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# Does Marijuana Decriminalization Make the Roads More Dangerous?

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Does Marijuana Decriminalization Make the Roads More Dangerous?

Daehyeon Kim

A thesis submitted to the faculty of  
Brigham Young University  
in partial fulfillment of the requirements for the degree of

Master of Science

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## ABSTRACT

### Does Marijuana Decriminalization Make the Roads More Dangerous?

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As the movement to decriminalize marijuana has gained more support throughout the United States, as of early 2017, 21 states have decriminalized the possession of a small amount of marijuana for personal recreational use, and more states are expected to decriminalize marijuana (GOVERNING 2017). Despite this strong move toward decriminalizing marijuana, however, the consequences of implementing such a policy are still very much unknown. One of the concerns regarding this movement to decriminalize marijuana is its potential impact on road safety (Schrader 2015; Roberts 2017; Halsey 2016). Although there are a few studies that have examined the association between marijuana use and availability and traffic fatalities, these studies are correlational in nature and show divergent outcomes (Anderson et al. 2011; Anderson and Ree 2014). Furthermore, these studies do not examine the impact of decriminalizing marijuana on road safety. In order to fill this gap, my research investigates the causal association between marijuana decriminalization and traffic fatalities by using the synthetic control method, pioneered by Abadie et al. (2010). This study estimates the causal effects of 2009 Massachusetts's marijuana decriminalization on Massachusetts' total traffic fatalities by comparing Massachusetts's trends in total traffic fatalities and its synthetic counterpart. The results of this study show a temporary increase in the number of total traffic fatalities in Massachusetts compared to its synthetic counterpart between 2009 and 2012, suggesting marijuana decriminalization's detrimental effect on road safety. Future studies should consider investigating the heterogeneous effects of marijuana decriminalization on traffic fatalities based on age groups, gender, and residential density and the causal mechanism between marijuana decriminalization and traffic fatalities.

Keywords: marijuana, marijuana decriminalization, traffic fatalities, road safety, policy

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## Does Marijuana Decriminalization Make the Roads More Dangerous?

According to a recent survey by Pew Research Center (2016), the average American's attitude towards marijuana use has become more tolerant over the past three decades. Compared to 1990, when only about 16% of Americans ages 18 or older supported marijuana legalization, in 2015 this had increased to about 53% (Pew Research Center 2016). As views toward marijuana use have softened, the movement to decriminalize marijuana has also gained more support throughout the United States, and, as of early 2017, 21 states have decriminalized the possession of a small amount of marijuana for personal recreational use. In addition, eight states have legalized recreational marijuana and 28 states have legalized medical marijuana (GOVERNING 2017).

Although support for relaxing marijuana laws has been increasing in recent years, the potential ramifications of decreasing or eliminating penalties for possession and use of marijuana through medical marijuana availability, decriminalization, or legalization are not clear. For example, as the laws about marijuana use among adults are relaxed or eliminated, will marijuana use among youth increase? Will there be more problems with marijuana dependence and abuse? Will crimes associated with intoxication—such as public nuisance offenses—increase? Additionally, whereas driving offenses associated with alcohol, such as driving under the influence (DUI) and driving while intoxicated (DWI), are a concern of many, there is also the related issue of driving under the influence of marijuana, which, in turn, is likely to make the roads more dangerous, leading to an increase in traffic fatalities (Schrader 2015; Roberts 2017; Halsey 2016). Thus, one of the potential ramifications that should be investigated is whether relaxing marijuana laws has an influence on the number of traffic fatalities. This will help us understand whether relaxing marijuana laws makes the roads more hazardous.

Recently, several media stories about DUI cases in which drivers were detected to be under the influence of marijuana have raised the public's concern about the effect of relaxing marijuana laws on road safety (Schrader 2015; Roberts 2017; Halsey 2016). The research literature to date generally does not support the argument that changing marijuana laws affects traffic fatalities, however (Anderson et al. 2011; Anderson and Ree 2014). Nevertheless, this research has been correlational in nature. As a result, the association between medical marijuana availability and road safety found from this research is likely spurious. Furthermore, this research has focused on the availability of medical marijuana rather than marijuana decriminalization. Thus, it is important to consider whether marijuana decriminalization has any effect on traffic fatalities. To date, no study has considered this issue.

In this study, I examine the impact of the 2009 Massachusetts marijuana decriminalization legislation on traffic fatalities to investigate the causal effect of marijuana decriminalization on traffic fatalities. Using a synthetic control method (SCM) (Abadie et al. 2010), I compare the trend in traffic fatalities in Massachusetts (the treated unit) to the traffic fatalities in a synthetic control – based on characteristics of similar states that did not decriminalize marijuana – to determine if there are differences in these trends. If there are differences in trends in traffic fatalities in Massachusetts relative to those in the synthetic control, this suggests that marijuana decriminalization caused a shift in this outcome of interest.

## LITERATURE REVIEW

### *The History of Marijuana Decriminalization in the United States*

The history of marijuana decriminalization in the United States traces back to the 1960s. In this decade, recreational marijuana use increased throughout the United States. Consequently, the public's view of marijuana use became more tolerant. Although marijuana possession

remained illegal at the federal level, this more tolerant view led several states to experiment with marijuana decriminalization in the 1970s. For example, in 1973 Oregon became the first state to decriminalize marijuana possession (Hardaway 2003). By the end of the 1970s, eight other states—Alaska, California, Colorado, Mississippi, New York, Nebraska, North Carolina, and Ohio—passed similar legislation (Davis 2015).

However, by the early 1980s, this movement stalled, partly because several scientific studies showed that there were various health risks associated with marijuana use. This period also hailed a rise in the conservative movement in the U.S., with a concomitant emphasis on deprecating marijuana use. Thus, generally there was little political desire to change marijuana laws at the state or federal level. In fact, some states, such as Alaska, recriminalized marijuana use in the 1990s (Davis 2015).

It was not until 2001 that Nevada broke this trend by decriminalizing marijuana (Davis 2015). Since 2001, more states have joined this movement. As of early 2017, 21 states have decriminalized possession of a small amount of marijuana, and 28 states allow some forms of medical marijuana based on a physician’s “legal recommendation” since they cannot legally “prescribe” marijuana under federal law (GOVERNING 2017). Furthermore, eight states and the District of Columbia have legalized recreational marijuana use for individuals who are 21 years or older (GOVERNING 2017).

#### *The 2009 Massachusetts Marijuana Decriminalization Initiative*

On January 2, 2009, Massachusetts implemented the Massachusetts Sensible Marijuana Policy initiative, also known as the 2009 Massachusetts marijuana decriminalization law. This new law reduced the legal penalty for possessing equal to or less than one ounce of marijuana to a civil infraction with a \$100 fine. Previous to this, possession of this amount was deemed a

misdemeanor, which could put offenders in jail for up to 6 months with a \$500 fine, including a citation in the CORI criminal records database. However, the new law requires minors to have their parents informed if they are found in possession of marijuana, with a penalty of community service and enrollment in drug awareness counseling. If they do not fulfill these requirements, the law requires them to pay up to a \$1,000 fine.

To my knowledge, there have been no studies evaluating the impact of the 2009 Massachusetts marijuana decriminalization law on various social outcomes, such as marijuana use or road safety. This signifies the need for studies examining the ramifications of this policy. Massachusetts also legalized medical marijuana on January 1, 2013, and legalized recreational marijuana on December 15, 2016 (Salsberg 2016). However, given that Massachusetts's first medical marijuana dispensary opened on June 24, 2015 and that the data utilized herein are from 1994 to 2014, it is unlikely that these shifts in marijuana policies influence my research (Marijuana Policy Project 2017). Moreover, the infrastructure for distributing and selling legal marijuana in Massachusetts is not yet in place.

Massachusetts is an ideal state to study the impact of marijuana decriminalization on trends in total traffic fatalities. The data used herein range from 1994 to 2014. In order to create a sound synthetic control, it is generally expected that the data include a sufficient number of observations during the pre-intervention periods. Furthermore, in order to examine the effect of the intervention, there should also be a sufficient number of observations during the post-intervention period. Since Massachusetts implemented its decriminalization policy in the beginning of 2009, it provides an adequate number of both pre-intervention and post-intervention periods. Furthermore, in order to examine the effect of marijuana decriminalization, the unit of interest should be from other similar treatment conditions such as medical marijuana laws or

recreational marijuana legalization during the period of years that this study examines, which is from 1994 to 2014. Massachusetts is the only state that meets this qualification. For these reasons, this study uses Massachusetts to examine the impact of marijuana decriminalization on road safety.

### *Marijuana Decriminalization and Marijuana Consumption*

Although two correlational studies conducted in the 1990s found no significant association between marijuana use and marijuana decriminalization (Thies and Register 1993; Pacula 1998), numerous studies conducted afterwards consistently show that decriminalizing marijuana is positively associated with marijuana consumption. For example, Staffer and Chalopka's (1999) analysis of the 1988, 1990, and 1991 National Household Surveys on Drug Abuse (NHSDA) found that implementing marijuana decriminalization was associated with about an 8.4% increase in marijuana use in the past month and a 7.6% increase in marijuana use in the past year. Pacula et al. (2003) also determined that marijuana decriminalization was positively correlated with marijuana use in their study of states that had decriminalized marijuana. Similarly, Miech et al. (2015) found from their analysis of Monitoring the Future (MTF) data that, following marijuana decriminalization in California in 2010, there was an increase in high school students' marijuana consumption compared to their counterparts in other states that had not decriminalized. In addition, several studies that analyzed the Australian National Drug Strategy Household Surveys data found that marijuana decriminalization had a positive effect on marijuana use (Cameron and William 2001; Zhao and Harris 2004; Hisao and Zhao 2010).

Even though Thies and Register (1993) and Pacula (1998) found no significant association between marijuana decriminalization and marijuana use, it is safe to conclude that

marijuana decriminalization generally increases marijuana use among individuals, given that both studies are correlational in nature and that Pacula's other study in 2003 found a positive association between marijuana decriminalization and its consumption (Pacula et al. 2003). Increased marijuana use may presage an increase in driving while under the influence of marijuana and thus increase the risk of traffic fatalities.

#### *Marijuana Use and Availability and Traffic Fatalities*

The studies discussed in the previous section indicated that marijuana decriminalization generally leads to an increase in marijuana use. However, this does not necessarily indicate that marijuana decriminalization affects traffic fatalities. Yet, at least one study implicates marijuana use in the prevalence of traffic fatalities. Using data from the U.S. Fatality Analysis Reporting System (1999–2010), Brady and Li (2014) determined that marijuana was the most commonly detected illicit drug among drivers involved in traffic fatalities. They also discovered that the prevalence of cannabidiol—the main psychoactive ingredient in marijuana—detected among drivers involved in traffic fatalities tripled from 1999 to 2010, increasing from 4.2% in 1999 to 12.2% in 2010 (Brady and Li 2014). Not surprisingly, however, the most common psychoactive substance found in these drivers was alcohol (39%). The authors warned, though, that the increase in the marijuana detection rate does not necessarily imply that marijuana use is a direct cause of traffic fatalities because cannabidiol can be detected through blood tests up to one week after marijuana use. This suggests that the increase in marijuana detected in cases of traffic fatalities could have simply been over-reported (Brady and Li 2014).

In contrast, studies have shown that making medical marijuana available is associated with a reduction in traffic fatalities. In a study that utilized longitudinal data, Anderson et al. (2011) controlled for state-level alcohol and traffic laws, as well as conditions in neighboring

states, and determined that the availability of medical marijuana had a statistically significant negative relationship with the rate of traffic fatalities. A similar study conducted in 2013 also discovered a negative association between medical marijuana and traffic fatalities (Anderson and Ree 2014). Moreover, Santaella-Tenorio et al. (2017) found from their analysis of the Fatality Analysis Reporting System's data between 1985 and 2014 that passing medical marijuana laws was strongly associated with a reduction in traffic fatalities among individuals ages 15 to 24, and particularly among those ages 25 to 44.

The results from these studies suggest that implementing policies that make available one form of marijuana, albeit only with the involvement of medical experts, lowers the prevalence of traffic fatalities. However, all three studies of marijuana and traffic fatalities were correlational in nature. Thus, there is a strong likelihood that the association between medical marijuana availability and traffic fatalities is spurious since many other unobserved factors were not accounted for. Furthermore, given that marijuana decriminalization is likely to influence a larger population than medical marijuana availability, it is risky to assume that the impact of marijuana decriminalization on the prevalence of traffic fatalities is similar to the impact of medical marijuana availability. For these reasons, alternative models able to adjust for observed and unobserved differences across states are needed in order to understand the causal association between marijuana decriminalization and the prevalence of traffic fatalities.

Based on the evidence to date it is not clear whether or in what manner marijuana decriminalization affects the prevalence of traffic fatalities. On the one hand, assuming that marijuana use increases following decriminalization, and that impairment due to marijuana use may lead to more risky driving and thus an increased risk in traffic fatalities, we might expect a positive effect of marijuana decriminalization on traffic fatalities. On the other hand, assuming

that marijuana decriminalization is similar in many respects to medical marijuana availability, the studies described earlier suggest that decriminalization may have no effect or lead to fewer traffic fatalities. To date no study has examined the effects of marijuana decriminalization on traffic fatalities. Not surprisingly, this area of study is currently devoid of theories that can guide researchers to hypothesize the potential association between marijuana decriminalization and traffic fatalities.

## HYPOTHESES

This study aims to uncover the causal relationship between the 2009 marijuana decriminalization legislation in Massachusetts and the subsequent number of total traffic fatalities using a synthetic control model. Specifically, this study tests two competing hypotheses: 1) the implementation of the 2009 marijuana decriminalization policy increased the number of traffic fatalities of Massachusetts compared to the number of traffic fatalities in the synthetic control state; and 2) the implementation of the 2009 marijuana decriminalization policy decreased or did not change the number of traffic fatalities of Massachusetts compared to the number of traffic fatalities in the synthetic control state.

## DATA & METHODS

### *Sample and Data*

The population from which the sample is drawn includes the 50 states in the United States between the years 1994 to 2014. Since the observations of this study's outcome variable—the number of total traffic fatalities—are only available from 1994 to 2014, we use observations from other variables between 1994 and 2014 only. The data utilized in this study are from a merged dataset of information from multiple sources that are identified in the appendix of this paper. All variables are longitudinal and provide state-level information.

### *Treatment Condition and Outcome Variable*

In order to measure the effect of the 2009 Massachusetts marijuana decriminalization policy on the prevalence of traffic fatalities in the state, this study uses the following two variables.

*The 2009 Massachusetts marijuana decriminalization policy implementation.* The treatment variable used in this study is identified by the year that Massachusetts implemented its decriminalization policy. Thus, it takes on a value of 0 for the years before 2009 and 1 for the years 2009 through 2014.

*Number of total traffic fatalities.* The data for this variable are from the Fatality Analysis Reporting System (FARS), which is collected by the National Highway Traffic Safety Administration Investigation (NHTSA). The FARS system provides the annual census of the number of individuals who died within 30 days of the motor vehicle traffic accidents on public roads in the USA. This study uses the number of total traffic fatalities instead of the prevalence of total traffic fatalities for two reasons. The first reason is to improve the fit between Massachusetts and its synthetic counterpart. Since the average observation of the prevalence of total traffic fatalities is such a small number, it does not produce a synthetic control unit that fits to Massachusetts as well as when using the number of total traffic fatalities. Second, since the synthetic control method adjusts for the differences in the population size across the states utilized in creating a synthetic control, this study uses the number of total traffic fatalities rather than the prevalence of total traffic fatalities.

### *Predictors of the Outcome of Interest*

The variables utilized to construct a synthetic control include the following variables. Unless otherwise noted, each variable is measured for each relevant year, 1994-2014. The

sources of each variable are provided in the appendix.

*Log state per capita real gross domestic product (GDP).* Oksanen et al.'s (2014) study found an association between traffic fatalities and income-level. Thus, it is important to adjust for *state per capita real GDP* in constructing a synthetic control. GDP measures the total U.S. dollar value of all services and goods produced in a specific geographic location during a particular period of time. In order to adjust for differences in the overall size of the states' economies and to improve its fit with the synthetic control, I created a per capita GDP measure, and then I logged the variable as Abadie et al. (2010) did in their study of the tobacco control to replicate California. Taking the natural log of per capita real GDP improves the fit between Massachusetts and its synthetic counterpart.

*Poverty ratio.* Oksanen et al. (2014) discovered that DUI offenders were more likely to be poorer than non-DUI offenders. Since engaging in DUI is directly associated with traffic fatalities, this study includes the states' *poverty ratio* as one of the predictors of total traffic fatalities. The ratio is calculated by dividing the number of people under the federal poverty line by the population of the state.

*Log marijuana use in past 30 days.* As discussed earlier, there is an association between marijuana use and the prevalence of traffic fatalities (Kelly et al. 2004, O'Malley and Johnston 2007, Brady and Li 2014). Thus, this study uses the state-level prevalence of *marijuana use in the past 30 days* as one of the predictors of the prevalence of traffic fatalities. Although these data are available only from 1999 to 2014, given that Massachusetts's marijuana decriminalization was in effect in 2009, including this variable as a predictor in constructing a synthetic control is likely to improve the resemblance of the synthetic control to Massachusetts.

The variable is calculated by taking the natural log of the number of Marijuana use in past 30 days in a state.

*Unemployment rate.* Nghiem et al. (2016) discovered a positive association between the unemployment rate and road traffic casualties. For this reason, this study includes the *state-level unemployment ratio* as one of the predictors of the prevalence of total traffic fatalities. The ratio is calculated by dividing the number of people under the federal poverty line by the population of the state.

*Log alcohol use in past 30 days.* As discussed earlier, numerous studies suggest that alcohol use is strongly associated with traffic fatalities. Therefore, this study includes log state-level alcohol use per capita as one of the predictors of prevalence of total traffic fatalities. The variable is calculated by taking the natural log of the number of Alcohol use in past 30 days in a state.

*Labor force ratio.* Both Pratt (2003) and Walters et al. (2013) found that traffic fatalities are the leading cause of death occurring at workplaces. Therefore, I expect that a state with a higher number of labor force is likely to experience more traffic fatalities than a state with a relatively lower number of labor force. For this reason, this study includes labor force ratio as one of the predictors of total traffic fatalities. The variable is calculated by dividing the total civilian labor force by civilian non-institutional population provided by the Bureau of Labor Statistics (BLS).

*Law enforcement officers.* DeAngelo and Hansen (2014) found from their study on the effect of Oregon State Police's mass lay off that there is a strong negative association between the number of traffic law enforcement officers and the number of total traffic fatalities.

Therefore, this study includes the number of law enforcement officers as a predictor variable of total traffic fatalities.

*Registered motor vehicle ratio.* It is typical to include the number of registered motor vehicles in studies investigating road safety because there is a positive correlation between the number of registered motor vehicles and the number of traffic fatalities (Neigheim et al. 2016; and Bijleveld et al. 2008). For this reason, this study includes the registered motor vehicle ratio as one of the predictors of the number of traffic fatalities. The variable is calculated by dividing the number of total registered motor vehicles by the number of total residents in a state.

*Licensed driver ratio.* Similar studies investigating the association between traffic fatalities and marijuana laws also utilized the number of licensed drivers in their studies, due to a positive correlation between the number of licensed drivers and the number of traffic fatalities (Santaella-Tenorio et al. 2017; Anderson and Ree 2014). Therefore, this study also includes Licensed Drivers Ratio in estimating the number of total traffic fatalities. This variable is calculated by dividing the number of total licensed drivers by the number of total residents in a state.

*Employment ratio.* One of the leading causes of death at workplaces is traffic accidents (Pratt 2003; Walters et al. 2013). Therefore, it is likely that a particular state's employment ratio is associated with the total traffic fatalities in the state. For this reason, this study uses employment ratio as one of the predictors of the number of total traffic fatalities.

*Log resident.* Similar studies investigating the association between traffic fatalities and marijuana laws also utilized the number of residents in their studies because of the positive association between the number of residents and the number of traffic fatalities (Santaella-Tenorio et al. 2017; Anderson and Ree 2014). Therefore, this study includes the log state-level

resident variable as one of the predictors of the number of total traffic fatalities. This variable is calculated by taking the natural log of the number of residents in a state.

### *Identifying Strategy and Analyses*

This study utilizes the synthetic control method (SCM) in order to identify the causal impact of Massachusetts's 2009 marijuana decriminalization policy on the number of total traffic fatalities in Massachusetts.

The SCM is appropriate for studies aiming to measure the causal effect of a policy or a natural disaster because the method resolves the issue of not having an assigned control group. For example, it is difficult to measure the causal effect of the implementation of Massachusetts's marijuana decriminalization policy on the number of traffic fatalities in the state since there is no counterfactual "Massachusetts" that did not decriminalize marijuana that can be compared with the actual Massachusetts that did decriminalize marijuana.

Traditionally, to study the causal effect of a policy researchers have used a difference-in-differences method by comparing their unit of interest with a similar unit that has not been treated with the policy, assuming that these two units are the same based on multiple observable characteristics. However, this method is vulnerable to bias because, even though one might be able to find a comparison unit that is similar to the unit of interest based on multiple observable characteristics, it is likely that they will be different due to unobservable characteristics, including those that affect trends in outcomes of interest. Similarly, researchers also have used a fixed effects method to study the causal effect of a policy because of its advantage in eliminating time-constant unobserved covariates across the comparison units. By removing the time-invariant differences in unobserved covariates that affect the outcome of interest between the treatment and control groups, the fixed effects model allows researchers to obtain unbiased

estimates of the treatment condition's effect on the outcome of interest. However, it is rather unrealistic to assume that the unobserved characteristics between the treatment and the control groups are time-invariant in many policy studies since many variables are time-variant in general, just as the variables utilized in this study are also time-variant. Thus, in the event of a case where the unobserved characteristics in both control and treatment units are not time-constant, it is likely to lead researchers to obtain biased estimators of the treatment effect.

In contrast to the fixed effects method, the SCM relaxes this assumption—that the unobserved characteristics between the treatment and the control groups are time-invariant—by allowing both the observed and unobserved characteristics in both the treatment and control units to vary over time (Abadie et al. 2010). Therefore, it ameliorates the chance of obtaining biased estimates. Furthermore, the SCM ameliorates the issue of not having a counterfactual and the issue of having a comparison unit that is too divergent in unobservable characteristics with the unit of interest. It utilizes a donor pool—a set of potential comparison units that did not experience the “intervention” that the unit of interest experienced—in creating a synthetic counterfactual (Abadie et al. 2010). The SCM creates a synthetic counterfactual by using a weighted average of the potential units in the donor pool in which  $W$  (the weight) is the value that the characteristics of the synthetic counterfactual that are best resembled by the characteristics of the treated unit (Abadie et al. 2015). Afterwards, by comparing the difference in the outcome variable between the unit of interest and the synthetic control unit, the causal effect of the intervention can be measured. Since more than one unit is utilized in creating the synthetic control, the chance of having statistically significant differences in the observable characteristics between the unit of interest and the control unit can be minimized compared to methods that have been traditionally used for similar studies.

The intuition behind this model is that only units that are similar in both observed and unobserved characteristics can exhibit similar trajectories of the outcome variable over an extensive duration of time. Therefore, only the intervention condition is accountable for a difference in the outcome variable between the unit of interest and the synthetic control unit (Abadie et al. 2015).

In order to utilize the SCM, the following assumptions should be met: 1) The sample is a longitudinal dataset in which the observations of all the units are made during the same time periods; 2) the sample has observations for both the pre-intervention periods and the post-intervention periods; 3) the units that are used to create a synthetic control should not experience a similar “intervention” of interest. In this study, for example, states that have had some form of medical marijuana or recreational marijuana law should not be used in creating a synthetic control.

I now provide a brief mathematical exposition about how to construct a synthetic control and how to find an intervention’s effect using this method. The equations and notation are derived from Abadie et al. (2015).

The model supposes that there are  $J + 1$  units where the first unit  $j = 1$  is the unit of interest, which is exposed to the intervention of interest, and the rest of units  $j = 2$  to  $j = J + 1$  are comparison units that are utilized to create a synthetic control. Suppose that there are pre-intervention periods  $T_0$  and post-intervention periods  $T_1$ , and both  $T_0$  and  $T_1$  are positive numbers, while  $T = T_0 + T_1$ .

Abadie et al. (2015, 5) defines that a synthetic control as “a weighted average of the units in the donor pool” and the sum of weights equal 1 while all the weights are greater than or equal

to 0 and lesser or equal to 1; thus, a synthetic control is a  $(J \times 1)$  vector of weights that can be represented as  $W=(w_2, \dots, w_{J+1})^t$ , while  $(w_2+\dots+w_{J+1}) = 1$  and  $0 \leq w_j \leq 1$  for  $j = (2, \dots, J)$ .

In order to construct a synthetic control that can be compared with the unit of interest to measure the effect of the intervention of interest as a counterfactual, the value of  $W$  needs to be selected as a value that makes the features of the pre-intervention synthetic control and the features of the pre-intervention unit of interest resemble one another the most.

Suppose that  $X_1$  is a  $(k \times 1)$  vector of the values of the pre-intervention features of the unit of interest and that  $X_0$  is a  $k \times J$  matrix of the values of the pre-intervention features of the donor pool's units. Thus, the differences between the features of the pre-intervention unit of interest and the features of the pre-intervention unit of a synthetic control are represented as a vector  $X_1 - X_0W$ . Therefore, in order to build a synthetic control that best resembles the features of the unit of interest, the selected value  $W$  should minimize the differences given by the vector  $X_1 - X_0W$ . In other words, if we suppose that  $X_{1m}$  represents the  $m$ th variable's value for the unit of interest and that  $X_{0m}$  represents the  $m$ th variable's value for the synthetic control, which is a weighted average of the units in the donor pool, then  $W$  should be selected so that minimizes  $\sum_{m=1}^k v_m (X_{1m} - X_{0m}W)^2$ , where  $v_m$  is a weight representing the  $m$ th variable's assigned relative importance when measuring the differences given by  $X_1 - X_0W$  (Abadie et al. 2015). In order to build a synthetic control that best resembles the features of the pre-intervention periods of the unit of interest, it is important to assign large values to those variables having a large predictive power on the outcome variable of the unit of interest.

After constructing a synthetic control as discussed earlier, the intervention's effect on the outcome variable can be measured in the following way. Suppose that  $Y_{jt}$  is the value of unit  $j$ 's

outcome variable at time  $t$  and that  $Y_1$  is a  $(T_1 \times 1)$  vector containing the outcome variable's values during the post-intervention periods for the unit of interest. This may be written as  $(Y_{1T_0+1}, \dots, Y_{1T})^t$  while  $Y_0$  is a  $(T_1 \times J)$  matrix where the column  $j$  collects the outcome variable's values during the post-intervention periods for unit  $j + 1$ . Thus, the effect of the intervention can be measured by comparing the post-intervention values of the outcome variable between the unit of interest and the synthetic control, which can be written as  $Y_1 - Y_0W^*$ . Therefore, the estimator of the intervention's effect for the post-intervention periods  $t$ , where  $t \geq T_0$  can be written as  $Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$ .

This study aims to construct a synthetic Massachusetts by utilizing a combination of states that had not decriminalized marijuana until at least 2014, using the process of creating a synthetic control explained earlier. In doing so, the study utilizes the ten variables that were listed earlier and are described in the appendix and 28 donor pool states that have not implemented any type of marijuana associated policies, such as marijuana decriminalization, medical marijuana laws, and recreational marijuana legalization during the period between 1994 and 2014. The donor pool includes the following states: Alabama, Arkansas, Delaware, Florida, Georgia, Hawaii, Iowa, Idaho, Illinois, Indiana, Kansas, Kentucky, Louisiana, Missouri, North Dakota, New Hampshire, Nevada, Oklahoma, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Wisconsin, West Virginia, and Wyoming. The synthetic Massachusetts is designed to replicate the trend in the number of total traffic fatalities that Massachusetts would have experienced had it not decriminalized marijuana in 2009. Afterwards, the study estimates the casual effect of Massachusetts's 2009 marijuana decriminalization by comparing the actual Massachusetts's and the synthetic Massachusetts's trends in the number of

total traffic fatalities. Finally, the study checks the robustness of the results from the comparison between actual Massachusetts and the synthetic Massachusetts by conducting placebo tests where each state in the donor pool is iteratively treated as the unit of interest instead of Massachusetts. If the placebo tests exhibit a similar treatment effect with the tests estimated for the actual Massachusetts as the unit of interest, the study concludes that there is no statistical evidence of a treatment effect between Massachusetts's 2009 marijuana decriminalization and the number of total traffic fatalities (Abadie et al. 2010).

## RESULTS

### *Constructing Synthetic Control and Analysis*

[Figure 1 about here]

Figure 1 displays the trends in total traffic fatalities in Massachusetts, the states in the donor pool, and United States during the period between 1994 and 2014. As Figure 1 exhibits, the trends in total traffic fatalities between the donor states and the United States are similar, whereas the trend in total traffic fatalities in Massachusetts is substantially lower. Although the total traffic fatalities began to diminish from 2005 until 2011 in both the donor states and the United States, the total traffic fatalities began to decrease in 2004 until 2009 in Massachusetts. Instead of diminishing like the trends in traffic fatalities in both the donor states and the United States, the trend in total traffic fatalities in Massachusetts begins to increase in Massachusetts in 2009. This coincides with the implementation of the 2009 marijuana decriminalization in Massachusetts. In addition, Massachusetts' trend in total traffic fatalities is more variable compared to both the donor states' and the United States' trends in total traffic fatalities. This suggests that it is likely to generate unreliable estimations of the effect of the 2009 marijuana decriminalization in Massachusetts if the researcher compares Massachusetts to another state in

the donor pool or the rest of the USA, because of the divergence in their trends in the total traffic fatalities. Therefore, in order to measure more accurately the effect of the 2009 marijuana decriminalization in Massachusetts, it is necessary to create a synthetic Massachusetts that not only resembles the features of the pre-marijuana decriminalization Massachusetts but also the trends in total traffic fatalities in Massachusetts prior to the implementation of the policy.

I construct a synthetic Massachusetts that reflects the features of the pre-marijuana decriminalization condition using the synthetic control techniques described earlier. And then I perform placebo tests to ensure that the estimated effects of the marijuana decriminalization on total traffic fatalities are not a merely coincidental but are due to the 2009 marijuana decriminalization policy.

[Table 1 about here]

Table 1 summarizes the characteristics of Massachusetts, Synthetic Massachusetts, and the donor states based on the mean values of those predictor variables utilized in creating a synthetic control unit in this study. As discussed in earlier, a synthetic control is created by choosing the value of  $W$  that makes the features of the pre-intervention synthetic control and the features of the pre-intervention unit of interest resemble each other the most. Table 1 suggests that the created synthetic version of Massachusetts resembles Massachusetts fairly well based on the mean values of the predictors utilized in creating this synthetic control. Compared to the mean predictor values of the average of those donor states, the synthetic control unit resembles the real Massachusetts much better.

[Table 2 about here]

Table 2 shows the weights assigned to each donor state in creating the synthetic Massachusetts. Those states that make the synthetic Massachusetts's trend in total traffic

fatalities closer to Massachusetts' pre-2009 trend in total traffic fatalities received more weights than other states as discussed in the previous section. Based on the values in Table 2, a combination of Delaware, Hawaii, Illinois, Louisiana, New Hampshire, and Pennsylvania best reproduce the trend in total traffic fatalities of the real Massachusetts prior to the implementation of the 2009 marijuana decriminalization.

[Figure 2 about here]

Figure 2 exhibits the trends in total traffic fatalities for Massachusetts and its synthetic control counterpart from 1994 to 2014. Although there are minor discrepancies, both trends resemble each other well during the pre-2009 marijuana decriminalization period. In tandem with the balanced predictor mean values shown in Table 1, Figure 2's trend line of the synthetic Massachusetts provides a plausible approximation of the number of total traffic fatalities in Massachusetts that would have occurred between 2009 and 2014 in the real Massachusetts in the absence of the 2009 marijuana decriminalization.

The estimation of the effect of 2009 marijuana decriminalization on Massachusetts' total traffic fatalities displayed by Figure 2 reveals a noticeable difference right after the implementation of this policy. Although the number of total traffic fatalities began to rise in Massachusetts in 2009 until 2013, its synthetic counterpart's number of total traffic fatalities continued to decline until 2012. This noticeable discrepancy in total traffic fatalities between the real Massachusetts and its synthetic counterpart after 2009 suggests a substantial positive effect of the 2009 marijuana decriminalization policy on the number of total traffic fatalities in Massachusetts, implying that the policy contributed to an increase in the number of traffic fatalities in Massachusetts. According to this synthetic control model, Massachusetts' number of total traffic fatalities during the period between 2009 and 2014 increased by 150 individuals, or

approximately 7.58%, due to the 2009 Massachusetts' marijuana decriminalization policy.

Although the total number of traffic fatalities in Massachusetts is greater than the total number of traffic fatalities in the synthetic Massachusetts since 2009, the two trend lines converged by 2014. This suggests that the positive effect of marijuana decriminalization on total traffic fatalities is likely to be temporary and dissipates after several years.

### *Placebo Tests*

In order to investigate the significance of the estimates found in the previous section, it is necessary to check if a similar magnitude of estimates can be obtained by conducting placebo tests. I conducted a series of placebo studies. The specifics are explained in Abadie et al. (2010). In brief, the placebo tests iteratively apply the same synthetic control method utilized to estimate the effect of the 2009 Massachusetts policy to each state in the donor pool. As a result, each state in the donor pool is iteratively treated as the unit of interest that receives this policy as the intervention, and its respective synthetic control is created in the process. Afterwards, the gap between each state's number of total fatalities and its synthetic counterpart is estimated for every year in the period ranging from 1994 to 2014.

If these placebo tests show similar gaps of magnitude with the gap from the synthetic control estimated for Massachusetts, this means that the results found in the previous section do not provide convincing evidence that the Massachusetts policy had a positive effect on traffic fatalities, because the results could have been driven entirely by random variation. On the other hand, if these placebo tests indicate that the gap estimated for Massachusetts is unusually larger than the gaps for the states in the donor pool, this means that the results obtained in the previous section are not likely to be due to random variation.

[Figure 3 about here]

In total, there are 28 states in the donor pool—Alabama, Arkansas, Delaware, Florida, Georgia, Hawaii, Iowa, Idaho, Illinois, Indiana, Kansas, Kentucky, Louisiana, Missouri, North Dakota, New Hampshire, Nevada, Oklahoma, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Wisconsin, West Virginia, and Wyoming. I applied the synthetic control method to each state to conduct 28 placebo tests. Figure 3 exhibits the results of these placebo tests. The gray lines denote the gaps in the trends in total traffic fatalities between each state in the donor pool and its respective synthetic counterpart, while the orange line represents the gap in total traffic fatalities between Massachusetts and its synthetic counterpart.

As Figure 3 shows, the synthetic Massachusetts has a good fit for total traffic fatalities prior to the implementation of the 2009 policy along with many other states. For example, Massachusetts and many donor pool states have lines that stay close to 0 during the pre-intervention period. Although the pre-2009 condition has a mean squared prediction error (MSPE)—average of the squared differences between traffic fatalities in the real Massachusetts and its synthetic counterpart from 1994 to 2014—in Massachusetts of 14.67, the pre-2009 policy median MSPE among the 28 donor states is 43.32, and the mean MSPE is 171.08. This suggests that a good number of the donor pool states can also produce their synthetic counterpart that has a relatively good fit for total traffic fatalities prior to the 2009 marijuana decriminalization. Figure 3 also suggests that the synthetic control method is unable to reproduce the trends in total traffic fatalities during the period 1994-2008 for some states.

For example, Texas' pre-2009 MSPE is 1324.44, while Florida's is 571.37. However, given that both states' average total traffic fatalities between 1994 and 2008 are over 3000, which is far greater than the donor pool's average 816.77, this does not come as a surprise since there is no combination of states within the donor pool that can reproduce these states' trends in

total traffic fatalities. Because of the difficulty in visually examining the fit of each state with its respective synthetic control due to the extreme outliers—Texas, Florida, and West Virginia in Figure 3, it is necessary to examine the fit of these other states more closely by dropping these extreme outliers.

As suggested by Abadie et al. (2010), if the synthetic Massachusetts' trends in total traffic fatalities fail to fit the trends in the real Massachusetts prior to the 2009 marijuana decriminalization, then there is a high chance that the post 2009 gap between the trends in total traffic fatalities between Massachusetts and its synthetic counterpart is driven entirely by a lack of fit rather than the effect of the 2009 policy. Therefore, if this is the case, it undermines the results. Similarly, this is also applied to the fit between each donor state and its synthetic counterpart. If a placebo test shows a poor fit between each state and its synthetic counterpart prior to 2009, then its gap after 2009 should be considered driven by a lack of fit, not by the effect of the 2009 policy. In order to examine the rarity of the gap in the trends in total traffic fatalities between Massachusetts and the synthetic Massachusetts, it is important to compare its gap with the gaps of other relatively well-fitting donor states.

[Figure 4 about here]

Figure 4 shows the results of placebo studies excluding those donor pool states with a pre-2009 MSPE that is four times larger than Massachusetts so that it becomes easier to compare the fit of each state with its respective synthetic counterpart. Furthermore, to make it easier to compare the lines in Figure 4 with their counterparts in Figure 3, the y-axis' scale in Figure 4 has been adjusted. These states include Alabama, Florida, Georgia, Illinois, Indiana, North Dakota, Oklahoma, Pennsylvania, South Dakota, Texas, Virginia, Wisconsin, and West Virginia.

Figure 4 includes 14 donor pool state (gray) and Massachusetts (orange). According to Figure 4, Massachusetts' post-2009 line is the most unusual line relative to other states; whereas Massachusetts' gap line prior to 2009 remains close to 0, it diverges quickly after 2009, making the gap in the trends in total traffic fatalities between Massachusetts and its synthetic counterpart the largest relative to other donor pool states during the post-2009 decriminalization period. On the other hand, a majority of the donor states do not show such a pattern, indicating a poor fit with their respective synthetic counterpart. Therefore, it is highly likely that the gap for Massachusetts in the post-2009 condition period is not obtained due to a lack of fit; rather, it is an evidence of the positive effect of the 2009 policy on total traffic fatalities in Massachusetts. However, it is still necessary to conduct one more placebo test in order to make sure that the results for Massachusetts are not driven entirely by random variation.

[Figure 5 about here]

According to Abadie et al. (2015), another way of evaluating the results is by examining the ratios between the post- decriminalization RMSPE and the pre-decriminalization RMSPE. Since RMSPE measures the magnitude of the gap in the outcome variable between the unit of interest and its synthetic control unit, a unit with a well-replicated synthetic control unit has a lower pre-intervention RMSPE relative to its counterparts (Abadie et al. 2015). Furthermore, if the synthetic control unit does not reproduce the outcome unit during the pre-intervention period, a large post-intervention RMSPE does not necessarily mean that the results support the effect of the intervention because it could be produced by a lack of fit between the synthetic control unit and its original unit. Therefore, by examining how small the pre-intervention RMSPE is and the ratio between the post-intervention RMSPE and the pre-intervention RMSPE, one can evaluate the notability of the results. In Figure 5, Massachusetts' RMSPE ratio ranks the second highest

after Georgia. However, given that Massachusetts's pre-intervention RMSPE is 14.67 while Georgia's pre-intervention RMSPE is 63.30, it is clear that Massachusetts' synthetic control has a much better fit with the trends in total traffic fatalities of its original unit prior to the 2009 policy compared to Georgia.

## DISCUSSION

Recently, the trend of relaxing the restrictions on marijuana possession, and its use, by decriminalizing marijuana has been gaining strong momentum across the United States. Currently, it is possible to possess a small amount of marijuana for personal recreational use without a criminal charge in 21 states (Governing 2017). Despite this strong move toward decriminalizing marijuana, however, the consequences of this policy are still very much unknown. For example, what are the implications of implementing this policy on the general public's health, on criminal behavior that might be influenced by marijuana use, and on road safety?

In order to better understand the ramifications of implementing these policies, this study investigated marijuana decriminalization's impact on road safety by examining its impact on traffic fatalities. To my knowledge, there have been no studies investigating the causal effect of marijuana decriminalization, which affects a larger proportion of the population than medical marijuana policies, on traffic fatalities. By utilizing the synthetic control method, this study overcomes the difficulty in finding an appropriate counterfactual. As a result, this research contributes to the literature by examining the causal impact of marijuana decriminalization policy on traffic fatalities.

The results of this study provide evidence of a temporary positive effect of the 2009 Massachusetts' marijuana decriminalization policy on the trend of total traffic fatalities in

Massachusetts. In addition, the placebo tests affirm these results by finding that it is highly unlikely that these effects are due to random variability. Although the impact of the 2009 Massachusetts policy appeared to increase fatalities from 2009 until 2012, the effect has begun to dissipate since 2012, and the gap between the trends in total fatalities between Massachusetts and its synthetic counterpart became almost non-existent by 2014.

The results of this study may help explain why previous studies on marijuana policy changes have found divergent outcomes. Brady and Li (2014) found that marijuana was the most commonly detected illicit drug among drivers involved in traffic fatalities from their study of the U.S. FARS data, suggesting that an increase in marijuana use and its availability is likely to increase the number of traffic fatalities. On the other hand, both Anderson et al.'s (2011) study and Anderson and Ree's (2014) study discovered a statistically significant negative association between medical marijuana availability and traffic fatalities. As discussed, the results from this study show an increase in the number of total traffic fatalities in Massachusetts compared to its synthetic counterpart in 2009 but a decline in the total traffic fatalities in Massachusetts since 2012, with the gap in the traffic fatalities in both units almost non-existent in 2014. This provides a potential explanation of these variable findings: the effect of changes in marijuana policy may be temporary and dissipate once the norms surrounding licit marijuana develop.

However, the findings from this study need to be taken with caution. Although the results indicate a temporary positive effect of marijuana decriminalization on traffic fatalities, this may not be the case in other states or countries that are highly divergent with Massachusetts in both their observable and unobservable characteristics. However, given that Massachusetts is a relatively mid-sized state that is not too divergent from a majority of the states within the U.S., I argue that this relationship is likely to be generalizable to a majority of states within the U.S.

This paper signifies the need for future studies investigating the causal association between marijuana decriminalization and traffic fatalities to see if the relationship found in Massachusetts still holds to be true in other parts of the U.S. or the world. Furthermore, in order to deepen the understanding of the impact of marijuana decriminalization, future studies should consider investigating the heterogeneous effects of marijuana decriminalization on traffic fatalities based on age groups, gender, and residential density since this study does not investigate the potential heterogeneous effects of marijuana decriminalization on traffic fatalities. Moreover, researchers should investigate whether the decline in the total traffic fatalities since 2012 in Massachusetts compared to its synthetic counterpart was caused by any events or policies in Massachusetts that I failed to account for in the synthetic control model used in this study, in order to understand the causes of this phenomenon. Finally, studies investigating why marijuana decriminalization is associated with an increase in traffic fatalities are needed in order to better understand the causal mechanism between marijuana decriminalization and traffic fatalities.

The findings from this study suggest that states considering decriminalizing marijuana should be prepared for the increased danger on their roads before implementing such policies. This study suggests that there is a causal association between marijuana decriminalization and traffic fatalities, albeit temporary. Preparing for this initial increase in the roads danger by implementing specific policies, such as increasing the number of traffic patrols, enacting strict laws punishing drivers driving under the influence of marijuana, and educating residents about the danger of driving under the influence of marijuana, is likely to prevent potential traffic accidents that would otherwise be likely to occur.

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## TABLES

*Table 1. Total Traffic Fatalities Predictor Means for the Pre-intervention Period (1994-2008)*

Variables	Massachusetts	Synthetic Control	Donor States
Total Traffic Fatalities(1994)	440	428.72	819.87
Total Traffic Fatalities(1999)	414	427.34	875.11
Total Traffic Fatalities(2004)	476	449.74	901.29
Total Traffic Fatalities(2008)	364	367.52	801.86
Licensed Driver Ratio	72.09	68.96	69.96
Poverty Ratio	10.43	10.41	12.15
Labor Force Ratio	67.73	67.63	67.26
ln Residents	15.65	14.50	14.99
Law Enforcement Officers	263.10	256.35	229.01
ln Total Past Month Marijuana Use	13.57	13.29	13.15
ln Total Past Month Alcohol Use	15.60	15.43	15.36
ln real GDP per capita	10.87	10.77	10.61
Unemployment Ratio	4.56	4.55	4.63
Registered Motor Vehicle Ratio	82.10	80.26	85.92
Employment Ratio	64.63	64.57	64.18

All Variables except Total Traffic Fatalities(1994, 1999, 2004, 2008), Law Enforcement Officers (1999-2008), ln Total Past Month Marijuana Use (1999-2008), ln Total Past Month Alcohol Use (1999-2008), are averaged for the period 1994-2008.

Table 2. Synthetic Control Weights

State	Weight	State	Weight
Alabama		Montana	
Alaska		Nebraska	
Arizona		Nevada	
Arkansas		New Hampshire	.067
California		New Jersey	
Colorado		New Mexico	
Connecticut		New York	
Delaware	.273	North Carolina	
Florida		North Dakota	
Georgia		Ohio	
Hawaii	.25	Oklahoma	
Idaho		Oregon	
Illinois	.091	Pennsylvania	.001
Indiana		Rhode Island	
Iowa		South Carolina	
Kansas		South Dakota	
Kentucky		Tennessee	
Louisiana	.069	Texas	
Maine		Utah	
Maryland		Vermont	
Massachusetts		Virginia	.001
Michigan		Washington	
Minnesota		West Virginia	.05
Mississippi		Wisconsin	.197
Missouri		Wyoming	

## FIGURES

Figure 1. Trends in Total Traffic Fatalities in Massachusetts, the Donor States Average, and the USA Average

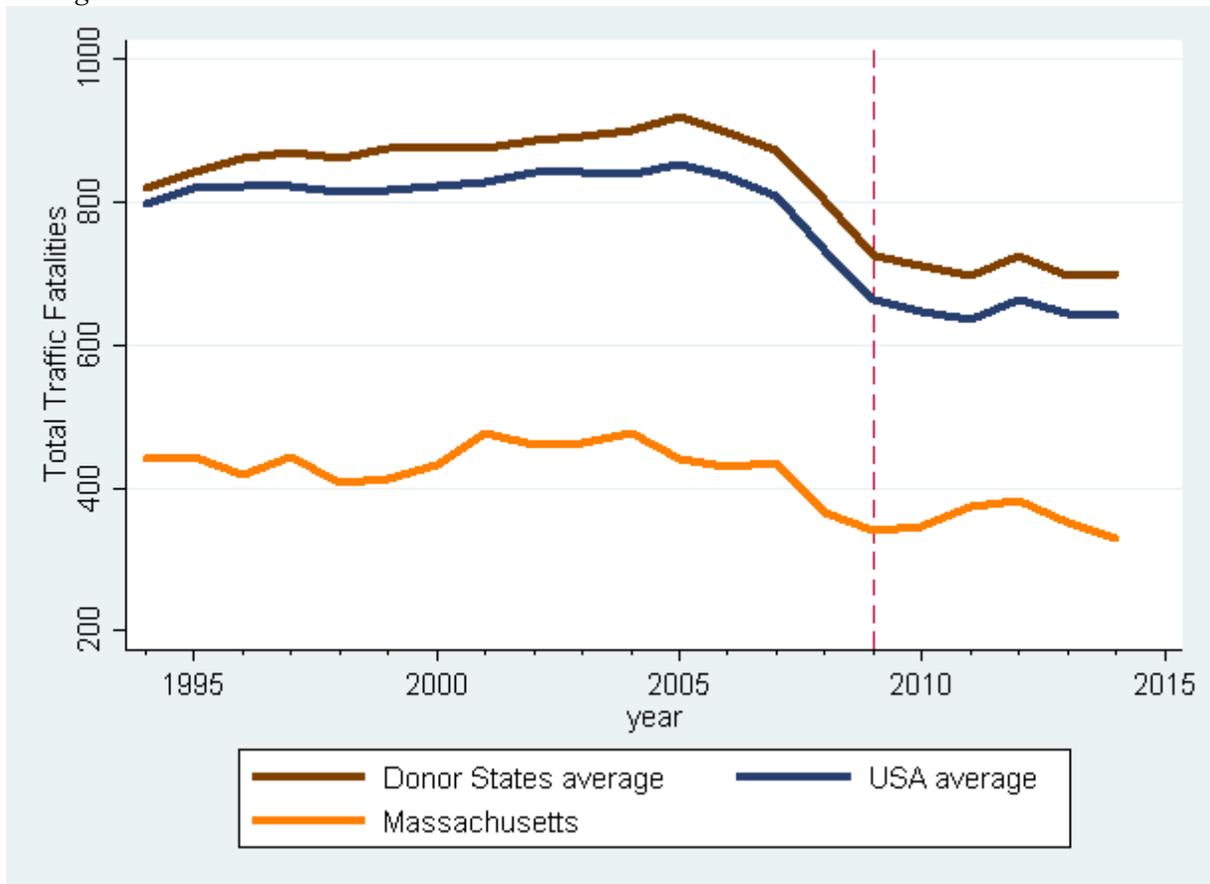


Figure 2. Trends in Total Traffic Fatalities in Massachusetts

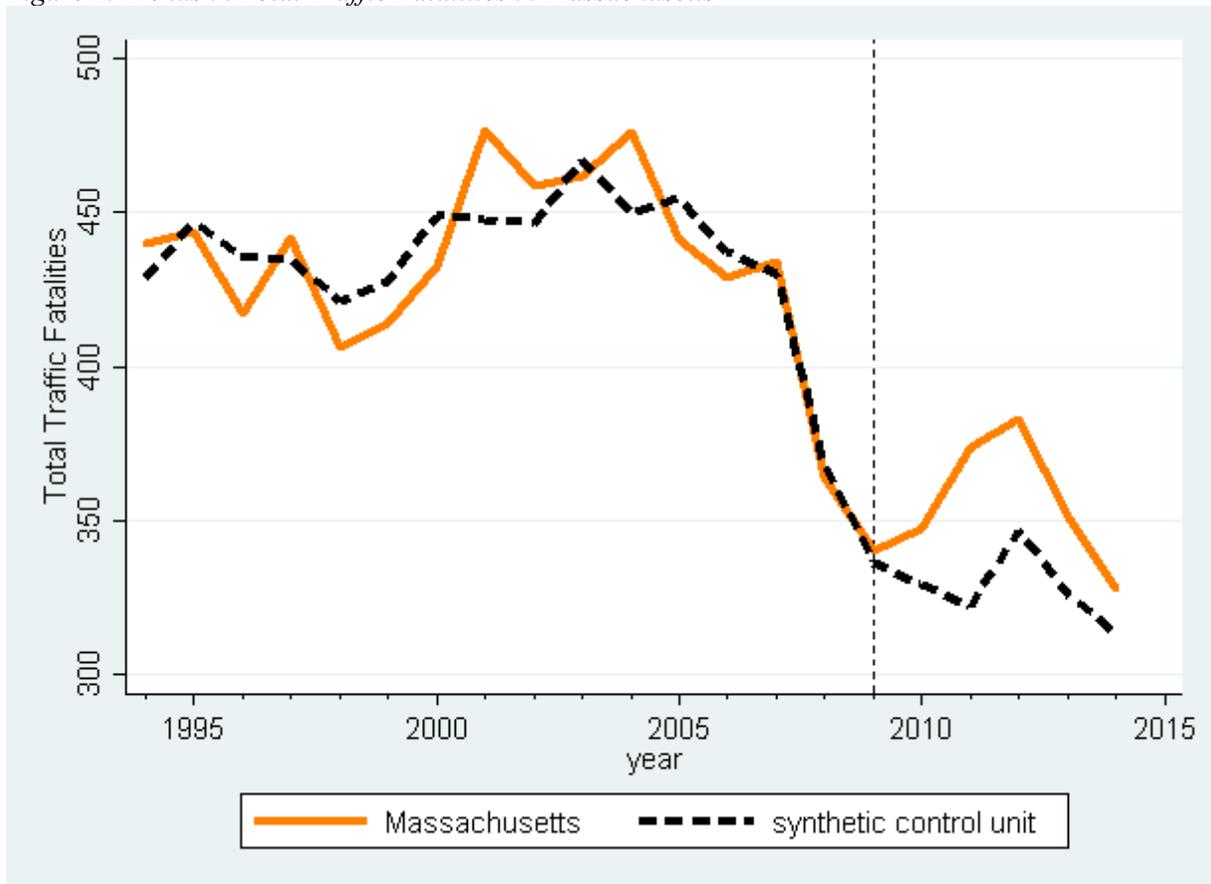


Figure 3. The Gap in Total Traffic Fatalities in All Donor States and Massachusetts

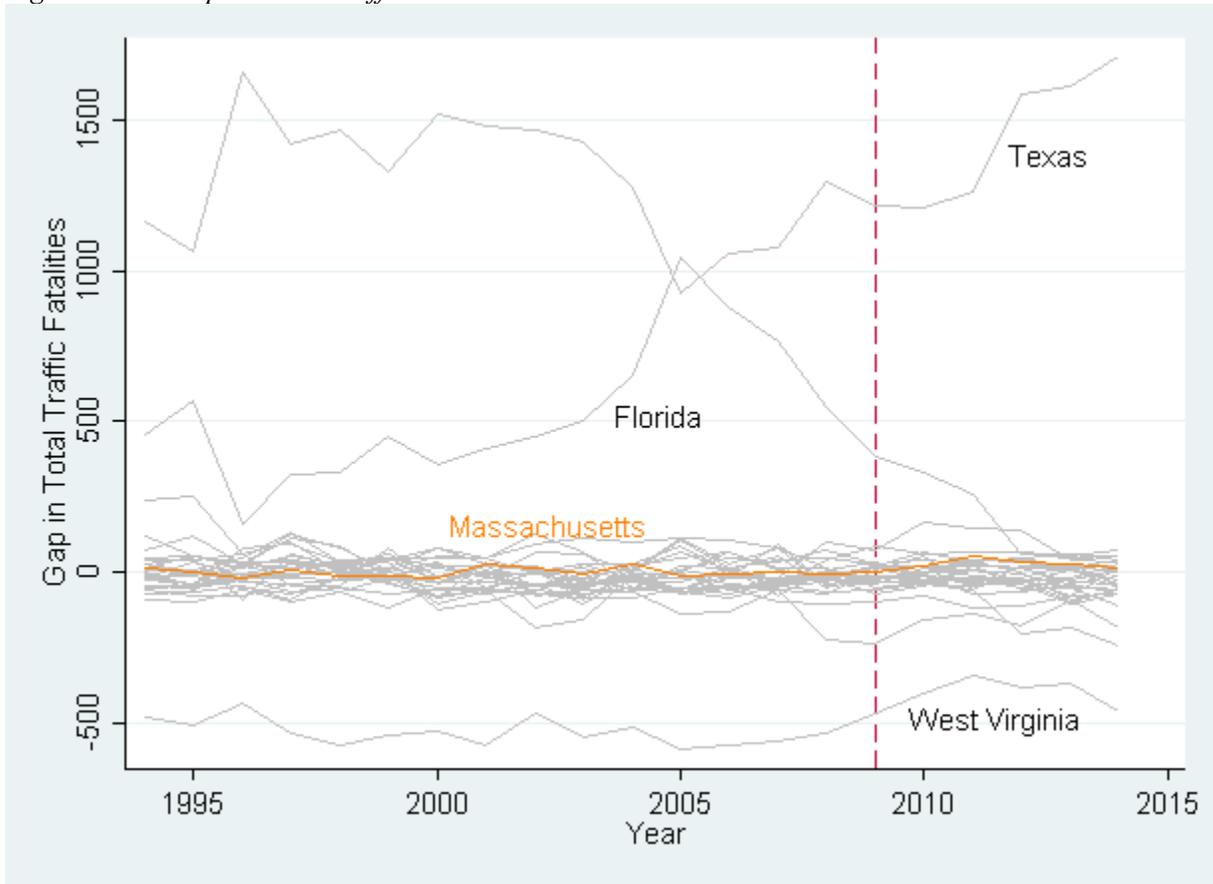


Figure 4. The Gap in Total Traffic Fatalities in Selected Donor States and Massachusetts

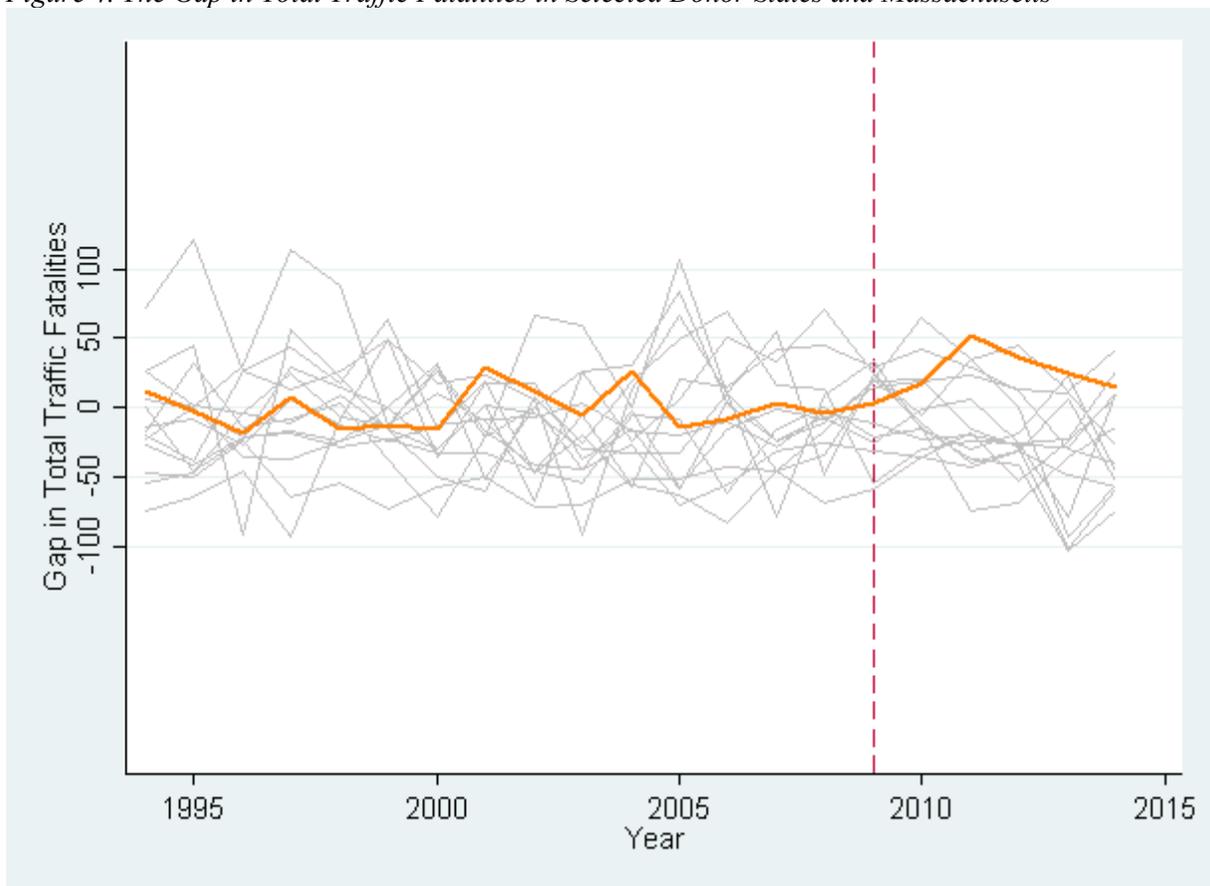
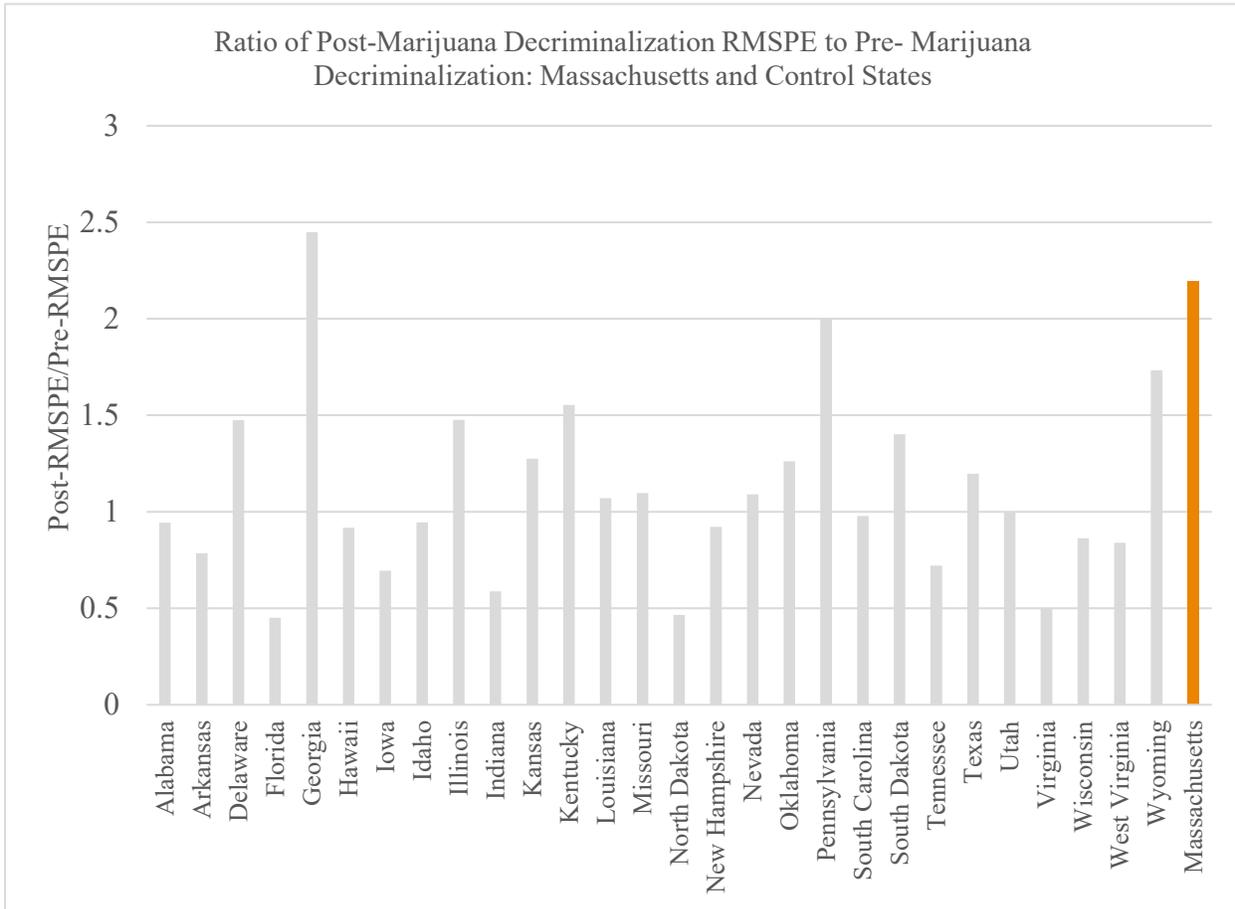


Figure 5. Ratio of Post-Marijuana Decriminalization RMSPE to Pre-Marijuana Decriminalization: Massachusetts and Control States



## APPENDIX

In this appendix, I describe the specific sources of the data used in this study. All the data used for the analysis are state-level, longitudinal data ranging from 1994 to 2014 unless they are specified.

- The number of total traffic fatalities. Source: The Fatality Analysis Reporting System (FARS).
- Licensed Drivers Ratio: Highway Statistics maintained by the Federal Highway Association.
- Registered Motor Vehicle Ratio: The Fatality Analysis Reporting System (FARS).
- Log Residents: The Fatality Analysis Reporting System (FARS).
- Law Enforcement Officers: The Federal Bureau of Investigation's the Uniform Crime Reports data.
- Log Marijuana use in the past 30 days. Source: The National Household Survey on Drug Abuse (NHSDA) and the National Survey of Drug Use and Health (NSDUH). These data were available from 1999 through 2014.
- Log Real per capita GDP. Source: Bureau of Economic Analysis
- Poverty ratio. Source: U.S. Bureau of the Census.
- Unemployment rate. Source: Bureau of Labor Statistics.
- Employment rate: Source: Bureau of Labor Statistics.
- Marijuana decriminalization. Source: the data were gathered by examining each state's legislature's website and by comparing with the information on [norml.org](http://norml.org).
- Medical marijuana decriminalization: the data were gathered by examining each state's legislature's website and by comparing with the information on [norml.org](http://norml.org).

- Recreational marijuana legalization: the data were gathered by examining each state's legislature's website and by comparing with the information on [norml.org](http://norml.org).
- Log Alcohol consumption per capita: The National Household Survey on Drug Abuse (NHSDA) and the National Survey of Drug Use and Health (NSDUH). These data were available from 1999 through 2014.