Towards Health Centered Drug Policy: An Analysis of Past and Developing Drug Policy

by

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ABSTRACT

Drug criminalization has disproportionately impacted communities of color and has insufficiently addressed substance use disorder and its associated risk of death through overdosing. Decriminalization has the potential to restore justice to communities decimated by traditional U.S. drug policy and could shift public focus towards medical approaches to treating addiction, however, inertia in drug policy persists, influenced by America's popular political beliefs about illicit substances. A long-standing narrative in the United States views marijuana as a "gateway drug" that introduces users to harder substances, which then have adverse effects on their health and livelihood. As a result, many argue that policies which decriminalize marijuana are exacerbating the problem of drug addiction. Seemingly in line with this argument, overdose-related deaths–largely driven by increases in opioid consumption–have soared in recent years, and at the same time an increasing number of states have decriminalized marijuana. Little work, however, has examined the extent to which marijuana legalization has *caused* an increase in overdose deaths. Here, we address this question. To examine the causal effect of marijuana legalization on overdose deaths, we combine state-year level data on marijuana policy and overdose deaths with state-of-the-art techniques from the field of causal inference, namely Two-Way Fixed Effect Difference-in-Differences analysis with Synthetic Control. We include data from all states that enacted one of five marijuana legalization policies between 2010 and 2020. We estimate the causal effect of each policy separately for each state, and then use meta-analysis to calculate the overall effect of each policy intervention. We find that the passage of medical marijuana legalization laws, the opening of recreational dispensaries, and the implementation of Medical marijuana patient ID programs had no significant effect on annual state overdose death rates. The opening of medical marijuana dispensaries and the passage of recreational marijuana legalization laws also had no significant overall effect on overdose death rates, but the effect of these policies varied significantly across states such that there were significant increases in some states and significant decreases in others. Overall, these findings contradict the popular claim that marijuana decriminalization leads to increased use of more dangerous drugs (and thus overdose deaths) in most cases – and more generally questions the characterization of marijuana as a gateway drug.

Thesis supervisor: David Rand
Title: Professor of Management Science and Cognitive Sciences

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Chapter 1

Introduction

U.S. incarceration rates dramatically soared in the 1980s as the country's view of crime, particularly drug-related crime, became increasingly negative [1]. In an attempt to crack down on illegal activity, President Ronald Reagan enacted the *Anti-Drug Abuse Act* in 1986 [2]. This legislation increased drug possession penalties, created minimum sentences for drug offenses, expanded drug enforcement funds, and created a disparity in the way crack cocaine crimes versus powder cocaine crimes were sentenced [2]. In the decades to come, being "tough on crime" became a popular political ideology and became an essential platform for election [3]. America's low tolerance for crime made way for harsh criminal policies which inevitably contributed to what is now commonly called mass incarceration [4]. According to data gathered from the Prison Policy Initiative, the United States currently incarcerates almost 2 million individuals [5]. The ACLU reports that the US accounts for approximately 5% of the world's population and over 20% of the world's incarcerated population [6]. Those incarcerated include youth in juvenile facilities, adults in jails during pretrial periods, individuals convicted of crimes serving time in prison, and those held in immigrant detention centers [1].

A minority of incarcerated Americans are detained for non-violent drug crimes, but drug policies, like all criminal policies, have undoubtedly contributed to the US mass incarceration phenomenon. The number of nonviolent drug offenders increased from 50,000 in 1980 to over 400,000 by 1997 [7]. Now, approximately 67,000 out of 145,000 federal prisoners are incarcerated due to a drug offense, and the same holds for 146,000 out of 1.042 million state prisoners [5]. There are also considerable racial disparities in drug incarceration rates. African-Americans and Hispanics/Latinos respectively make up 13.6% and 18.9% of the United States population according to US Census data, however, according to a 2015 report by the Bureau of Justice Statistics, they accounted for 39% and 37% of federal narcotics incarcerations [8]. The criminal justice system's attention to illicit substance use and distribution has increased the US prison population and produced externalities for minority communities without putting an end to drug use.

Criminal policies are positioned to reduce harm to society by identifying crimes and removing troublesome actors that pose a risk to municipalities [9]. In many cases of violent crimes, criminal justice policies have succeeded in that effort. However, drug use is a peculiar type of crime because those most at risk of experiencing the damage of substance use are the users themselves. Illicit drugs are known to have adverse effects when taken in excess, leading to poor mental and physical health and sometimes death [10]. Drug policies that emphasize criminalization not only induce difficult sanctions for individuals whose biggest threat is largely to themselves, these policies also fail to address the most dire issue related to drug use: overdosing.

Drug overdosing, largely driven by the synthetic opioid fentanyl, is the leading cause of death for adults aged 18-45 in the US [11]. Fentanyl is typically applied in cancer treatment and other medical settings to treat pain, but when manufactured illicitly, this substance can be misused to engender intense feelings of euphoria [12]. Illegally manufactured fentanyl is lethal and has the potential to be laced in any street drug, including cocaine, ketamine, methamphetamine, and heroin [13]–[16]. There are other opioids available to users. Some prescribed opioids include oxycodone, hydrocodone, codeine, and morphine, and a commonly known illegal opioid is heroin [17]. To properly tackle this issue of substance use disorder and overdosing, non-profit organizations in some US cities and states are championing harm reduction and recovery approaches [18]. Drug harm reduction involves giving users the knowledge and resources to minimize their risk of overdose [19]. An essential harm reduction agent is naloxone, a nasal spray technology that, when administered correctly and in a timely manner, reverses the effects of an overdose [20]. Fentanyl testing strips are another harm reduction tool that allow individuals to test a sample of their drugs for fentanyl before consumption [21]. Drug policies that promote harm reduction principles like carrying naloxone and using fentanyl testing strips have the potential to save lives in a way that criminalization policies are incapable of doing.

In this thesis, we explore past and currently evolving drug policies and their effect on communities and on public health. In chapter 2 we examine the knowledge assessment of law makers pertaining to illicit substances and substance use in the 1980s, when harsh anti-drug laws became popular. We subsequently delve into the externalities of drug criminalization in chapter 3. From there, we pivot to investigate the relationship between drug decriminalization and overdosing. A long-standing narrative in the United States views marijuana as a "gateway drug" that introduces users to harder substances, which then have adverse effects on their health and livelihood. As a result, many argue that policies which decriminalize marijuana are exacerbating the problem of drug addiction. In chapters 4 and 5 we explain the research question, method, and data that comprise our analysis. We combine state-year level data on marijuana policy and overdose deaths with and use contemporary techniques from the field of causal inference, namely Two-Way Fixed Effect Difference-in-Differences analyses with Synthetic Control. We include data from states that enacted one of five marijuana legalization policies between 2010 and 2020. In chapter 6 we expound our analysis and present results. This thesis ends with policy recommendations in chapter 7 and a final conclusion chapter that includes ideas for future work in this area.

Chapter 2

Knowledge Assessment of Prohibition and Drug Effects

Knowledge assessment is vital to writing effective policies. Information that informs the laws should be, at a minimum, correct and also contain as little bias as possible. Inaccurate intelligence and withheld knowledge may lead to critical and lasting consequences, like those born out of American drug policy. We posit that inertia in drug policy stems from early narratives surrounding the effects of drugs and the character of people who engage in drug use. There are parallels between America's alcohol prohibition period and the ongoing drug prohibition, and we argue that the US should have drawn from this past experience which ultimately led to the creation of dangerous illicit markets. Further, we discuss the research conducted by scientists on drugs and drug users before the start of the drug war, and we highlight findings that were seemingly ignored.

2.1 Parallels to Alcohol Prohibition

Reviewing the alcohol prohibition period sheds light on the available information about the consequences of banning substances that should have shaped US legislatures' decisions when creating drug policies at the start of the *War on Drugs*. The alcohol prohibition movement started as a response to the numerous social problems, including crime, poor health and hygiene, and corruption taking place in America during the mid-1800s [22]. The *Volstead Act*, also known as *National prohibition*, went into effect in January of 1920 and lasted until 1933. Like the war on drugs, prohibition was also accompanied by a significant investment of government finances needed to enforce it. $6.3 million went towards enforcing national prohibition in 1920, and the cost increased to $13.4 million by 1930 [23]. Though economists like Clark Warburton in 1932 show that alcohol consumption fell by 20 percent during the prohibition era, banning alcohol did not abolish American alcohol consumption [24]. This decrease in consumption was accompanied by unintended consequences, the main one being an increase in the potency of the product, a phenomenon known as "The Iron Law of Prohibition" coined by Richard Cowen [25]. "The Iron Law of Prohibition" also accounts for the variability in potency in beverages. A not-so surprising outcome of alcohol's higher potency, participants in the illegal alcohol market shifted towards buying and selling stronger versions of alcohol; consumers and producers switched from beer to liquor [22]. Prohibition may have lowered the number of alcoholic beverages being sold in the U.S., but the increased and variable potency enabled conditions that made alcohol consumption even more dangerous.

Crime rates increased directly following the passage of the *Volstead Act* as a result of higher numbers of arrests for drunk and disorderly conduct as well as drunk driving. Corruption penetrated all levels of government as crime rates climbed, influencing police officers, politicians, and the Bureau of Prohibition itself to accept bribes from bootleggers and moonshiners [22]. After 14 years of ongoing failed attempts to improve society through prohibition, the *Volstead Act* was repealed.

The case of prohibition was not properly assessed when anti-drug laws were popularized in the 1980s. Prohibiting alcohol, the United States most widely used mind and body altering substance, did not have the outcomes proponents of prohibition expected. Indeed, criminalizing alcohol only made the market for alcohol more threatening and susceptible to corruption. Policy makers at the start of the war on drugs presumably knew this history and were aware of these oversights, and still deployed a prohibition approach in handling drugs. A careful examination of the the *Volstead Act's* aftermath could have kept America from repeating similar failures, saving taxpayers billions in cost to enforce the drug war while preserving the livelihoods lost to incarceration and adverse health effects of drugs.

2.2 Knowledge of Effects of Drugs Prior to 1986

Drug policy's aim should be to reduce societal harm from excessive drug use through enhancing individual and public health while also reducing crime [26]. Examining the use of available scientific information related to drugs and drug users between the 1980s and now is critically important to understanding American drug policy. Policy makers used available intelligence on drugs to create narratives that influenced their voting decisions as well as the language used to draft drug policies. Walking through from the past four decades reveals the incremental amount of change that has been made in drug policy while exposing a vast change in public attitudes towards drug criminalization policies. Understanding the sources knowledge and vantage points that informed early drug policy is an essential first step in overcoming America's reluctance to change.

Our exploration begins with an examination of the scientific literature on drug use from 1960 to 1986. This period is pivotal due to its historical relevance: the 1960s witnessed a rise in drug use, aligning with the emergence of the "flower child" and *anti-Vietnam War* movement. The analysis extends up to 1986, the year the *Anti-Drug Abuse Act* was enacted.

2.2.1 Cocaine

Scientific knowledge about cocaine in the 1980s primarily pertained to the adverse health effects it posed to drug users. Written in 1985 by Dale Chitwood, "Patterns and Consequences of Cocaine use" synthesized studies from the 1970s and 80s on the effects of using cocaine and emphasized findings on health consequences based on type of ingestion (smoking versus intranasal), frequency, and amount [27]. Chitwood's review found that early-stage stimulation consequentially produced dry mouth, sweating, irregular or increased heart rate, distorted vision, teeth grinding, headache, changes in breathing, nausea, dizziness and tremors. He found that advanced use could cause convulsions and unconsciousness. Studies from the 1970s also pointed to increased violent criminality of cocaine users as a response to their psychological dependency to the drug, showing that increased cocaine consumption among males made them more likely to be perpetrators of violence and that regular cocaine use among females made them more prone to prostitution [28]. The physical impact associated with withdrawal from a drug and the economic motivation to steal and commit violent crime to overcome withdrawal effects were among the explanations for why cocaine users were more prone to criminality [28]. Absent from these studies were the economic conditions that often lead people to turn to violent crime or prostitution to sustain their drug habit. Both mental and physical health effects of cocaine were undermined by 80s era drug policies which evidently sought to punish rather than provide support to those addicted.

2.2.2 Crack Cocaine

When combined with water and baking soda, cocaine becomes solid, transforming into its rock form called crack cocaine and is known to be more addictive than powder cocaine [29]. Dembo et al. wrote extensively on effects of crack cocaine in 1990 and focused on behavioral effects of crack cocaine users, employment and crime. The found lower rates of employment and higher rates of crime among crack cocaine users compared to powder cocaine users [30]. Findings like these may have been part of the justification for harsher sentencing laws for crack cocaine users, but still neglected the financial hardship and poverty induced mental pressure that crack cocaine users typically experience more than powder cocaine users.

2.2.3 Cannabis or Marijuana

Information on the effects of marijuana in the 1980s, again, centered around health consequences and behavioral effects. Research in the 1970s on the neuropsychological effects of marijuana revealed that its consumption impaired mental processes, with higher consumption leading to raised levels of impairment [31]. In 1985, Taylor and Myerscough found that higher doses of cannabis decreased levels of aggression [32]. A literature review from 1986 found in Pharmacological Reviews examined existing literature on the acute and chronic effects of marijuana and reported that marijuana increased pulse rates, decreased or had no effect on blood pressure, decreased muscle strength, augmented appetite, and reddened eyes. The literature review also found that marijuana changed pupil size, respiratory rate, and deep tendon reflexes[33]. Overall, even with the existence of these acute side effects, this literature review asserted that marijuana was a relatively safe drug that is comparable to tobacco or alcohol, both legal substances at the time of this study's publishing.

2.2.4 Methamphetamine

There was limited scientific information available about the effects of methamphetamine on humans in the 1980s. It seems, for ethical reasons, that experiments were largely performed to find methamphetamine's effect on animals. Methamphetamine was seen to cause long-term depleted levels of dopamine and serotonin in rats [34]. One study which looked at the human effect of methamphetamine, as well as 4 other drugs (amphetamine, ephedrine, phenmetrazine, and methylphenidate) found that the substance elevated blood pressure, respiratory rates, and excretion of epinephrine [35].

2.2.5 Heroin

Heroin was also primarily shown to have adverse health effects on users. A major finding exposed heroin's propensity for addiction, being cited as more addictive than morphine, an opioid regularly used to treat pain in medical settings [36]. Poor dental health was documented as an unfortunate side effect of heroin addiction [37]. Babor, et al. found that heroin use was linked to social withdrawal and sleep deprivation [38].

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Though the existing scientific knowledge on drugs concerned the health effects imposed on the individual consuming the drug, and some concerned the behavioral effects that could impact those who come into contact with the drug user, politicians in the 80s chose to make drug use a criminal problem, positioning the effects of drugs as a threat to the nation and safety of others. Criminalization was a bipartisan tactic in handling the effects of drugs. According to the Drug Policy Alliance, President Clinton originally chose the position of treatment over incarceration in his 1992 presidential campaign, but defaulted to the approach of past administrations once entering the oval office [39]. The bipartisan campaign to label drug users as inadequate members of society stifled the drug using community's ability to get help in overcoming these adverse health effects, leaving many in a cycle of incarceration and poverty.

Chapter 3

Externalities of Criminal Drug Policy

An abundance of suspected and convicted drug offenders living behind bars is an understandably expected outcome from decades of criminal drug policy. The amount of nonviolent drug offenders climbed from 50,000 in 1980 to over 400,000 by 1997 [7]. Roughly 67,000 out of 145,000 federal prisoners are currently incarcerated because of drug offenses, and this is also true for 146,000 out of 1.042 million state prisoners [5]. The direct impacts of America's criminalization approach are widely known, so this chapter is dedicated to criminalization's external effects. Externalities include unintended negative consequences or external costs of policies and economic activities that are incurred by communities and outside parties. Surveying American drug policy's externalities reveals the undue harm posed to society through pursuing high penalties for drug users and distributors. After all, individuals who use substances are members of our society as well, and the harm done to them, their families, and their communities should be identified and overcome so inequities in criminal detention, health, and economic opportunity.

We'll begin by addressing racial disparities in arrests and sentencing which have resulted from disproportionate policing and incarceration rates in poor and ethnic minority communities in the US. The second externality addressed in this chapter is the economic cost of drug law enforcement incurred by municipal governments and taxpayers. Lastly, we'll discuss detrimental mental and physical health externalities borne to all members of the incarcerated community living in poorly kept facilities overcrowded with drug users.

3.1 Community Externalities

Communities of color are more likely than white communities to experience the social costs of drug incarceration. African-Americans and Hispanics/Latinos respectively make up 13.6% and 18.9% of the United States population according to US Census data, however, according to a 2015 report by the Bureau of Justice Statistics, they accounted for 39% and 37% of federal narcotics incarceration [8]. Higher incarceration rates do not necessarily equate to significantly higher rates of drug use in minority communities. Humensky found that white adolescents and young adults are actually more likely than their non-white counterparts to have tried marijuana and other illicit drugs [40]. Differences in incarceration rates can be traced to drug war policies that imposed harsher sentences for drugs most commonly used by communities of color, a clear example being the ongoing sentencing length disparity for crack versus powder cocaine offenses. The *Anti-Drug Abuse Act* of 1986 penalized crack cocaine relative to pure cocaine at a ratio of 100 to 1, administering 5-year minimum sentences for 500 grams of pure cocaine while concurrently issuing the same 5-year minimum for 5 grams of crack cocaine [41]. Crack cocaine users were disproportionately African American and Hispanic in the 1980s [42]. These unequal sentencing lengths are just one example of a racial disparity that, as we will see, continues to permeate America's approach to handling drugs and drug users. In an attempt to shrink this gap in crack versus pure cocaine sentence severity, President Barack Obama's administration brought the ratio down from 100:1 to, now, 18:1 [43]. However, this 18:1 ratio still perpetuates more extreme criminalization for racial minorities, and other individuals, who use the more heavily sanctioned form of coke. Racial demographics of drug defendants differ quite a bit by drug. By 2012, 88% of federal crack defendants were Black, and by the same year, black defendants were 32.3% of Powder cocaine defendants, 38.8% of heroin defendants, 13.9% of Marijuana defendants, and 2.5% of meth defendants [44]. Enforcing steeper penalties on drugs used predominantly by minorities not only creates an inequitable disposition in incarceration, it also contrives other harsh realities for the minority communities affected.

3.2 Economic Externalities

The racial disparity in drug sentences has economic implications for minority communities as well. Due to a history of U.S policies that enabled discrimination in the job market, education, housing, and land ownership, African Americans have not been able to equally benefit from the same economic opportunities as their white counterparts over the years [45]. Disproportionate incarceration rates inhibit the prospect of the African American community reaching economic parity because job opportunities are slim after being released from prison. Citi Bank reports that only 55% of former prisoners earn income within the first year of release from prison, with the median earning being $10,090 [44]. The report also shows that former inmates have an unemployment rate 5 times the size of the population that has never been incarcerated. Citi bank expands on this unemployment phenomenon saying that 44% of African American women, and 35% of African American men, who were formerly incarcerated are unemployed, and that information pointing to a criminal background reduces employment call back rates for former prisoners by 50% [44].

The drug war has been an economic burden for the greater society as well. Labor productivity and tax revenue is affected when we shrink the workforce by taking people away from the job market [46]. Tax dollars are also impacted by the considerable amounts of tax revenue that financially supports our carceral system. On average, approximately $80 billion is allocated towards public jails and prisons annually [47].

Imprisoning drug criminals and overcrowding prisons also presents economic externalities for the incarceration facilities themselves. Overly incarcerated facilities result in significant budget constraints for local government run jails and prisons [48]. Further, increasing the capacity of jails and prisons also puts a strain on inmate transportation services [49]. Policy reform could reduce the number of inmates incarcerated for drugs and alleviate the financial weight of maintaining our criminal justice system which often exceeds its capacity.

3.3 Health Externalities

Overcrowding jails and prisons with non-violent drug offenders worsens inmate conditions which can have poor effects on health. Overcrowding impairs mental health, being "significantly associated with depression and hostility" [50]. One study found that suicides were significantly increased in facilities where overcrowding and violence were present [51]. There are physical health externalities as well. Research shows that overcrowding leads to a higher risk of contracting serious physical illnesses like Tuberculosis [52], HIV [53] and COVID-19 [54] . Overcrowding adds pressure on employees who help maintain the health of inmates, such as healthcare workers, food service providers, sanitation employees, and correctional officers - who experience a unique strain of dealing with increased levels of violence resulting from overcrowding [55].

In addition to the mass incarceration and overcrowding problem, inadequate drug policy has played a role in cultivating another immense health issue. Past approaches to curtailing drug use have proven ineffective in reducing the health risks that drug abuse poses. Incarceration may put a pause on drug use, but narcotics convicts are likely to reuse drugs after leaving confinement [56]. Nearly 75% of former inmates with substance use disorder relapse in the first three months following their release [57]. Relapsing can have life threatening consequences due to the drug users' lower tolerance gained in confinement. Studies have found that post-incarceration substance use presents a higher risk for drug overdosing [58].

3.4 Overcoming the Externalities

Now, the United States is experiencing an opioid overdose crisis, prompting many to reconsider other mechanisms that may lead to better health outcomes for drug users. Post-incarceration drug overdosing is a criminal drug policy externality that clearly effects the formally incarcerated, but drug-users as a whole are at increased risk overdosing due to the lack of policy-supported medical frameworks needed to properly tackle this issue. Criminally focused drug policy has diverted focus away from treating substance use disorder medically. Some states in the US are now moving away from criminalization, particularly by legalizing marijuana. Though marijuana isn't a driver of drug overdose deaths, a long-standing narrative in the United States illustrates marijuana as a "gateway drug" that leads users to engage in riskier drug-use which compromise their mental and physical health. In the next chapter, we'll describe our study which seeks to uncover the causal link between drug decriminalization and overdose rates.

Chapter 4

Decriminalization and Health: the Causal Effect of Marijuana Policy on Overdose Death Rates

According to the marijuana gateway hypothesis, drug use follows a predictable pattern in which individuals who use legal drugs, like tobacco and alcohol, are more likely to use marijuana [59]. In accordance with this pattern, marijuana users have a greater susceptibility to using harder substances [60]. This hypothesis would suggest that making marijuana more accessible would lead to more consumption of drugs that have a greater overdose mortality threat. Overdosing is the most dire outcome of drug abuse and is an essential metric to monitor when assessing the efficacy of drug policy. Drug related overdose deaths have been on the rise in the past few decades. Figure 4.1, pulled from an online report provided by the National Institute on Drug Abuse (NIDA), shows the increase in overdose deaths between 1999 and 2021. Also, more Americans have access to marijuana as a result because of state legalization laws, as shown in Figure 4.2 (chart pulled from Statista).

4.1 Research Question and Policy Interventions

In this study, we try to find the causal effect of state marijuana laws and programs on overdose deaths rates. We consider the following five marijuana policy interventions:

1. medical marijuana laws (MMLs)
2. medical marijuana dispensary openings
3. medical marijuana patient ID programs
4. recreational marijuana laws (RMLs)
5. recreational marijuana dispensary openings

We divide marijuana policy into these five dimensions because states enact marijuana policies differently, which impacts how and when marijuana becomes easily available to end

National Drug-Involved Overdose Deaths*, 1999 - 2021

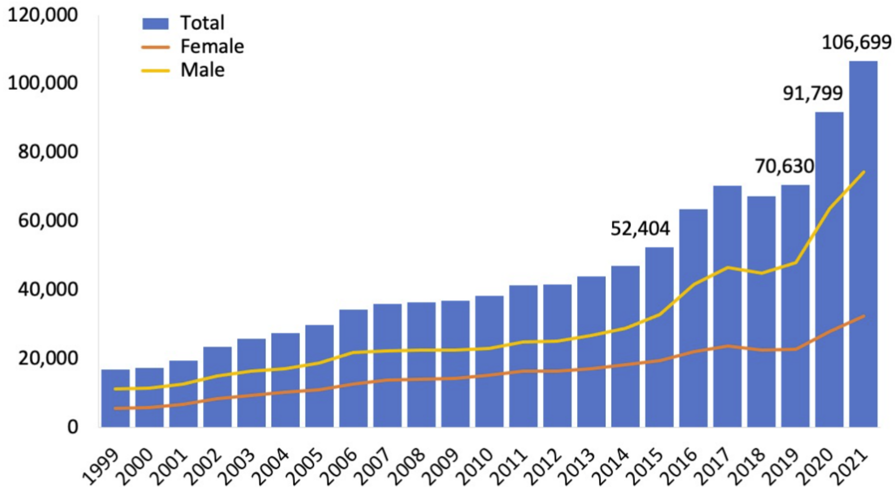

Figure 4.1: This chart was pulled from the *Drug Overdose Death Rates* online report written by the NIDA.(https://nida.nih.gov/research-topics/trends-statistics/overdose-death-rates) *Includes deaths with underlying causes of unintentional drug poisoning (X40–X44), suicide drug poisoning (X60–X64), homicide drug poisoning (X85), or drug poisoning of undetermined intent (Y10–Y14), as coded in the International Classification of Diseases, 10th Revision. Source: Centers for Disease Control and Prevention, National Center for Health Statistics. Multiple Cause of Death 1999-2021 on CDC WONDER Online Database, released 1/2023.

Number of Americans (in millions) living in states with legal recreational or medical marijuana, by year of approval*

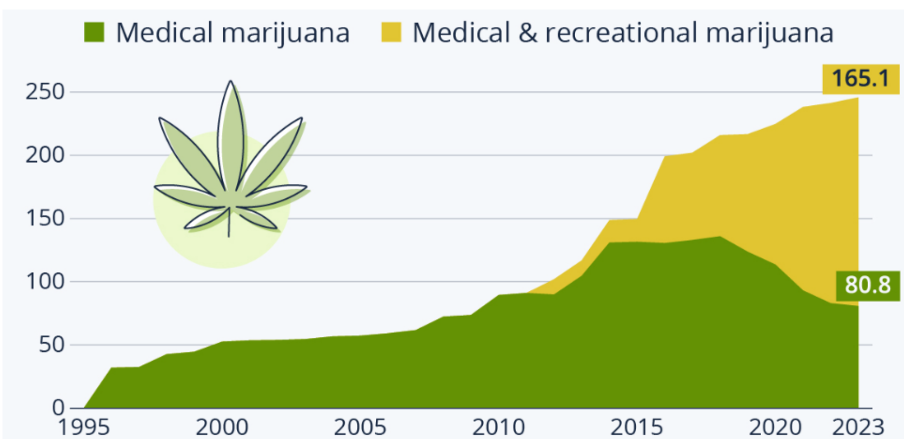

Figure 4.2: This chart was generated by Statista using Census Bureau data (https://www.statista.com/chart/30710/people-living-in-legal-weed-states/). *some might not be in effect/implemented yet. Excludes CBD laws, decriminalization, reduced penalties, local/territory initiatives (except D.C.). LA counted from 2020. Sources: Census Bureau, Statista research.

consumers. A state legalizing medical marijuana doesn't mean the state has created a program that allows doctors to prescribe the substance, and legal recreational marijuana doesn't necessarily mean that citizens in a given state have an avenue to purchase the substance. (1) MMLs and (4) RMLs refer to laws that legalize medical or recreational marijuana, respectively, and are represented in the data by the laws' effect dates. (2) Medical marijuana dispensaries and (5) recreational marijuana dispensaries are represented in the data by the date the first dispensary of that kind opened in a particular state. (3) Medical marijuana patient ID programs are different depending on state. For states that have medical dispensaries, patient IDs are given to medical marijuana patients so they can purchase medical cannabis. In states that don't have dispensaries, patient ID programs give patients protection from prosecutions for possessing, and sometimes even growing, small amounts of cannabis. We estimate each of the policy intervention's effects on overdose mortality rates between the years 2010 and 2020 using a Difference-in-Differences approach with synthetic control at a state-by-state level. States that did not have at least seven years in the pre-policy intervention period between 2010 and 2020. We exclude these states because Synthetic Control requires a sufficient amount of data to match the trend in the treated pre-period to that of the synthetically created control, and the 'R' package that we were using, gsynth, deems seven pre-periods as sufficient. Finally, we implement a meta-analysis to find the overall pooled effect of each policy intervention. We will explain synthetic control more in the latter parts of this chapter.

4.2 Literature Review

Existing research on the relationship between marijuana laws and opioid overdose mortality is mixed. Using panel regression to examine 812 counties in the United States that opened legal marijuana dispensaries, Hsu and Kovacs found that dispensary counts were associated with decreased opioid overdose death rates, but found no evidence of a causal relationship [61]. Shover et. al used a generalized linear model with robust standard errors for select states that legalized cannabis between 1999 and 2017 and found a positive causal relationship between MMLs and opioid overdose mortality, but found that opioid overdose mortality had no significant relationship with RMLs[62]. Chan, Burkhardt, and Flyr used difference-in-differences on 29 states and D.C. to uncover the causal relationship between marijuana laws and opioid mortality and found that access to recreational marijuana decreased opioid mortality by 20% to 35% [63]. In 2020, Alcocer used synthetic control in finding that Colorado's recreational marijuana legislation had no effect on the state's opioid overdose deaths between 1999 and 2017 [64].

Our study is the first to study the effect of all five of the aforementioned policy interventions using a Difference-in-Difference approach with Synthetic Control. The paper that most resembles ours comes from Chan, Burkhardt, and Flyr, but differs in that we take DiD a step further by using synthetic control to create the counterfactual and we examine an extra marijuana policy, medical patient ID programs. Our analysis appears to be the most comprehensive econometric analysis of the causal relationship between states' marijuana policies and opioid overdose deaths.

4.3 Two-way Fixed Effects Difference in Difference

We use DiD to find the effect of our 5 marijuana policy interventions, and we fit a two-way fixed effects model adding state and year as fixed effects. This fixed effects approach allows for unobserved heterogeneity at the unit dimension (state) and the time dimension (year). Our the regression model for each of our five DiD studies is as follows:

$$Y_{ij} = \alpha + \beta S_{ij} + \gamma T_{ij} + \delta(S_{ij} \times T_{ij}) + C_{ij} + \phi_i + \tau_j + \epsilon_{ij}$$

where Y_{ij} represents our outcome variable, overdose mortality rate in basis points, for state i in year t (more about basis points mortality rate calculation in the following Data chapter). Our constant is α. S_{ij} is an indicator variable that is equal to 1 if the state is from the treatment group and 0 if not. T_{ij} is the time-specific indicator that is equal to 1 if the observation is in the post-treatment period and 0 otherwise. Our independent variable of interest is the interaction term $S_{ij} \times T_{ij}$ which captures the marijuana policies effect on the outcome variable. C_{ij} is a vector of state-year level covariates which includes poverty rate, median household income, proportion of white citizens, and proportion of female citizens. ϕ_{ij} is our state fixed effect, τ_{ij} is our year fixed effect, and ϵ_{ij} is the state-year level error term. Again, this same exact model was used to find the effect of each of the five policies.

4.4 Synthetic control

Drug decriminalization coupled with harm reduction policies may play a role in reducing overdose rates in the United States and should have a clear impact on reducing incarceration rates. Twenty-six states, and D.C., have decriminalized marijuana to some extent [65]. Accurately assessing the impact of marijuana policies on overdose rates can be challenging due to various confounding factors and recency in drug policy changes limiting the amount of empirical evidence. Synthetic control methods have emerged as a valuable tool to estimate the causal effects of policy interventions like drug decriminalization at the state and city levels. Synthetic control is a statistical technique that constructs a "synthetic" control unit, which is a weighted combination of control units that closely resemble the treated unit (i.e., the state that implemented the marijuana policy). The synthetic control is created using pre-treatment data from similar control units that did not implement the policy [66].

By comparing the post-treatment outcomes of the treated unit with the outcomes predicted by the synthetic control, the causal effect of marijuana policy can be estimated. This method accounts for both observed and unobserved confounding factors, providing a counterfactual scenario of what would have happened in the absence of the policy change. Using synthetic control to analyze the effects of drug decriminalization offers several advantages. It allows for the evaluation of the policies' impact in real-world settings, where randomized controlled trials are often unfeasible or unethical. Further, it provides a rigorous and transparent approach, enhancing the credibility of the findings [66]. The synthetic control model generates a weighted combination of control units that closely approximate the treated unit's pre-treatment trajectory. Comparing the actual outcomes of the treated unit with the synthetic control's predicted outcomes yields the causal effect estimate.

Furthermore, by comparing the results across different jurisdictions, it is possible to identify variations in the effects of drug decriminalization, leading to a better understanding of the factors that shape policy outcomes. We examine these estimate variations across states in our meta-analysis which we introduce in the next section. While no single methodology can fully capture the complexity of policy interventions, synthetic control provides a powerful tool for policy evaluation and evidence-based decision-making.

4.5 Meta-Analysis

The first phase of our analysis involves multiple DiD studies for each of our five marijuana policy interventions, where DiD with synthetic control conducted on one state represents one study. To pool our results together and find overall effects of, we next incorporate a random-effects meta-analysis model. A random-effects meta-analysis model allows for the true effect size of an intervention to differ in each study, though it may be the case that the studies have one true effect size [67]. Our study assumes that effect sizes may be different across studies due to factors that characterize a state's population that we do not control for, like political affiliations, that impact overdose mortality rates. Future iterations of this study will include more covariates which will influence whether we use a fixed-effect model or a random-effects meta-analysis model.

We use forest plots which graph each state's average treatment effect on the treated and the corresponding standard errors. These plots also provide the overall effect estimate of the study, denoted by a black diamond. Our forest plots will be presented in the Analysis and Results chapter.

Chapter 5

Data

The time frame of this study is from 2010 to 2020. The data for this project were assembled from various sources and are outlined below in 4 categories: 1) marijuana policy intervention data, 2) overdose mortality data, 3) yearly income data, 4) Demographic data.

5.1 Marijuana Policy Intervention Data

To test the effect of marijuana policy , we decided to create a dataset that contained the five policy interventions of interest ourselves. The benefit of personally generating the dataset is purely educational, in that it taught the researchers how complex drug decriminalization can be and how inconsistent the process is from state to state. In many states, a law will go into effect that legalizes the use of medical or recreational marijuana, but that doesn't mean citizens have an avenue to obtain marijuana in their state. In the case of medical marijuana, patients in many states had to wait for a medical marijuana patient ID program to become available before accessing the substance. Some states unveiled medical marijuana dispensaries after passing a MML. Other states both created a patient ID program then later opened medical marijuana dispensaries after passing MMLs. Similarly, most states have a gap between passing RMLs and opening recreational marijuana dispensaries.

This dataset was meticulously assembled by googling whether or not (and when) each of the 50 United States enacted a MML, RML, and/or made available medical marijuana ID programs, medical marijuana dispensaries, or recreational marijuana dispensaries. For MMLs and RMLs, the name of the policy and the policy's effect date were recorded. For patient ID programs, we recorded the date the program first became available for patients to register. Finally, we recorded the date that the first medical or recreational marijuana store opened in each state where dispensaries were accessible. Our DiD analysis only required we use the year of the policy intervention, so exact dates were recorded but were not involved in finding the effect of the five policies.

5.2 Overdose Mortality Data

The dependent variable in this analysis is yearly, state mortality rates in basis points. A basis point is equivalent to one one-hundredth of a percent and is used in our study to remove the difficulty of analyzing and interpreting raw mortality rates which can be quite small. The mortality rate in basis points is calculated by multiplying a state's raw mortality rate by $10,000$. The overdose mortality data were pulled from the National Center for Health Statistics Mortality Data on CDC Wonder and included annual overdose deaths by state and race. CDC Wonder suppresses cause of death amounts for sub populations if there are less than 16 individuals in that sub population who died of a given cause in the specified unit of time (i.e. year or month). This means, for certain races, we were unable to see the number of people who died of an overdose in a given state for a particular year. CDC wonder does this to protect confidentiality of patients whose data comprise the mortality dataset by making it difficult to pinpoint and disclose individuals' identities. An issue here is that, because of this data suppression, some of our values for state overdose deaths may be slightly off. In future iterations of this project we plan to use restricted CDC mortality data that does not suppress mortality counts to provide precise calculations for overdose mortality rate.

5.3 Yearly Income and Poverty Data

Income and poverty rate variables are used as covariates. Annual median household incomes by state were collected from the Federal Reserve Economic Data (FRED) for the 2010-2020 time frame. Separately, annual state poverty rates were pulled from the American Community Survey (ACS) data accessed through using the census API in 'R'. For 2010 and 2011 we used the ACS one year estimates. For 2012-2020 we used the ACS 5-year survey data.

5.4 Demographic Data

We used demographic covariates as well. Year-state percentages of white citizens and year-state percentages of female citizens were collected to represent state race and gender composition into our model. These covariates can be found in the model output (see Appendix) under the names wratio (representing "white ratio") and fratio (representing "female ratio"). This data was downloaded directly from the U.S. census website and has the following title.

Age, Sex, Race, and Hispanic Origin (5 race alone or in combination groups)

https://www.census.gov/programs-surveys/popest/technical-documentation/research/evaluation-estimates/2020-evaluation-estimates/2010s-state-detail.html

Chapter 6

Analysis and Results

This section focuses on the meta-analysis conducted on each of our five marijuana policy interventions: 1) Medical Marijuana Laws (MMLs), 2) medical patient ID programs, 3) medical marijuana dispensaries, 4) Recreational Marijuana Laws (RMLs), and 5) recreational marijuana dispensaries. Our goal is to see which states' overdose mortality rates were positively or negatively impacted by these five treatments, and to also determine which treatments had significant overall effects. It's important to note that as a precursor to this meta-analysis, TWFE DiD with synthetic control was conducted on states that introduced each treatment between 2010 and 2020 and also had at least 7 years of pre-treatment periods in that time frame. The counterfactual plots and model output containing the *Average Treatment Effect on the Treated*, the *Treatment Effect by Period*, and *Coefficients for the Covariates* for each treatment-state pair can be found in the Appendix.

6.1 Treatment: MMLs

We examined the effect of MMLs on state overdose mortality rates in six states: Utah, Virginia, Oklahoma, West Virginia, North Dakota, and Missouri. Figure 6.1 displays a forest plot which charts the estimate (and confidence interval) for each of the aforementioned six states. MMLs had no significant effect on changing overdose mortality rates in any of these states. The overall effect of MMLs, denoted by the black diamond corresponding to the RE model towards the bottom of the figure, was negative but insignificant in changing overdose death rates in these six states.

6.2 Treatment: Medical Marijuana Patient ID Programs

The nine states we investigated that introduced patient ID programs are Pennsylvania, Utah, Oklahoma, Maryland, Arkansas, Missouri, North Dakota, Ohio, and Virginia. As shown in Figure 6.2, the only state that yielded significantly lower overdose mortality rates in the post-treatment period than its synthetic control was Pennsylvania. The forest plot shows that the overall effect of patient ID programs is negative and significant, suggesting that medical marijuana patient ID programs significantly reduced overdose death rates for the states in our study.

6.3 Treatment: Medical Marijuana Dispensary Openings

Ohio, Pennsylvania, Arkansas, Utah, Oklahoma, Maryland, Missouri, North Dakota, Montana, Hawaii, California, Virginia, and Louisiana were the states studied to find the effect of medical marijuana dispensary openings. Figure 6.3 shows that medical marijuana dispensaries effectively lowered potential overdose death rates in Ohio, Pennsylvania, and Arkansas, but California and Louisiana experienced an opposite significant effect. Overall, the meta-analysis shows that medical marijuana dispensaries had no effect on state overdose mortality rates, though future research should be conducted to understand why some states experienced significantly positive effects and others yielded significantly negative effects.

6.4 Treatment: RMLs

We examined the effect of RMLs in Nevada, Maine, Vermont, Illinois, and Arizona. Figure 6.4 shows that RMLs had a significant and negative impact on state overdose rates in Nevada, but a significantly positive effect in Arizona. As evidenced by the zero RE Model estimate, RMLs had no effect on state overdose mortality rates, however, more research should be done to understand why Nevada and Arizona had such opposing effects.

6.5 Treatment: Recreational Marijuana Dispensary Openings

To understand the effect of recreational marijuana dispensaries, we studied Nevada, Michigan, Maine, California, Colorado, Massachusetts, and Illinois. Figure 6.5 shows that recreational marijuana dispensaries effectively reduced overdose mortality rates in Nevada. Overall, the effect of recreational dispensary openings was insignificant.

6.6 Results Summary

Of the 5 marijuana policy interventions included in this study, MMLs were the only policy intervention that had no significant effect on altering overdose mortality rates in any state. Recreational Marijuana dispensaries had a significant effect on reducing overdose mortality rates in one state but were overall ineffective in changing fatal overdose potential. Medical patient ID programs were the only policy intervention that obtained an overall significant effect after pooling estimates from all of the treated states. Since medical patient ID programs have crucially different implementations between states, future studies should examine how these programs' effects differ between states that have medical marijuana dispensaries versus states that do not.

Medical marijuana dispensaries and RMLs had a mix of results, with some state overdose mortality rates significantly elevating, some significantly declining, and others experiencing no significant effect at all. Overall, the meta-analysis showed that medical marijuana dispensaries and RMLs were not significantly effective in changing overdose mortality rates. These results suggest that marijuana legalization laws and dispensary openings may have state effects, but overall are not leading to higher overdose fatality rates. Alternatively, these findings do not support the claim that marijuana legalization and dispensary availability have an impact on reducing overall overdose deaths rates. It is extremely important to note that some versions of RMLs and medical marijuana dispensary roll-outs *did* in fact increase harder drug use and associated state overdose deaths rates. Future research should seek to understand these state level differences and uncover the mechanisms that drive overdose death rate growth that seemingly result from these two policies in certain states.

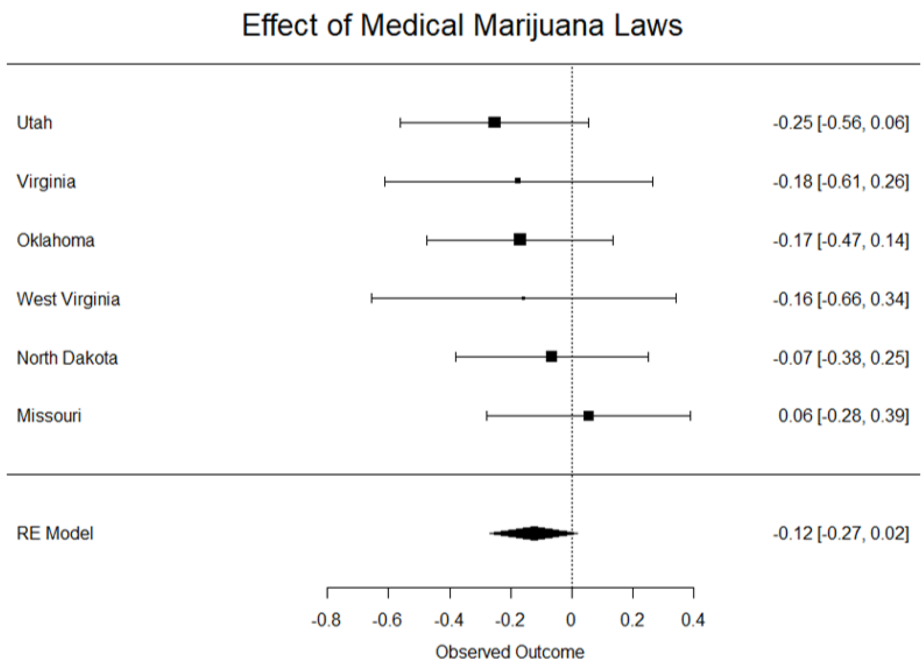

Figure 6.1: Forest Plot showing estimates and confidence intervals for the effect of MMLs on overdose mortality rates in basis points. Overall effect of the random-effects model is negative but insignificant

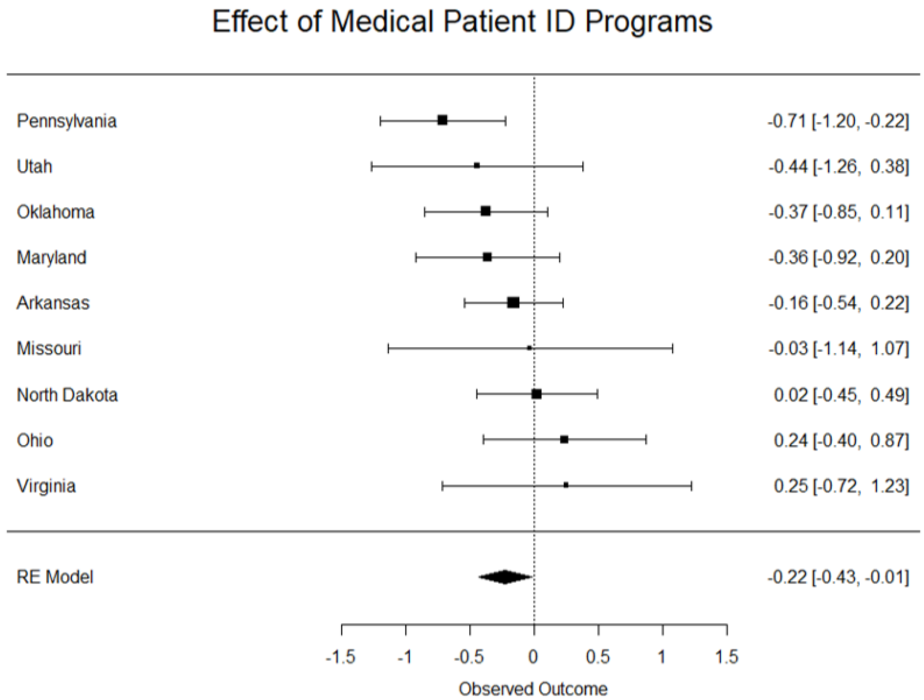

Figure 6.2: Forest Plot showing estimates and confidence intervals for the effect of Patient ID Programs on state overdose mortality rates in basis points.

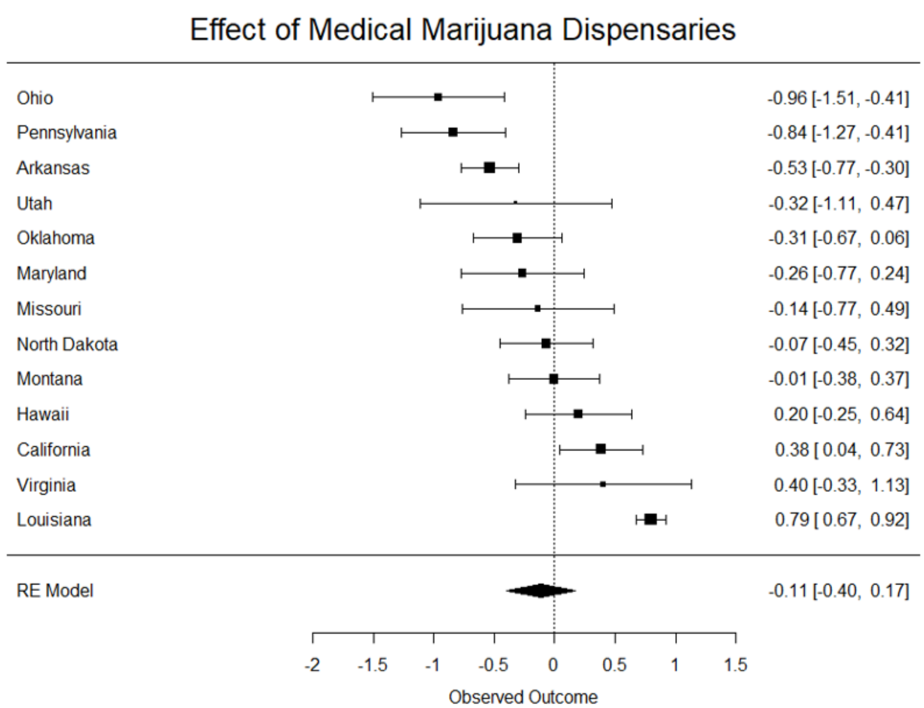

Figure 6.3: Forest Plot showing estimates and confidence intervals for the effect of Medical Marijuana Dispensaries on state mortality rates in basis points.

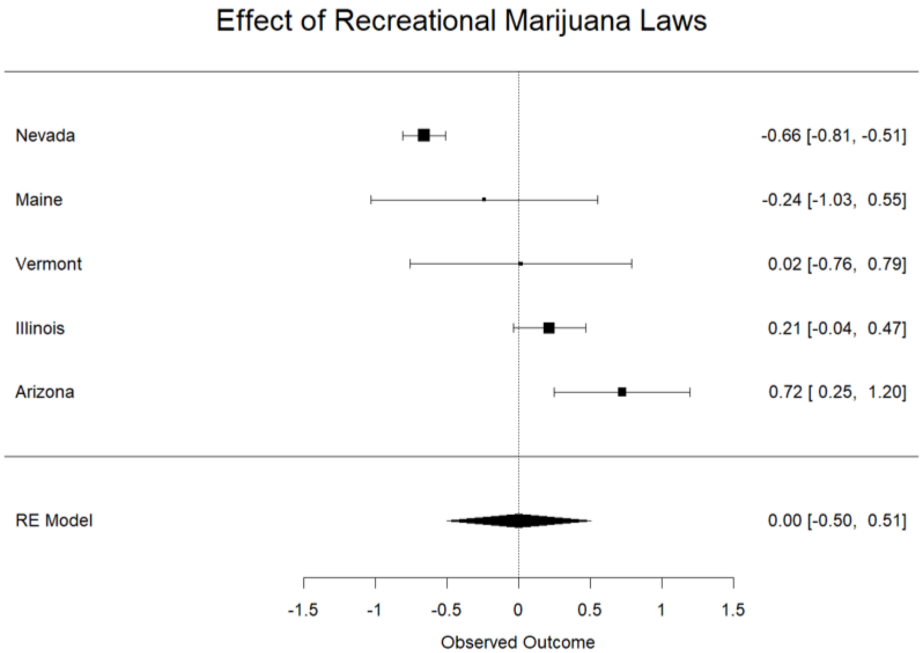

Figure 6.4: Forest Plot showing the estimates and confidence intervals for the effect of RMLs on state overdose mortality rates in basis points.

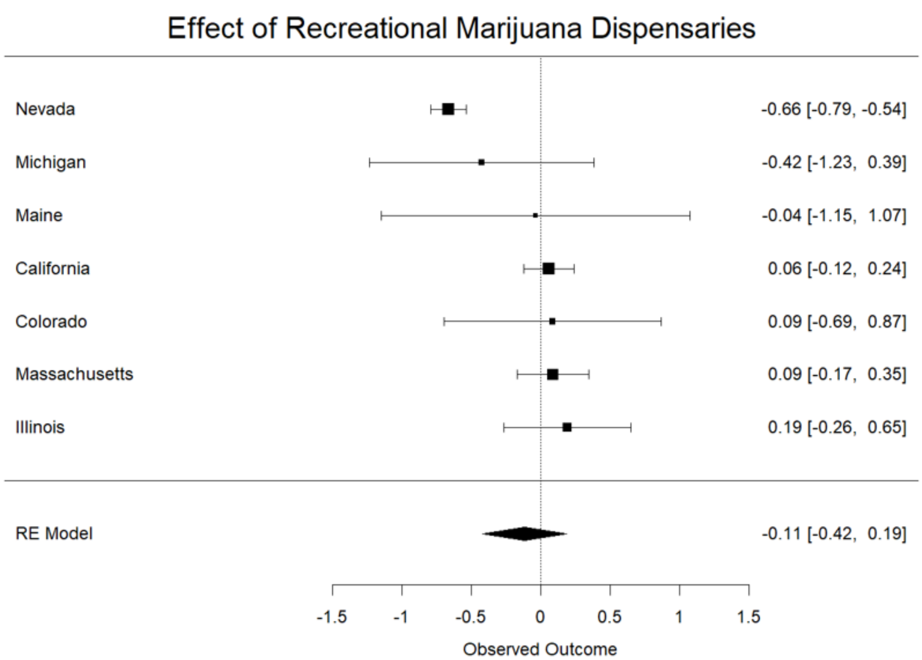

Figure 6.5: Forest Plots showing the estimates and confidence intervals for the effect of Recreational Marijuana Dispensaries on state overdose rates in basis points.

Chapter 7

Policy recommendations: Alternatives to mitigate externalities

At least 24 countries have decriminalized drugs to some degree [68]. Following Portugal's decision to decriminalize all drugs in 2001, the country saw a decrease in illicit drug use while neighboring EU countries experienced dramatic increases in addiction and usage [69]. Switzerland experienced decreases in HIV transmission and fatal overdoses in 2008 after implementing a four-pillar drug policy model which included prevention, treatment, harm reduction, and law enforcement [70]. The Netherlands is another example country that has seen reductions in overdose fatalities following their decriminalization decision [70]. These countries have realized that you cannot declare war on a substance, you can only declare war on people. The exemplary health outcomes of these countries' drug policies are among the reasons I recommend decriminalizing all drugs in the United States as a first step to overcoming the externalities of harmful drug policies.

Police departments have used drug criminalization as a mechanism to over-police and harass poor and minority communities. Across a few drug categories, minorities are disproportionately represented in drug crime rates, with crack cocaine being the most startling example. If we want to work towards a more equitable society where fewer people have to experience the harsh realities of police brutality, taking away the excuse to over-police and over-incarcerate certain sub-populations is an important first action. Decriminalization should undoubtedly be accompanied by the expungement of records for people previously convicted of non-violent drug crimes. Expunging these individuals' records will open employment opportunities, making them better contributing members to the nation's economy while also securing their individual and families' well-being.

The person most at risk of experiencing the dangerous effects of drugs is the user them self. We should not punish people for putting themselves in harm's way. Instead, our approach should be rooted in empathy to best help them. Overdose prevention and treatment programs are another way to reduce harm to poor and minority communities that disproportionately experience the negative externalities of drug use. Naloxone access is an essential part of harm reduction initiatives, which aim to diminish the damaging effects of drug abuse. All 50 states have made this product available in an effort to reduce overdose fatalities [71]. This product is offered in public libraries for free in select cities; states like Iowa, Delaware, and Ohio have statewide programs that provide naloxone to its citizens for free [72]. McClellan, C., et al showed that opioid overdoses fell by 14% when states increased access to naloxone [73].

Legalization is the ultimate means to ensuring safety among drug users. The United States experienced a substantial increase in opioid related fatalities during the COVID-19 pandemic, largely driven by fentanyl overdosing [74]. In recent years, fentanyl has made its way into the illicit drug market, causing many Americans to accidentally overdose on drugs laced with lethal amounts of the substance. Since we know that criminalization does not keep people from using drugs, monitoring the manufacturing and distribution of all drugs through legal channels is the best way to keep the drug-using community safe from the fatal effects of laced substances that have higher than normal likelihoods of killing consumers.

Chapter 8

Conclusion

Drug policy has been a contentious topic of legislation in the United States for decades and has contributed to the United States topping the incarceration leader board. The external costs of these policies have predominantly been absorbed by poor and minority communities by means of detaining a disproportionate amount of individuals in these vulnerable communities and negatively impacting these populations' economic potential as a whole. Incarcerated individuals often deal with poor mental and physical health as a result of overcrowding in detainment facilities. Local governments also experience unwanted effects of overcrowding, straining their budgets and stretching jail and prison staff thin.

Policy makers at the start of the drug war had knowledge available to steer them in another direction but chose to lean into criminalization as the primary approach to handling drug use in America. Ignoring the lessons from alcohol prohibition and turning a blind eye to the overwhelming scientific production of knowledge on the health implications of drug abuse, America missed an opportunity to offer compassion to individuals who use drugs to escape the harsh realities of life. Treating drug use medically, with harm reduction and counseling at the center of this approach, could have saved many who have lost their life to overdosing or incarceration.

We are now in a time when varying degrees of drug decriminalization are being adopted by several states in America. Synthetic control methods provide a robust and credible approach to estimate the causal effects of drug decriminalization policies at the state and city levels. By leveraging pre-treatment data from similar control units, these methods offer valuable insights into the impact of such policies on a range of outcome measures. Through using TWFE DiD with synthetic control, we found that MMLs were ineffective in changing overdose mortality rates at the state and national level. Medical marijuana patient ID programs were significant in reducing state overdose death rates, however, subsequent studies should seek these effects in states that already had medical marijuana dispensaries compared to those who do not. Medical dispensaries and RMLs yielded significantly higher state overdose morality rates in some states, and significantly lower rates in others. Recreational marijuana dispensaries led to a decline in Nevada's overdose mortality rate, but had no effect overall or on mortality rates in any of the other states we studied.

The next steps of this research will include implementing a meta-regression analysis to ascertain the driving forces of the state differences in state mortality rates we found resulting from these policy treatments. Further, since states that did not have at least seven years in the pre-treatment period were excluded from our analysis, successive research will include data that spans from 1999 onward so more states are accounted for in the synthetic control design.

The absence of an overall causal relationship between recreational marijuana laws and state overdose rates calls into question laws that ban all types of drugs, especially drugs that have an extremely low probability of inducing an overdose. If the objective of criminal drug policy centers around reducing the negative individual health effects of drug use, its worth exploring if drug decriminalization impacts overdose rates in other contexts. Given the externalities highlighted in this thesis, there may be higher levels welfare that can be achieved by decriminalizing other illicit drugs.

Appendix A

Appendix

Figure A.1: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Medical Marijuana Law (MML) in Missouri

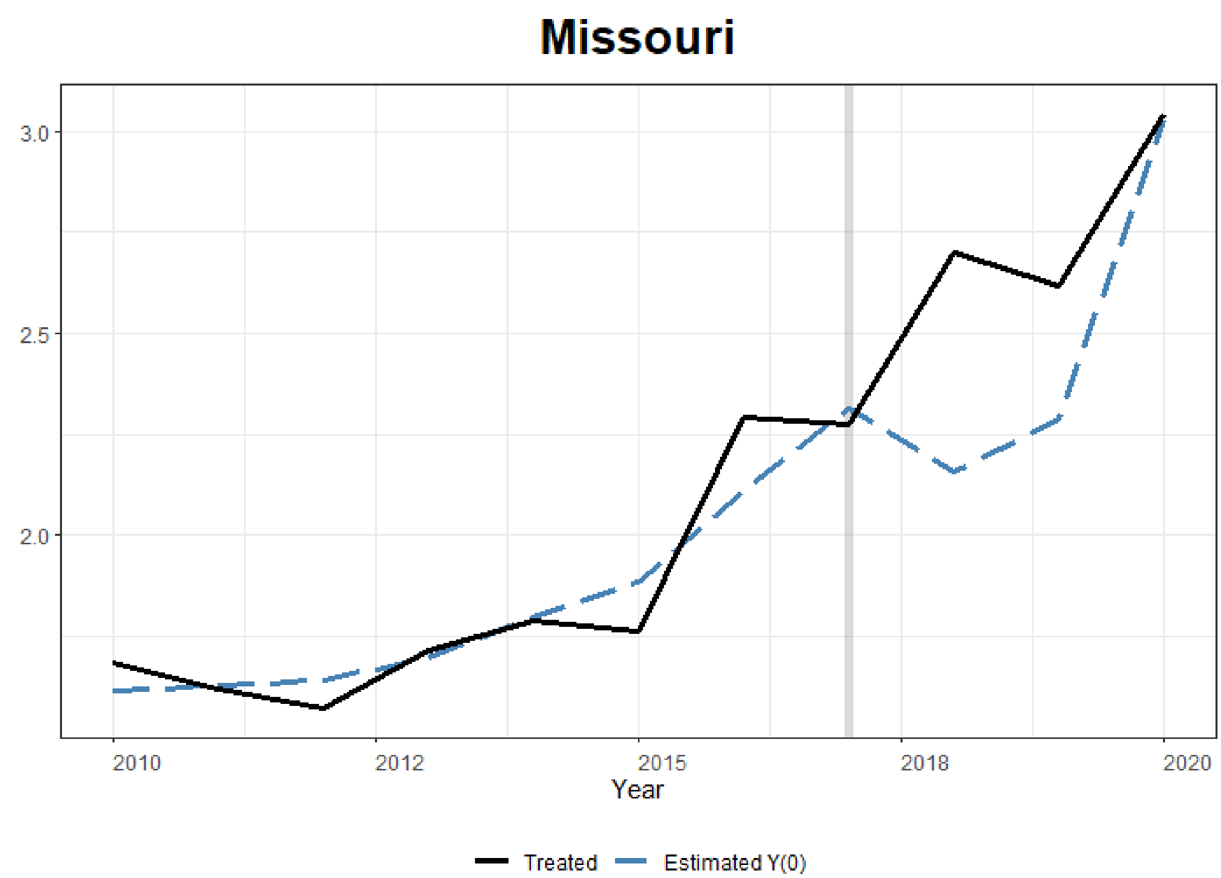

Table A.1: Average Treatment Effect on the Treated: MML in Missouri

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.2938	0.1942	-0.08681	0.6745	0.1303

Table A.2: Treatment Effect by Period (including Pre-treatment Periods): MML in Missouri

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	0.069209	0.08428	-0.09597	0.23439	0.41153	0
-6	-0.010861	0.08734	-0.18204	0.16032	0.90104	0
-5	-0.066960	0.06707	-0.19842	0.06450	0.31812	0
-4	0.017684	0.07067	-0.12083	0.15620	0.80241	0
-3	-0.008878	0.07711	-0.16001	0.14226	0.90834	0
-2	-0.120556	0.06002	-0.23819	-0.00292	0.04458	0
-1	0.185133	0.06519	0.05737	0.31290	0.00451	0
0	-0.037307	0.05037	-0.13603	0.06142	0.45891	0
1	0.540891	0.14515	0.25640	0.82539	0.00019	1
2	0.329184	0.18529	-0.03397	0.69234	0.07563	1
3	0.011409	0.39274	-0.75835	0.78116	0.97683	1

Table A.3: Coefficients for the Covariates: MML in Missouri

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-9.405e-07	3.667e-06	-8.127e-06	6.246e-06	0.7976
fratio	-1.185e+00	1.553e+01	-3.162e+01	2.925e+01	0.9392
wratio	2.195e+01	2.305e+00	1.743e+01	2.647e+01	0.0000
Poverty_rate	-1.806e-01	2.651e-02	-2.325e-01	-1.286e-01	9.783e-12

Figure A.2: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the MML in North Dakota

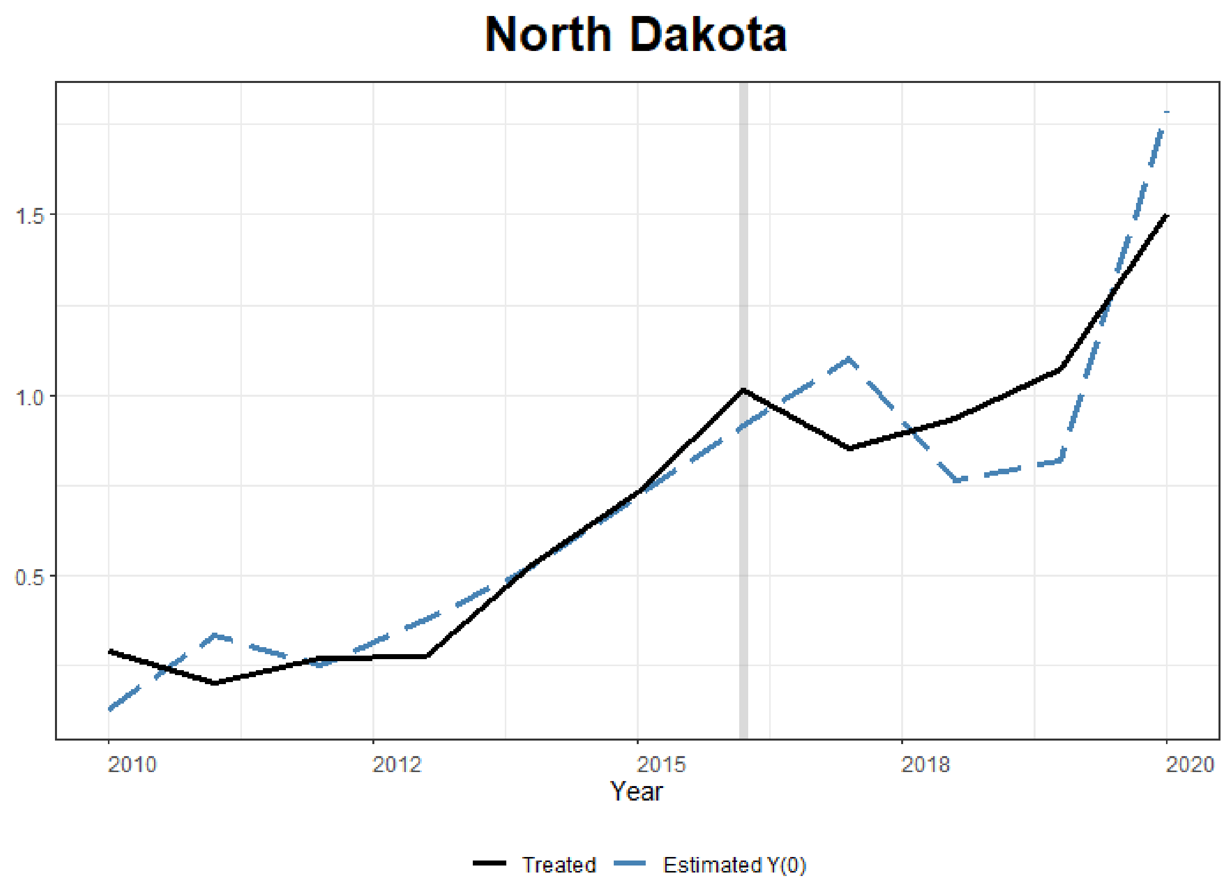

Table A.4: Average Treatment Effect on the Treated: MML in North Dakota

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.02741	0.1771	-0.3744	0.3196	0.877

Table A.5: Treatment Effect by Period (including Pre-treatment Periods): MML in North Dakota

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	0.157861	0.06373	0.03295	0.282772	0.01325	0
-5	-0.131734	0.07158	-0.27203	0.008557	0.06571	0
-4	0.019144	0.06579	-0.10979	0.148081	0.77105	0
-3	-0.103136	0.05916	-0.21910	0.012824	0.08130	0
-2	0.007053	0.05969	-0.10994	0.124047	0.90594	0
-1	0.009067	0.05042	-0.08975	0.107886	0.85729	0
0	0.096739	0.03187	0.03428	0.159198	0.00240	0
1	-0.251031	0.15543	-0.55567	0.053609	0.10630	1
2	0.170494	0.19889	-0.21933	0.560317	0.39133	1
3	0.254068	0.21000	-0.15753	0.665666	0.22634	1
4	-0.283156	0.34237	-0.95420	0.387884	0.40822	1

Table A.6: Coefficients for the Covariates: MML in North Dakota

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-2.031e-06	3.905e-06	-9.684e-06	5.622e-06	0.603
fratio	-2.074e+01	1.298e+01	-4.618e+01	4.696e+00	0.110
wratio	2.065e+01	2.129e+00	1.647e+01	2.482e+01	0.000
Poverty_rate	-1.745e-01	2.559e-02	-2.246e-01	-1.243e-01	9.153e-12

Figure A.3: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the MML in Oklahoma

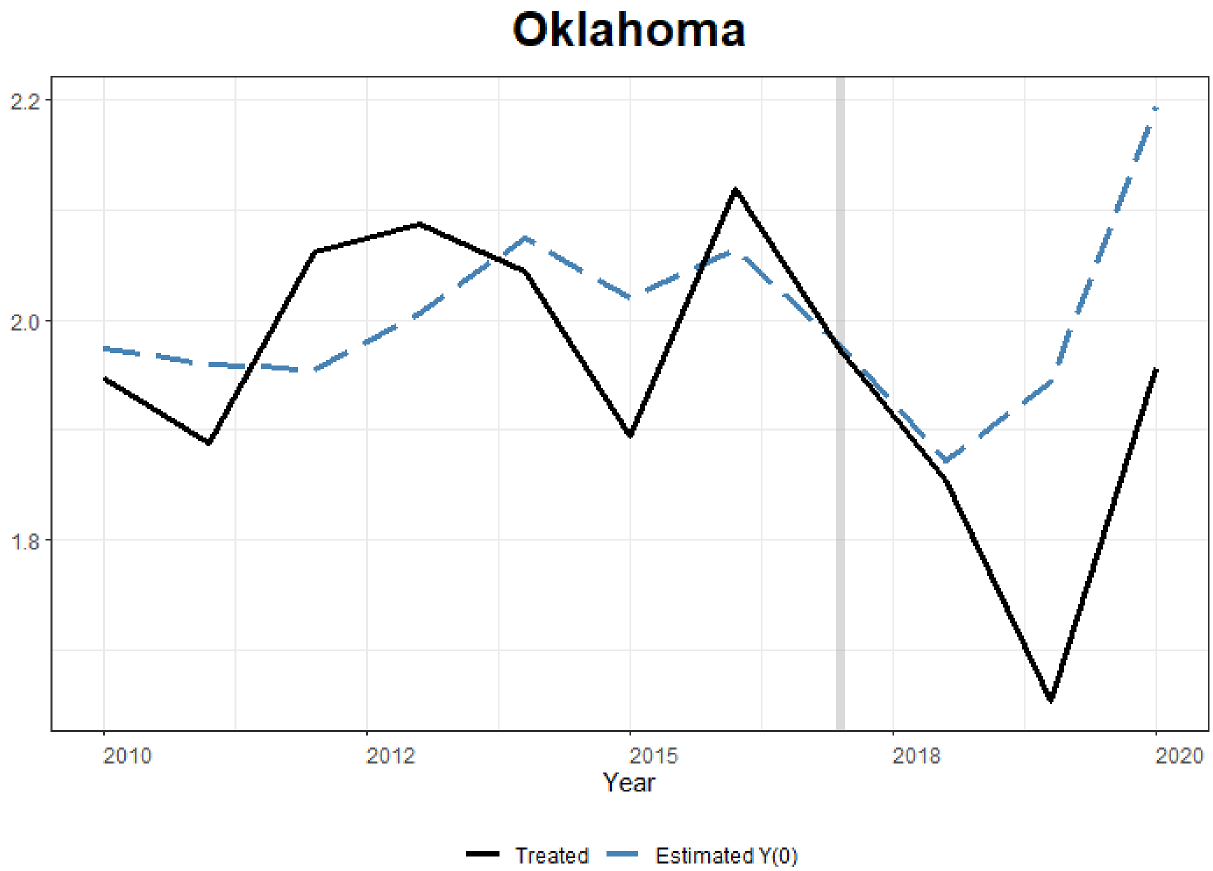

Table A.7: Average Treatment Effect on the Treated: MML in Oklahoma

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.1814	0.2063	-0.5858	0.2229	0.3792

Table A.8: Treatment Effect by Period (including Pre-treatment Periods): MML in Oklahoma

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.02684	0.08599	-0.19537	0.14170	0.75496	0
-6	-0.07239	0.08549	-0.23994	0.09516	0.39712	0
-5	0.10775	0.06792	-0.02537	0.24086	0.11264	0
-4	0.08203	0.06831	-0.05186	0.21593	0.22982	0
-3	-0.03117	0.07615	-0.18043	0.11808	0.68228	0
-2	-0.12569	0.05693	-0.23728	-0.01411	0.02726	0
-1	0.05526	0.06834	-0.07869	0.18921	0.41879	0
0	-0.00611	0.04777	-0.09974	0.08752	0.89823	0
1	-0.01732	0.15449	-0.32012	0.28549	0.91075	1
2	-0.28983	0.18390	-0.65026	0.07060	0.11501	1
3	-0.23720	0.42532	-1.07082	0.59642	0.57705	1

Table A.9: Coefficients for the Covariates: MML in Oklahoma

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	5.728e-07	4.013e-06	-7.293e-06	8.439e-06	8.865e-01
fratio	2.674e+00	1.632e+01	-2.931e+01	3.466e+01	8.698e-01
wratio	2.224e+01	2.401e+00	1.754e+01	2.695e+01	0.000e+00
Poverty_rate	-1.741e-01	2.650e-02	-2.260e-01	-1.221e-01	5.118e-11

Figure A.4: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the MML in Utah

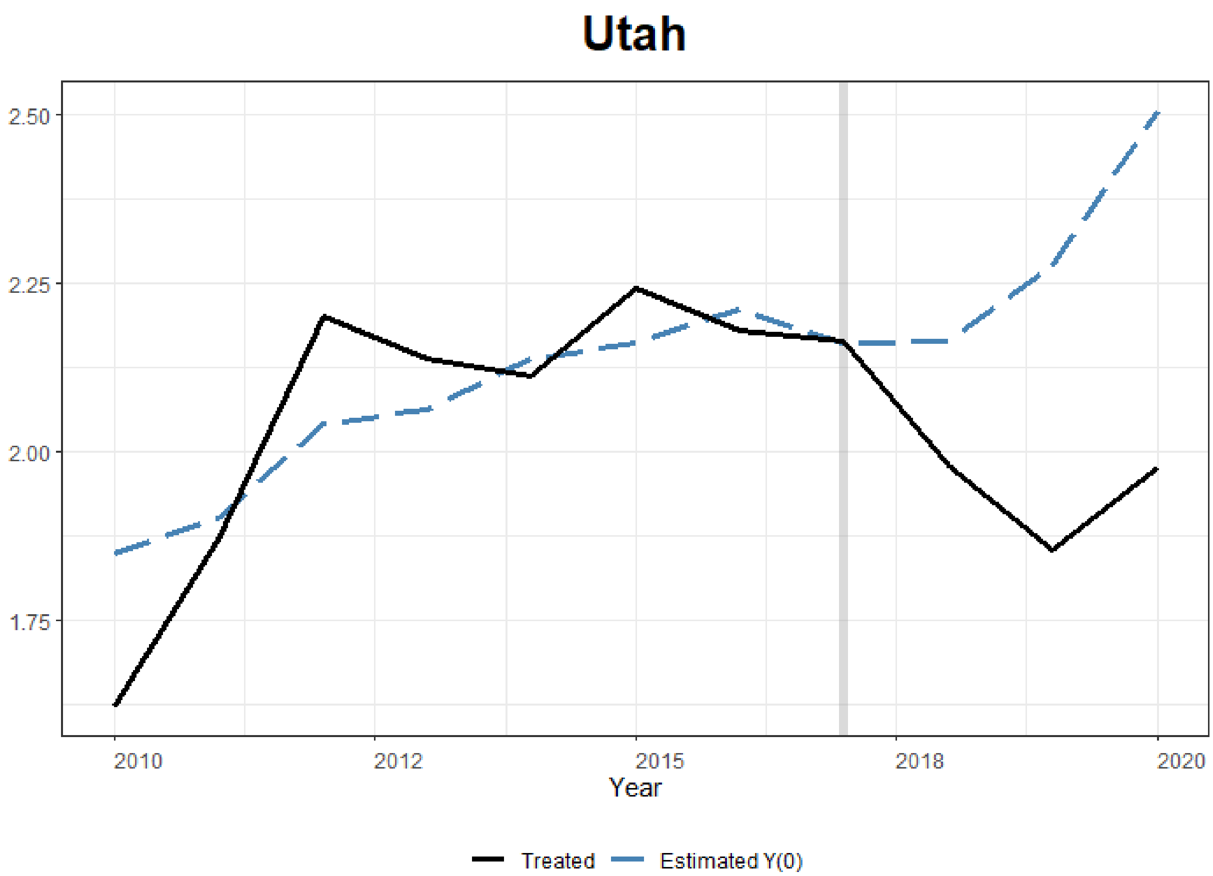

Table A.10: Average Treatment Effect on the Treated: MML in Utah

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.3785	0.2051	-0.7806	0.02356	0.06502

Table A.11: Treatment Effect by Period (including Pre-treatment Periods): MML in Utah

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.226414	0.08663	-0.39620	-0.05663	0.008957	0
-6	-0.032015	0.08374	-0.19615	0.13212	0.702243	0
-5	0.158563	0.06483	0.03151	0.28562	0.014446	0
-4	0.075468	0.06537	-0.05265	0.20359	0.248301	0
-3	-0.025952	0.07279	-0.16861	0.11671	0.721430	0
-2	0.080406	0.05302	-0.02352	0.18433	0.129403	0
-1	-0.031010	0.06647	-0.16128	0.09926	0.640823	0
0	0.002549	0.04503	-0.08570	0.09080	0.954858	0
1	-0.184696	0.16273	-0.50364	0.13425	0.256380	1
2	-0.421898	0.19255	-0.79929	-0.04450	0.028446	1
3	-0.528947	0.41375	-1.33987	0.28198	0.201096	1

Table A.12: Coefficients for the Covariates: MML in Utah

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.907e-07	4.056e-06	-8.339e-06	7.558e-06	9.233e-01
fratio	1.205e+01	1.612e+01	-1.955e+01	4.364e+01	4.549e-01
wratio	2.056e+01	2.293e+00	1.606e+01	2.505e+01	0.000e+00
Poverty_rate	-1.601e-01	2.724e-02	-2.135e-01	-1.067e-01	4.138e-09

Figure A.5: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the MML in Virginia

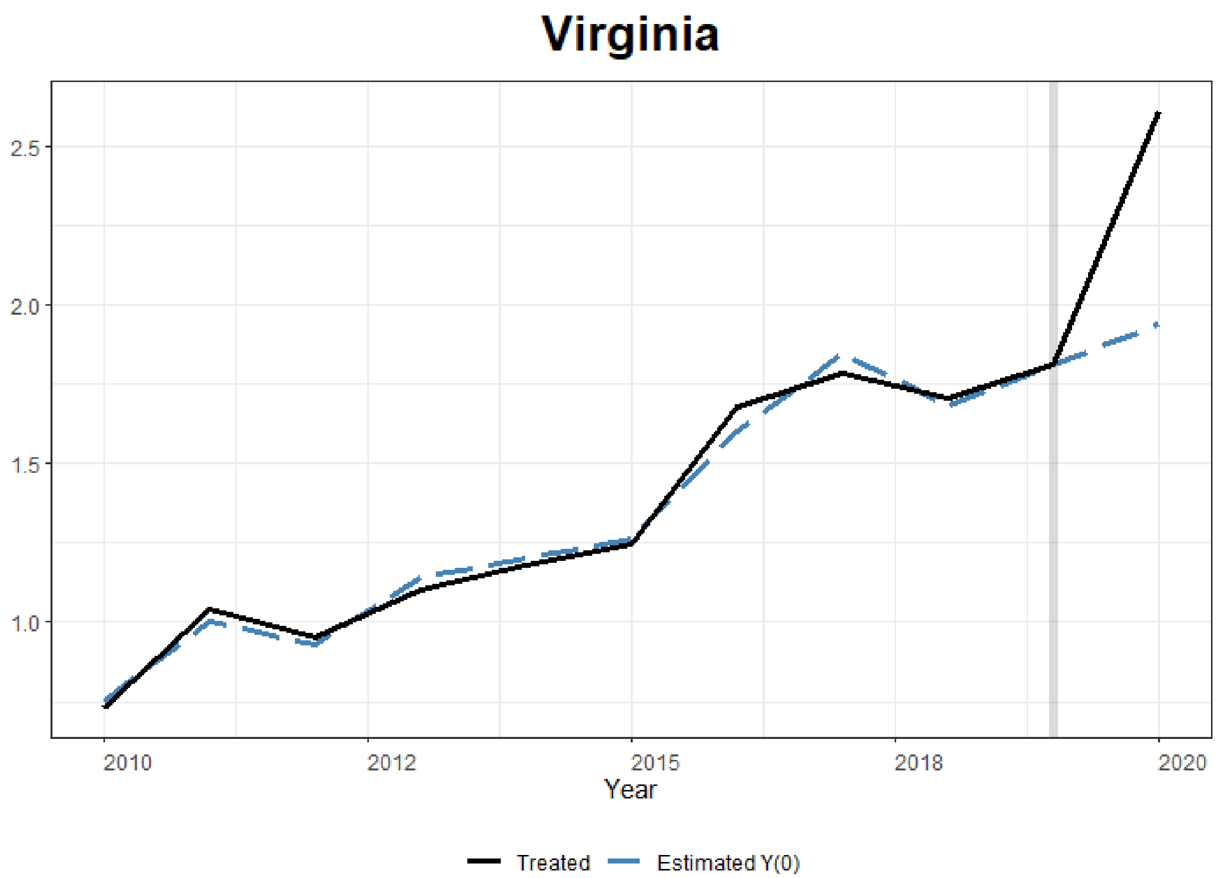

Table A.13: Average Treatment Effect on the Treated: MML in Virginia

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.6699	0.08485	0.5036	0.8362	2.887e-15

Table A.14: Treatment Effect by Period (including Pre-treatment Periods): MML in Virginia

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	-0.0185119	0.02314	-0.06387	0.026851	4.238e-01	0
-8	0.0385648	0.02882	-0.01793	0.095057	1.809e-01	0
-7	0.0228336	0.04648	-0.06826	0.113928	6.232e-01	0
-6	-0.0403822	0.02498	-0.08935	0.008587	1.060e-01	0
-5	-0.0223015	0.04103	-0.10273	0.058125	5.868e-01	0
-4	-0.0191480	0.03434	-0.08646	0.048165	5.772e-01	0
-3	0.0765936	0.03233	0.01324	0.139950	1.781e-02	0
-2	-0.0622480	0.02921	-0.11950	-0.004994	3.310e-02	0
-1	0.0242621	0.03271	-0.03985	0.088376	4.583e-01	0
0	-0.0006845	0.02953	-0.05856	0.057195	9.815e-01	0
1	0.6698548	0.08485	0.50356	0.836152	2.887e-15	1

Table A.15: Coefficients for the Covariates: MML in Virginia

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-4.241e-08	2.804e-06	-5.538e-06	5.453e-06	9.879e-01
fratio	1.287e+01	3.012e+00	6.968e+00	1.878e+01	1.928e-05
wratio	1.749e+01	3.695e-01	1.676e+01	1.821e+01	0.000e+00
Poverty_rate	-1.416e-01	9.479e-03	-1.602e-01	-1.231e-01	0.000e+00

Figure A.6: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the MML in West Virginia

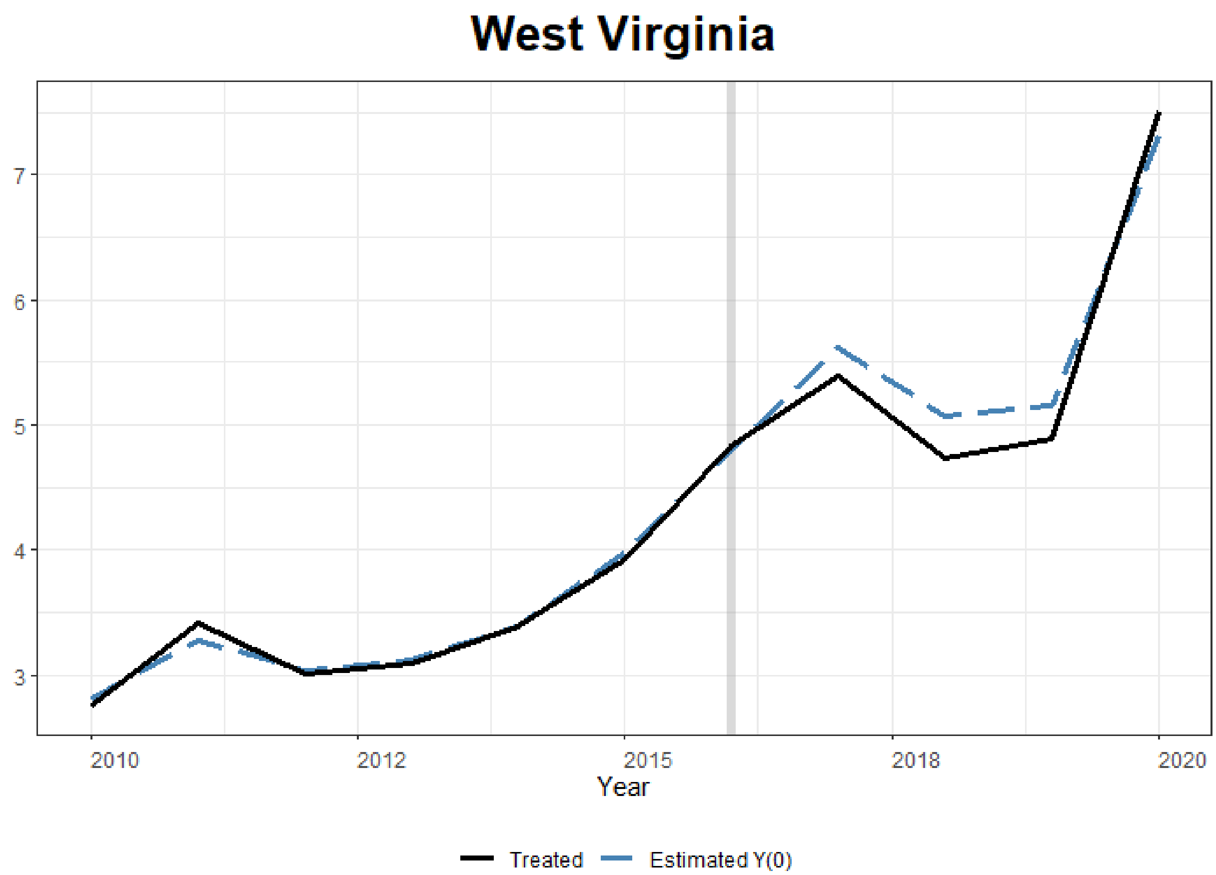

Table A.16: Average Treatment Effect on the Treated: MML in West Virginia

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.1576	0.2527	-0.653	0.3377	0.5328

Table A.17: Treatment Effect by Period (including Pre-treatment Periods): MML in West Virginia

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	-0.058102	0.06112	-0.177896	0.06169	0.34179	0
-5	0.144986	0.06232	0.022850	0.26712	0.01998	0
-4	-0.027111	0.04500	-0.115305	0.06108	0.54684	0
-3	-0.030691	0.05272	-0.134025	0.07264	0.56048	0
-2	0.005632	0.05466	-0.101501	0.11277	0.91793	0
-1	-0.043767	0.03903	-0.120260	0.03273	0.26210	0
0	0.039120	0.01829	0.003268	0.07497	0.03246	0
1	-0.223980	0.19999	-0.615953	0.16799	0.26273	1
2	-0.336590	0.27479	-0.875177	0.20200	0.22062	1
3	-0.264770	0.29334	-0.839712	0.31017	0.36674	1
4	0.194776	0.52250	-0.829298	1.21885	0.70931	1

Table A.18: Coefficients for the Covariates: MML in West Virginia

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-2.713e-06	3.823e-06	-1.021e-05	4.780e-06	4.779e-01
fratio	-2.972e+01	1.682e+01	-6.269e+01	3.239e+00	7.716e-02
wratio	2.808e+01	2.332e+00	2.351e+01	3.265e+01	0.000e+00
Poverty_rate	-1.351e-01	3.143e-02	-1.967e-01	-7.350e-02	1.718e-05

Figure A.7: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Arkansas

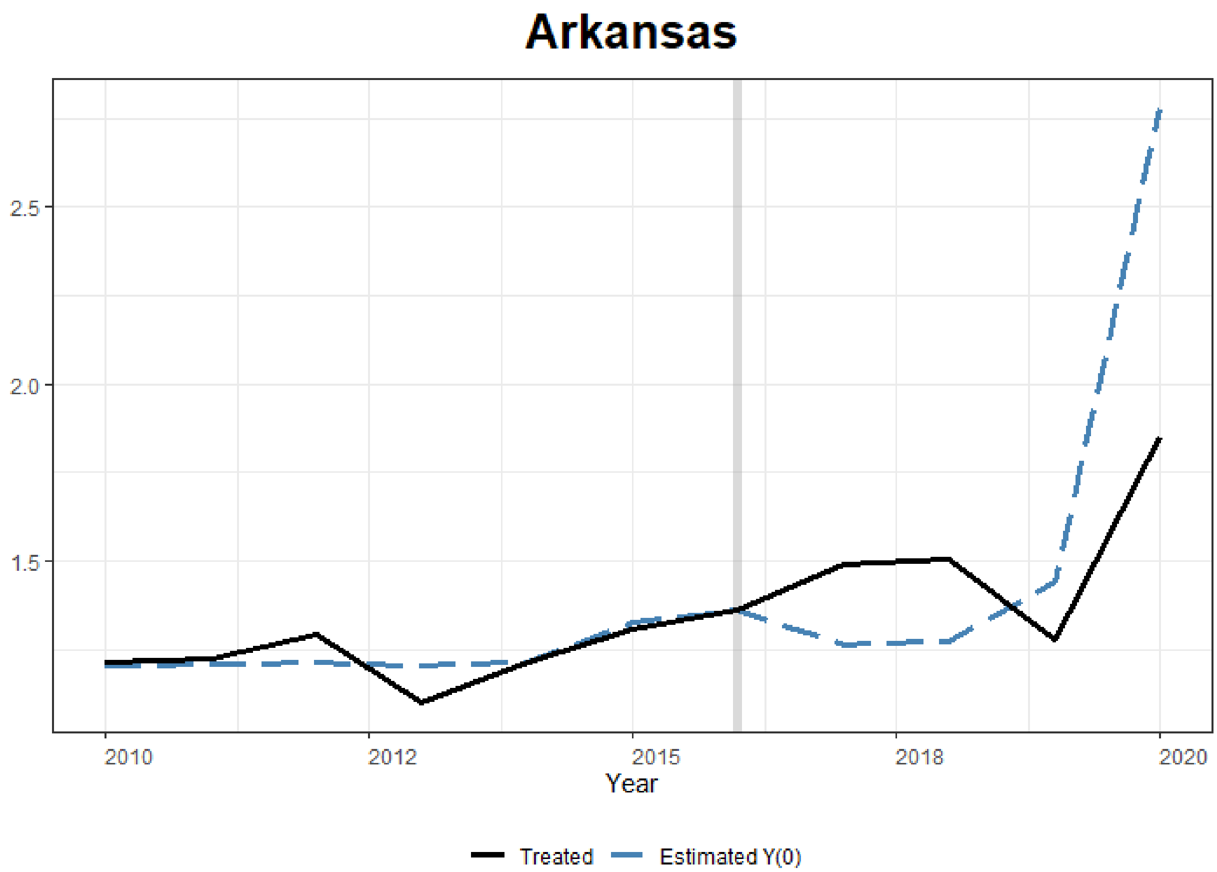

Table A.19: Average Treatment Effect on the Treated: Patient ID Program in Arkansas

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.1566	0.1878	-0.5247	0.2115	0.4045

Table A.20: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Arkansas

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	0.0134443	0.05996	-0.10407	0.13096	0.822581	0
-5	0.0150333	0.07090	-0.12393	0.15400	0.832086	0
-4	0.0774262	0.05708	-0.03444	0.18930	0.174934	0
-3	-0.1058308	0.07627	-0.25531	0.04365	0.165237	0
-2	-0.0008563	0.04532	-0.08968	0.08796	0.984925	0
-1	-0.0168148	0.04773	-0.11036	0.07673	0.724598	0
0	-0.0033610	0.03905	-0.07989	0.07317	0.931402	0
1	0.2274886	0.15602	-0.07831	0.53329	0.144830	1
2	0.2330082	0.26968	-0.29555	0.76157	0.387575	1
3	-0.1606234	0.27200	-0.69373	0.37248	0.554831	1
4	-0.9261566	0.34903	-1.61024	-0.24207	0.007966	1

Table A.21: Coefficients for the Covariates: Patient ID Program in Arkansas

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-4.459e-06	3.889e-06	-1.208e-05	3.162e-06	0.251502
fratio	-2.583e+01	8.921e+00	-4.331e+01	-8.346e+00	0.003785
wratio	3.900e+01	1.396e+00	3.626e+01	4.174e+01	0.000000
Poverty_rate	5.337e-02	2.415e-02	6.040e-03	1.007e-01	0.027102

Figure A.8: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Maryland

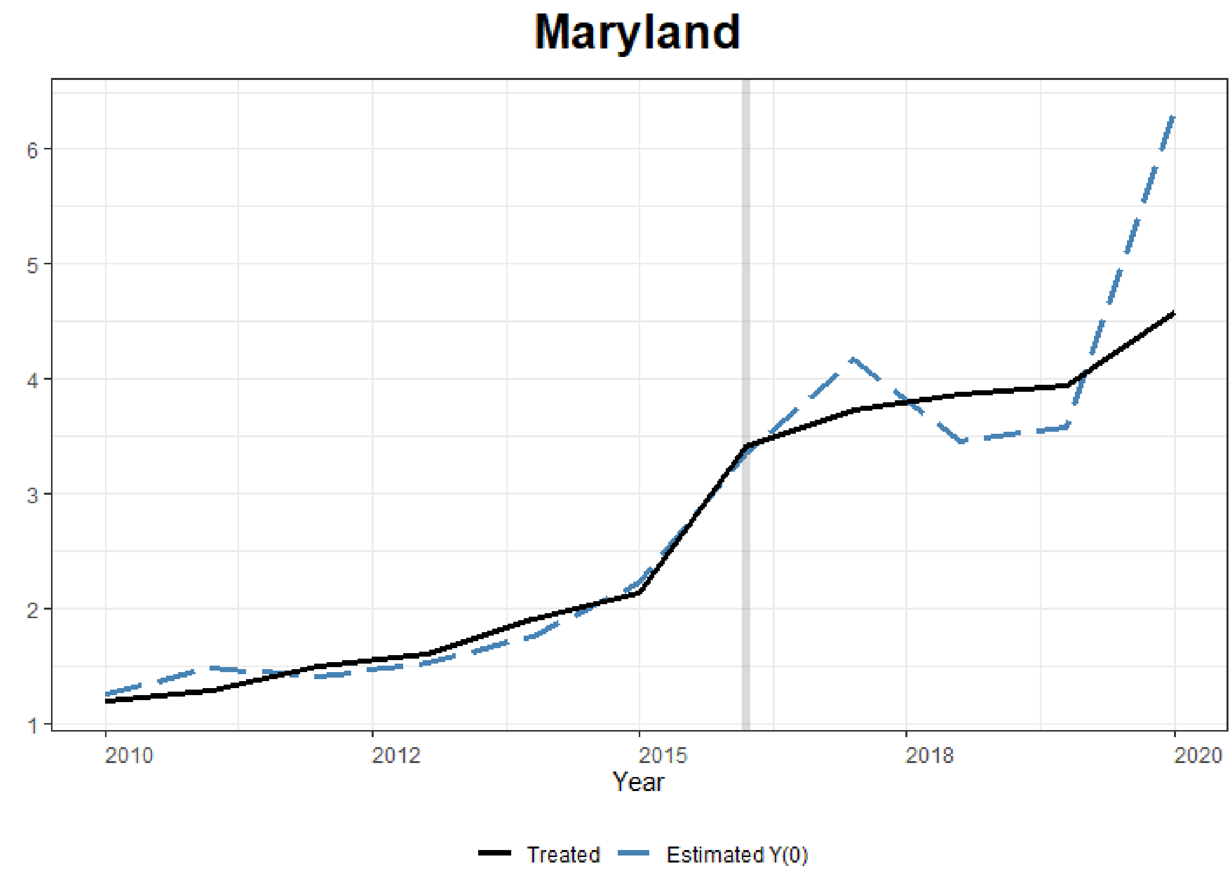

Table A.22: Average Treatment Effect on the Treated: Patient ID Program in Maryland

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.3624	0.2883	-0.9275	0.2027	0.2088

Table A.23: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Maryland

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	-0.07019	0.07229	-0.21188	0.071496	0.331572	0
-5	-0.18764	0.06984	-0.32453	-0.050753	0.007218	0
-4	0.09084	0.05415	-0.01529	0.196978	0.093417	0
-3	0.07049	0.07626	-0.07897	0.219953	0.355305	0
-2	0.15293	0.05446	0.04620	0.259658	0.004981	0
-1	-0.08963	0.04428	-0.17642	-0.002847	0.042944	0
0	0.06178	0.02502	0.01275	0.110807	0.013525	0
1	-0.44877	0.16735	-0.77678	-0.120765	0.007328	1
2	0.40083	0.29762	-0.18249	0.984156	0.178047	1
3	0.36293	0.31345	-0.25142	0.977279	0.246922	1
4	-1.76448	0.62528	-2.99000	-0.538954	0.004774	1

Table A.24: Coefficients for the Covariates: Patient ID Program in Maryland

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.818e-06	4.344e-06	-1.233e-05	4.697e-06	0.37951
fratio	-1.464e+01	1.401e+01	-4.210e+01	1.281e+01	0.29576
wratio	3.326e+01	2.216e+00	2.892e+01	3.760e+01	0.00000
Poverty_rate	5.393e-02	2.881e-02	-2.542e-03	1.104e-01	0.06124

Figure A.9: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Missouri

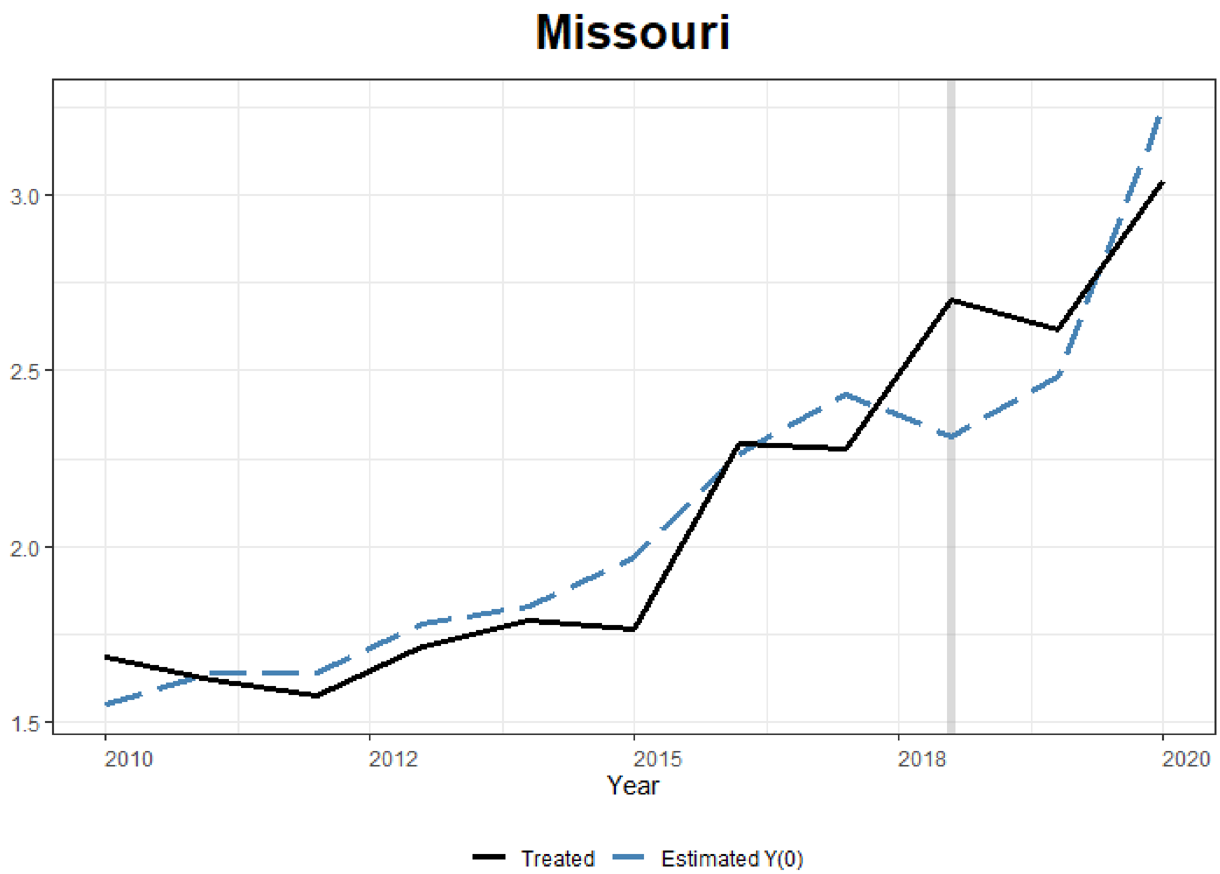

Table A.25: Average Treatment Effect on the Treated: Patient ID Program in Missouri

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.03207	0.5712	-1.152	1.088	0.9552

Table A.26: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Missouri

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-8	0.13500	0.24808	-0.3512	0.62123	0.58631	0
-7	-0.02164	0.18063	-0.3757	0.33239	0.90462	0
-6	-0.06760	0.21624	-0.4914	0.35621	0.75456	0
-5	-0.06332	0.22870	-0.5116	0.38493	0.78188	0
-4	-0.04101	0.17495	-0.3839	0.30189	0.81467	0
-3	-0.20593	0.09221	-0.3867	-0.02519	0.02554	0
-2	0.03025	0.23167	-0.4238	0.48431	0.89611	0
-1	-0.15293	0.43284	-1.0013	0.69542	0.72386	0
0	0.38718	0.30811	-0.2167	0.99106	0.20889	0
1	0.13688	0.33810	-0.5258	0.79955	0.68559	1
2	-0.20103	0.85819	-1.8830	1.4810	0.81480	1

Table A.27: Coefficients for the Covariates: Patient ID Program in Missouri

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-4.890e-06	1.091e-05	-2.627e-05	1.649e-05	0.65391
fratio	-2.707e+01	9.974e+01	-2.225e+02	1.684e+02	0.78609
wratio	3.973e+01	2.052e+01	-4.852e-01	7.994e+01	0.05283
Poverty_rate	6.648e-02	1.370e-01	-2.021e-01	3.350e-01	0.62752

Figure A.10: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in North Dakota

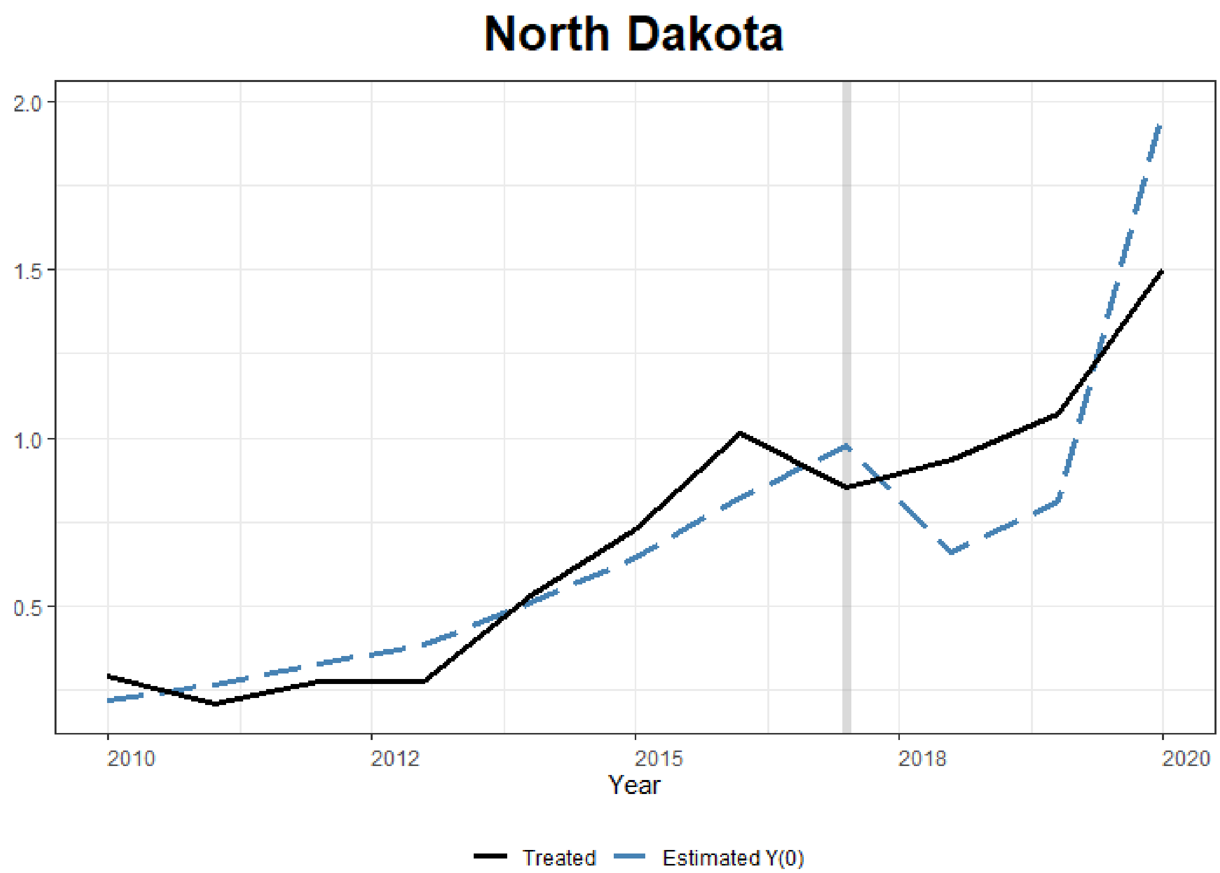

Table A.28: Average Treatment Effect on the Treated: Patient ID Program in North Dakota

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.022	0.2324	-0.4335	0.4775	0.9246

Table A.29: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in North Dakota

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	0.07013	0.08129	-0.08920	0.22946	0.3882968	0
-6	-0.05917	0.08926	-0.23412	0.11578	0.5073819	0
-5	-0.05245	0.06507	-0.17997	0.07508	0.4202141	0
-4	-0.10919	0.09170	-0.28892	0.07055	0.2337891	0
-3	0.02097	0.05652	-0.08980	0.13174	0.7106324	0
-2	0.08201	0.06350	-0.04245	0.20648	0.1965214	0
-1	0.19457	0.05450	0.08774	0.30139	0.0003572	0
0	-0.12359	0.04380	-0.20944	-0.03774	0.0047791	0
1	0.27830	0.20103	-0.11571	0.67230	0.1662411	1
2	0.26033	0.22178	-0.17435	0.69502	0.2404671	1
3	-0.47264	0.44347	-1.34182	0.39654	0.2865224	1

Table A.30: Coefficients for the Covariates: Patient ID Program in North Dakota

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-6.465e-06	4.560e-06	-1.540e-05	2.472e-06	0.1562
fratio	-5.384e+01	1.321e+01	-7.973e+01	-2.795e+01	4.589e-05
wratio	3.842e+01	2.381e+00	3.376e+01	4.309e+01	0.000e+00
Poverty_rate	4.294e-02	2.475e-02	-5.574e-03	9.145e-02	0.08278

Figure A.11: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Ohio

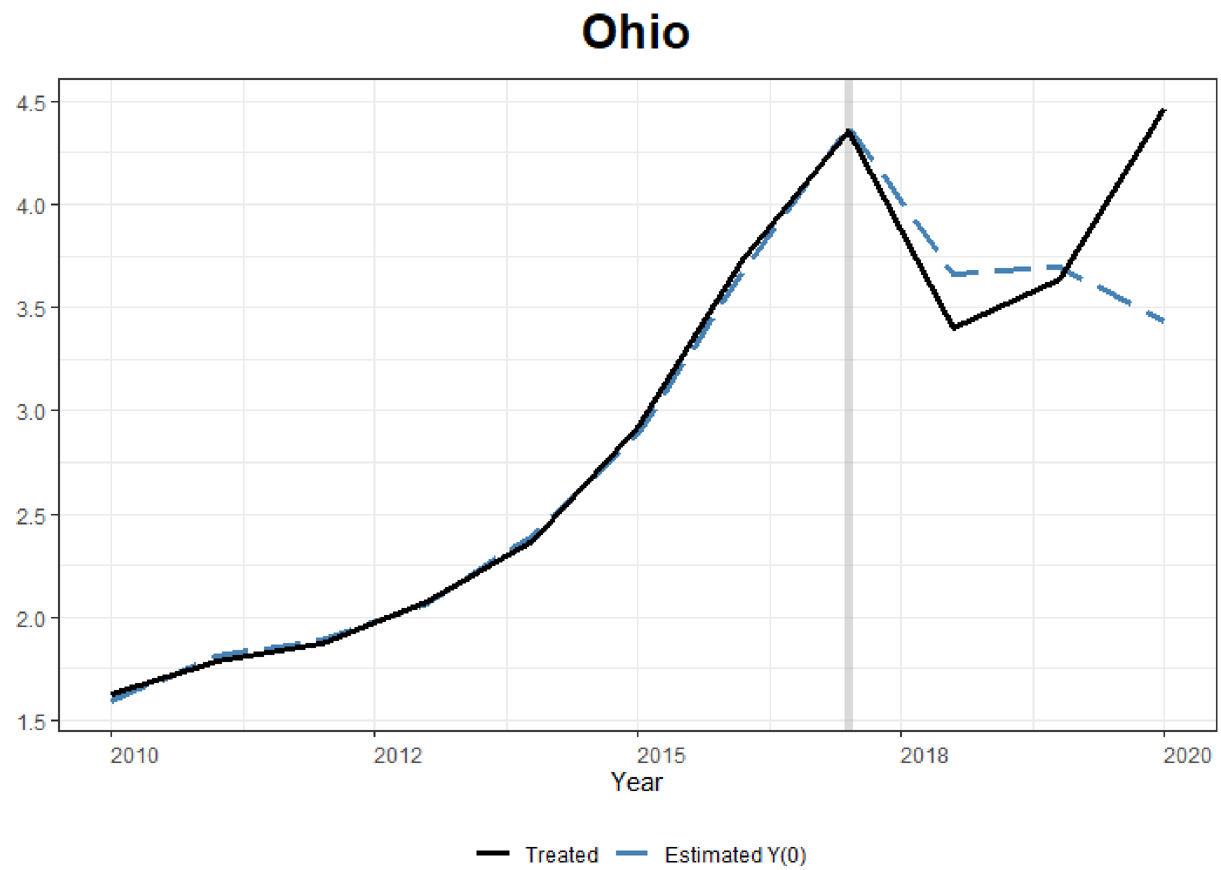

Table A.31: Average Treatment Effect on the Treated: Patient ID Program in Ohio

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.2373	0.3202	-0.3902	0.8649	0.4586

Table A.32: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Ohio

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	0.033597	0.05035	-0.06508	0.13228	0.504583	0
-6	-0.033001	0.05425	-0.13934	0.07334	0.543016	0
-5	-0.016470	0.03638	-0.08778	0.05484	0.650781	0
-4	0.004138	0.05568	-0.10499	0.11326	0.940748	0
-3	-0.026164	0.03314	-0.09111	0.03879	0.429803	0
-2	0.035793	0.03390	-0.03065	0.10224	0.291077	0
-1	0.053198	0.03829	-0.02186	0.12825	0.164769	0
0	-0.022895	0.03003	-0.08176	0.03597	0.445877	0
1	-0.257803	0.40945	-1.06031	0.54470	0.528935	1
2	-0.056720	0.44369	-0.92634	0.81290	0.898279	1
3	1.026492	0.34199	0.35621	1.69677	0.002686	1

Table A.33: Coefficients for the Covariates: Patient ID Program in Ohio

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-2.915e-06	3.919e-06	-1.060e-05	4.766e-06	0.4570
fratio	-3.868e+01	9.248e+00	-5.680e+01	-2.055e+01	2.882e-05
wratio	3.904e+01	1.544e+00	3.601e+01	4.207e+01	0.0000
Poverty_rate	3.623e-02	2.553e-02	-1.382e-02	8.628e-02	0.1560

Figure A.12: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Oklahoma

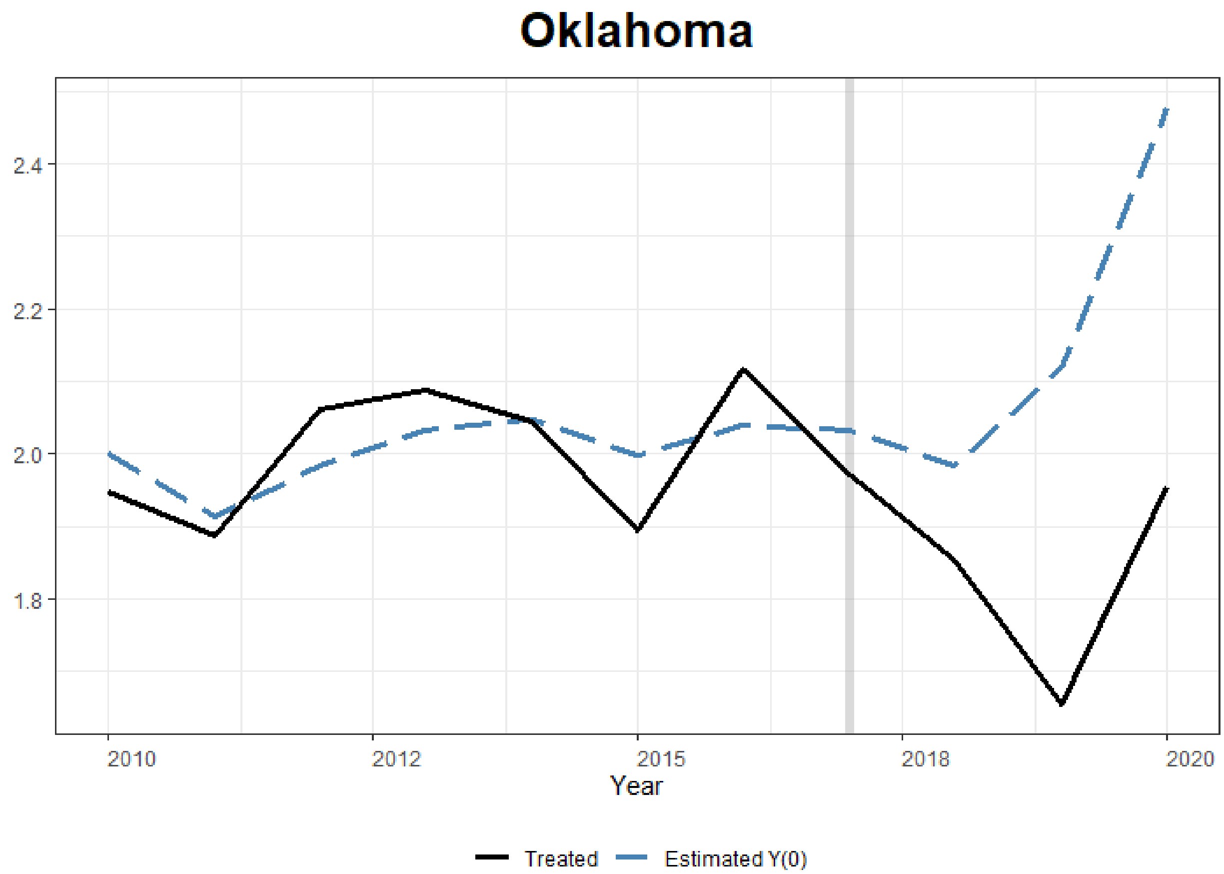

Table A.34: Average Treatment Effect on the Treated: Patient ID Program in Oklahoma

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.3715	0.2495	-0.8606	0.1175	0.1365

Table A.35: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Oklahoma

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.053636	0.09707	-0.24389	0.13662	0.58058	0
-6	-0.025903	0.09232	-0.20684	0.15504	0.77903	0
-5	0.077273	0.06711	-0.05427	0.20881	0.24957	0
-4	0.054418	0.08891	-0.11984	0.22867	0.54049	0
-3	-0.002384	0.06981	-0.13922	0.13445	0.97275	0
-2	-0.104766	0.06107	-0.22447	0.01493	0.08627	0
-1	0.078481	0.05489	-0.02911	0.18607	0.15279	0
0	-0.059728	0.04343	-0.14484	0.02538	0.16900	0
1	-0.129713	0.19955	-0.52082	0.26139	0.51567	1
2	-0.464611	0.22738	-0.91026	-0.01896	0.04102	1
3	-0.520310	0.48356	-1.46807	0.42745	0.28193	1

Table A.36: Coefficients for the Covariates: Patient ID Program in Oklahoma

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-4.635e-06	4.200e-06	-1.287e-05	3.597e-06	0.26976
fratio	-2.534e+01	1.389e+01	-5.257e+01	1.882e+00	0.06808
wratio	4.032e+01	2.489e+00	3.545e+01	4.520e+01	0.00000
Poverty_rate	5.813e-02	2.669e-02	5.813e-03	1.105e-01	0.02943

Figure A.13: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Pennsylvania

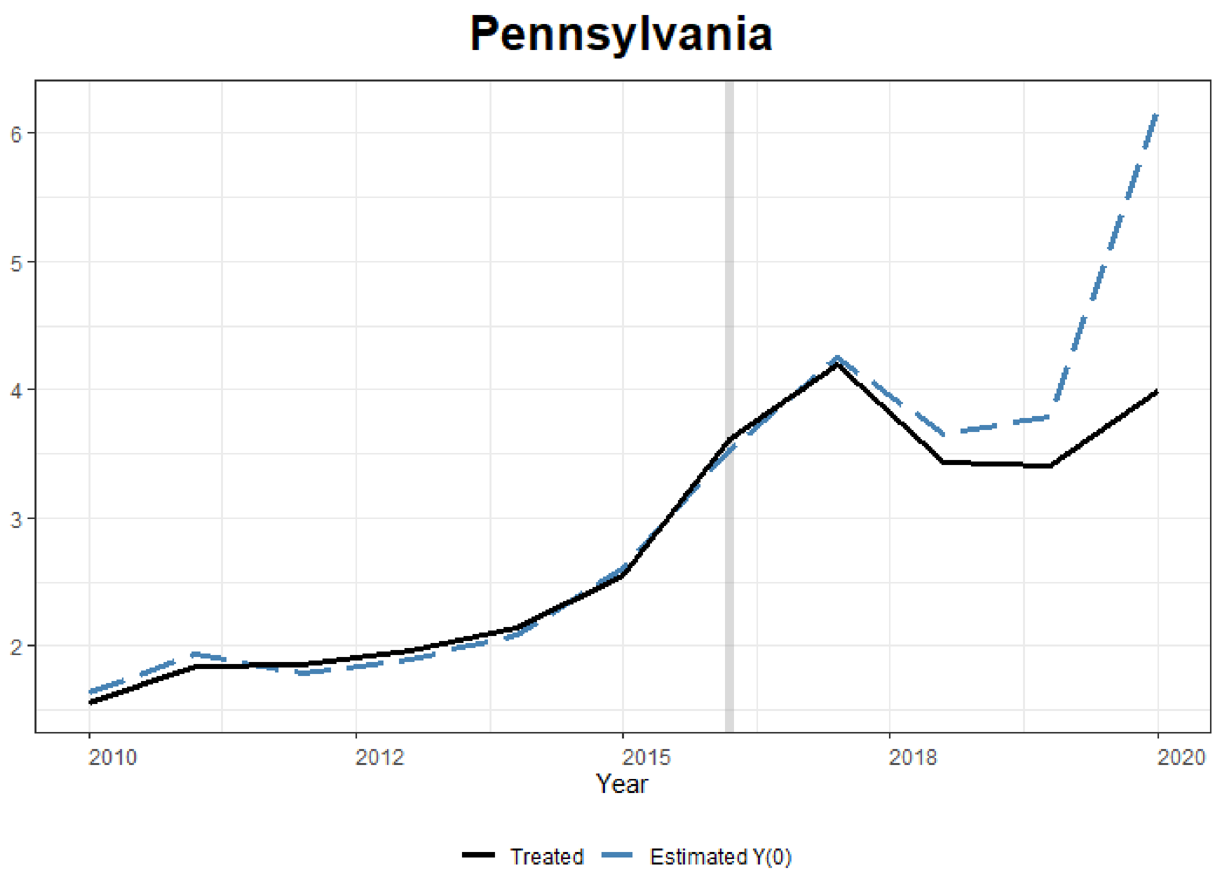

Table A.37: Average Treatment Effect on the Treated: Patient ID Program in Pennsylvania

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.7085	0.2595	-1.217	-0.1998	0.006339

Table A.38: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Pennsylvania

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	-0.08381	0.07682	-0.23437	0.06675	0.2752492	0
-5	-0.09761	0.07343	-0.24152	0.04631	0.1837433	0
-4	0.06581	0.05463	-0.04126	0.17289	0.2283459	0
-3	0.06525	0.08415	-0.09967	0.23017	0.4380873	0
-2	0.05419	0.05781	-0.05912	0.16750	0.3485429	0
-1	-0.05202	0.04932	-0.14868	0.04463	0.2914640	0
0	0.09109	0.02546	0.04120	0.14099	0.0003460	0
1	-0.05616	0.15468	-0.35931	0.24700	0.7165584	1
2	-0.21315	0.27735	-0.75675	0.33044	0.4421652	1
3	-0.38255	0.29609	-0.96287	0.19777	0.1963499	1
4	-2.18210	0.56553	-3.29051	-1.07368	0.0001141	1

Table A.39: Coefficients for the Covariates: Patient ID Program in Pennsylvania

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.602e-06	4.615e-06	-1.265e-05	5.443e-06	0.43509
fratio	-3.224e+01	1.418e+01	-6.004e+01	-4.438e+00	0.02304
wratio	3.811e+01	2.341e+00	3.352e+01	4.270e+01	0.00000
Poverty_rate	2.934e-02	3.087e-02	-3.117e-02	8.985e-02	0.34193

Figure A.14: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Utah

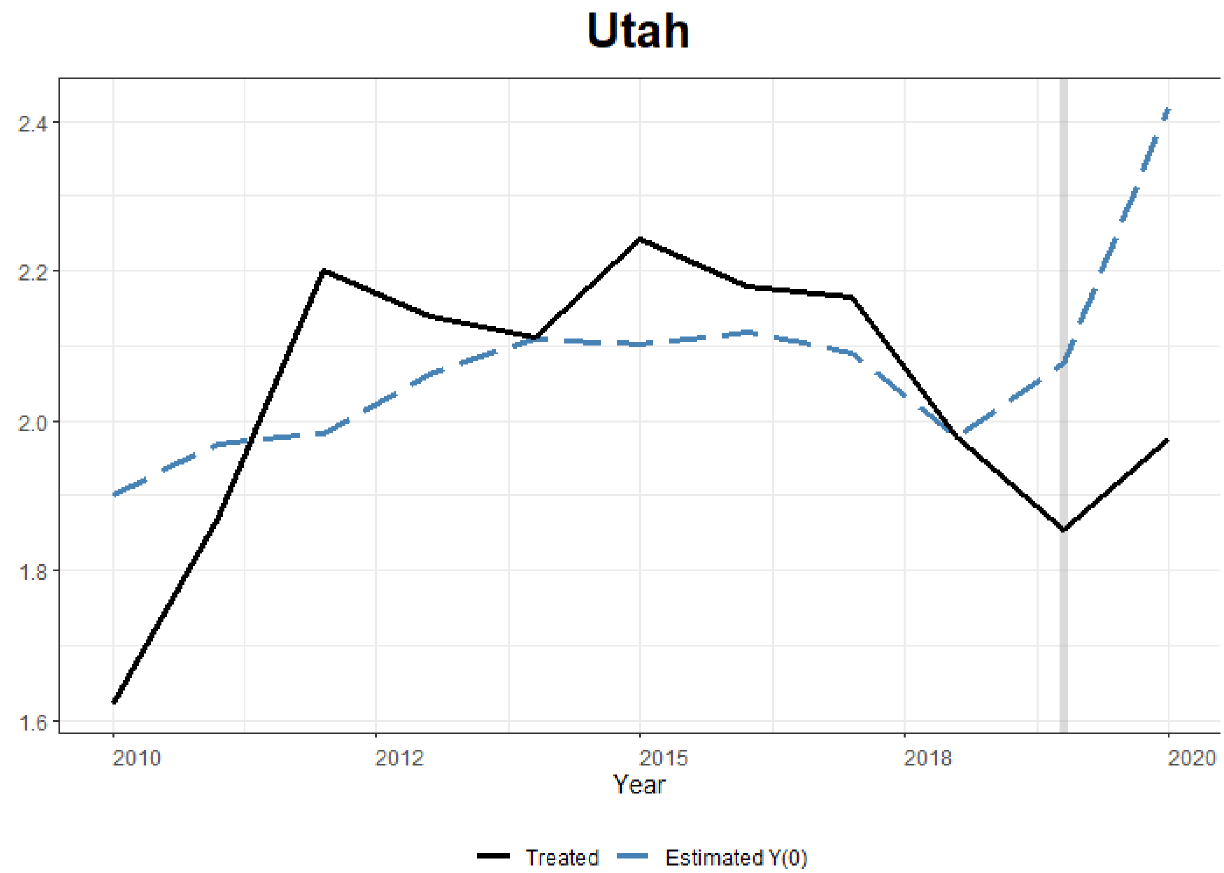

Table A.40: Average Treatment Effect on the Treated: Patient ID Program in Utah

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.4414	0.4326	-1.289	0.4065	0.3076

Table A.41: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Utah

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	-0.277456	0.10401	-0.481307	-0.07360	0.007638	0
-8	-0.097815	0.09553	-0.285052	0.08942	0.305877	0
-7	0.218189	0.06818	0.084557	0.35182	0.001374	0
-6	0.077705	0.09487	-0.108228	0.26364	0.412725	0
-5	0.002552	0.06640	-0.127592	0.13270	0.969347	0
-4	0.140249	0.06811	0.006761	0.27374	0.039472	0
-3	0.062090	0.11129	-0.156033	0.28021	0.576903	0
-2	0.073759	0.09778	-0.117887	0.26540	0.450651	0
-1	0.001221	0.10828	-0.211007	0.21345	0.991002	0
0	-0.221918	0.12378	-0.464527	0.02069	0.073004	0
1	-0.441389	0.43262	-1.289310	0.40653	0.307601	1

Table A.42: Coefficients for the Covariates: Patient ID Program in Utah

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-8.284e-06	4.213e-06	-1.654e-05	-2.757e-08	0.049240
fratio	-1.529e+01	1.392e+01	-4.256e+01	1.199e+01	0.271991
wratio	3.753e+01	2.357e+00	3.291e+01	4.215e+01	0.000000
Poverty_rate	8.186e-02	2.563e-02	3.161e-02	1.321e-01	0.001407

Figure A.15: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Patient ID Program in Virginia

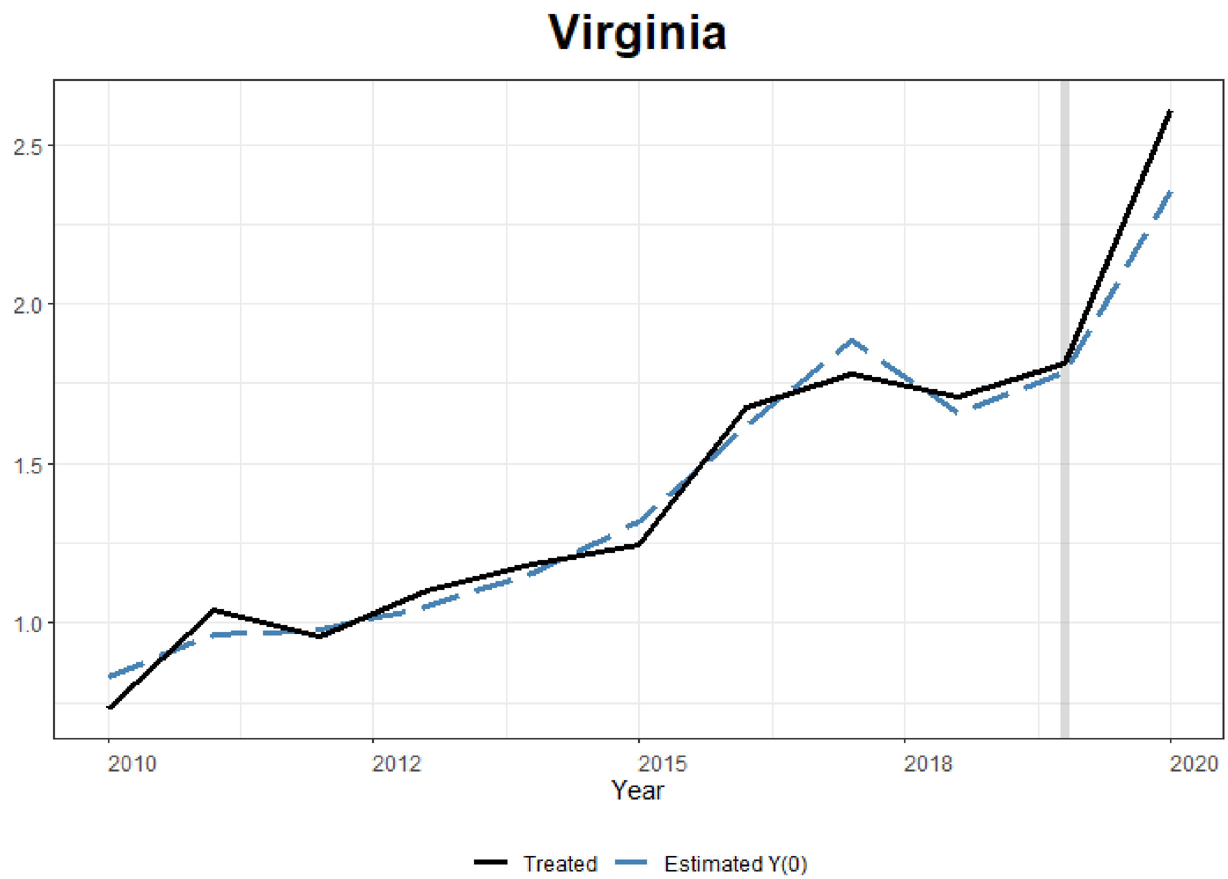

Table A.43: Average Treatment Effect on the Treated: Patient ID Program in Virginia

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.2536	0.4593	-0.6465	1.154	0.5808

Table A.44: Treatment Effect by Period (including Pre-treatment Periods): Patient ID Program in Virginia

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	-0.09800	0.08077	-0.25630	0.06030	0.2250	0
-8	0.08019	0.07520	-0.06720	0.22758	0.2863	0
-7	-0.02517	0.06158	-0.14586	0.09551	0.6827	0
-6	0.05125	0.07034	-0.08662	0.18911	0.4663	0
-5	0.02393	0.05439	-0.08267	0.13054	0.6599	0
-4	-0.07315	0.06071	-0.19214	0.04584	0.2283	0
-3	0.06357	0.07110	-0.07578	0.20292	0.3713	0
-2	-0.10236	0.06929	-0.23817	0.03345	0.1396	0
-1	0.04810	0.07800	-0.10478	0.20098	0.5375	0
0	0.02357	0.08381	-0.14070	0.18784	0.7785	0
1	0.25362	0.45927	-0.64653	1.15377	0.5808	1

Table A.45: Coefficients for the Covariates: Patient ID Program in Virginia

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-4.044e-06	3.419e-06	-1.075e-05	2.658e-06	0.2370
fratio	-2.308e+01	9.050e+00	-4.082e+01	-5.344e+00	0.01076
wratio	3.804e+01	1.345e+00	3.541e+01	4.068e+01	0.0000
Poverty_rate	8.464e-02	2.145e-02	4.259e-02	1.267e-01	0.00007956

Figure A.16: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Arkansas

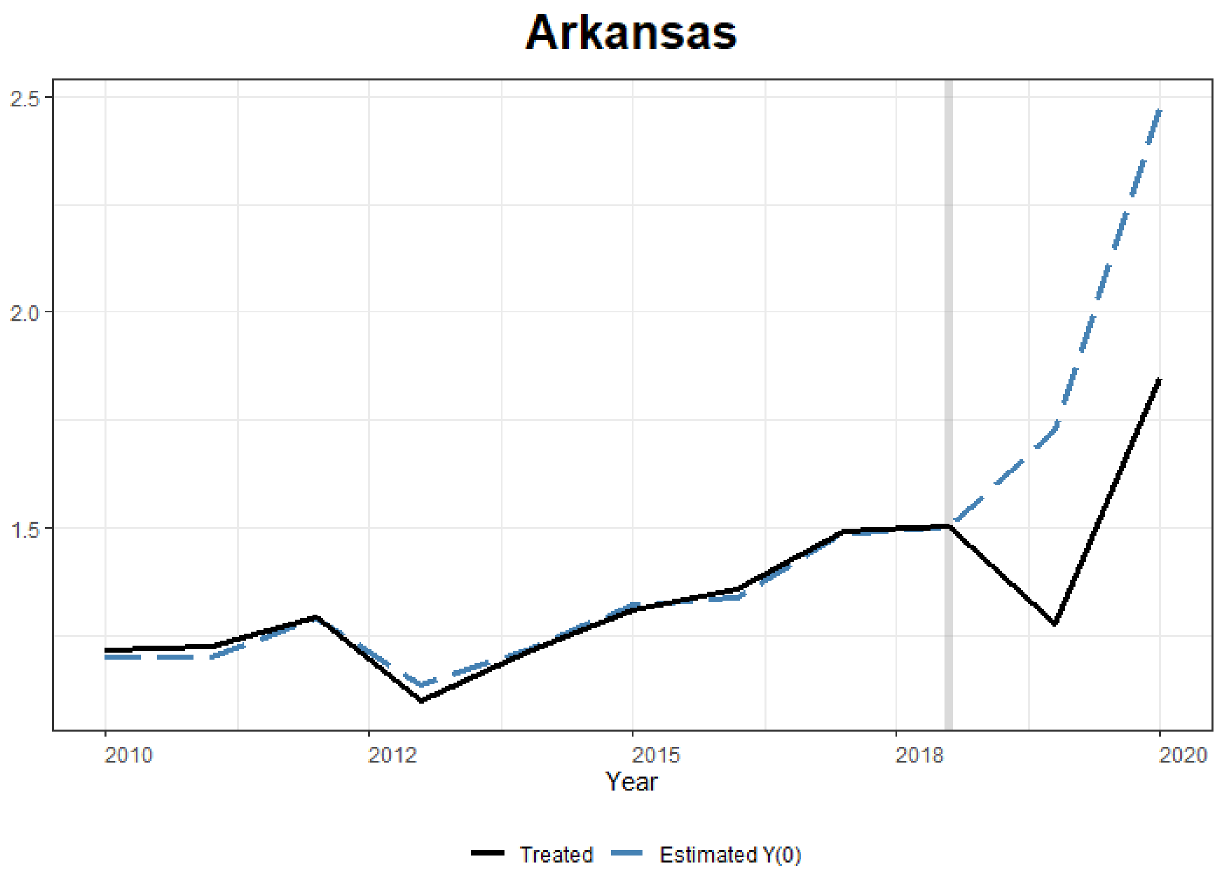

Table A.46: Average Treatment Effect on the Treated: Medical Dispensaries in Arkansas

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.5329	0.1229	-0.7738	-0.2921	1.445e-05

Table A.47: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Arkansas

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-8	0.013106	0.03730	-0.06001	0.08622	0.7253359	0
-7	0.021983	0.05607	-0.08792	0.13189	0.6950284	0
-6	0.001262	0.03205	-0.06155	0.06407	0.9685812	0
-5	-0.03721	0.03770	-0.11110	0.03668	0.3236229	0
-4	-0.00354	0.03997	-0.08189	0.07481	0.9294171	0
-3	-0.01152	0.04924	-0.10803	0.08500	0.8150945	0
-2	0.020317	0.02742	-0.03343	0.07407	0.4587928	0
-1	0.004843	0.03896	-0.07153	0.08121	0.9010939	0
0	0.005222	0.02631	-0.04635	0.05680	0.8426916	0
1	-0.44662	0.11130	-0.66477	-0.22848	0.0000600	1
2	-0.61921	0.17279	-0.95788	-0.28055	0.0003389	1

Table A.48: Coefficients for the Covariates: Medical Dispensaries in Arkansas

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.078e-06	2.225e-06	-7.438e-06	1.282e-06	0.1664
fratio	-7.070e+01	4.524e+00	-7.956e+01	-6.183e+01	0.0000
wratio	3.983e+01	7.571e-01	3.834e+01	4.131e+01	0.0000
Poverty_rate	-1.441e-02	8.551e-03	-3.117e-02	2.352e-03	0.0920

Figure A.17: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in California

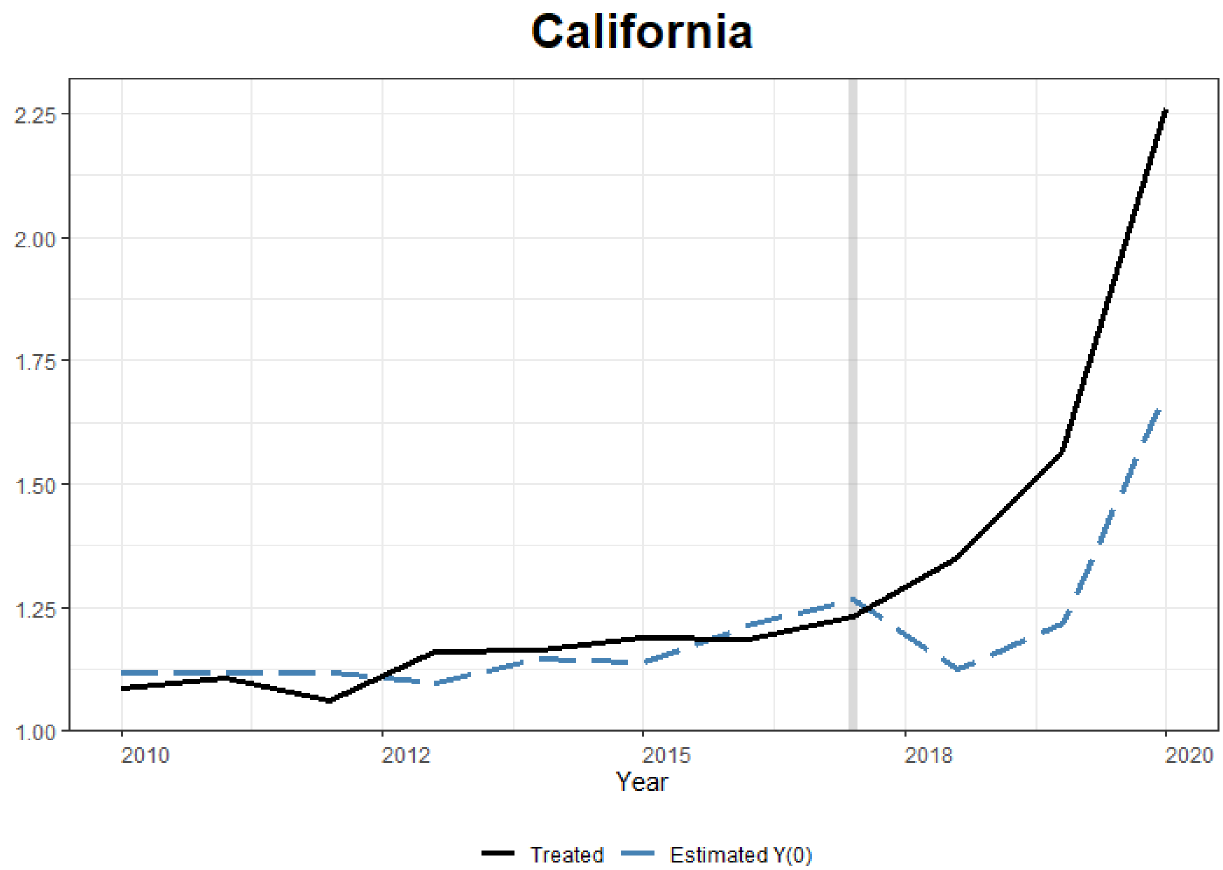

Table A.49: Average Treatment Effect on the Treated: Medical Dispensaries in California

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.3844	0.1799	0.03175	0.737	0.03265

Table A.50: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in California

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.031021	0.11345	-0.25337	0.19133	0.78452	0
-6	-0.009334	0.08920	-0.18415	0.16549	0.91666	0
-5	-0.057187	0.09305	-0.23957	0.12519	0.53884	0
-4	0.063516	0.07304	-0.07964	0.20668	0.38453	0
-3	0.019235	0.07226	-0.12239	0.16086	0.79009	0
-2	0.049314	0.06035	-0.06897	0.16760	0.41386	0
-1	-0.029843	0.06906	-0.16519	0.10550	0.66562	0
0	-0.034881	0.05560	-0.14386	0.07409	0.53043	0
1	0.226456	0.17500	-0.11653	0.56944	0.19565	1
2	0.349198	0.18371	-0.01087	0.70926	0.05733	1
3	0.577526	0.38734	-0.18164	1.33669	0.13596	1

Table A.51: Coefficients for the Covariates: Medical Dispensaries in California

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.478e-06	3.744e-06	-1.082e-05	3.860e-06	0.3529
fratio	-6.914e+01	1.513e+01	-9.880e+01	-3.948e+01	4.894e-06
wratio	4.102e+01	2.583e+00	3.596e+01	4.608e+01	0.0000
Poverty_rate	-1.384e-02	2.170e-02	-5.638e-02	2.869e-02	0.5235

Figure A.18: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in California

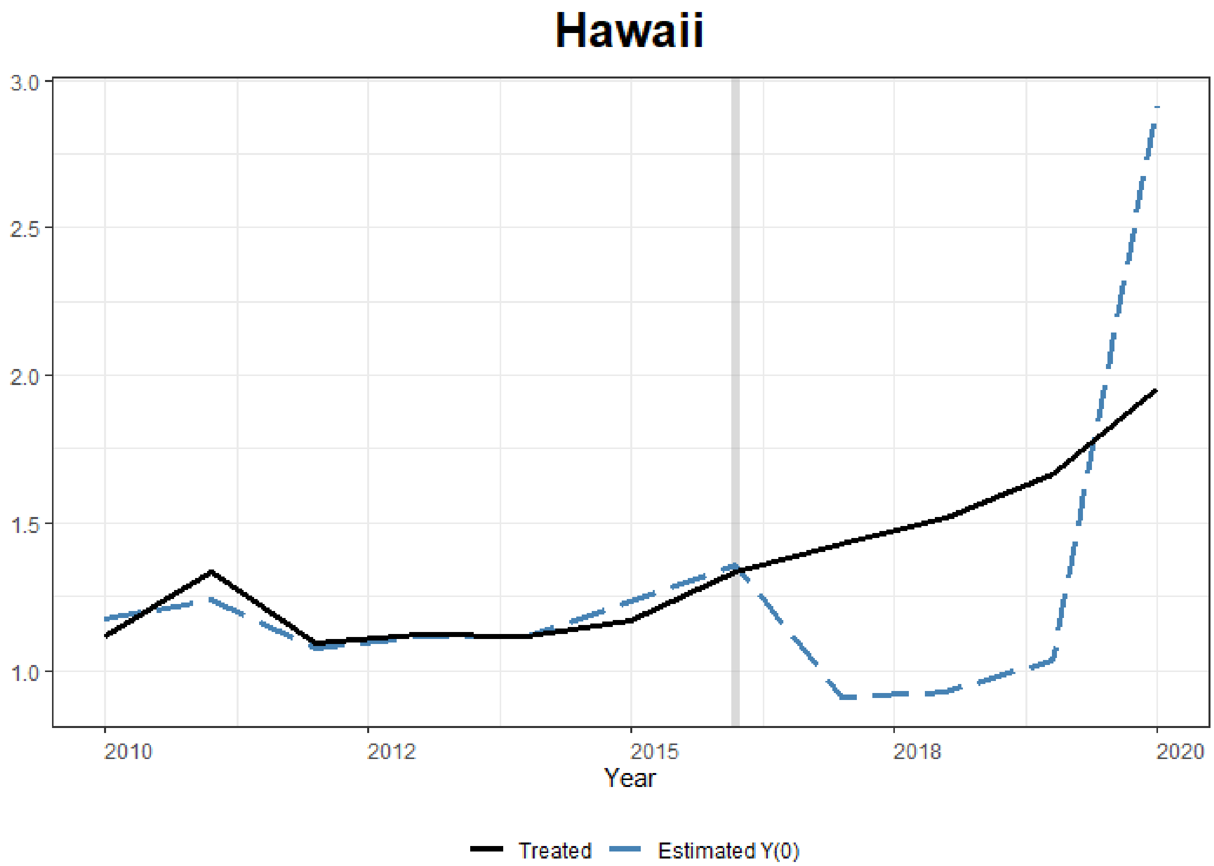

Table A.52: Average Treatment Effect on the Treated: Medical Dispensaries in Hawaii

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.1977	0.2299	-0.2529	0.6484	0.3898

Table A.53: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Hawaii

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	-0.064305	0.05702	-0.17606	0.04745	0.259417	0
-5	0.091189	0.04642	0.000199	0.18218	0.049500	0
-4	0.019971	0.05759	-0.09290	0.13284	0.728762	0
-3	0.009172	0.04020	-0.06961	0.08796	0.819511	0
-2	-0.004580	0.03076	-0.06487	0.05571	0.881643	0
-1	-0.060380	0.03774	-0.13435	0.01360	0.109666	0
0	-0.022373	0.02999	-0.08115	0.03640	0.455646	0
1	0.523838	0.22125	0.09019	0.95748	0.017903	1
2	0.591905	0.36342	-0.12038	1.30419	0.103373	1
3	0.630814	0.34869	-0.05260	1.31423	0.070434	1
4	-0.955646	0.30814	-1.55959	-0.35170	0.001927	1

Table A.54: Coefficients for the Covariates: Medical Dispensaries in Hawaii

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-6.304e-06	3.237e-06	-1.265e-05	4.032e-08	0.05147
fratio	-5.238e+01	8.842e+00	-6.971e+01	-3.505e+01	3.137e-09
wratio	3.387e+01	1.205e+00	3.151e+01	3.623e+01	0.0000
Poverty_rate	-2.020e-02	2.025e-02	-5.989e-02	1.948e-02	0.3184

Figure A.19: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Louisiana

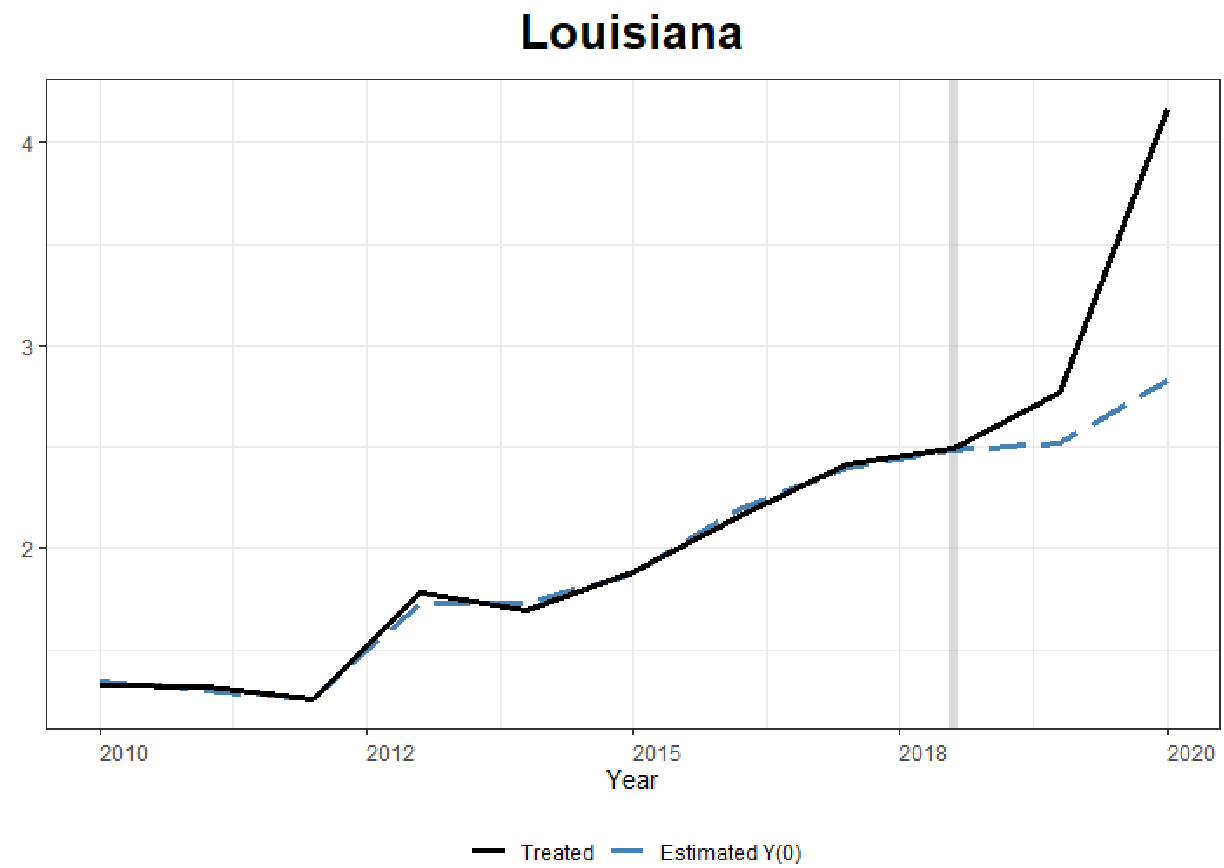

Table A.55: Average Treatment Effect on the Treated: Medical Dispensaries in Louisiana

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.7936	0.06246	0.6712	0.916	0

Table A.56: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Louisiana

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-8	-0.0180994	0.02351	-0.064176	0.027977	0.44136	0
-7	0.0180305	0.03089	-0.042517	0.078578	0.55945	0
-6	0.0001753	0.01718	-0.033506	0.033857	0.99186	0
-5	0.0506104	0.02277	0.005986	0.095235	0.02623	0
-4	-0.0344820	0.03015	-0.093584	0.024620	0.25283	0
-3	0.0059658	0.03845	-0.069395	0.081326	0.87670	0
-2	-0.0340031	0.01932	-0.071877	0.003871	0.07847	0
-1	0.0180105	0.02248	-0.026051	0.062072	0.42304	0
0	0.0056548	0.01743	-0.028504	0.039814	0.74559	0
1	0.2529003	0.13444	-0.010595	0.516395	0.05995	1
2	1.3342698	0.04390	1.248233	1.420307	0.00000	1

Table A.57: Coefficients for the Covariates: Medical Dispensaries in Louisiana

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-2.123e-06	1.311e-06	-4.693e-06	4.476e-07	0.105521
fratio	-5.091e+01	1.973e+00	-5.477e+01	-4.704e+01	0.000000
wratio	4.148e+01	1.693e-01	4.114e+01	4.181e+01	0.000000
Poverty_rate	1.255e-02	4.859e-03	3.030e-03	2.208e-02	0.009778

Figure A.20: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Maryland

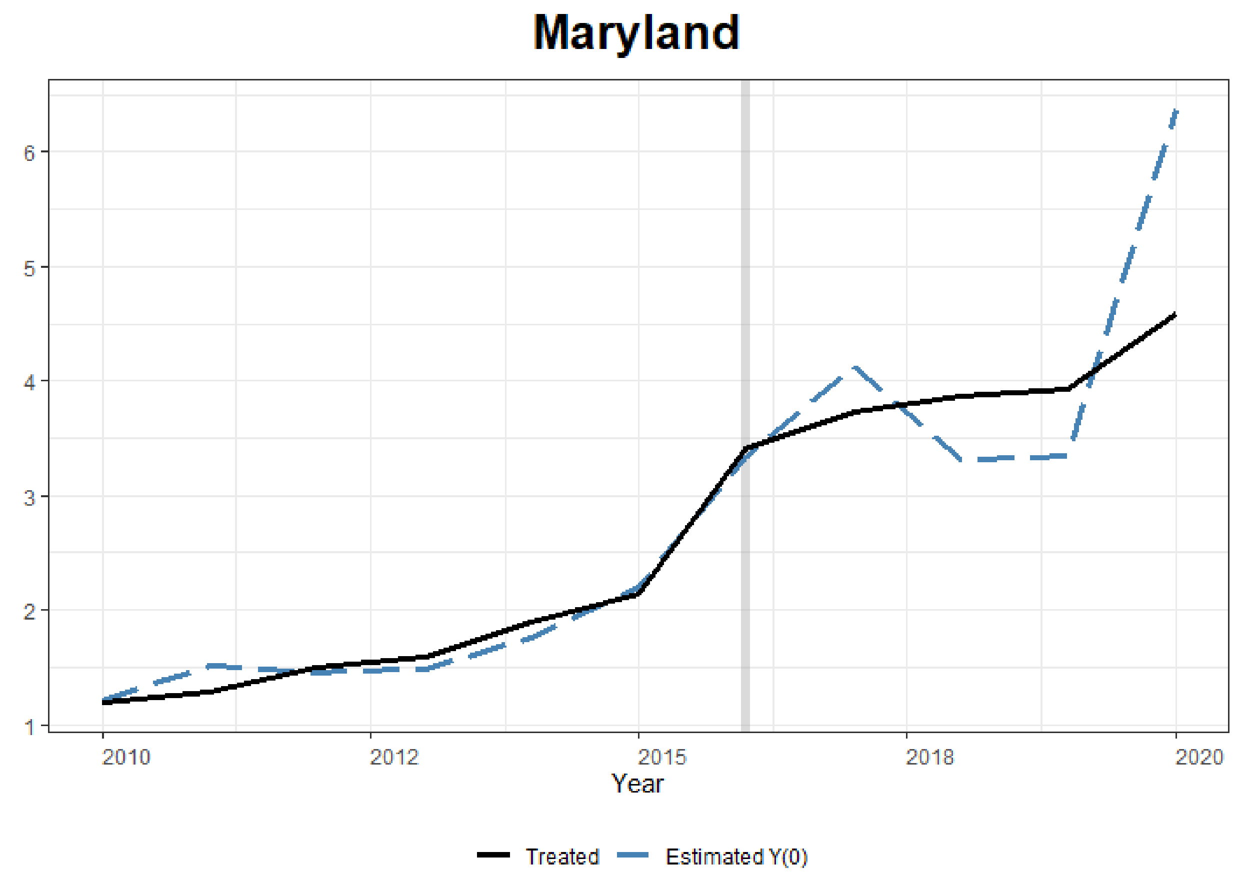

Table A.58: Average Treatment Effect on the Treated: Medical Dispensaries in Maryland

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.2644	0.2617	-0.7773	0.2485	0.3123

Table A.59: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Maryland

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	-0.02847	0.07916	-0.18363	0.12669	0.719129	0
-5	-0.23419	0.07226	-0.37581	-0.09256	0.001192	0
-4	0.04027	0.07032	-0.09756	0.17810	0.566864	0
-3	0.10701	0.05701	-0.00473	0.21875	0.060509	0
-2	0.14267	0.05617	0.03258	0.25276	0.011084	0
-1	-0.06601	0.04197	-0.14826	0.01625	0.115758	0
0	0.07648	0.02563	0.02626	0.12671	0.002841	0
1	-0.40818	0.20818	-0.81621	-0.00015	0.049919	1
2	0.54909	0.29327	-0.02571	1.12389	0.061167	1
3	0.58068	0.28568	0.02075	1.14061	0.042095	1
4	-1.77913	0.55951	-2.87575	-0.68252	0.001474	1

Table A.60: Coefficients for the Covariates: Medical Dispensaries in Maryland

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-1.817e-06	3.807e-06	-9.278e-06	5.643e-06	0.6330
fratio	-6.256e+01	1.467e+01	-9.131e+01	-3.381e+01	0.00002001
wratio	3.445e+01	2.309e+00	2.992e+01	3.898e+01	0.0000
Poverty_rate	-2.297e-02	2.534e-02	-7.263e-02	2.669e-02	0.3646

Figure A.21: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Missouri

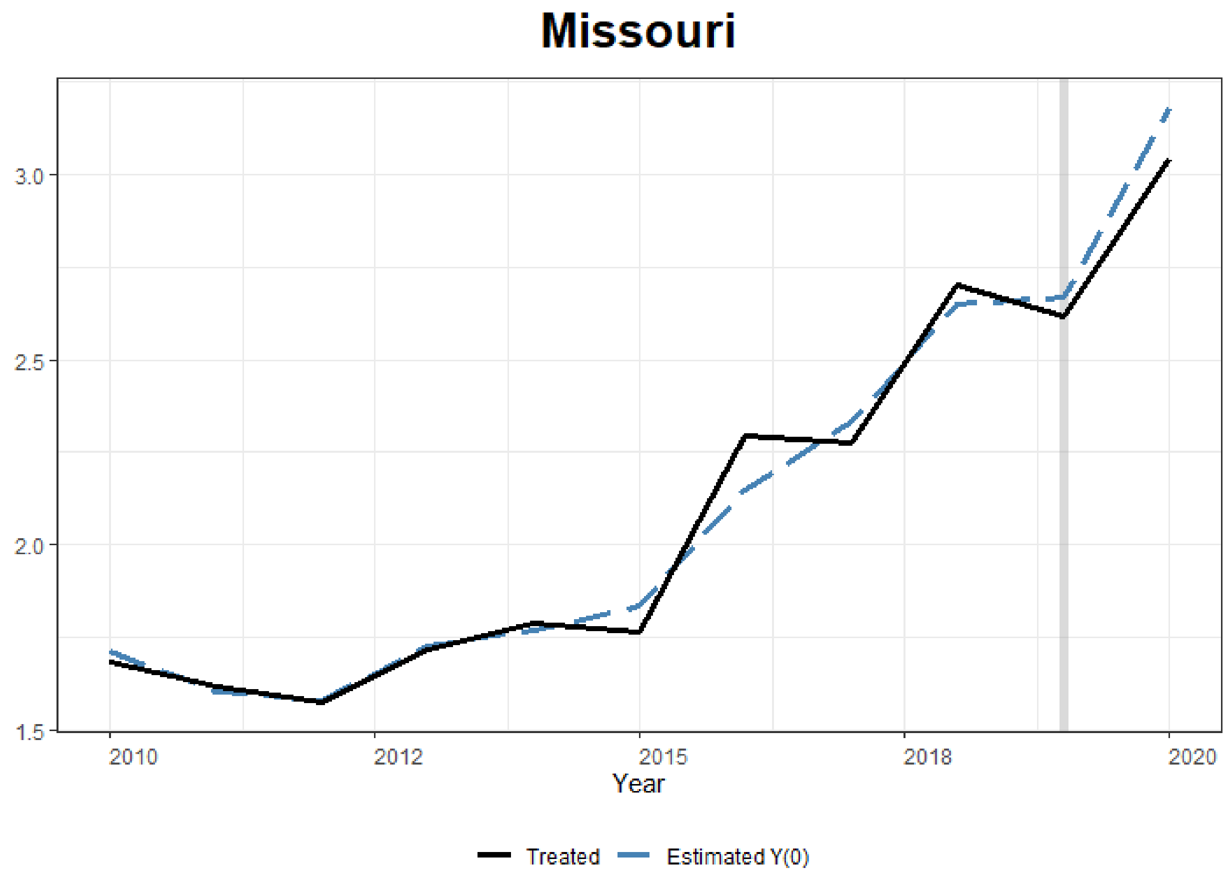

Table A.61: Average Treatment Effect on the Treated: Medical Dispensaries in Missouri

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.1368	0.2908	-0.7068	0.4332	0.6381

Table A.62: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Missouri

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	-0.026995	0.04579	-0.11674	0.06275	0.5555	0
-8	0.016487	0.05980	-0.10073	0.13370	0.7828	0
-7	-0.004786	0.07223	-0.14636	0.13679	0.9472	0
-6	-0.009076	0.04969	-0.10647	0.08832	0.8551	0
-5	0.020823	0.04318	-0.06381	0.10545	0.6296	0
-4	-0.069890	0.04732	-0.16264	0.02286	0.1397	0
-3	0.146376	0.05806	0.03257	0.26018	0.0117	0
-2	-0.055437	0.04496	-0.14357	0.03269	0.2176	0
-1	0.047758	0.04354	-0.03758	0.13310	0.2727	0
0	-0.052408	0.05988	-0.16977	0.06496	0.3815	0
1	-0.136781	0.29082	-0.70679	0.43322	0.6381	1

Table A.63: Coefficients for the Covariates: Medical Dispensaries in Missouri

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.540e-06	2.392e-06	-8.229e-06	1.149e-06	0.1390
fratio	-7.268e+01	6.229e+00	-8.489e+01	-6.047e+01	0.0000
wratio	4.120e+01	8.021e-01	3.963e+01	4.277e+01	0.0000
Poverty_rate	-1.480e-02	1.149e-02	-3.733e-02	7.726e-03	0.1978

Figure A.22: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Montana

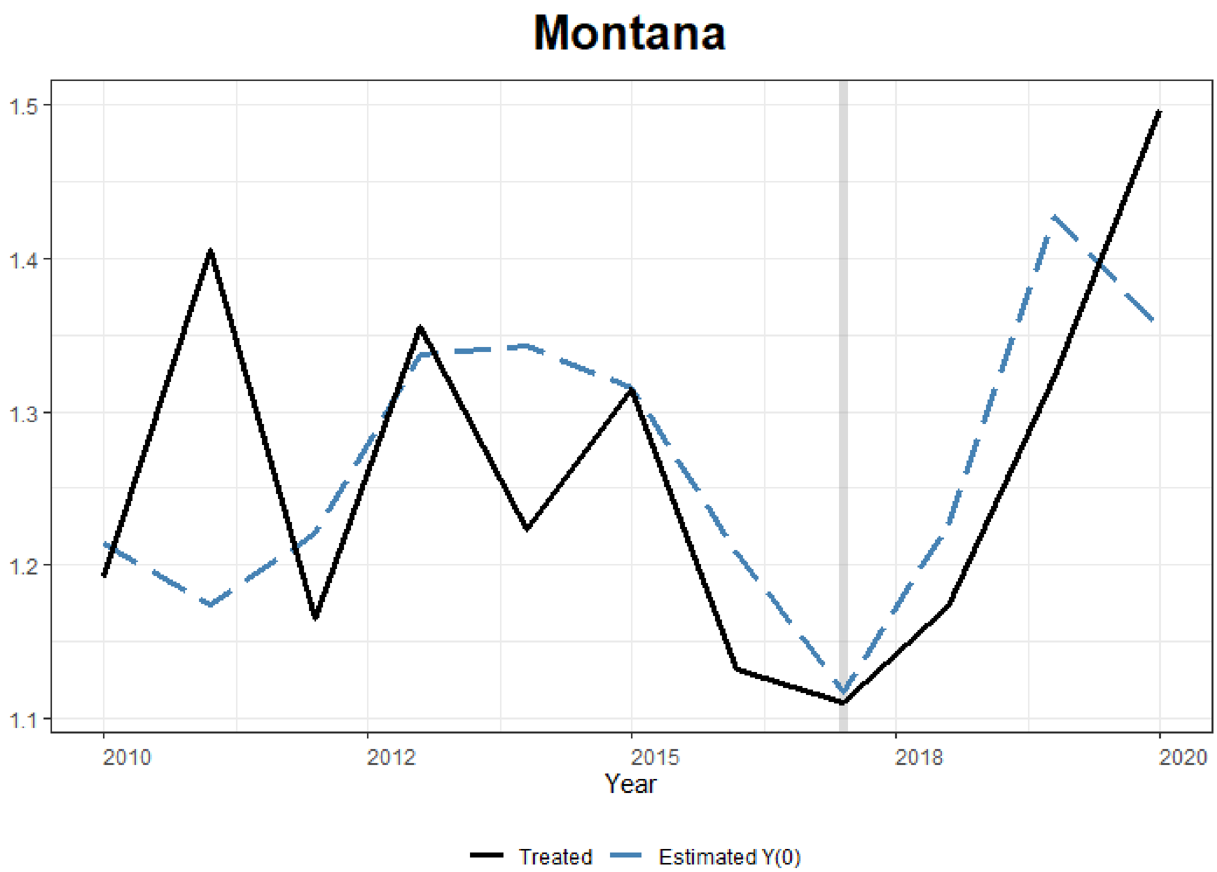

Table A.64: Average Treatment Effect on the Treated: Medical Dispensaries in Montana

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.005004	0.2041	-0.4051	0.3951	0.9804

Table A.65: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Montana

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.022037	0.11853	-0.25435	0.21028	0.85251	0
-6	0.230448	0.08227	0.06921	0.39169	0.00509	0
-5	-0.056013	0.09966	-0.25135	0.13933	0.57410	0
-4	0.018617	0.07399	-0.12639	0.16363	0.80133	0
-3	-0.119273	0.07009	-0.25665	0.01810	0.08882	0
-2	-0.001175	0.05675	-0.11240	0.11005	0.98348	0
-1	-0.076973	0.06787	-0.21000	0.05606	0.25677	0
0	-0.007808	0.05071	-0.10719	0.09158	0.87763	0
1	-0.053815	0.17890	-0.40445	0.29682	0.76356	1
2	-0.103307	0.18038	-0.45685	0.25024	0.56684	1
3	0.142110	0.44176	-0.72372	1.00794	0.74769	1

Table A.66: Coefficients for the Covariates: Medical Dispensaries in Montana

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-5.501e-06	3.963e-06	-1.327e-05	2.267e-06	0.1651
fratio	-6.662e+01	1.502e+01	-9.607e+01	-3.717e+01	0.000009239
wratio	3.761e+01	2.444e+00	3.282e+01	4.240e+01	0.0000
Poverty_rate	-2.684e-02	2.249e-02	-7.092e-02	1.723e-02	0.2326

Figure A.23: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in North Dakota

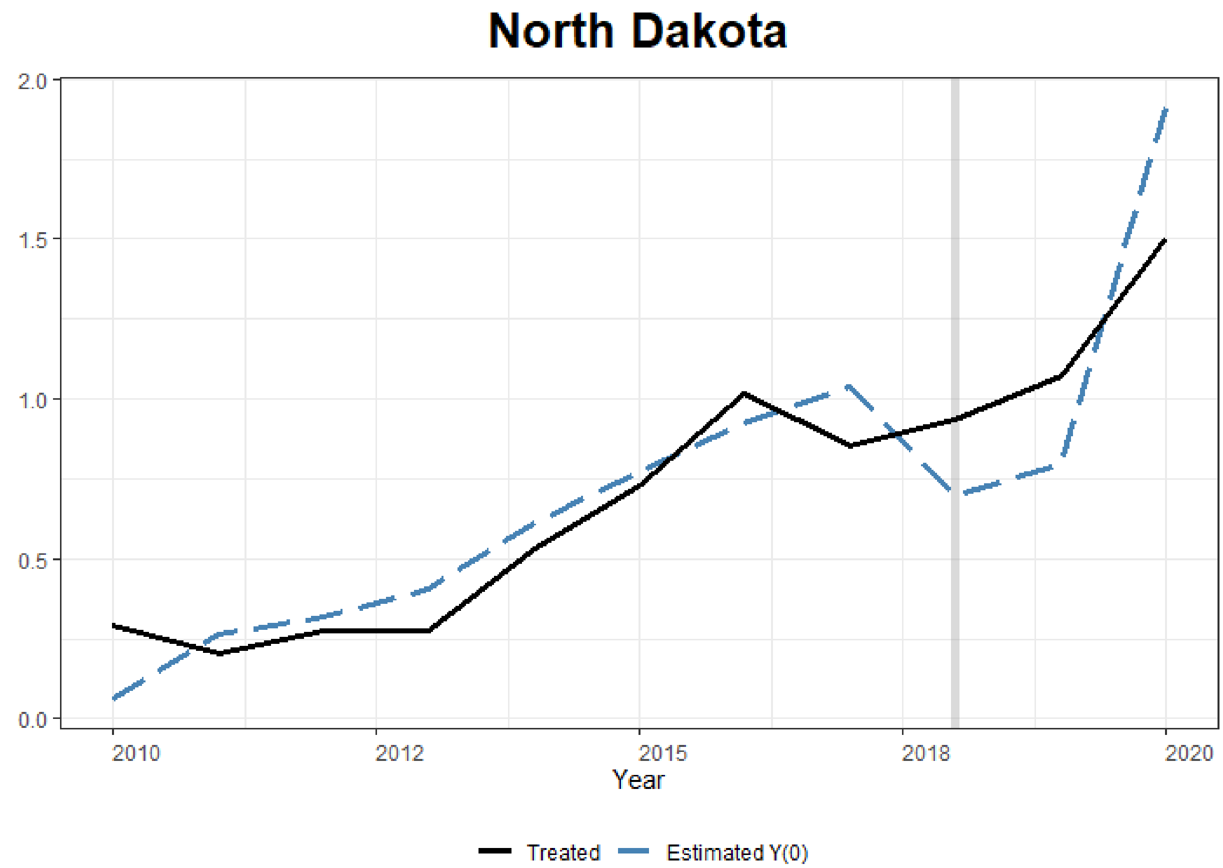

Table A.67: Average Treatment Effect on the Treated: Medical Dispensaries in North Dakota

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.06756	0.1943	-0.4484	0.3132	0.7281

Table A.68: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in North Dakota

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-8	0.22917	0.09809	0.03693	0.42142	0.01947	0
-7	-0.05719	0.08121	-0.21635	0.10197	0.48129	0
-6	-0.04611	0.09883	-0.23981	0.14760	0.64085	0
-5	-0.12806	0.06463	-0.25474	-0.00138	0.04755	0
-4	-0.08067	0.05912	-0.19655	0.03520	0.17238	0
-3	-0.04043	0.06728	-0.17229	0.09143	0.54785	0
-2	0.08877	0.08662	-0.08099	0.25854	0.30542	0
-1	-0.18540	0.06183	-0.30660	-0.06421	0.00271	0
0	0.24310	0.11352	0.02060	0.46559	0.03224	0
1	0.27418	0.13337	0.01278	0.53558	0.03980	1
2	-0.40929	0.36075	-1.11635	0.29776	0.25656	1

Table A.69: Coefficients for the Covariates: Medical Dispensaries in North Dakota

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-4.110e-06	3.772e-06	-1.150e-05	3.283e-06	0.2759
fratio	-8.030e+01	1.261e+01	-1.050e+02	-5.558e+01	1.932e-10
wratio	3.606e+01	2.399e+00	3.136e+01	4.076e+01	0.0000
Poverty_rate	-2.291e-02	2.090e-02	-6.387e-02	1.806e-02	0.2731

Figure A.24: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Ohio

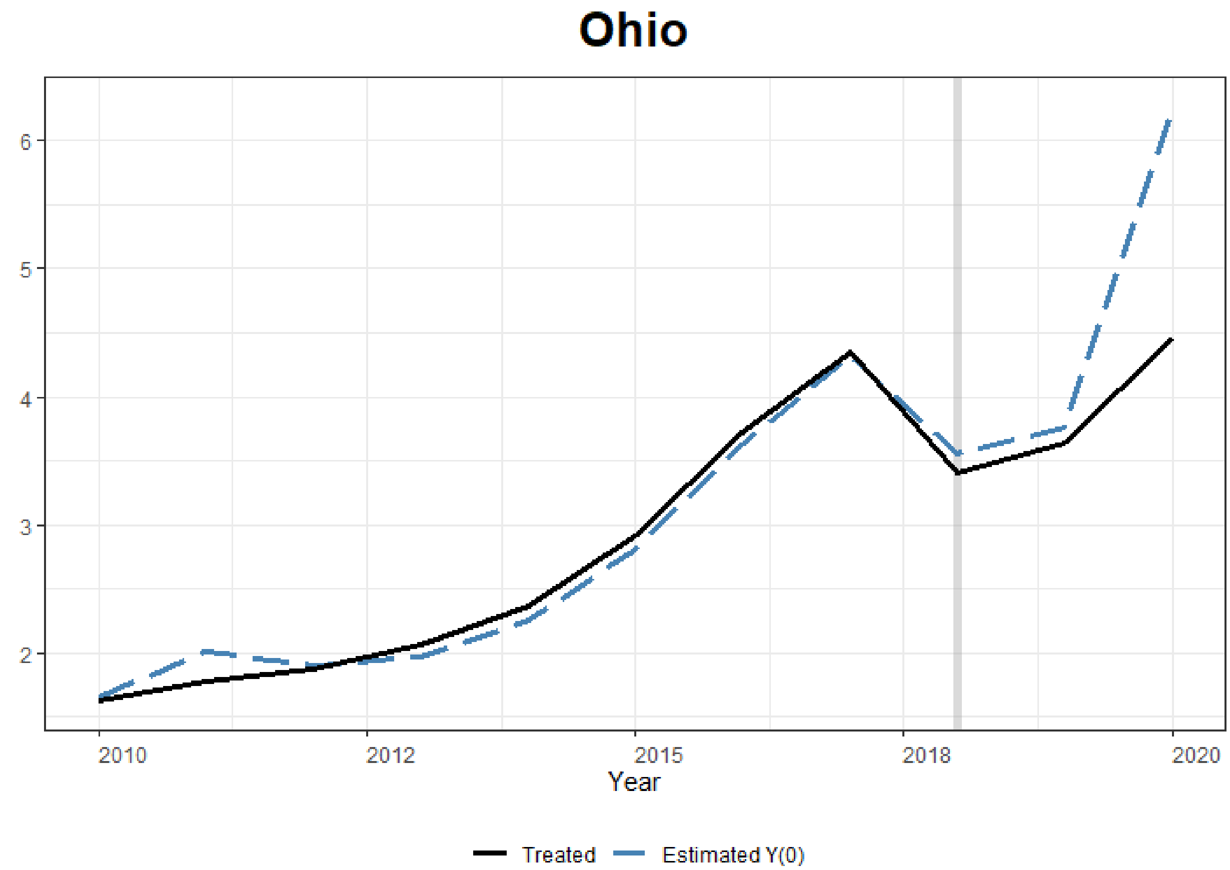

Table A.70: Average Treatment Effect on the Treated: Medical Dispensaries in Ohio

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.06756	0.1943	-0.4484	0.3132	0.7281

Table A.71: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Ohio

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-8	0.22917	0.09809	0.03693	0.42142	0.01947	0
-7	-0.05719	0.08121	-0.21635	0.10197	0.48129	0
-6	-0.04611	0.09883	-0.23981	0.14760	0.64085	0
-5	-0.12806	0.06463	-0.25474	-0.00138	0.04755	0
-4	-0.08067	0.05912	-0.19655	0.03520	0.17238	0
-3	-0.04043	0.06728	-0.17229	0.09143	0.54785	0
-2	0.08877	0.08662	-0.08099	0.25854	0.30542	0
-1	-0.18540	0.06183	-0.30660	-0.06421	0.00271	0
0	0.24310	0.11352	0.02060	0.46559	0.03224	0
1	0.27418	0.13337	0.01278	0.53558	0.03980	1
2	-0.40929	0.36075	-1.11635	0.29776	0.25656	1

Table A.72: Coefficients for the Covariates: Medical Dispensaries in Ohio

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-4.110e-06	3.772e-06	-1.150e-05	3.283e-06	0.2759
fratio	-8.030e+01	1.261e+01	-1.050e+02	-5.558e+01	1.932e-10
wratio	3.606e+01	2.399e+00	3.136e+01	4.076e+01	0.0000
Poverty_rate	-2.291e-02	2.090e-02	-6.387e-02	1.806e-02	0.2731

Figure A.25: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Oklahoma

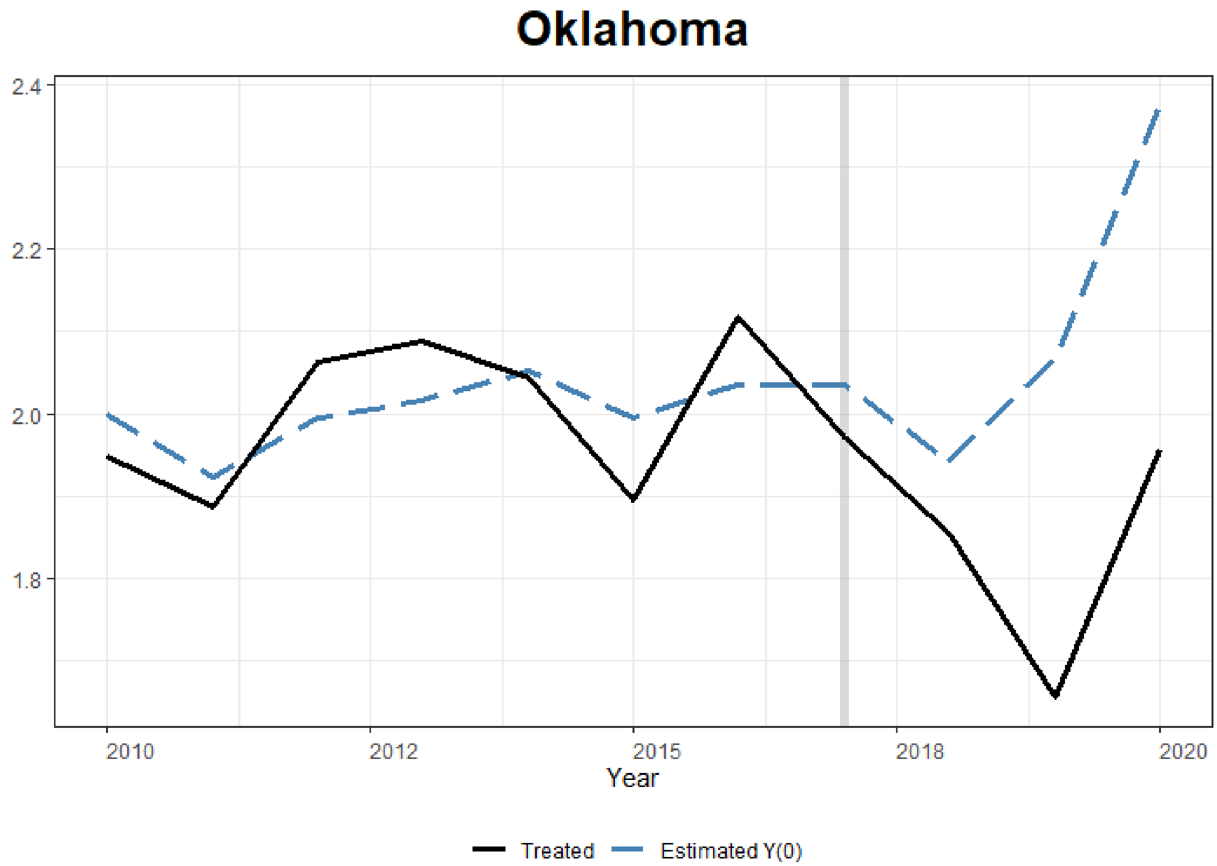

Table A.73: Average Treatment Effect on the Treated: Medical Dispensaries in Oklahoma

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.306	0.1773	-0.6535	0.04153	0.08439

Table A.74: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Oklahoma

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.052831	0.11432	-0.27689	0.17123	0.64398	0
-6	-0.034779	0.08927	-0.20975	0.14019	0.69685	0
-5	0.068505	0.10127	-0.12999	0.26700	0.49877	0
-4	0.071820	0.07130	-0.06793	0.21157	0.31381	0
-3	-0.007908	0.07772	-0.16024	0.14442	0.91896	0
-2	-0.100631	0.06000	-0.21822	0.01696	0.09349	0
-1	0.082339	0.07002	-0.05491	0.21959	0.23965	0
0	-0.063896	0.05186	-0.16555	0.03776	0.21796	0
1	-0.088171	0.16523	-0.41202	0.23568	0.59360	1
2	-0.412026	0.17152	-0.74820	-0.07585	0.01630	1
3	-0.417828	0.39510	-1.19222	0.35656	0.29028	1

Table A.75: Coefficients for the Covariates: Medical Dispensaries in Oklahoma

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-2.623e-06	3.964e-06	-1.039e-05	5.146e-06	0.5081
fratio	-6.789e+01	1.518e+01	-9.764e+01	-3.815e+01	7.692e-06
wratio	4.121e+01	2.496e+00	3.632e+01	4.610e+01	0.0000
Poverty_rate	-1.356e-02	2.312e-02	-5.887e-02	3.176e-02	0.5576

Figure A.26: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Pennsylvania

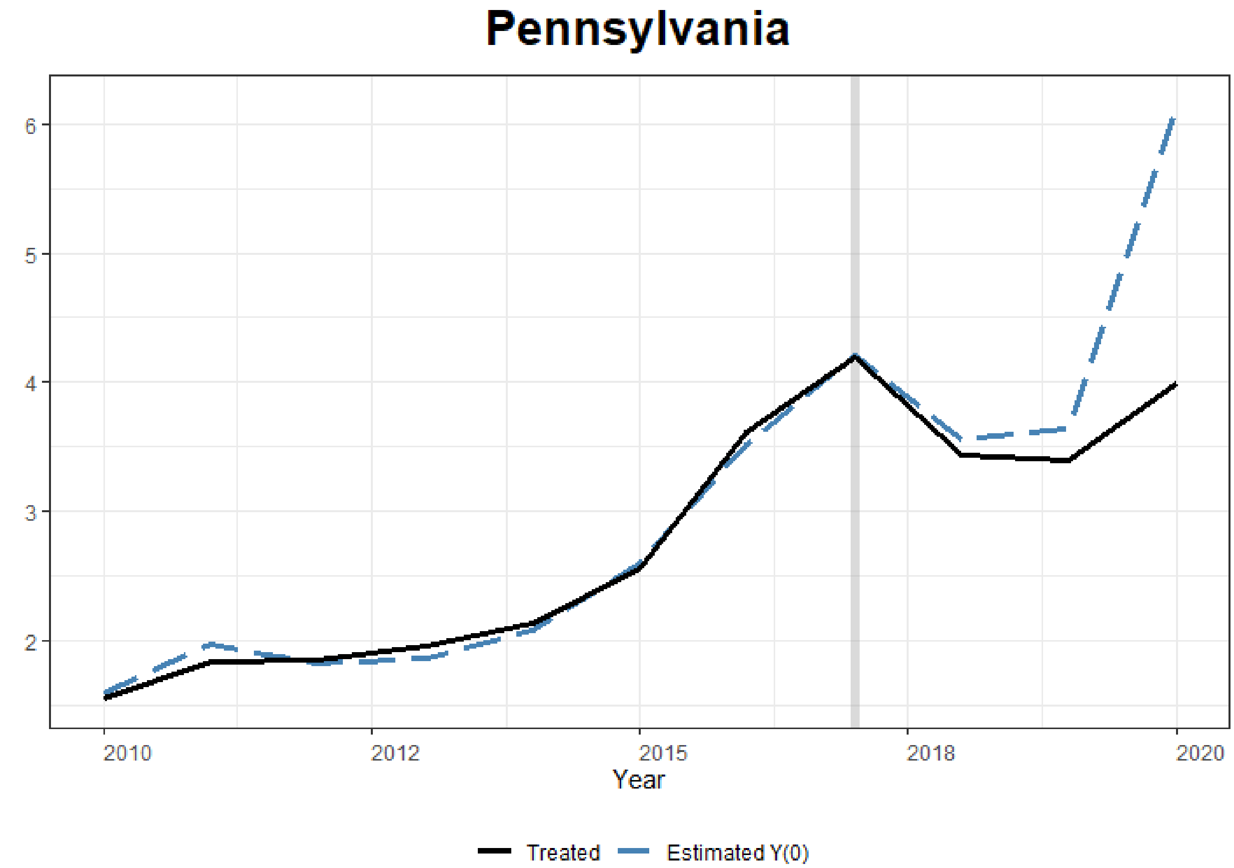

Table A.76: Average Treatment Effect on the Treated: Medical Dispensaries in Pennsylvania

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.8367	0.2282	-1.284	-0.3894	0.0002462

Table A.77: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Pennsylvania

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.04785	0.08922	-0.22272	0.12702	0.5918	0
-6	-0.13288	0.07576	-0.28136	0.01560	0.07943	0
-5	0.02192	0.08470	-0.14408	0.18792	0.7958	0
-4	0.09606	0.06254	-0.02653	0.21864	0.1246	0
-3	0.04856	0.06183	-0.07263	0.16975	0.4322	0
-2	-0.04370	0.05289	-0.14736	0.05996	0.4087	0
-1	0.10137	0.06208	-0.02031	0.22305	0.1025	0
0	-0.00955	0.04519	-0.09811	0.07901	0.8326	0
1	-0.12095	0.20824	-0.52910	0.28721	0.5614	1
2	-0.24237	0.21114	-0.65620	0.17145	0.2510	1
3	-2.14673	0.50530	-3.13709	-1.15636	0.00002	1

Table A.78: Coefficients for the Covariates: Medical Dispensaries in Pennsylvania

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.434e-06	3.977e-06	-1.123e-05	4.361e-06	0.3879
fratio	-8.727e+01	1.505e+01	-1.168e+02	-5.777e+01	6.730e-09
wratio	3.803e+01	2.435e+00	3.326e+01	4.280e+01	0.0000
Poverty_rate	-2.059e-02	2.370e-02	-6.705e-02	2.587e-02	0.3850

Figure A.27: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Utah

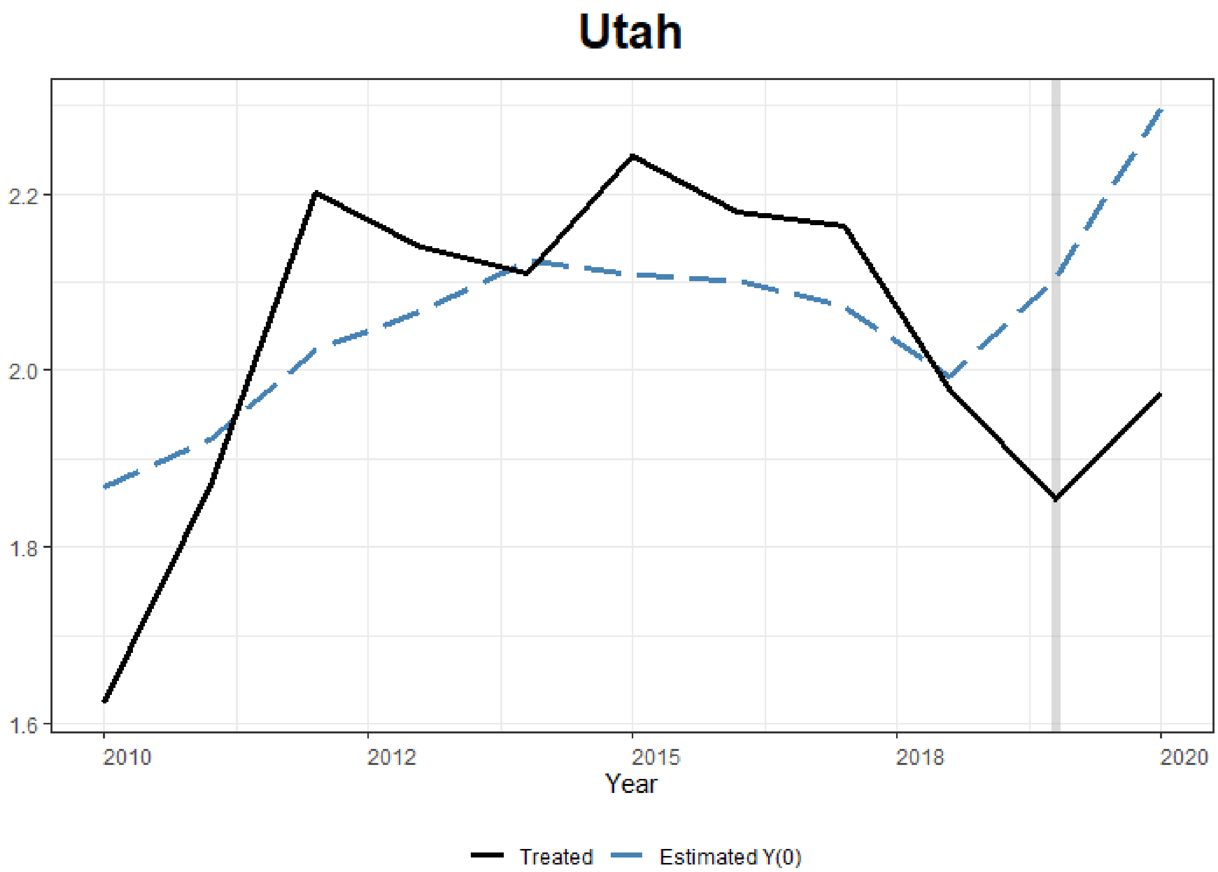

Table A.79: Average Treatment Effect on the Treated: Medical Dispensaries in Utah

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.3204	0.4041	-1.112	0.4716	0.4278

Table A.80: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Utah

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	-0.24429	0.12359	-0.48652	-0.00205	0.04809	0
-8	-0.05057	0.08690	-0.22090	0.11976	0.56061	0
-7	0.17694	0.09117	-0.00175	0.35563	0.05228	0
-6	0.07232	0.07073	-0.06631	0.21095	0.30657	0
-5	-0.01216	0.07159	-0.15249	0.12816	0.86508	0
-4	0.13507	0.06526	0.00716	0.26299	0.03848	0
-3	0.07830	0.09763	-0.11305	0.26965	0.42256	0
-2	0.09201	0.07795	-0.06077	0.24479	0.23787	0
-1	-0.01371	0.10026	-0.21021	0.18279	0.89123	0
0	-0.25041	0.10121	-0.44878	-0.05205	0.01335	0
1	-0.32044	0.40412	-1.11249	0.47162	0.42782	1

Table A.81: Coefficients for the Covariates: Medical Dispensaries in Utah

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-5.900e-06	3.874e-06	-1.349e-05	1.692e-06	0.1277
fratio	-5.854e+01	1.549e+01	-8.890e+01	-2.818e+01	0.0002
wratio	3.992e+01	2.518e+00	3.499e+01	4.486e+01	0.0000
Poverty_rate	9.057e-03	2.319e-02	-3.639e-02	5.451e-02	0.6961

Figure A.28: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to Medical Dispensary Openings in Virginia

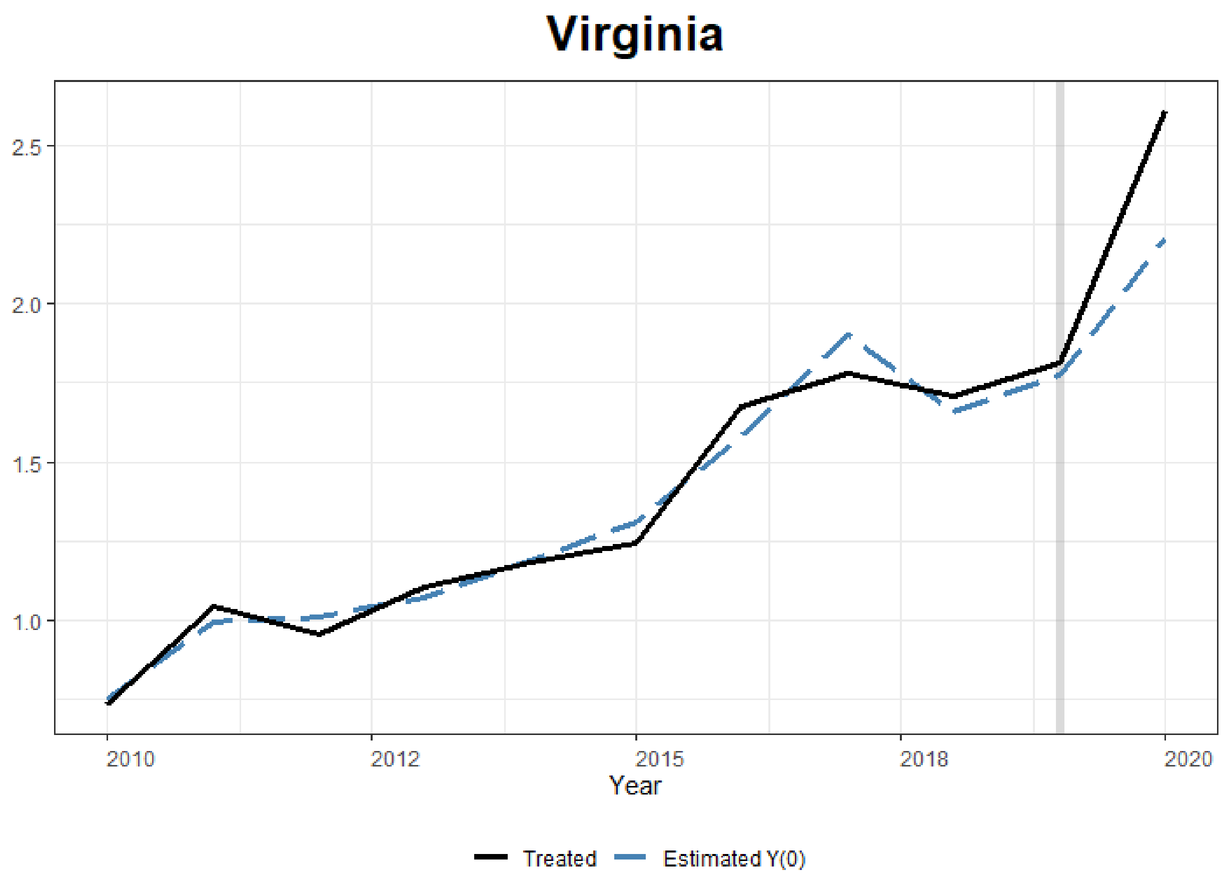

Table A.82: Average Treatment Effect on the Treated: Medical Dispensaries in Virginia

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.4036	0.3787	-0.3387	1.146	0.2866

Table A.83: Treatment Effect by Period (including Pre-treatment Periods): Medical Dispensaries in Virginia

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	-0.01931	0.07635	-0.16896	0.13034	0.80034	0
-8	0.04584	0.07106	-0.09344	0.18513	0.51886	0
-7	-0.05698	0.07830	-0.21045	0.09650	0.46684	0
-6	0.03299	0.05744	-0.07959	0.14558	0.56569	0
-5	-0.00421	0.05297	-0.10804	0.09961	0.93659	0
-4	-0.06546	0.05925	-0.18159	0.05068	0.26931	0
-3	0.09577	0.07187	-0.04509	0.23664	0.18268	0
-2	-0.12140	0.06614	-0.25104	0.00824	0.06644	0
-1	0.05054	0.08123	-0.10868	0.20975	0.53386	0
0	0.04067	0.07653	-0.10933	0.19067	0.59513	0
1	0.40363	0.37874	-0.33870	1.14595	0.28656	1

Table A.84: Coefficients for the Covariates: Medical Dispensaries in Virginia

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-3.498e-06	3.304e-06	-9.973e-06	2.977e-06	0.2897
fratio	-6.675e+01	8.999e+00	-8.439e+01	-4.911e+01	1.190e-13
wratio	3.901e+01	9.558e-01	3.714e+01	4.088e+01	0.0000
Poverty_rate	-6.073e-04	1.926e-02	-3.836e-02	3.714e-02	0.9748

Figure A.29: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Marijuana Law (RML) in Arizona

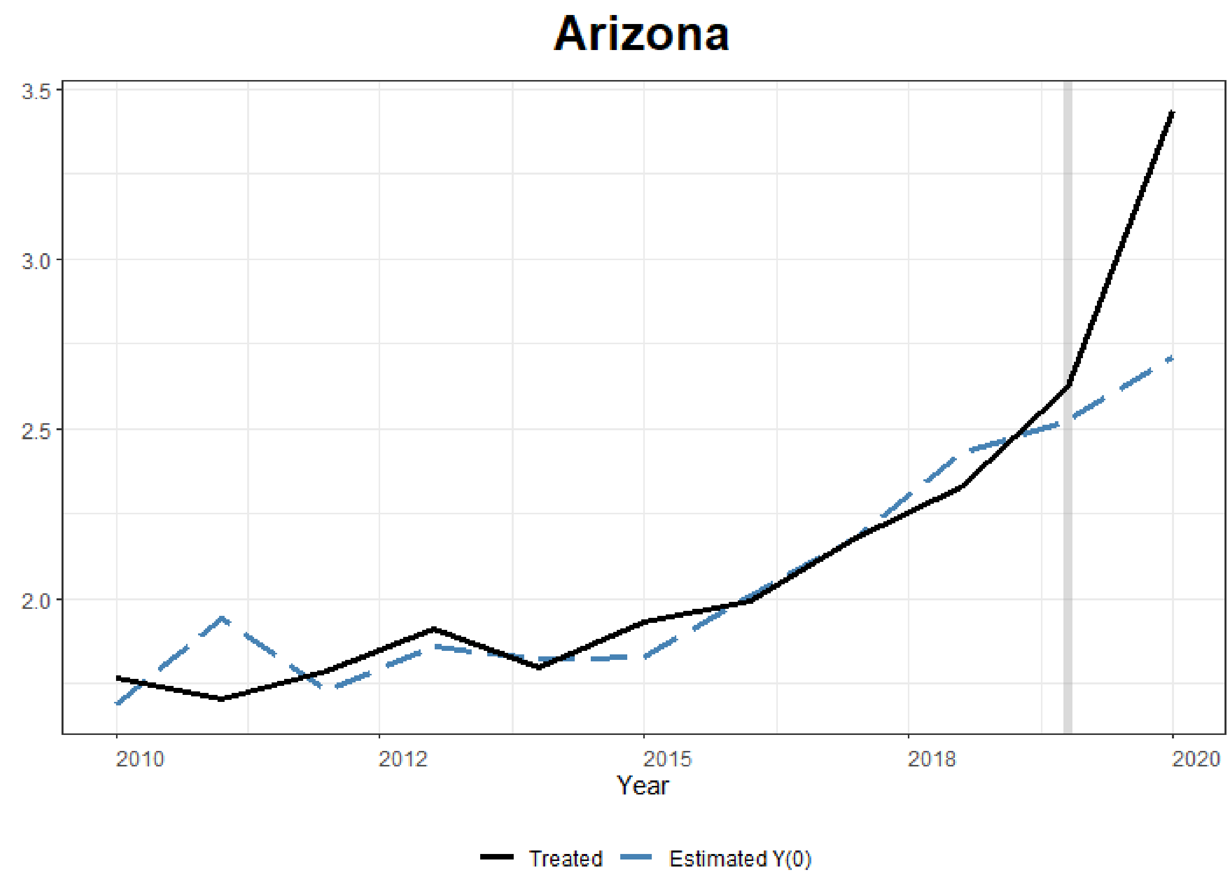

Table A.85: Average Treatment Effect on the Treated: RML in Arizona

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.7245	0.2347	0.2645	1.185	0.002022

Table A.86: Treatment Effect by Period (including Pre-treatment Periods): RML in Arizona

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	0.078122	0.09854	-0.11501	0.27125	0.427884	0
-8	-0.23561	0.10337	-0.43820	-0.03301	0.022646	0
-7	0.056114	0.10360	-0.14693	0.25916	0.588051	0
-6	0.053936	0.09529	-0.13283	0.24070	0.571376	0
-5	-0.02376	0.08340	-0.18722	0.13969	0.775698	0
-4	0.101729	0.09516	-0.08477	0.28823	0.285039	0
-3	-0.01505	0.06813	-0.14858	0.11849	0.825206	0
-2	0.001774	0.10441	-0.20286	0.20641	0.986441	0
-1	-0.09885	0.05867	-0.21384	0.01614	0.092003	0
0	0.093705	0.07492	-0.05313	0.24054	0.211025	0
1	0.724504	0.23470	0.26450	1.18451	0.002022	1

Table A.87: Coefficients for the Covariates: RML in Arizona

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	4.587e-06	3.470e-06	-2.214e-06	1.139e-05	0.18622
fratio	1.268e+01	5.952e+00	1.018e+00	2.435e+01	0.03309
wratio	-1.243e+01	8.563e-01	-1.411e+01	-1.075e+01	0.00000
Poverty_rate	2.606e-01	1.236e-02	2.363e-01	2.848e-01	0.00000

Figure A.30: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the RML in Illinois

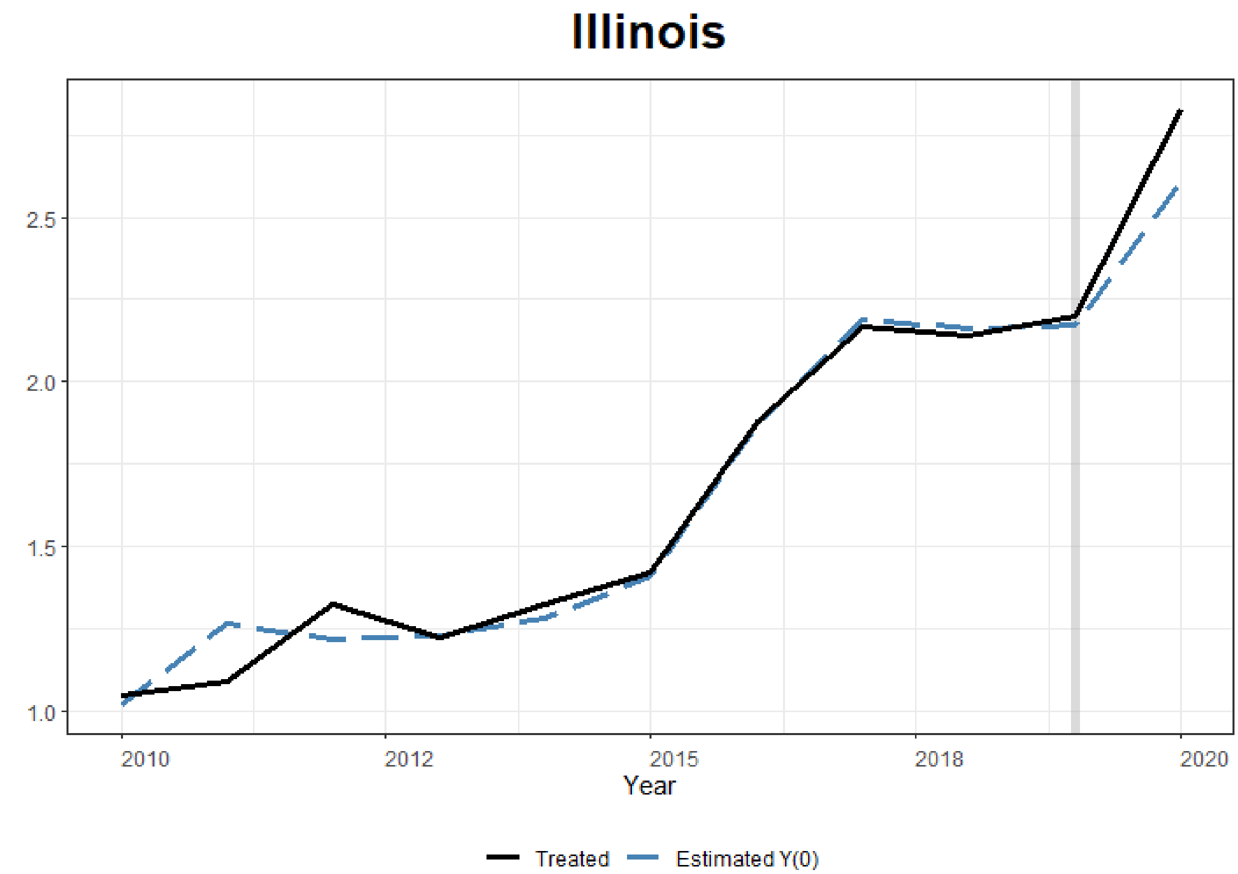

Table A.88: Average Treatment Effect on the Treated: RML in Illinois

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.215	0.1396	-0.05859	0.4885	0.1235

Table A.89: Treatment Effect by Period (including Pre-treatment Periods): RML in Illinois

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	0.026585	0.09718	-0.16389	0.21706	0.78443	0
-8	-0.17615	0.10673	-0.38533	0.03303	0.09884	0
-7	0.105594	0.08073	-0.05262	0.26381	0.19085	0
-6	-0.00490	0.09897	-0.19888	0.18909	0.96054	0
-5	0.042797	0.06474	-0.08410	0.16969	0.50859	0
-4	0.012939	0.06371	-0.11194	0.13782	0.83907	0
-3	0.012885	0.06856	-0.12148	0.14725	0.85092	0
-2	-0.02345	0.05892	-0.13893	0.09204	0.69067	0
-1	-0.02296	0.05824	-0.13712	0.09119	0.69340	0
0	0.025669	0.06121	-0.09430	0.14563	0.67494	0
1	0.214956	0.13957	-0.05859	0.48851	0.12353	1

Table A.90: Coefficients for the Covariates: RML in Illinois

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	6.306e-06	2.262e-06	1.872e-06	1.074e-05	0.0053101
fratio	1.443e+01	3.893e+00	6.804e+00	2.206e+01	0.0002091
wratio	-1.229e+01	5.269e-01	-1.332e+01	-1.125e+01	0.0000000
Poverty_rate	2.766e-01	8.374e-03	2.602e-01	2.930e-01	0.0000000

Figure A.31: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the RML in Maine

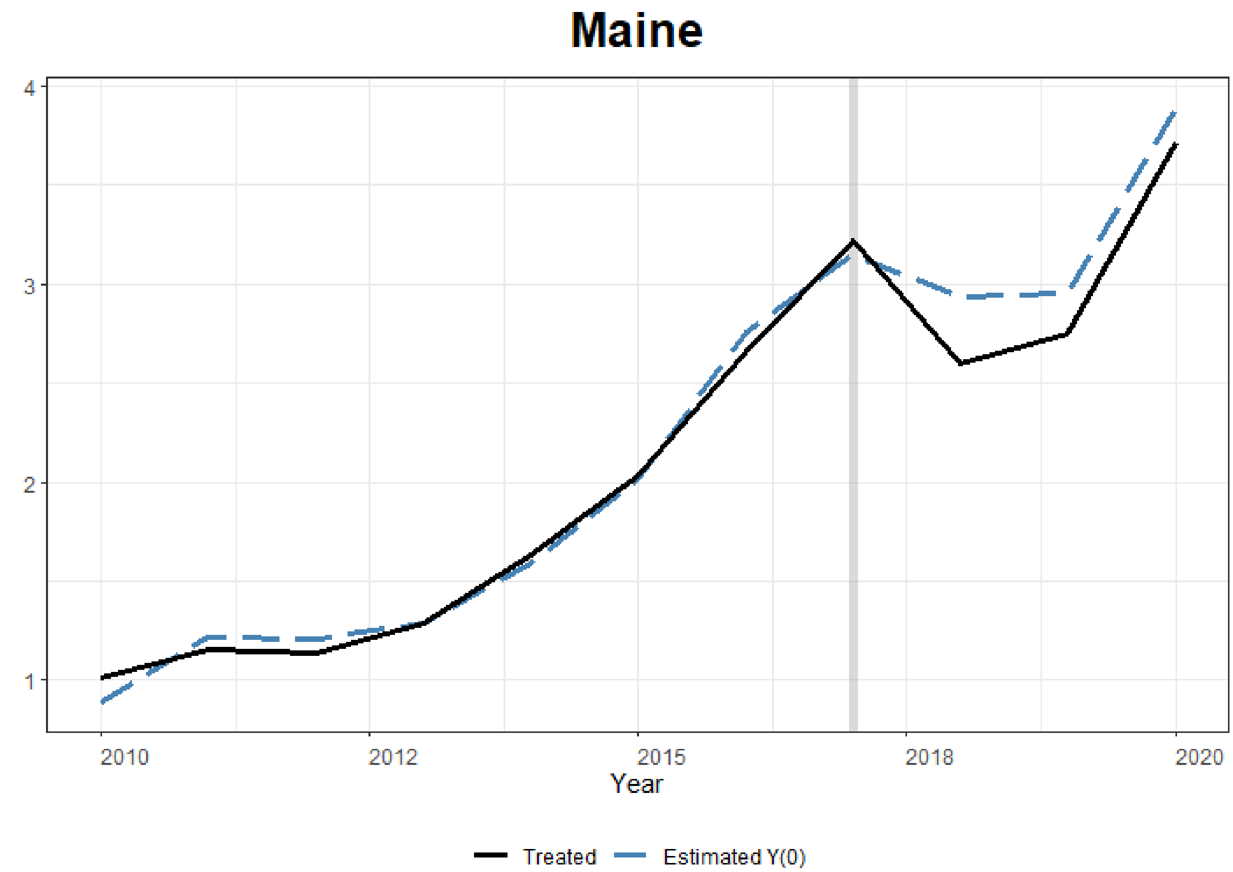

Table A.91: Average Treatment Effect on the Treated: RML in Maine

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.241	0.3999	-1.025	0.5428	0.5467

Table A.92: Treatment Effect by Period (including Pre-treatment Periods): RML in Maine

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	0.120904	0.13637	-0.1464	0.38818	0.3753	0
-6	-0.06418	0.11257	-0.2848	0.15646	0.5686	0
-5	-0.07238	0.11059	-0.2891	0.14437	0.5128	0
-4	-0.00642	0.11018	-0.2224	0.20954	0.9535	0
-3	0.03711	0.12144	-0.2009	0.27513	0.7599	0
-2	0.017618	0.15672	-0.2895	0.32478	0.9105	0
-1	-0.10011	0.08751	-0.2716	0.07141	0.2526	0
0	0.072183	0.11757	-0.1582	0.30261	0.5392	0
1	-0.33499	0.32657	-0.9751	0.30508	0.3050	1
2	-0.21016	0.38696	-0.9686	0.54826	0.5870	1
3	-0.17794	0.68543	-1.5214	1.16548	0.7952	1

Table A.93: Coefficients for the Covariates: RML in Maine

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-6.574e-06	4.977e-06	-1.633e-05	3.181e-06	1.866e-01
fratio	1.933e+01	1.656e+01	-1.312e+01	5.178e+01	2.430e-01
wratio	-1.074e+01	1.783e+00	-1.423e+01	-7.240e+00	1.743e-09
Poverty_rate	2.377e-01	3.162e-02	1.757e-01	2.996e-01	5.684e-14

Figure A.32: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the RML in Nevada

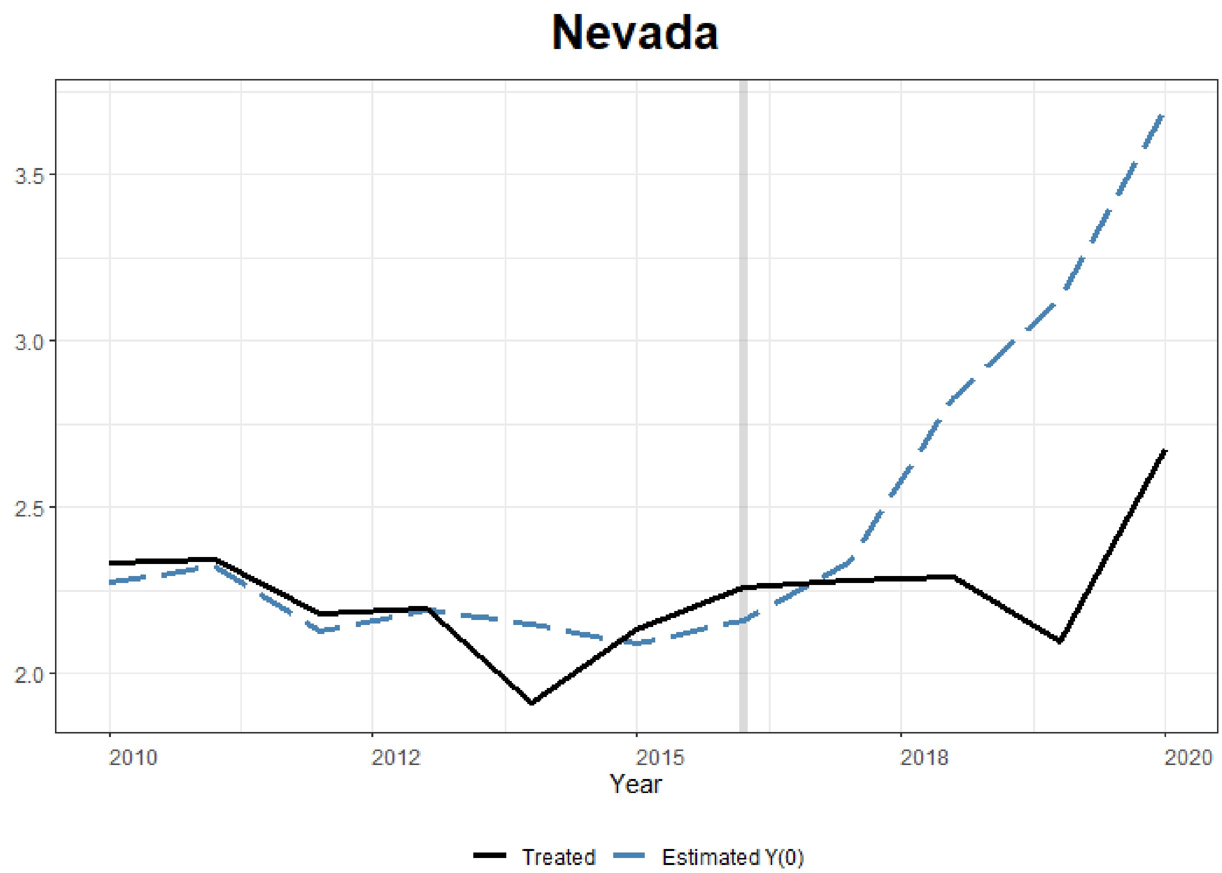

Table A.94: Average Treatment Effect on the Treated: RML in Nevada

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.6619	0.07729	-0.8134	-0.5105	0

Table A.95: Treatment Effect by Period (including Pre-treatment Periods): RML in Nevada

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	0.06140	0.08292	-0.10112	0.22390	0.4590	0
-5	0.02228	0.10519	-0.18388	0.22840	0.8322	0
-4	0.05537	0.08939	-0.11984	0.23060	0.5356	0
-3	0.00091	0.09355	-0.18245	0.18430	0.9922	0
-2	-0.23806	0.06840	-0.37212	-0.10400	0.0005	0
-1	0.04221	0.06985	-0.09469	0.17910	0.5456	0
0	0.09846	0.06662	-0.03211	0.22900	0.1394	0
1	-0.05569	0.18854	-0.42524	0.31380	0.7677	1
2	-0.53653	0.16733	-0.86449	-0.20860	0.0013	1
3	-1.03336	0.16857	-1.36376	-0.70300	8.78e-10	1
4	-1.02215	0.18083	-1.37656	-0.66770	1.58e-08	1

Table A.96: Coefficients for the Covariates: RML in Nevada

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	2.817e-06	3.154e-06	-3.365e-06	8.999e-06	0.3718
fratio	-8.954	5.921	-20.56	2.651	0.1305
wratio	-8.098	0.8486	-9.761	-6.435	0.0000
Poverty_rate	0.2607	0.01168	0.2378	0.2836	0.0000

Figure A.33: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the RML in Vermont

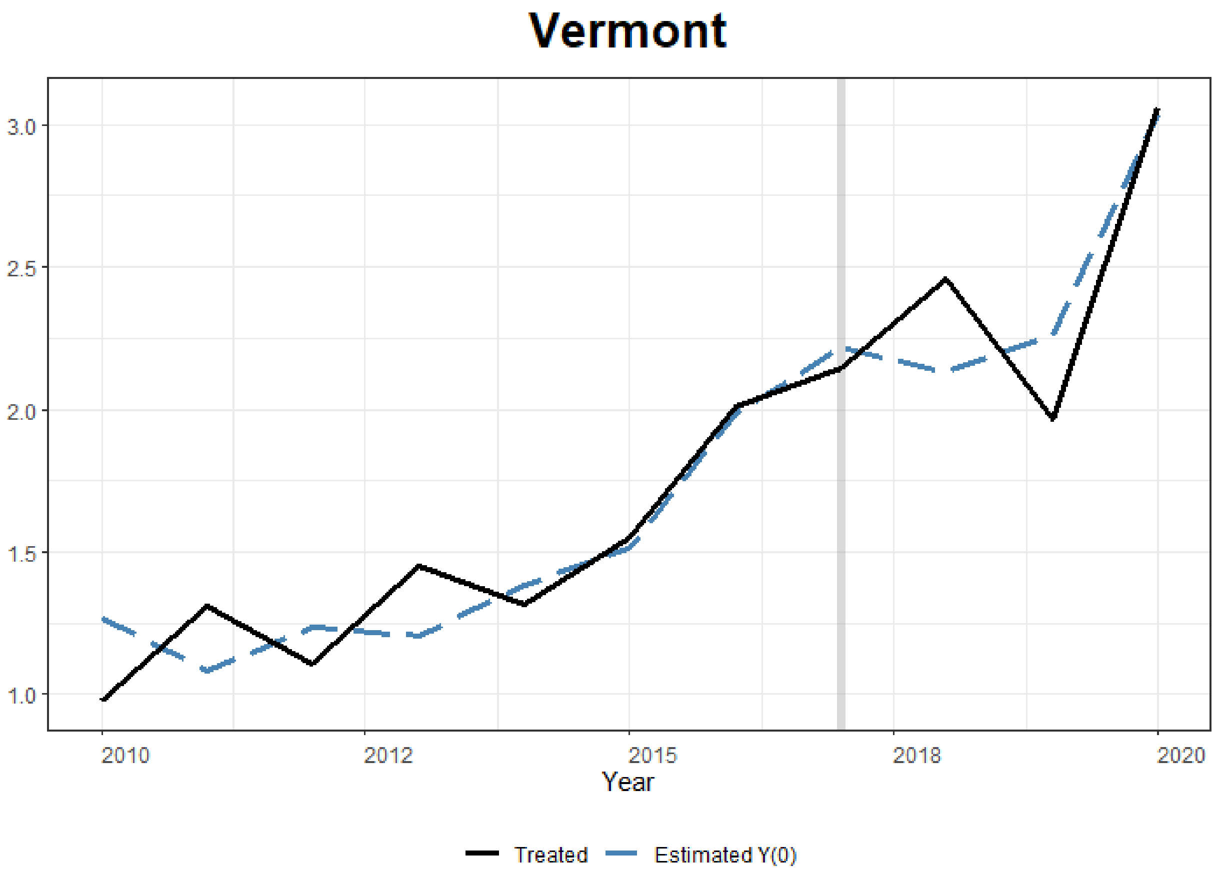

Table A.97: Average Treatment Effect on the Treated: RML in Vermont

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.01729	0.3718	-0.7114	0.7459	0.9629

Table A.98: Treatment Effect by Period (including Pre-treatment Periods): RML in Vermont

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.28834	0.12795	-0.53912	-0.03757	0.02422	0
-6	0.23075	0.11975	-0.00395	0.46546	0.05398	0
-5	-0.12512	0.11145	-0.34355	0.09331	0.26157	0
-4	0.24446	0.10528	0.03811	0.45081	0.02023	0
-3	-0.06737	0.11025	-0.28346	0.14871	0.54114	0
-2	0.03782	0.14998	-0.25613	0.33177	0.80091	0
-1	0.02581	0.08614	-0.14302	0.19465	0.76444	0
0	-0.07539	0.11459	-0.29997	0.14920	0.51060	0
1	0.32192	0.31699	-0.29936	0.94320	0.30984	1
2	-0.29409	0.37086	-1.02095	0.43277	0.42778	1
3	0.02405	0.61853	-1.18824	1.23634	0.96899	1

Table A.99: Coefficients for the Covariates: RML in Vermont

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-6.102e-06	4.732e-06	-1.538e-05	3.172e-06	0.1972
fratio	15.76	15.78	-15.16	46.68	0.3177
wratio	-12.49	1.657	-15.74	-9.247	4.663e-14
Poverty_rate	0.2183	0.03074	0.1581	0.2786	1.218e-12

Figure A.34: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Dispensary Openings in California

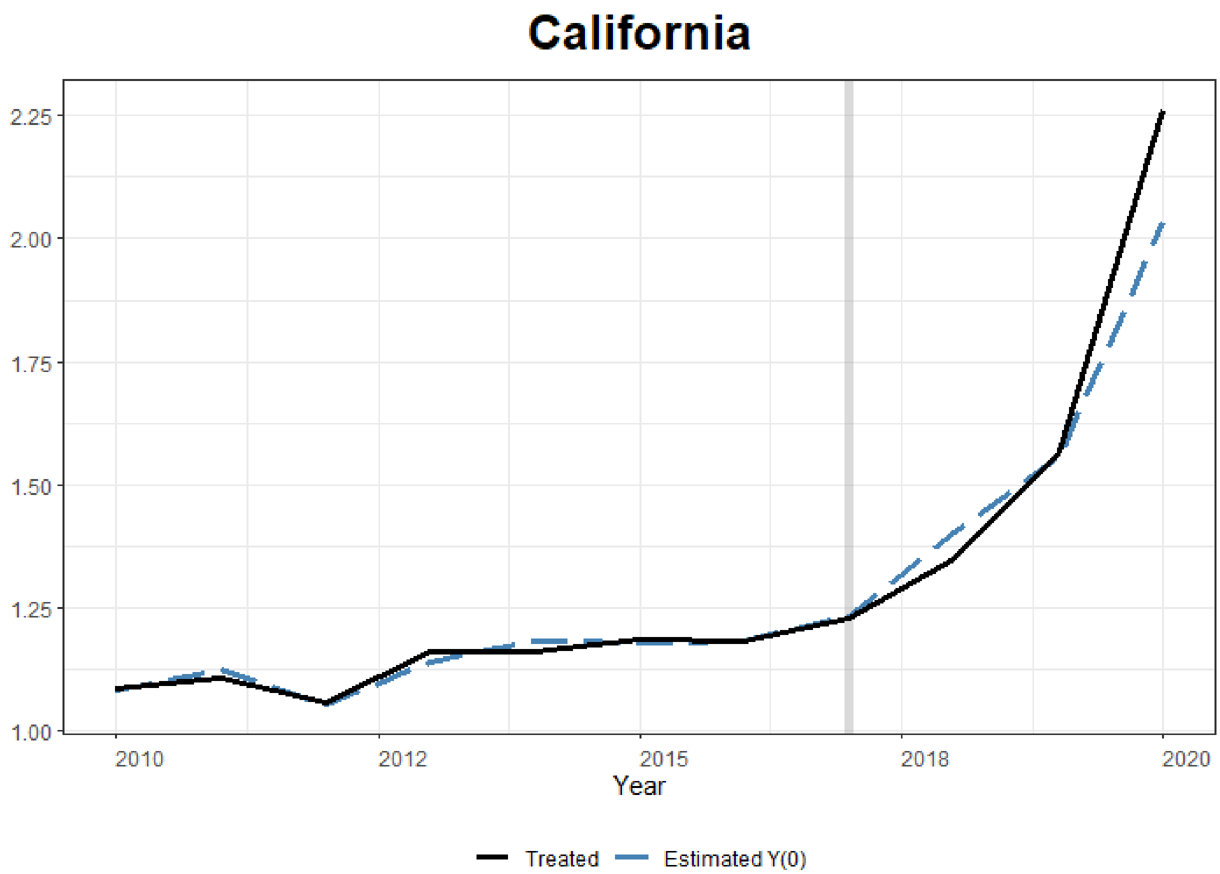

Table A.100: Average Treatment Effect on the Treated: Recreational Dispensaries in California

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.06196	0.09595	-0.1261	0.25	0.5184

Table A.101: Treatment Effect by Period (including Pre-treatment Periods): Recreational Dispensaries in California

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	0.004828	0.08843	-0.16850	0.17816	0.95646	0
-6	-0.018664	0.10397	-0.22244	0.18511	0.85753	0
-5	0.003179	0.07555	-0.14490	0.15126	0.96644	0
-4	0.020438	0.09192	-0.15973	0.20061	0.82405	0
-3	-0.018403	0.06591	-0.14759	0.11079	0.78010	0
-2	0.009625	0.05429	-0.09678	0.11602	0.85928	0
-1	0.002277	0.06294	-0.12109	0.12564	0.97114	0
0	-0.001405	0.04554	-0.09067	0.08786	0.97540	0
1	-0.052150	0.16284	-0.37131	0.26701	0.74878	1
2	0.009813	0.14793	-0.28013	0.29976	0.94711	1
3	0.228216	0.10702	0.01847	0.43796	0.03296	1

Table A.102: Coefficients for the Covariates: Recreational Dispensaries in California

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	6.204e-06	2.081e-06	2.125e-06	1.028e-05	0.002869
fratio	4.920	3.508	-1.956	11.800	0.160795
wratio	-11.560	0.4504	-12.450	-10.680	0.000000
Poverty_rate	0.2485	0.008323	0.2322	0.2649	0.000000

Figure A.35: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Dispensary Openings in Colorado

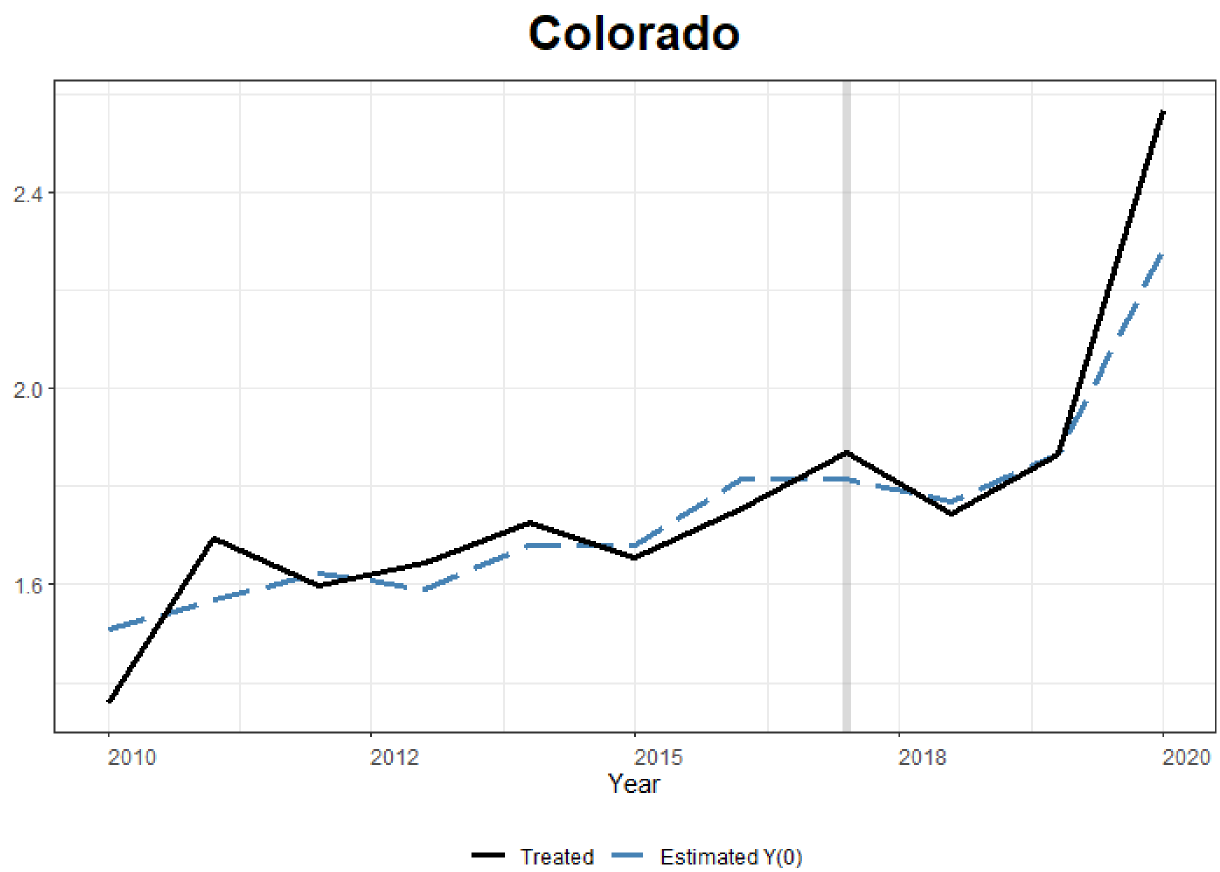

Table A.103: Average Treatment Effect on the Treated: Recreational Dispensaries in Colorado

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.08663	0.3958	-0.6891	0.8623	0.8267

Table A.104: Treatment Effect by Period (including Pre-treatment Periods): Recreational Dispensaries in Colorado

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	-0.148248	0.14597	-0.4343	0.1379	0.3098	0
-6	0.123970	0.11875	-0.1088	0.3567	0.2965	0
-5	-0.025777	0.11571	-0.2526	0.2010	0.8237	0
-4	0.053341	0.11628	-0.1746	0.2812	0.6464	0
-3	0.047210	0.12218	-0.1923	0.2867	0.6992	0
-2	-0.025465	0.15946	-0.3380	0.2871	0.8731	0
-1	-0.061499	0.08788	-0.2337	0.1107	0.4841	0
0	0.051909	0.11752	-0.1784	0.2822	0.6587	0
1	-0.025668	0.32693	-0.6664	0.6151	0.9374	1
2	0.001191	0.39853	-0.7799	0.7823	0.9976	1
3	0.284371	0.64762	-0.9849	1.5537	0.6606	1

Table A.105: Coefficients for the Covariates: Recreational Dispensaries in Colorado

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-6.478e-06	4.866e-06	-1.602e-05	3.061e-06	0.1832
fratio	18.20	16.57	-14.28	50.67	0.2721
wratio	-13.18	1.619	-16.36	-10.01	4.441e-16
Poverty_rate	0.1955	0.03196	0.1328	0.2581	9.614e-10

Figure A.36: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Dispensary Openings in Illinois

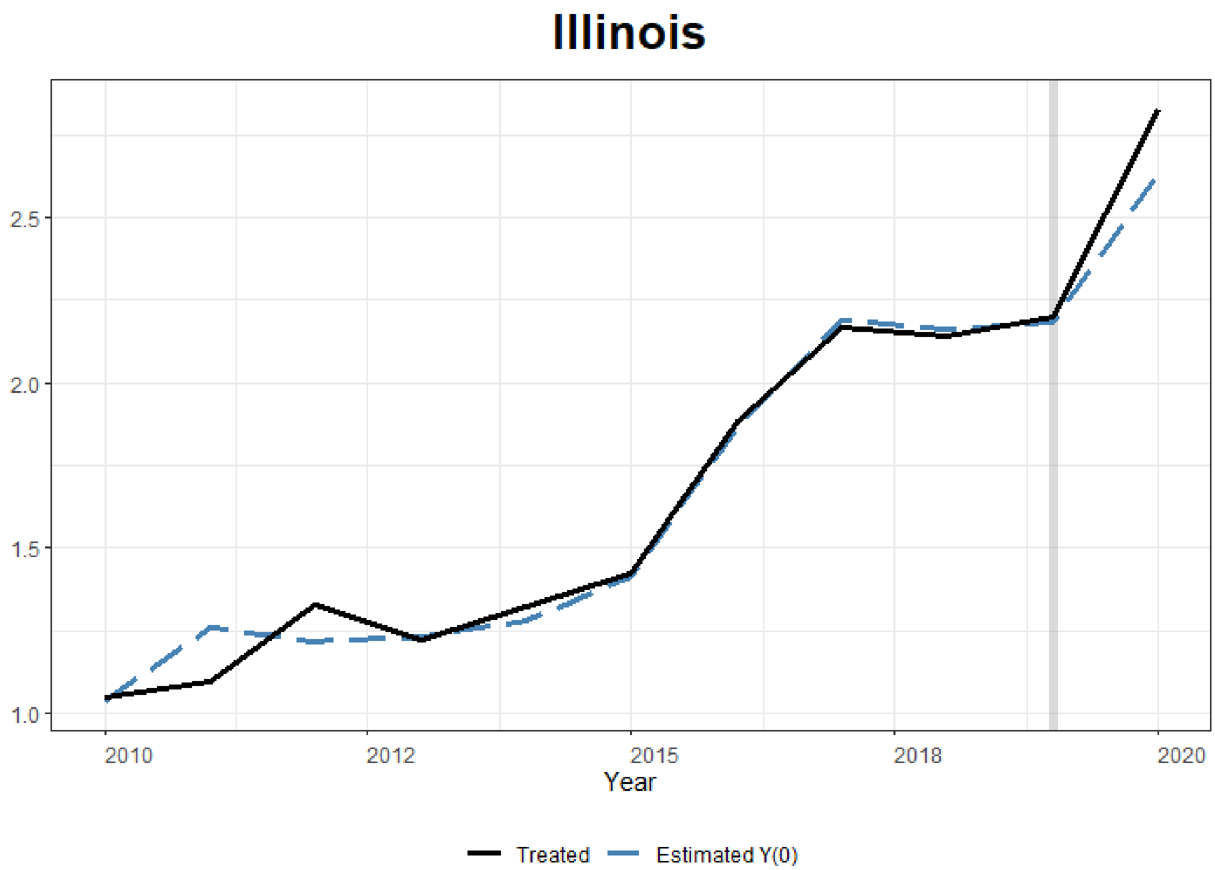

Table A.106: Average Treatment Effect on the Treated: Recreational Dispensaries in Illinois

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.1939	0.2099	-0.2175	0.6052	0.3556

Table A.107: Treatment Effect by Period (including Pre-treatment Periods): Recreational Dispensaries in Illinois

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	0.011842	0.09202	-0.16851	0.19220	0.8976	0
-8	-0.163472	0.11607	-0.39097	0.06402	0.1590	0
-7	0.109092	0.07556	-0.03900	0.25718	0.1488	0
-6	-0.006879	0.09438	-0.19185	0.17809	0.9419	0
-5	0.042797	0.06480	-0.08421	0.16980	0.5090	0
-4	0.012509	0.06372	-0.11237	0.13739	0.8444	0
-3	0.014912	0.06720	-0.11680	0.14662	0.8244	0
-2	-0.020615	0.05584	-0.13005	0.08882	0.7120	0
-1	-0.018470	0.06525	-0.14635	0.10941	0.7771	0
0	0.017008	0.06390	-0.10823	0.14224	0.7901	0
1	0.193884	0.20987	-0.21746	0.60523	0.3556	1

Table A.108: Coefficients for the Covariates: Recreational Dispensaries in Illinois

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	5.669e-06	2.370e-06	1.024e-06	1.031e-05	0.016748
fratio	11.44	3.658	4.268	18.61	0.001768
wratio	-12.61	0.4705	-13.53	-11.68	0.000000
Poverty_rate	0.2415	0.008573	0.2247	0.2583	0.000000

Figure A.37: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Dispensary Openings in Maine

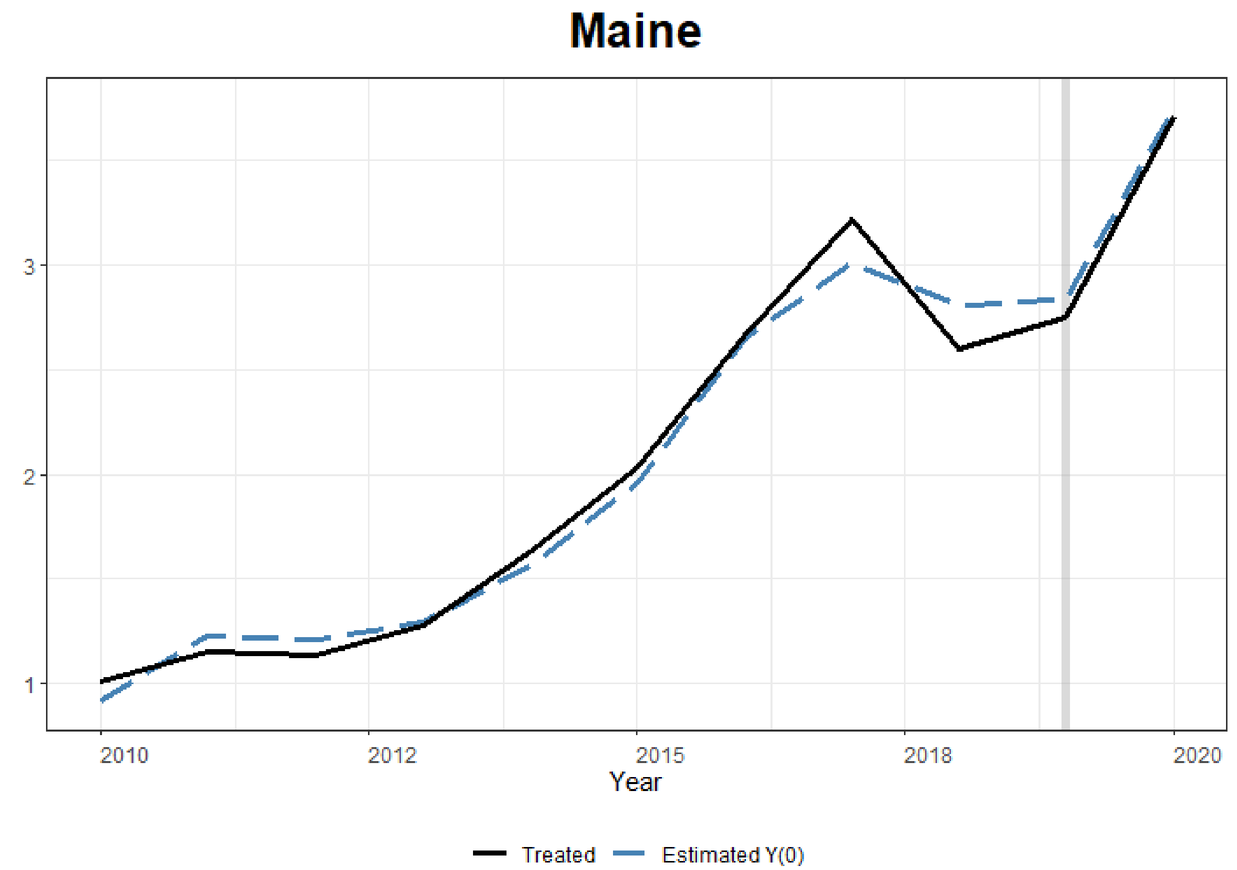

Table A.109: Average Treatment Effect on the Treated: Recreational Dispensaries in Maine

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.03582	0.603	-1.218	1.146	0.9526

Table A.110: Treatment Effect by Period (including Pre-treatment Periods): Recreational Dispensaries in Maine

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-9	0.08928	0.1523	-0.20928	0.3878	0.5578	0
-8	-0.07588	0.1217	-0.31436	0.1626	0.5329	0
-7	-0.07423	0.1121	-0.29404	0.1456	0.5080	0
-6	-0.01538	0.1105	-0.23203	0.2013	0.8893	0
-5	0.06265	0.1285	-0.18929	0.3146	0.6260	0
-4	0.07322	0.1937	-0.30642	0.4529	0.7054	0
-3	0.01087	0.1809	-0.34375	0.3655	0.9521	0
-2	0.21321	0.1537	-0.08797	0.5144	0.1653	0
-1	-0.20773	0.1582	-0.51774	0.1023	0.1891	0
0	-0.08855	0.2185	-0.51682	0.3397	0.6853	0
1	-0.03582	0.603	-1.21777	1.1461	0.9526	1

Table A.111: Coefficients for the Covariates: Recreational Dispensaries in Maine

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-6.569e-06	4.905e-06	-1.618e-05	3.045e-06	0.1805
fratio	16.54	15.60	-14.04	47.12	0.2891
wratio	-10.41	1.695	-13.74	-7.091	8.047e-10
Poverty_rate	0.2029	0.03129	0.1415	0.2642	8.973e-11

Figure A.38: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Dispensary Openings in Massachusetts

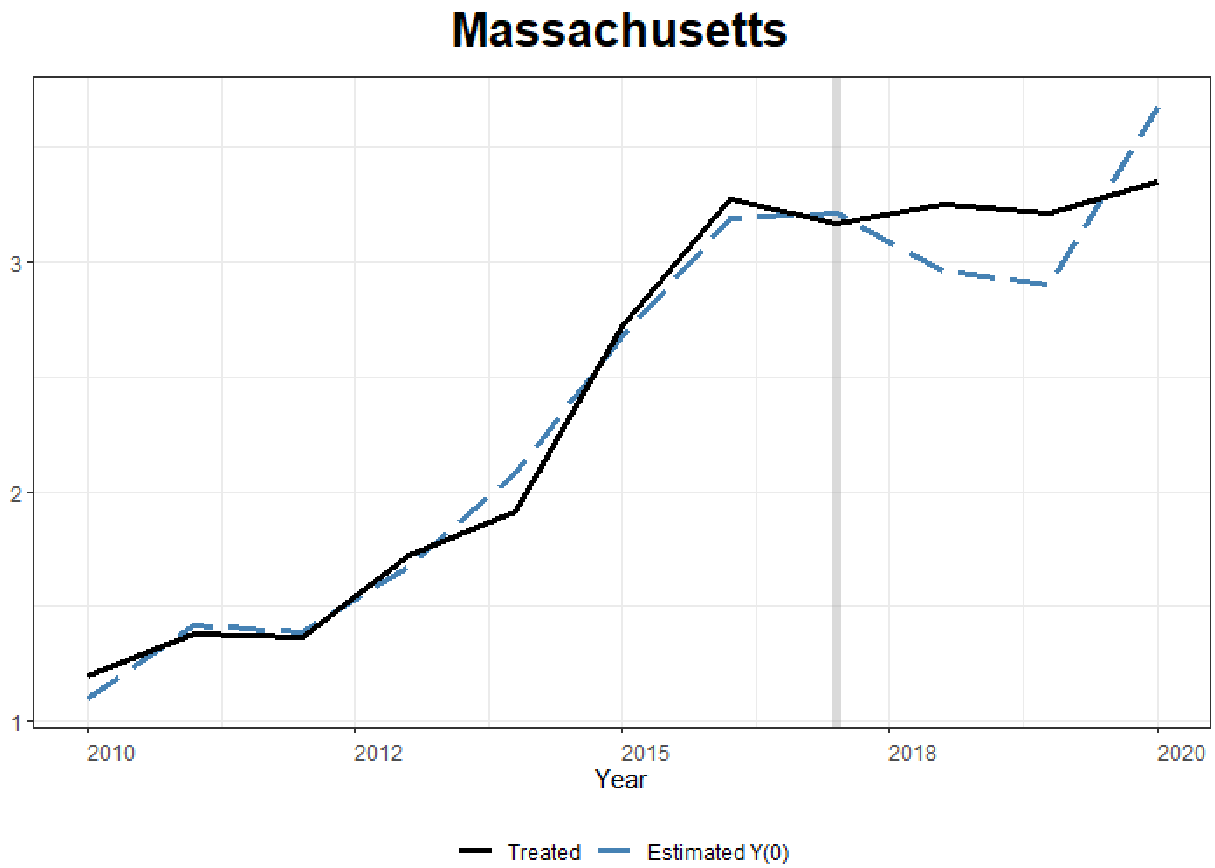

Table A.112: Average Treatment Effect on the Treated: Recreational Dispensaries in Massachusetts

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	0.09127	0.1294	-0.1624	0.3449	0.4807

Table A.113: Treatment Effect by Period (including Pre-treatment Periods): Recreational Dispensaries in Massachusetts

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-7	0.09483	0.08324	-0.06831	0.25798	0.25458	0
-6	-0.03943	0.10216	-0.23965	0.16079	0.69952	0
-5	-0.01725	0.07547	-0.16516	0.13066	0.81923	0
-4	0.04556	0.08421	-0.11949	0.21062	0.58846	0
-3	-0.16642	0.06374	-0.29136	-0.04149	0.00903	0
-2	0.05036	0.05289	-0.05330	0.15402	0.34098	0
-1	0.08378	0.06158	-0.03691	0.20447	0.17364	0
0	-0.04862	0.04387	-0.13461	0.03737	0.26775	0
1	0.29182	0.20742	-0.11471	0.69835	0.15945	1
2	0.31016	0.17657	-0.03591	0.65622	0.07899	1
3	-0.32817	0.13403	-0.59086	-0.06548	0.01435	1

Table A.114: Coefficients for the Covariates: Recreational Dispensaries in Massachusetts

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	5.093e-06	2.851e-06	-4.951e-07	1.068e-05	0.07405
fratio	17.30	3.396	10.65	23.96	3.499e-07
wratio	-16.26	0.464	-17.17	-15.35	0.000
Poverty_rate	0.2416	0.01097	0.2201	0.2631	0.000

Figure A.39: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Dispensary Openings in Michigan

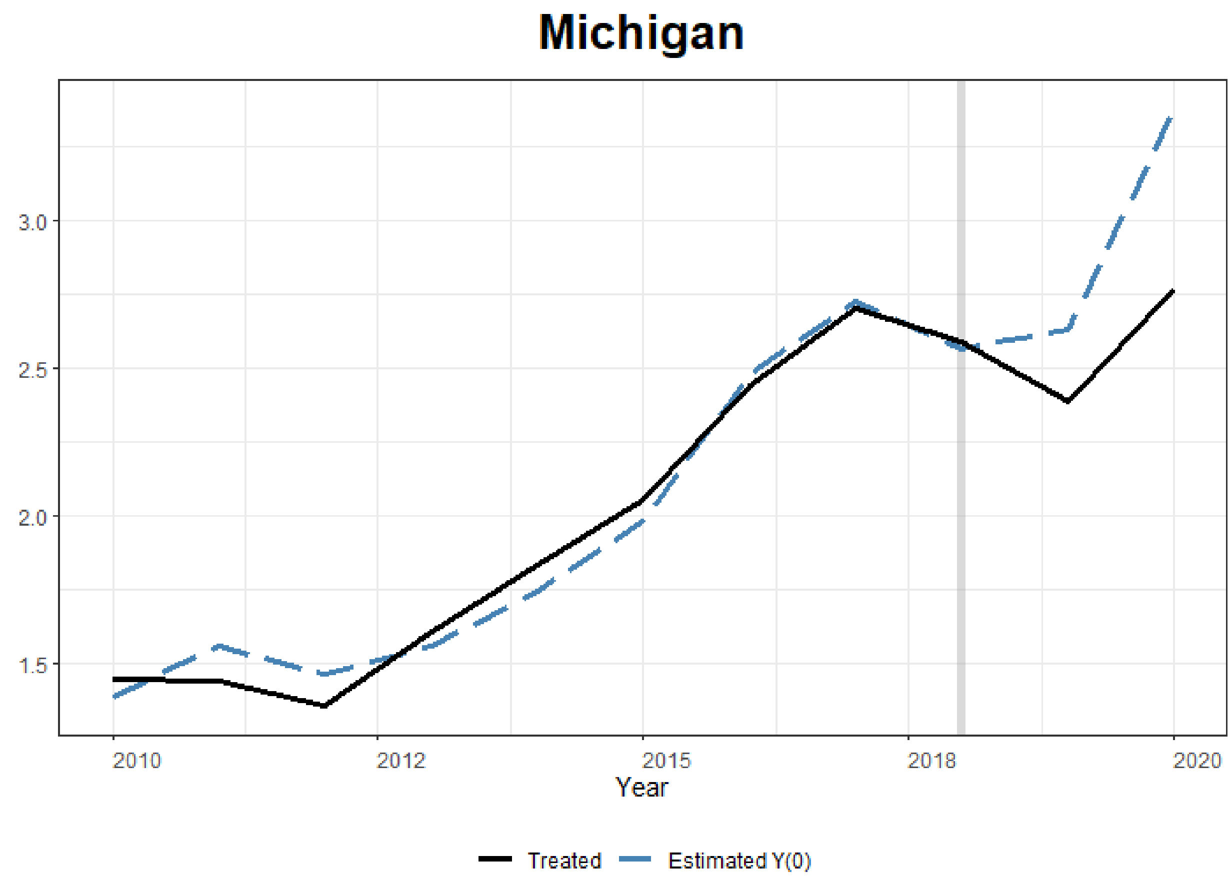

Table A.115: Average Treatment Effect on the Treated: Recreational Dispensaries in Michigan

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.4219	0.4076	-1.221	0.377	0.3006

Table A.116: Treatment Effect by Period (including Pre-treatment Periods): Recreational Dispensaries in Michigan

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-8	0.06021	0.1353	-0.2050	0.3254	0.6563	0
-7	-0.11894	0.1158	-0.3458	0.1079	0.3042	0
-6	-0.10322	0.1068	-0.3126	0.1061	0.3338	0
-5	0.04849	0.1103	-0.1678	0.2647	0.6603	0
-4	0.08893	0.1149	-0.1364	0.3142	0.4391	0
-3	0.07272	0.1688	-0.2581	0.4035	0.6666	0
-2	-0.03976	0.1366	-0.3075	0.2280	0.7710	0
-1	-0.02257	0.1234	-0.2645	0.2193	0.8549	0
0	0.02502	0.2043	-0.3755	0.4255	0.9025	0
1	-0.24000	0.3064	-0.8405	0.3605	0.4334	1
2	-0.60372	0.6094	-1.7981	0.5906	0.3218	1

Table A.117: Coefficients for the Covariates: Recreational Dispensaries in Michigan

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	-5.820e-06	4.707e-06	-1.505e-05	3.407e-06	0.2163
fratio	6.803	15.25	-23.09	36.69	0.6555
wratio	-11.45	1.650	-14.69	-8.219	3.927e-12
Poverty_rate	0.1889	0.02999	0.1301	0.2476	3.026e-10

Figure A.40: Counter Factual Plot: Pre and Post Overdose Death Rates in Basis Points corresponding to the Recreational Dispensary Openings in Nevada

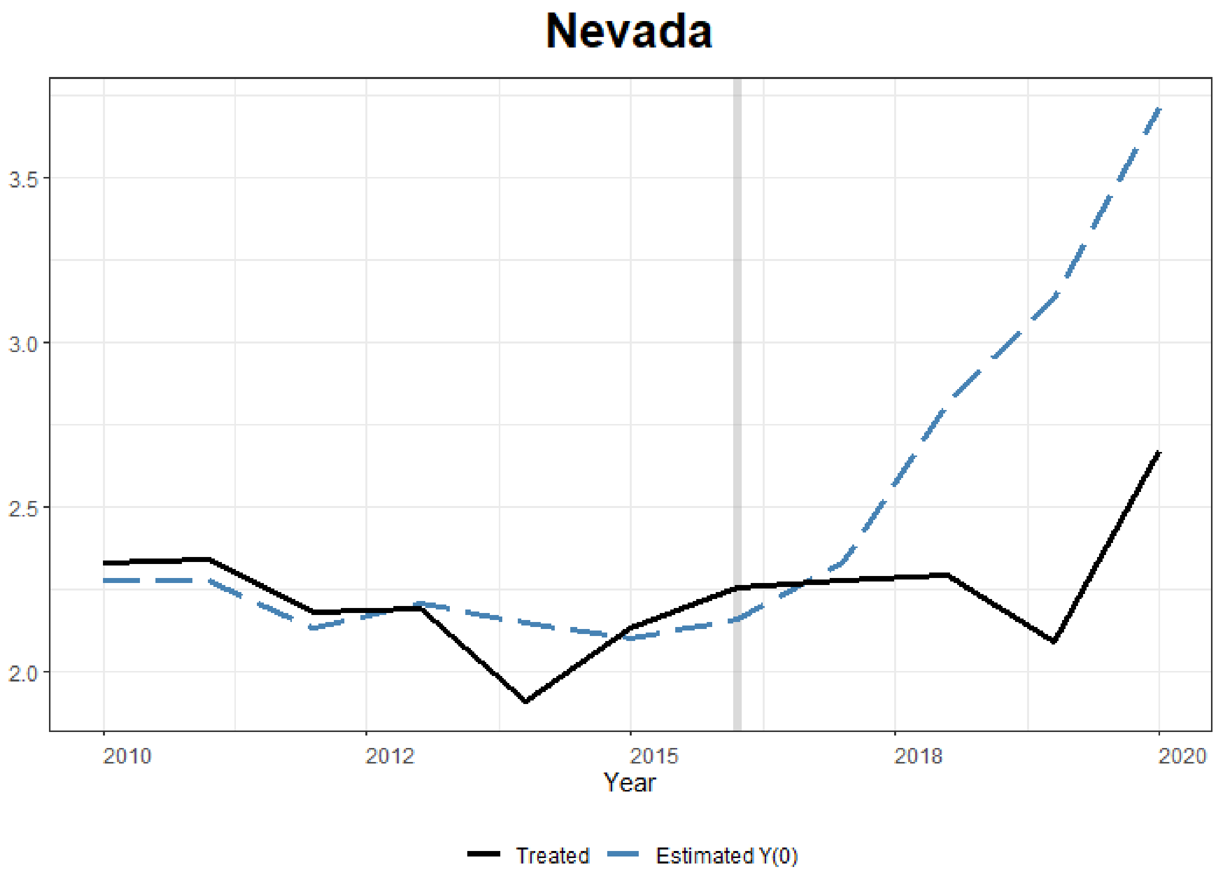

Table A.118: Average Treatment Effect on the Treated: Recreational Dispensaries in Nevada

	Estimate	S.E.	CI.lower	CI.upper	p.value
ATT.avg	-0.6637	0.07108	-0.803	-0.5244	0

Table A.119: Treatment Effect by Period (including Pre-treatment Periods): Recreational Dispensaries in Nevada

Period	ATT	S.E.	CI.lower	CI.upper	p.value	n.Treated
-6	0.05372	0.08927	-0.12124	0.2287	0.5473	0
-5	0.06301	0.10961	-0.15183	0.2778	0.5654	0
-4	0.04468	0.08784	-0.12749	0.2169	0.6110	0
-3	-0.01605	0.09066	-0.19374	0.1616	0.8595	0
-2	-0.23884	0.06907	-0.37420	-0.1035	0.0005442	0
-1	0.03245	0.06715	-0.09916	0.1641	0.6289	0
0	0.09837	0.06207	-0.02329	0.2200	0.1130	0
1	-0.05377	0.18442	-0.41523	0.3077	0.7706	1
2	-0.52258	0.16225	-0.84059	-0.2046	0.001278	1
3	-1.03808	0.16432	-1.36014	-0.7160	2.66e-10	1
4	-1.04039	0.15410	-1.34241	-0.7384	1.463e-11	1

Table A.120: Coefficients for the Covariates: Recreational Dispensaries in Nevada

Covariate	β	S.E.	CI.lower	CI.upper	p.value
income	3.161e-06	2.841e-06	-2.406e-06	8.729e-06	0.26578
fratio	-11.09	5.762	-22.39	0.1985	0.05417
wratio	-8.622	0.8414	-10.27	-6.973	0.00000
Poverty_rate	0.2285	0.01034	0.2082	0.2488	0.00000

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