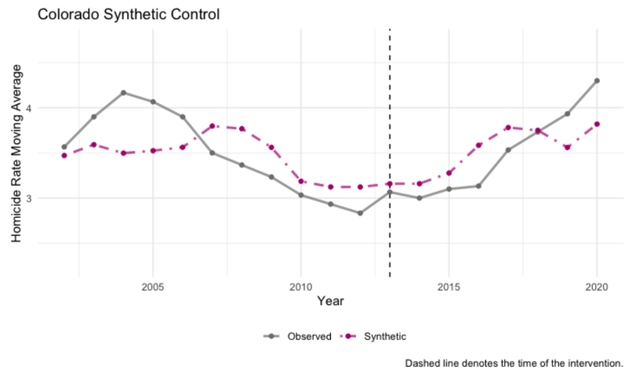
Table 28: Homicide Rate Predictor Means

State	Oregon		Colorado		Washington		Pennsylvania	
Variable	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic	Treated	Synthetic
Homicide Rate	2.32	2.32	3.49	3.49	2.88	2.88	5.44	5.47

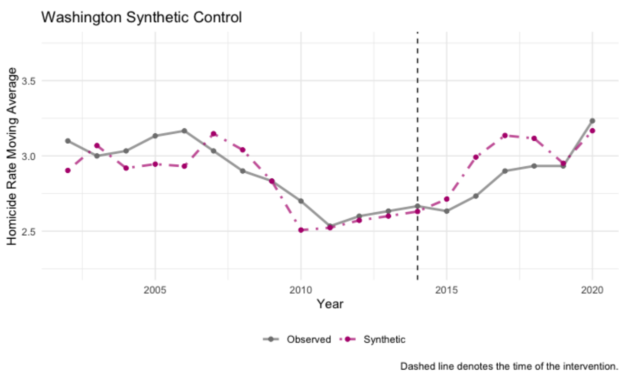
Figure 19: Synthetic Control Plots



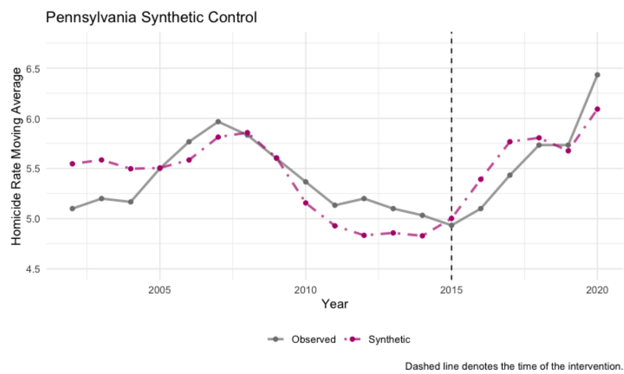
(a) Actual & Synthetic OR Homicide Rates



(b) Actual & Synthetic CO Homicide Rates

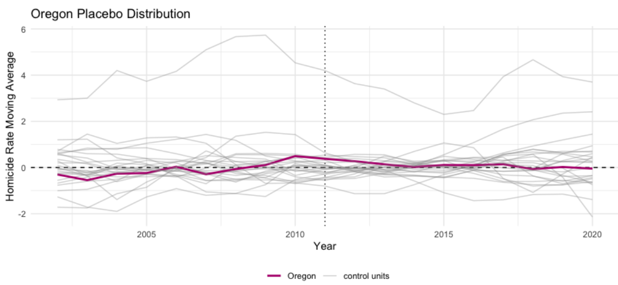


(c) Actual & Synthetic WA Homicide Rates

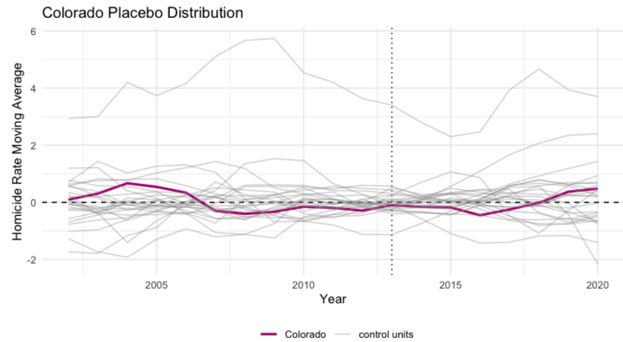


(d) Actual & Synthetic PA Homicide Rates

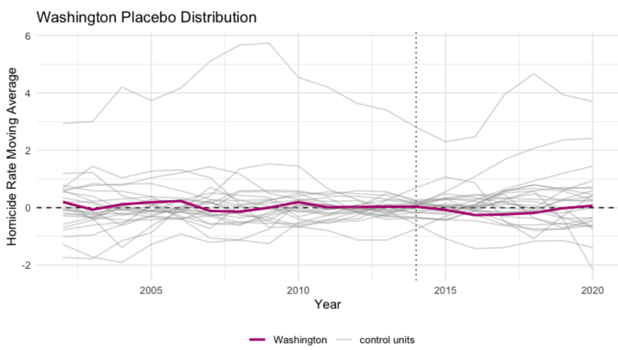
Figure 20: Placebo Tests



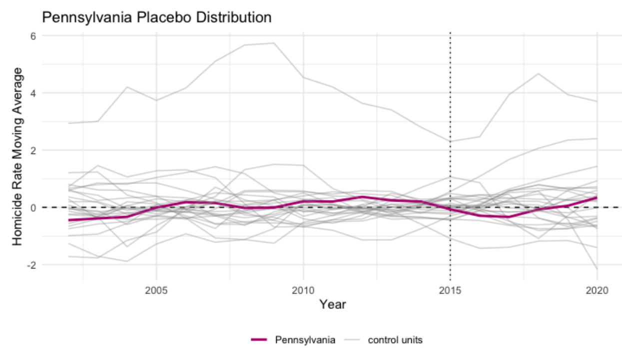
(a) Oregon Placebo Tests



(b) Colorado Placebo Tests



(c) Washington Placebo Tests



(d) Pennsylvania Placebo Tests