Essays on the Economics of Marijuana

By

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Abstract

In the United States, despite its classification as a Schedule I[1] drug under federal law, statewide marijuana liberalization has become a trend in the past few decades. As of January 2020, 33 states and the District of Columbia have passed medical marijuana laws (MMLs) while 13 states and the District of Columbia have passed recreational marijuana laws (RMLs). The liberalization policies may have ambiguous impacts on the economy and public health if we account for the additional spending to compensate the negative externalities such as the potential increase in crime, accidents and the overall health of individuals that are associated with the laws. My goal is to fill in the gaps and contribute to the existing literature by providing empirical evidence using econometric techniques.

This dissertation addresses three aspects in regard to marijuana liberalization: the potential effects on college students' risky behavioral changes and mental health outcomes, its association with traffic accidents and fatalities, as well as the impact on tax revenues among other recreational drugs such as tobacco and alcohol.

The first chapter explores the effect of MMLs on college students' mental health. Given the legal passage of marijuana for medicinal purposes, it reduces the cost for students to consume marijuana since severity of punishment is a cost associated with consumption (Becker, 1968). In addition, Buckner et al. (2007) suggests that young adults tend to be the prominent users of marijuana for recreational purposes. By using the restricted version of the Healthy Mind Study Questionnaires data set that contains the names of higher education institutions, demographic information on students,

[1] According to the Controlled Substance Act, a Schedule I drug must have a "high potential for abuse" and "no currently accepted medical use in treatment in the United States."

their academic performances, self–reported mental health conditions as well as their lifestyles and risky behaviors, it allows one to assess whether there is an impact on students' mental health due to the legal and easier access to marijuana.

The second chapter highlights the effect of state–level marijuana liberalization, from medical to recreational laws, on traffic fatalities. In 2017, there was an estimation of over 35,000 accidents involving a fatality (National Center for Statistics and Analysis, 2018). The motivation of this chapter is to seek the relationship between marijuana laws and subsequent increased marijuana consumption either alone or in concert with alcohol and traffic safety.

The third chapter[2] extends the analysis by determining the impact of city–level cannabis decriminalization on fatal traffic crashes in US cities. Unlike MMLs, which are associated with fewer fatal crashes, cities experienced a relative increase in fatal crashes involving young male drivers following marijuana decriminalization.

The fourth chapter[3] focuses on the new source of "sin" taxation for U.S. states with the enactment of recreational marijuana laws. Extensive economic research literature on the optimal taxation of goods and services is used in order to raise government revenue, distort consumer behaviors and provide incentives to guide economic investment and research. In this chapter, we examine the effect of the recent enactment of RMLs on state–level tax revenues on the sales of other "sin" goods, specifically alcohol and tobacco products. Using difference–in–differences design with quarterly state–level tax revenue data for alcohol, tobacco and marijuana (for states which have enacted RMLs) as well as demographics from 2010–2016, this study estimates the fiscal impact of RMLs on aggregate sales of alcohol and tobacco products.

[2]This is a co–authored paper with Amanda C. Cook, Department of Economics, Bowling Green State University, and Rhet A. Smith, Department of Economics and Finance, University of Arkansas at Little Rock. The chapter is published in the American Journal of Public Health 110, no. 3 (March 1, 2020): pp. 363–369.

[3]This is a co–authored paper with Scott Dallman, Department of Applied Economics, University of Minnesota.

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All remaining errors are my own.

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Chapter 1

The Impact of Medical Marijuana Laws on College Students' Mental Health, Drugs Substitutability, and Academic Outcomes

1.1 Introduction

According to the National Institution of Mental Health (HIMH), mental health illnesses, also known as mental disorders or psychiatric disorders, are common in the United States and are affecting tens of millions of people each year. Despite its prevalence in the population, NIMH suggests that only half of the people who suffer from mental illnesses receive treatment. Mental illnesses come in various forms from obsessive-compulsive disorder, eating disorder, personality disorder, social disorder, anxiety disorder, depression, post-traumatic disorder, schizophrenia, to many others. Suicide – a consequence that often stems from mental disorders – is the second leading cause of death in the U.S. among individuals age from 10 to 34, and is followed by death related to homicide and alcohol and drugs.

Existing literature suggests that college students are a demographic group with growing concern, especially in regard to students with mental health problems. Reetz et al. (2014) shows among 4.7 million college students surveyed, approximately 42% experience anxiety, 36% of depression, 16% suicidal ideation, and 10% alcohol abuse. Despite the increasing concern about college students' mental health, no prior studies have specifically explored the relationship between the recent marijuana legalization policies and mental health of students in higher education.

Medically speaking, there are a number of channels that could lead to mental disorders. Studies that have analyzed the human genome (the complete set of genes) have found evidence linking single–nucleotide polymorphisms (SNP, a variation in a single base pair in a DNA sequence) and mental disorders. More specifically, SNPs are associated with a range of psychiatric disorders such as schizophrenia, bipolar disorder, and major depression. (Cross-Disorder Group of the Psychiatric Genomics Consortium and others, 2013; Flint & Kendler, 2014). Adversity of certain genes, such as 5–HTT and SLC6A4, are often associated with depression symptoms (Caspi et al., 2003; Pezawas et al., 2008; Aguilera et al., 2009).

While genetics is not the sole origin of mental illness, researchers have been attempting to identify the roots through social and cultural context, as well as examining whether or not risky behaviors such as drug use and addiction play a role in it. In most cases, aside from biological inheritance like genetic links, it is not surprising that mental health problems such as anxiety and depression are prevailing among students in higher education. Students' psychological distress could be coming directly from their academic studies, studying abroad in the United States as international students, financial worries, and concerns of entering the labor market. Stallman (2010) shows that compared to the general population, university students have an extremely high prevalence of mental health problems and is evidence of the at–risk nature of this demographic population. A clear implication derived from this study is that early interventions can prevent deterioration of mental health among students.

It has been well–established in the literature that there is a critical need of mental health support for college students (Mori, 2000; Kitzrow, 2003; Eisenberg et al., 2009; Auerbach et al., 2016). Traditionally, to cope with mental distress or mental disorders, medical professionals often recommend students seek help through psychotherapy or medication.

Psychiatric studies have shown the effectiveness of psychotherapy (also commonly known as "talk therapy") to patients who seek treatment. Psychotherapy is associated with a great reduction in depressive, social, and attention problems (Thornicroft & Susser, 2001; Wampold, 2001; Tonge et al., 2009). Despite the benefits in terms of mental health and other related outcomes, depending on the disorders, the utilization of mental health services is as low as 16% according to Eisenberg et al. (2007). This study also shows that even with access to free psychotherapy and basic health services, students with mental illness still would not receive treatment. This is due to social stigmas, such as receiving treatment is a sign of poor mental health, which is also a well–established concern in the literature (Segal et al., 2005; Barney et al., 2006; Pedersen & Paves, 2014; Clement et al., 2015).

In addition to psychotherapy, treating mental illnesses with prescribed psychiatric medications alone or together with psychotherapy are also common options (Hollon et al., 2005). Some popular psychiatric medications include selective serotonin reuptake inhibitors (SSRIs) prescribed as antidepressants (e.g. Fluoxetine, Citalopram, and Sertraline), anti–psychotics (e.g. Chlorpromazine and Halperiodol) to treat attention–deficit hyperactivity disorder, post–tramatic stress disorder, and eating disorders, mood stabilizers (e.g. Carbamazepine and Lamotrigine), and anti–anxiety medications (e.g. Clonazepa and Alprazolam). Although medication plays a role in treating several mental disorders and conditions, side effects like nausea and vomiting, weight gain, diarrhea, sleepiness, and sexual problems are highly prevalent (DiBonaventura et al., 2012) as documented by the U.S. Food and Drug Administration. As a result, Cooper et al. (2007) shows that avoidance of side effects is one of the main reasons patients resist taking prescription drugs.

Although not recommended by medical experts, there exists individuals who self–medicate outside of professional guidance. As defined by the Organization (1998), "self–medication is the selection and use of medicines by individuals to treat self–recognized illnesses or symptoms." Despite that some drugs are legal and some are prohibited for recreational use in the U.S., alcohol among other substances like cannabis, cocaine, amphetamines, and opioid are most frequently used for self–medication (Robinson et al., 2009). Harris & Edlund (2005) provide evidence that mental health deterioration can be derived from self–medication. Specifically, the use of illicit drugs other than marijuana is associated with an increase (from 3.2 to 4.4 percent) in unmet need for mental health care. In contrast, it is worth noting that there is *no* evidence showing self–medicating with marijuana is associated with either unmet need or mental health care use.

Despite the federal prohibition status, some U.S. states have been moving towards marijuana liberalization in the past decade. An example of an unintended consequence is the substitutability among traditional psychiatric or recreational drugs. In addition, policies may result in the potential change of behaviors such as the likelihood of seeking medical help and the reduction of social stigma. Variation in academic performance is a further potential consequence of psychiatric medication and/or recreational drug use. While Marie & Zölitz (2017) study the effect of losing legal access to recreational marijuana on students' academic achievement, no prior studies in economics have explored the relationship between marijuana laws and college students' mental health or relating medical marijuana laws (MMLs) to students academic performance.

The goal of this chapter aims at examining the variation of the mental health and both prescribed and recreational drug use among college students succeeding the passage of state medical marijuana laws and sheds light on the inadvertent public health impact from cannabis legalization. I focus on the medical marijuana legalization and discuss its mechanism in a later section with regard to students having a potential of switching from self–medication to treating mental health through legal access to marijuana. Subsequently, I explore the academic outcomes stemming from the policy variation. The main contributions of this study are twofold. First, I provide a comprehensive literature review of studies from the fields of medicine, psychiatry, and psychology. Second, this study allows for a deeper understanding of how marijuana liberalization impacts college students' mental health, an issue that had been neglected in the economics literature. The results from the analysis lend an important contribution to the literature by providing evidence of self–medication prior to MMLs.

1.2 Background

1.2.1 Marijuana Laws in the United States

In the last century, the United States has undergone a vast array of changes with regard to marijuana–related policies. From no federal regulation on any marijuana possession or consumption in the early 20th century, to the Marihuana Tax Act in 1937 [1]. Marijuana was then classified as Schedule

[1] Marihuana Tax Act began restricting usage including for medicinal purposes.

I drug in 1970 in the Controlled Substance Act. As stated in the U.S. Drug Enforcement Agency, Schedule I drugs have characteristics of "high potential for abuse" and "no currently accepted medical use in treatment in the United States."

Despite prohibition at the federal level in the United States, statewide marijuana legalization has become a trend in the past two decades. Figures A.1–A.5 in the Appendix show the overall marijuana law changes across the U.S. since 2000, and the expansion is most noticeable since the issuance of the Ogden (2009) Memorandum.[2]. Following the Memorandum in 2009, more state governments began to liberalize marijuana policies from conditionally legalizing marijuana for medicinal purposes to full legalization for recreational use. Table 1.1 shows all effective dates of state medical marijuana laws and recreational marijuana laws (RMLs) in the U.S., with dates verified through Thomson Reuters Westlaw and the National Conference of State Legislatures. Due to the legal protection within the legalized states and the deprioritization of prosecution from the federal government, the uncertainty in the marijuana market has drastically reduced, as legal costs of operating marijuana–related business from the suppliers have been lowered. Likewise, the laws decrease the non–pecuniary costs of consuming marijuana for both medical and recreational consumers.

1.2.2 Trends of Mental Health Illness, Prescription Drugs Use, and Recreational Drugs Use

Based on the data from the National Survey on Drug Use and Health, in which is administered by the Substance Abuse and Mental Health Services Administration (SAMHSA), the trend graphs of mental health need and drug use behaviors among various age groups are displayed as follows. Figures 1.1 and 1.2 show the trends of any mental illness and major depressive episode in the past year among all ages in the past 10 years. Trends have been steady for most age groups except between the ages of 18 to 25, a prominent age group that attends college. The uptake is particularly

[2] Ogden Memorandum directs U.S. attorneys to "not focus federal resources in your States on individuals whose actions are in clear and unambiguous compliance with existing state laws providing for the medical use of marijuana"

noticeable starting in 2013. Figure 1.3 presents the significance of mental health received among 18–25 year–old individuals with 35–45 percent of this demographic group. Figure 1.4 presents the types of mental health services patients received. Prescription medication has been a consistent portion of all types of treatments when comparing inpatient and outpatient. These figures also serve as a motivation of the reason of focusing on college students and their behavioral changes upon prescription drugs in this study.

Figures 1.5–1.8 present the recreational drug use throughout the past one and a half decades. While alcohol consumption has been steady for 18–25 year–olds, there is a gradual decrease in cigarette use. This has been an ongoing effort and one of the targets met according to the Office of National Drug Control Policy during the Obama Administration Office of National Drug Control Policy (2017). On the other hand, a distinct of upward trend can be seen in the past 5 years for both cocaine and marijuana use. This is also one of the reasons that motivates this study to examine whether MMLs have an impact of the spillover effect on recreational drug use such as the ones mentioned above.

1.2.3 Marijuana Use and Mental Health

Marijuana users can consume marijuana through either inhalation or ingestion. The drug itself contains numerous chemicals called cannabinoids. Some commonly known cannabinoids include cannabidiol (CBD) and tetrahydrocannabinoil (THC). THC is a foreign chemical to the human body that binds with cannabinoid receptors and activates neurons to cause different effects on one's mind and body. In medical and clinical psychology journals, some studies recognize the effectiveness of consuming marijuana as part of medical treatments on certain syndromes. Even though number of physicians in clinical practice perceive marijuana's therapeutic potential such as pain relief and easing symptoms such as nausea and vomiting (Charuvastra et al., 2005; Woolridge et al., 2005; Irvine, 2006), the effect of marijuana usage on mental health overall is ambiguous depending on whether usage is part of a medical treatment or merely for recreational purposes.

With a careful systematic review of literature on the potential influence of the use of cannabis for therapeutic purposes (CTP), some clinical studies propose similar findings of pinpointing non–negative to positive effect on mental health with a few exceptions (Hill, 2015)[3]. Denson & Earleywine (2006) find evidence where the most depressed participants who used marijuana once per week or less have an improvement on their mood and positive effect compared to non–users. Some studies also find that users benefit from CTP by reducing anxiety, depression, stress, and PTSD symptoms (Ogborne et al., 2000; Mikuriya, 2004; Ware et al., 2010; Bonn-Miller et al., 2014; Webb & Webb, 2014).

While a handful of studies recommend that marijuana use for medicinal purposes have a desirable impact on treating anxiety, depression, and other mental illnesses, some researchers suggest that medical cannabis does not seem to be effective in treating depression (Levin et al., 2013) and is associated with psychotic symptoms (Minozzi et al., 2010). Although no causality was claimed, evidence is strongest especially when marijuana consumption is for the propose of recreation. A few studies also suggest that cannabis use could lead to adverse health outcomes (Rey & Tennant, 2002; Gage et al., 2016) such as triggering the onset or relapse of schizophrenia in predisposed individuals as well as exacerbating the symptoms, showing association with later development of other psychotic symptoms and schizophrenia.

On the other hand, research indicates that recreational use of marijuana leads to undesired mental health outcomes such as increase in probability of having depression, acute negative effects on attention, memory, and information processing (Moore et al., 2007; Crean et al., 2011; Cairns et al., 2014). Despite inconsistent findings among medical marijuana use and recreational marijuana use, U.S. states have been taking legal actions liberalizing marijuana consumption for either purpose. The following section covers the economics literature that focuses on the externalities and spillover effects or unintended consequences of medical cannabis legalization.

[3]See Walsh et al. (2017) for a comprehensive literature review on the cannabis use as therapeutic purposes as well as reviews of non–medical cannabis use and mental health, including anxiety, depression, mania, bipolar disorder, suicide attempts as well as associations with other substances use.

1.2.4 MMLs, Spillover Effects on Recreational Substances

An expanding number of studies in the literature have explored whether the enactment of MMLs has an effect on consumption of marijuana regardless of its purpose. Literature has explored the spillovers for recreational use as well as other common drugs such as alcohol, cigarettes, and cocaine among youths and adults. With evidence from National Survey for Drug Use and Health (NSDUH), economists find an association of an overall increase in marijuana consumption among adults with MMLs (Wen et al., 2015; Sabia & Nguyen, 2018). When focusing on younger demographics, results are inconsistent. Using Youth Risk Behavior Surveys, the National Longitudinal Survey of Youth 1997, Anderson et al. (2015) finds no evidence of a positive impact on consumption of marijuana post medical marijuana legalization on teenagers. On the other hand, Wen et al. (2015) estimate a 5 percent increase in the probability of past–year marijuana use initiation, which attributes to MML implementation supported by data from NSDUH. Note that a common limitation of these studies is that authors cannot observe whether the marijuana consumption was used for therapeutic or recreational reasons and it is impossible to distinguish due to the data constraints. Yet, as reasoned in Choi et al. (2019), an increase in medical marijuana use is less likely among younger individuals, so there is a possibility of spillovers to recreational use among this demographic group.

Analogously, researchers have also explored the relationship between MMLs and other recreational drugs. More specifically, mixed results are presented in the literature on alcohol use due to the passage of MMLs. Anderson et al. (2013) find MMLs are related to reduction of the probability of binge drinking. Similarity, Pacula et al. (2015) show a negative association between alcohol use and MMLs when examining some specific policy dimensions like registry, dispensaries, and home cultivation.

1.2.5 Marijuana Laws and College Students Performance

Most psychological studies have revealed a correlation between recreational marijuana use and academic outcomes. Lynskey & Hall (2000) find an association between cannabis use and poor educational performance ranging from poor school performance, lower grade point average, less satisfaction with school, negative attitudes to school, as well as increased rates of school absenteeism. In addition, Macleod et al. (2004) provide evidence of association with cannabis use lowers educational attainment. However, both studies recognize the interpretation as mere correlational and do not provide a casual mechanism. While it has been a challenge for most medical literature to establish causality, an economics study in the Netherlands was the first one to provide casual evidence with recreational marijuana policy change (Marie & Zölitz, 2017). In the paper, authors exploit a unique natural experiment and identified an exogenous variation, a temporary policy change in the city of Maastricht that restricted legal access to recreational cannabis based on nationality. Using data from one of the largest schools in Maastricht, School of Business and Economics, the authors show that students who lost legal access to recreational marijuana improved academic performance.

In the United States, the recent relaxation of marijuana policies are providing residents legal access to marijuana, the cost for college students to obtain and consume it has drastically decreased compared to the pre–legalization period. It is compelling to investigate whether marijuana liberalization has any impact on students' mental health as well as other critical outcomes such as prescription drug substitutability and academic outcomes among college students.

Figure 1.1: Any Mental Illness in the Past Year among Adults Aged 18 or Older: 2008–2018

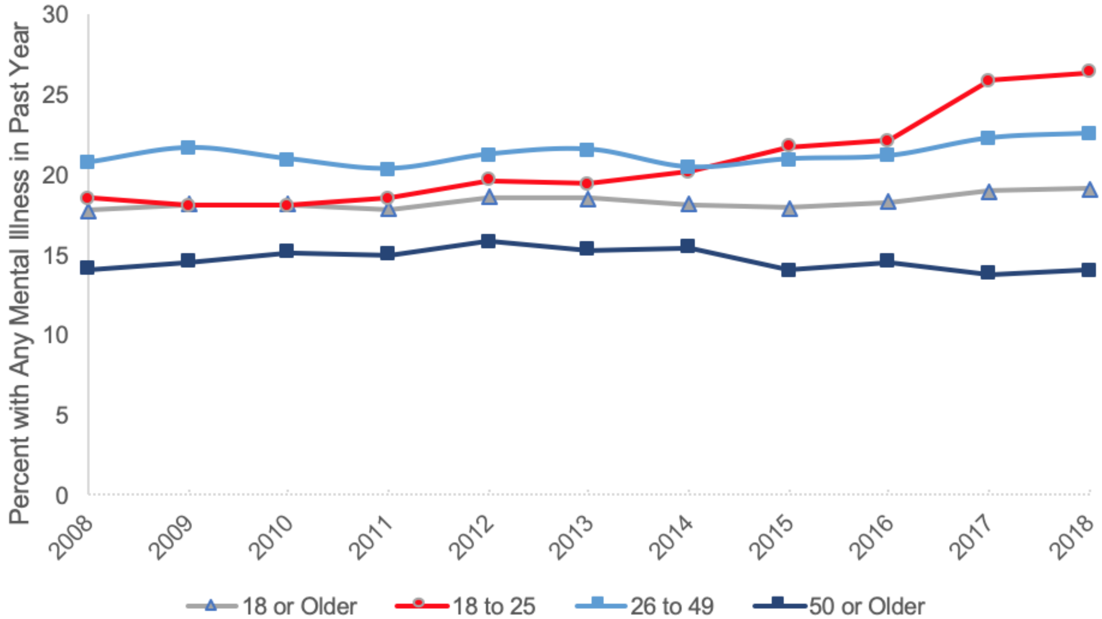


Figure 1.2: Major Depressive Episode in the Past Year among Adults Aged 18 or Older: 2005–2018

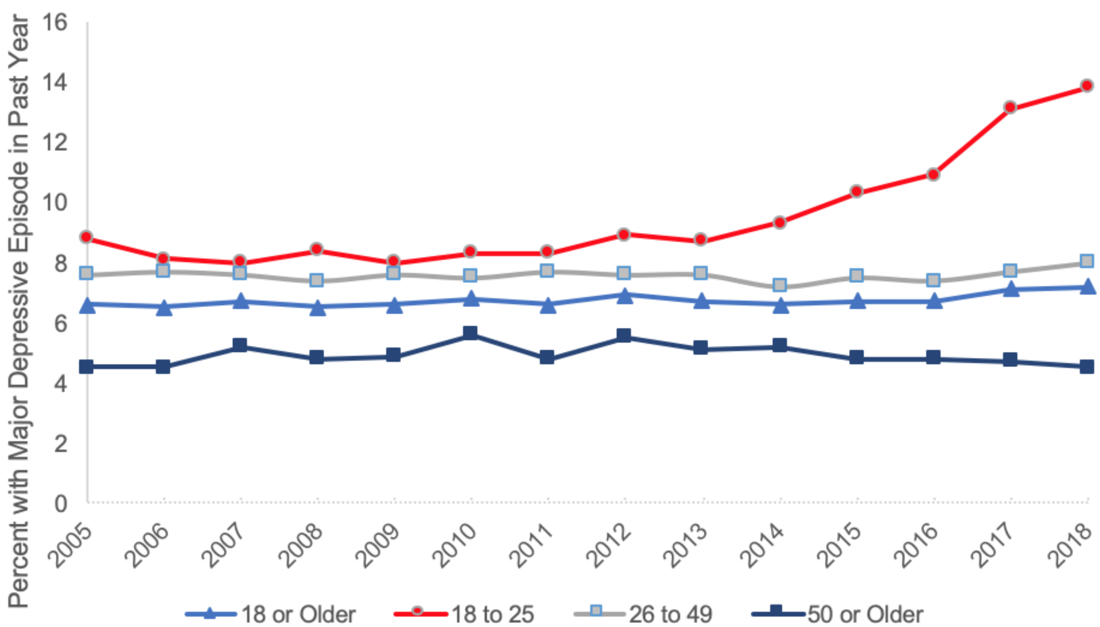


Figure 1.3: Any Mental Health Services Received in the Past Year
among Adults Aged 18 or Older with Any Mental Illness in the Past Year: 2008–2018

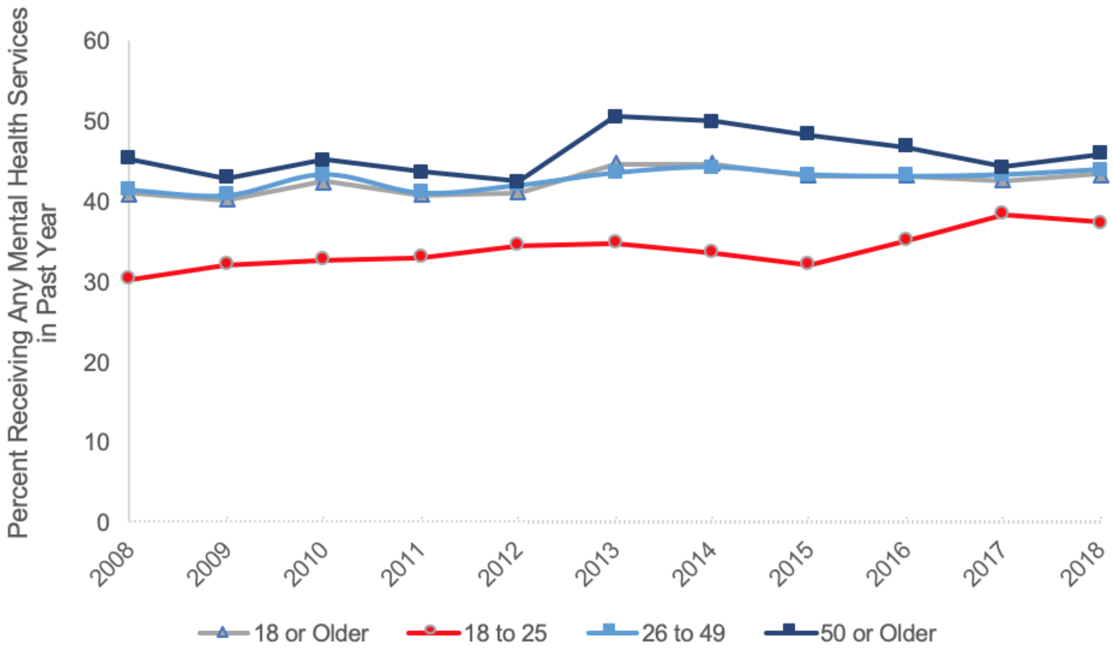


Figure 1.4: Type of Mental Health Services Received in the Past Year
among Adults Aged 18 or Older: 2002–2018

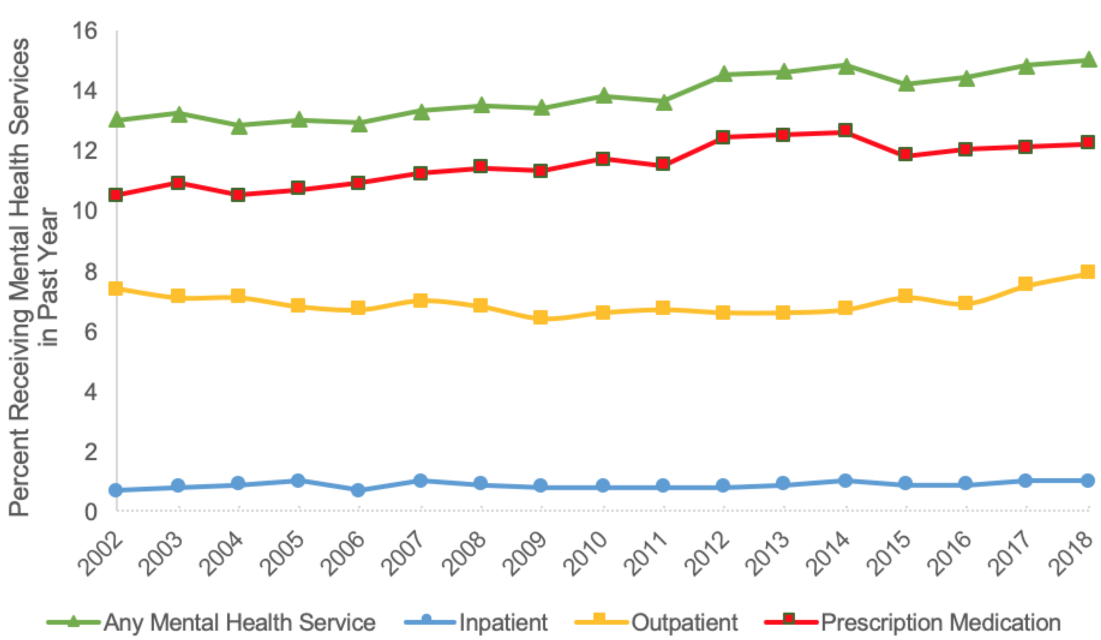


Figure 1.5: Past Month Alcohol Use among People Aged 12 or Older: 2002–2018

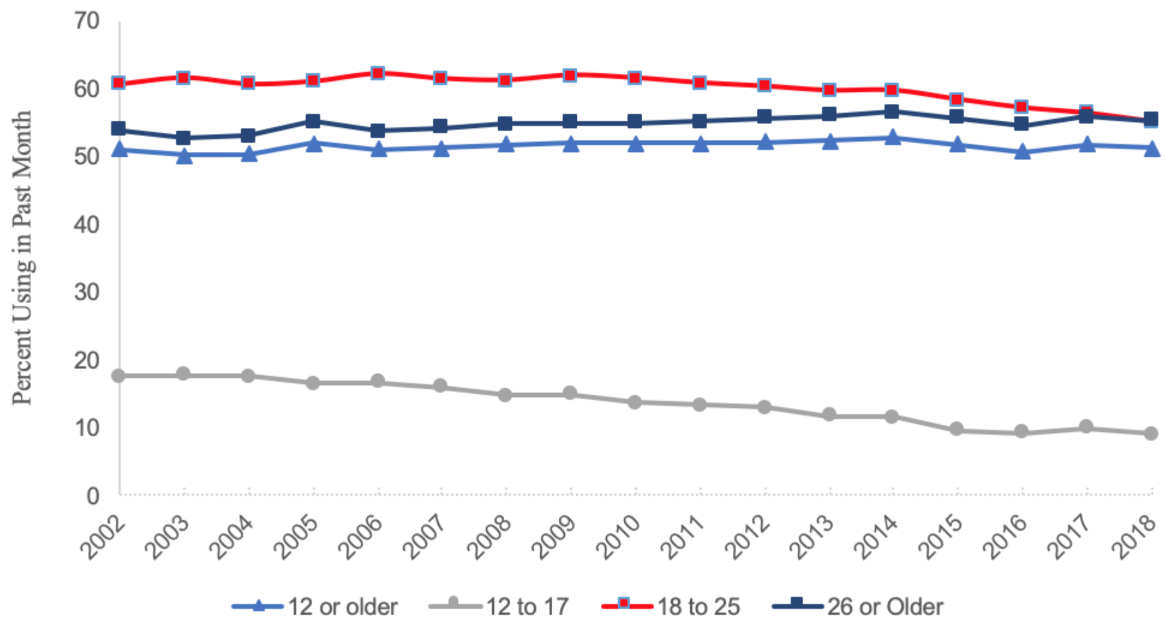


Figure 1.6: Past Month Cigarette Use among People Aged 12 or Older: 2002–2018

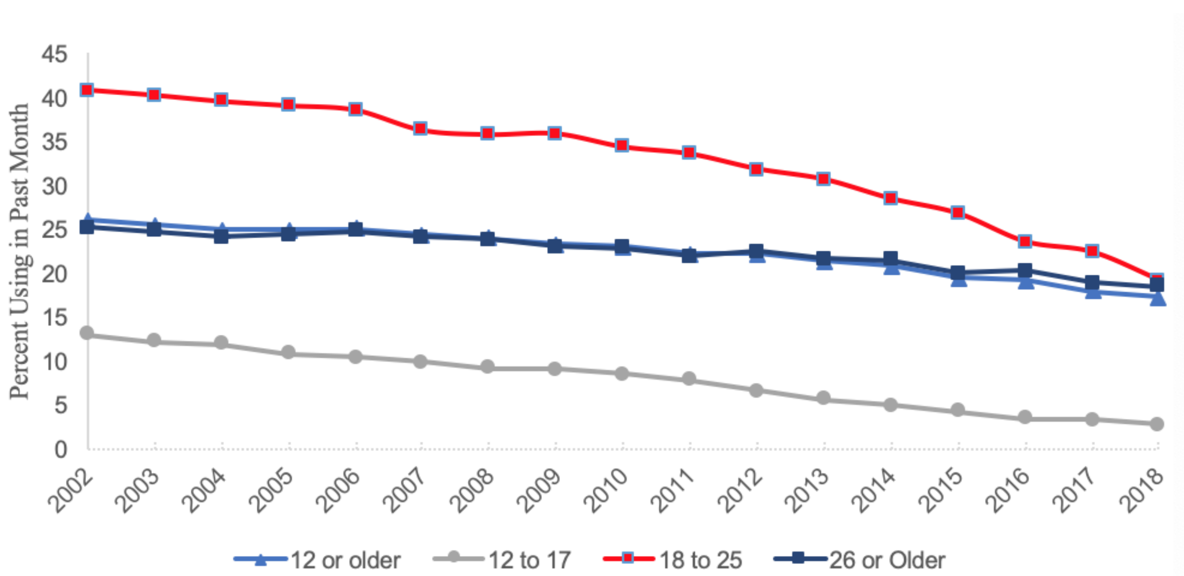


Figure 1.7: Past Year Cocaine Use among People Aged 12 or Older: 2002–2018

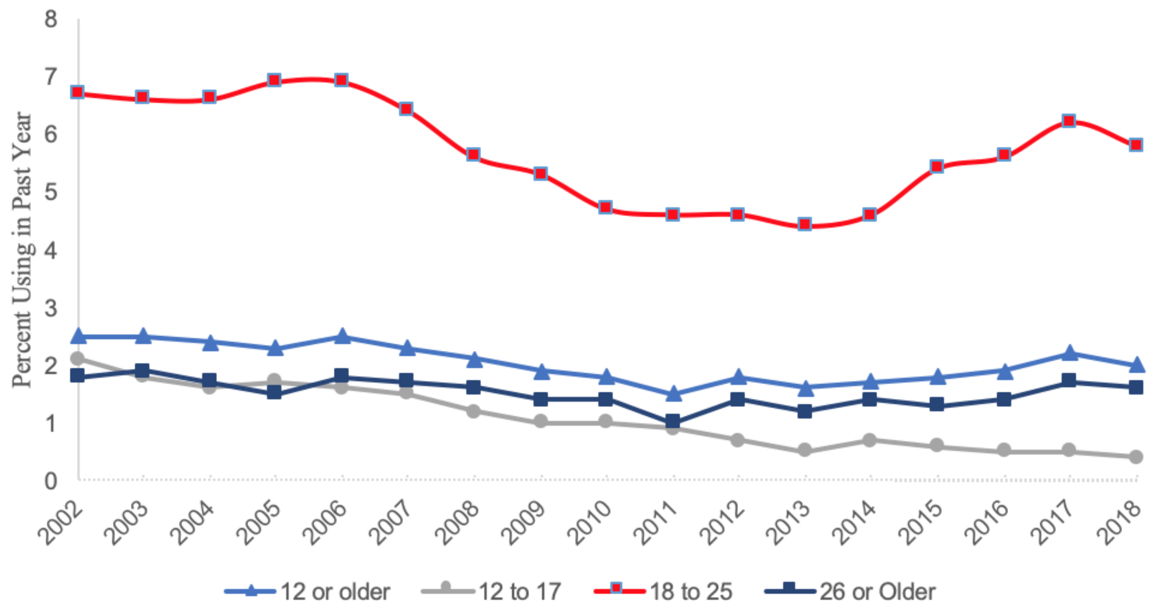
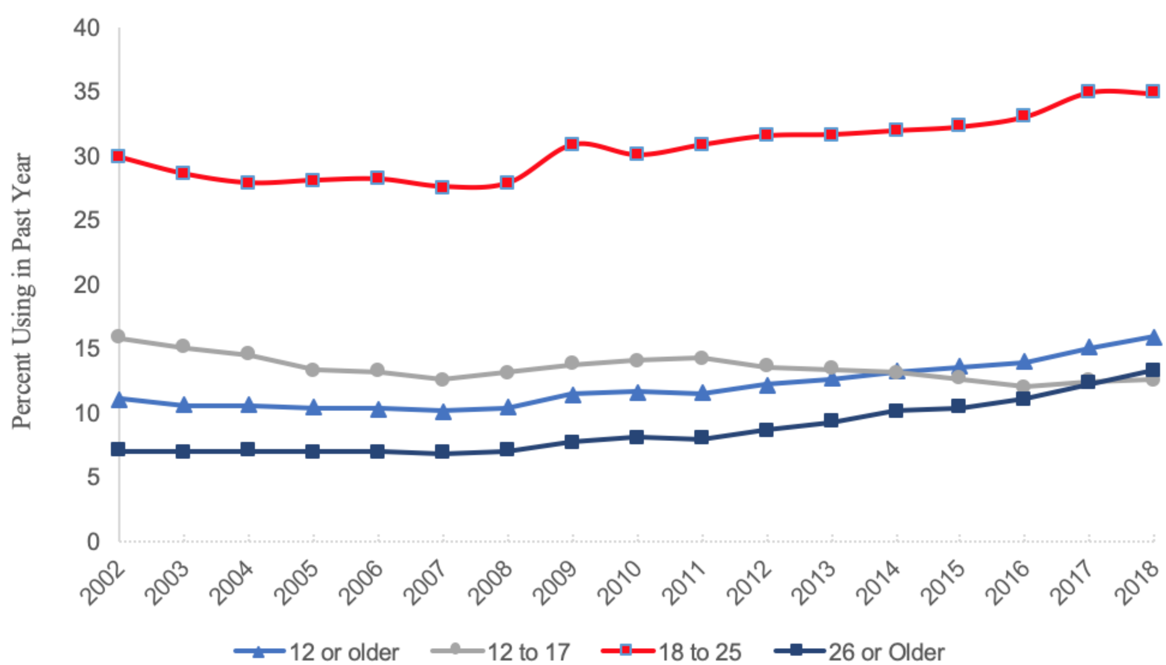


Figure 1.8: Past Year Marijuana Use among People Aged 12 or Older: 2002–2018



1.3 Data

In this study, I employ the Healthy Mind Survey (HMS) data set that contains data from 2009 to 2017 academic years. There are collectively over 150 colleges and universities in the U.S., which are shown in Figure A.6 (the few institutions outside of the country are excluded from the sample) that have participated in HMS studies. The complete list of participated institutions can be found in Table A.1 in the Appendix. HMS is a national web–based survey conducted by the University of Michigan. There are over 200,000 student observations throughout the sample period. Note that all states that passed RMLs have also previously passed MMLs. In order to get a clearer interpretation of the effect from medical marijuana legalization implementation, I remove states that have legalized marijuana for recreational purposes to avoid unclear mechanism of drug consumption.

Questions in the survey help identify information on students' health statuses, needs, access and barriers to treatment, utilization of services, social and academic environments. The outcomes of students' healthy lifestyles, such as drug use behaviors, mental health as well as academic performance can also be observed in the questionnaires. Regarding the comprehensiveness of the data set, it includes students' demographics and their background characteristics such as past and current financial situation, religious beliefs, and whether the student is living on campus at the time of the survey.

1.3.1 *Screening of mental health concerns*

The data on individual mental health statuses come in two forms. First, several clinically recognized questionnaires are embedded within HMS. Although the questionnaires should not be replacing professional assessments, they serve as an indicator of mental health concerns. Patient Health Questionnaire–9 (PHQ–9), for instance, provides reliable evidence and a valid measure of depression severity (Kroenke et al., 2001). Nine questions are asked to the respondent in PHQ–9.

A sample PHQ–9 question: *"Over the last 2 weeks, how often have you been bothered by any* *of the following problems? Little interest or pleasure in doing things (Not at all, several days, more than half the days, nearly every day)"*

Based on a series of answers, a score is computed and serves as an indication of severity of depression. Score 0–4 represents no to minimal depression, 5–9 represents mild depression, 10–14 represents moderate depression, 15–19 represents moderately severe depression, 20–27 represents severe depression. See Figure A.7 in the Appendix for the complete set of questions.

With a similar approach, the Generalized Anxiety Disorder (GAD–7) questionnaire within the HMS, is developed by psychologists with a set of seven questions. The total score computed from the respondent's answers can be used as a screening measure of panic, social anxiety, and PTSD. Due to the change of the scoring scales of the questionnaires across different years during the sample period, I harmonized and coded one if a student has any screening of anxiety disorder and zero otherwise. Figure A.8 presents all of the questions from the questionnaire.

A sample GAD–7 question: *"Over the last 2 weeks, how often have you been bothered by any of the following problems? Feeling nervous, anxious, or edge (Not at all, several days, more than half the days, nearly every day)"*

1.3.2 *Self reported professional diagnoses*

Second, rather than utilizing screen tests in the survey, the survey includes self–reported professional diagnosed mental illnesses and health statuses, as well as various health and risky behavior topics, such as drug use, ever experienced sexual assault, and discrimination. The dependent variables of interest in regard to mental outcomes for this study are screening of severity of depression (from having any depression, mild depression, to severe depression), panic, and anxiety disorder, as well as having serious suicidal thoughts within the past year.

1.3.3 *Prescription, recreational drug use, and academic outcomes*

The HMS also comes with self–reported prescription drug use for psychiatric purposes. In addition, recreational drug use including both legal drinking, smoking cigarettes, and illegal consumption of marijuana for recreational purposes are documented in the survey. In correspondence to students' academic achievement, the HMS includes data from both administrative and self reported grade point average. Results were categorized from A, A-, B+, B, B-, C+, and so forth. These variables are exceptionally relevant and fascinating as I later explain the mechanism of students' behavioral changes since the medical marijuana legalization.

1.3.4 *Overall descriptive statistics*

In the restricted version of the data set, school names become identifiable. With this information, I linked each individual to the state of the college/university. This is essential as this study focuses on the impact of state–level marijuana laws on college students' mental health. Table 1.2 shows the descriptive statistics of key variables. The majority of students are white (about 65 percent) and are aged between 18 and 22 years old. Distribution among demographics and students' academic achievements are also comparable. One variable that is worth mentioning is the raw patient health questionnaire (PHQ–9) score. On column 3, the average score in MML states is slightly higher than the non–MML states. Recall that the higher the score is, the more severe depression is.

When comparing recreational drug use across MML states and non–MML states, proportion of students exhibiting risky behaviors appear to be commensurate. As shown in Table 1.2, 53 percent of students in non–MML states had binge drinking in the past 14 days at the day of the survey compared to 51 percent in MML states. Proportion of students who reported smoking any cigarettes in the past 30 days are approximately the same at 15 percent.

The outcomes of interest in the paper can be grouped into three categories: 1) mental health outcomes (both screening and self–reported professional diagnosis), 2) prescription and recreational drug use, and 3) academic efforts and outcomes. General mental health screenings include depression and anxiety disorder, self–reported suicidal ideation in the past, and medically diagnosed mental illnesses. Drug use variables consist of prescription and recreational drugs such as recreational marijuana, alcohol, cigarettes, and some other psychoactive drugs like cocaine and heroin. Academic outcomes are estimated using students' grade point average as a proxy.

1.4 Empirical Strategies

The appropriate research design for this study is to employ a difference–in–differences (DID) approach due to the exogenous policy variation. First, I estimate a fixed effect ordinary least squares regression given by

$$MentalHealthOutcomes_{ist} = \beta_o + \beta_1 MML_{st} + X_{ist}\beta_2 + \beta_3 Unemploy_{st} + u_s + w_t + \varepsilon_{ist}$$

where i represents a student who lives in state, s, and is surveyed at year, t. Mental health outcomes include the PHQ–9 score, screenings for depression and anxiety disorder, suicidal ideation in the past as well as reported professionally diagnosed mental illnesses. MML_{st} (represents $MML * Post_{st}$) is equal to one if a state enacts a medical marijuana law at time, t. X_{ist} is a vector of student i's characteristics such as gender, age, race/ ethnicity, whether the student is an international student, undergraduate or graduate, and/or if ever experienced discrimination. $Unemploy$ represents the unemployment rates to control for macroeconomic conditions. Since an analysis of cross–sectional OLS suffers confounding unobservable characteristics across state and time, it is reasonable to estimate the effect of MMLs by incorporating state (u_s) and year (w_t) fixed effects. Standard errors are clustered at the school level.

In a similar fashion, I am interested in the change of recreational and psychiatric prescription drug use with the passage of MML. The specific corresponding outcomes include binge drinking in the past 14 days, any cigarette use in the past 30 days, any recreational marijuana use in the past 30 days, and any psychiatric prescription medication in the past 12 months.

$$DrugUseOutcomes_{ist} = \beta_o + \beta_1 MML_{st} + X_{ist}\beta_2 + \beta_3 Unemploy_{st} + u_s + w_t + \varepsilon_{ist}$$

Last, I explicitly investigate their grade point average in order to explore the effect of MML on students' academic outcomes. Due to the structure of the survey, these outcomes are ordinal variables. It is then logical to estimate using an ordered logit method.

$$AcademicOutcomes_{ist} = \beta_o + \beta_1 MML_{st} + X_{ist}\beta_2 + \beta_3 Unemploy_{st} + u_s + w_t + \varepsilon_{ist}$$

It is important to recognize that linear regression is based upon an assumption that the outcome is continuous with errors which are normally distributed. Other than the variable PHQ–9 score that I am examining, other mental health outcome variables are either in dichotomous or ordinal measures. Hence, the assumption is clearly violated; instead, a logit or an ordered logit seem to be more appropriate estimation methods as previous applied economics studies have employed (Robson & Bennett, 2000). To encapsulate the essence of a generic form of an ordered logit model, the model is built around a latent regression, where

$$y_i^* = \beta' \mathbf{Z} + v_i$$

In this paper, for example, y_i^* are $MentalHealthOutcomes$ or $AcademicOutcomes$. $\mathbf{Z}$ are the DID interaction term and covariates. K are given categories that are ordered in nature and instead of y_i^*, the following is observed:

$$y = 1 \quad if \quad \lambda_0 \leq y^* < \lambda_1$$

$$y = 2 \quad if \quad \lambda_1 \leq y^* < \lambda_2$$

$$y = 3 \quad if \quad \lambda_2 \leq y^* < \lambda_3$$

$$\vdots$$

$$y = K \quad if \quad \lambda_{k-1} \leq y^*$$

where λ's are the threshold parameters, estimated with the β vector, u is assumed to have a standard logistic distribution. With the assumption of Φ being the continuous and twice differentiable cumulative logistic distribution, ϕ being the logistic density function and $u \sim N(0,1)$, the probability for the k-th outcome is given by the ordered logit model

$$\Phi(\lambda_k - \beta'\mathbf{Z}) - \Phi(\lambda_{k-1} - \beta'\mathbf{Z})$$

The coefficient differs by a scale factor and hence no interpretation can be made in regard to the magnitude of the coefficients. Rather, it can only be interpreted as more likely or less likely to be in the higher category. On the other hand, the marginal effect of MML in the probability of outcome of k (in other words, the k-th response) is computed as

$$\frac{\delta Prob[y=k|\mathbf{Z}]}{\delta MML} = [\phi(\lambda_k - \beta'\mathbf{Z}) - \phi(\lambda_{k-1} - \beta'\mathbf{Z})]\beta_1$$

It is the slope of the curve relating an enactment of an MML to $Prob[y=k|\mathbf{Z}]$, holding all other variables constant. Correspondingly, marginal change from a logit model is simply replacing $y=k$ with $y=1$ on an outcome of interest rather than having k categories in an ordinal variable.

1.5 Results and Sensitivity Analyses

1.5.1 *Mental health outcomes*

The results in Table 1.3 whos the effect of MMLs on depression screening using the PHQ–9 raw score. In column (1), an ordinary least squares model is employed. The coefficient on *MML* reported in column (1) implies that MMLs are associated with a .41 points increase in the PHQ–9 score – students experience more depressive symptoms with the passage of medical laws. However, after including the year and state fixed effects in column (2) to control for time–invariant unobservable state characteristics and unobservable variables that are constant across states but vary over time, the coefficient has dropped and lost statistical significance at the traditional levels. When analyzing the score using an ordered logit model with 6 categories of severity of depression on column (3), I also find a similar result where there is no evidence that MMLs have an impact on depression screening. To validate the results from ordered logit, I create dummy variables of various severity of depression based on the raw depression scores and analyze each depression group using a logit model approach. Tables 1.4–1.6 show the impact of MMLs on different levels of depression severity screenings. Columns (1)'s and (4)'s represent the OLS model and columns (2)'s and (5)'s represent estimations using a logit model and finally columns (3)'s and (6)'s present the average marginal effect of *MML*. The statistically insignificant findings from logit model of Tables 1.4 and 1.5 suggest that no conclusive inference can be made whether MMLs have an impact on different levels of depression among students. In Table 1.7, I estimate the effect of MMLs on other mental health concerns. Specifically, I explore the relationship between legalization and anxiety screening or suicidal ideation. Although the coefficients on the average marginal effect are negative (-2 percent and -.05 percent respectively) for both outcomes of interest, neither estimation was statistically significant. Using evidence of mental screening, I have consistently shown that there are no statistical differences on mental health outcomes between MMLs states and states without any marijuana laws.

1.5.2 *Drugs substitutability outcomes*

Next, I explore the drugs substitutability among both psychiatric prescription drugs and drugs for recreational purposes. On the HMS, it asks respondents whether they have taken any of the prescription medications in the past 12 months. In the survey, psychiatric prescription medications are listed as psychostimulants, antidepressants, anti–psychotics, anti–anxiety medications, mood stabilizers, and sleep medications. With strong evidence shown on Table 1.8, MMLs are associated with a decrease in any psychiatric prescription drugs as listed in the survey. Again, column (1) shows estimation using an OLS model, column (2) shows coefficient estimated using logit technique. For easier interpretation, average marginal effected is computed and is presented under column (3). In terms of explanatory power, both models are satisfactory. I find a consistent negative impact on prescription drugs consumption in the past 12 months at the time of the survey.

Individuals who live in MML states has a 8.9 percent decrease on prescription drugs consumption.

I further investigate the recreational drug use reported by students after the statewide medical marijuana legalization. In particular, the question that is being asked in the survey is the following:

"How often, if ever, have you used any of the substances listed below? Do not include anything you used prescribed to you by a doctor."

Table 1.9 presents results on illicit drug use on marijuana as well as cocaine among college students. Across all columns, it is evident that MMLs are associated with a negative illicit drug use on both marijuana and cocaine. Column (3), it shows that MMLs leads to a 4.8 percent decrease in illegal marijuana consumption and column (6) shows that there is slight decrease in cocaine use for about 0.85 percent. Table 10 provides estimations of its effect on binge drinking on the past 14 days and smoked any cigarettes in the past 30 days. The results suggest that there is no strong evidence of changes in consumption on either binge drinking or cigarette consumption.

1.5.3 *Academic outcomes*

I analyze how MMLs affect students' behavioral changes on their study. In Table 1.11 shows that students neither spend more nor less time on their study post–MML. Furthermore, I analyze students' academic outcomes by using students' grade point average (GPA) as a proxy. Table 1.12 shows the estimated coefficient of the ordered logit model. A certain amount of care is necessary for the interpretation of coefficients on ordered logit regressions. A positively signed coefficient implies an increase in the odds ratio or higher values of explanatory variables imply higher GPA tier–group. Overall, with medical marijuana legalization, there is an indication of fewer students falling into the lower tier–groups (such as D+ or below and C-) and more students falling into the higher tier–groups (such as A and A-).

1.5.4 *Sensitivity Analyses*

I perform various forms of sensitivity tests, by including different sub–group analyses. I divide up the sample into undergraduate versus graduate students, white versus non–white students, and males versus females. By doing so, it allows me to examine whether there exists heterogeneous effects across genders and demographics. In addition, as robustness checks, I restrict the sample to students aged 25 or under, and drop Illinois and New York since those states approximately account for 20 percent of the entire data set. These tests allow me to rule out the possibility that effects are solely driven by surveyed students from these populous states. All sensitivity analyses tables are displayed on the Appendix. Tables A.2–A.9 present sensitivity tests on PHQ–9 scores. Tables A.10–A.17 present sensitivity tests on anxiety screening and suicidal ideation. Tables A.18–A.25 present sensitivity tests on psychiatric prescription drugs use. Tables A.26–A.33 present sensitivity tests on illicit drugs use. Lastly, Tables A.34–A.41 present sensitivity tests on other sin goods consumption, specifically binge drinking and cigarette consumption. Concisely, results generally passed all types of sensitivity tests mentioned above and provided very similar qualitative results across all sub–samples.

1.6 Channels and Mechanisms

Using individual–level data from Healthy Minds Study, I do not find evidence of medical marijuana legalization having an impact on college students' mental health. MMLs neither improve nor deteriorate college students' mental health outcomes in terms of symptoms or diagnoses such as depression, anxiety, and suicidal ideation. Results are consistent when examining both mental health screenings embedded in the survey as well as the self–reported responses. These findings reflect the divisive conclusions from the medical field on the effectiveness of medicinal cannabis (Parmar et al., 2016).

Two findings in this study are particularly noteworthy as I attempt to reveal the mechanism behind students' risky behavioral changes: 1) MMLs lead to a reduction in consumption of both recreational marijuana and cocaine; 2) a decrease of intake of psychiatric prescription drugs post MMLs. Per prior empirical studies, self–medication practices with nonprescription medication are highly prevalent among university students (Sawalha, 2008; Zafar et al., 2008; Ali et al., 2010; Klemenc-Ketis et al., 2010). Using recreational drugs, such as marijuana and cocaine, are explicitly highlighted as examples of self–medication practice (Almasdy & Sharrif, 2011). Recently, health economists have begun to understand the motivation behind self–medication from a theoretical approach. Darden & Papageorge (2018) developed a theory on rational self–medication and suggested a mechanism of rational self–medication. Their finding unveils the provision of safer treatment options could avert self–medication with dangerous or addictive substances. In other words, if one perceives a safer and more effective treatment, one will substitute towards such option. As some states acknowledge the effectiveness of treatment with cannabis, this paper shows empirical evidence of this theoretical model. College students may be substituting away from recreational drugs, marijuana and cocaine in particular, to a safer option: medical cannabis under physicians' recommendation. Applying the model suggested by Darden & Papageorge (2018) to the newly available medicinal marijuana, the decrease in both prescription medicines and recreational drugs use hints that benefits of consuming medical marijuana outweigh the costs. Despite no strong evidence of improving mental health with medical legalization, other perceived benefits including lower social stigma are attached to medical marijuana as opposed to prescription medicine.

In addition, although it is impossible to disentangle which channel contributes to the results given the limitation of the data, studies find that both alcohol and cigarette consumption are prevalent in terms of self–medication and coping with stress in a college environment (Miller et al., 2002; Magid et al., 2009; Benson et al., 2015). This suggests a more plausible explanation is where students are not substituting away from alcohol and cigarettes due to their costs and benefits analysis among the recreational drugs, prescription drugs, and medical marijuana.

The passing of MMLs does not result in a variation on students' time spent on their studies. Using the reported grade point average, results suggest an improvement in academic performance among college students in MML states. This can potentially be explained by the reduction of side–effects with medical marijuana use compared with the traditional prescription medication. In a recent neuroscience study, Hudson et al. (2019) provide medical evidence that cannabidiol (CBD) in cannabis lowers psychiatric side effects such as anxiety–like behaviors. Schofield et al. (2006), a psychiatric study, also reveals one of the reasons of using cannabis in psychosis is to relieve psychotic symptoms like "decrease suspiciousness" and mitigate side effects of anti–psychotic medication. Based on this evidence, students who are using medical marijuana may experience less severe side effects that usually hinder students' ability to study efficiently. With the comparable similar hours of study, better quality of study sessions can lead to better academic performance, which is reflected in their GPA.

1.7 Policy Implication and Limitations

This paper sheds light on students' well–being in a number of ways. First, the enactment of medical marijuana laws is not associated with better or worse mental health outcomes as some physicians may have anticipated. A key spillover is the substitution between medical marijuana and psychiatric prescription drugs. There is evidence from prior research suggesting self–medication. This study offers an indication that students might be shifting away from consuming illicit marijuana and cocaine to provisioned medical marijuana post legalization. Yet, we do not see significant behavioral changes among alcohol and tobacco use with MMLs. The intuition and mechanism of such changes are backed by the economic theory of rational self–medication. In addition to some biological sciences that propose fewer negative side effects when consuming marijuana for medicinal purposes, psychiatric studies also indicate that one of the reasons individuals choose to self medicate is to lessen side–effects. The reduced side–effect symptoms may not have improved mental health *per se* but the ability to study more competently and eventually lead to better academic outcomes.

Using students from across the U.S. universities and colleges, this allows analyses to be carried out to examine the overall effectiveness of the laws – providing a new option for patients and expecting to improve ones' health outcomes. According to the results presented in this paper, mental health outcomes are neither improved nor deteriorated among college students. The direct impact is yet to be scrutinized. However, the unintended consequence of the laws lead to a reduction in certain recreational drugs use, approximately 5 percent in marijuana and 1 percent in cocaine use.

According to the Office of National Drug Control Policy (2017), the U.S. has met or exceeded the target for alcohol and tobacco use among young adults aged 18–25. Yet targets for all other illicit drugs have yet to be met (targeted at 16.9 percent and actual consumption at 20.5 percent to–date). In this study, I provide suggestive results on lower cocaine consumption with the passage of MMLs. With regard to the analyses of total health care costs, chronic drug users generate about $1000 in excess services utilization per individual, relative to non–drug users (French et al., 2000). Applying to this figure study, $.92–$1.65 million dollars of health care services is saved from cocaine abuse alone during the sample period [4]. I extrapolate and do a back–of–the–envelope calculation for the cost savings contributed to only cocaine–related drug use among college students. There is a potential conservation of 1.15 billion dollars annually from drug–related health care services across students in higher education.

A proposed mechanism of switching from recreational drugs to medical marijuana include 1) accessing quality assured medical marijuana and 2) the reduction of side–effects. Since medical marijuana became legalized, most legal states require testing to assure the quality of cannabis products[5]. Aside from the change of legal status, MMLs allow users to switch to a safer option if one merely switched from illegal marijuana for self medication. Furthermore, self–medication is not recommended as individuals are exposed to higher risks and adverse effects such as a development of substance abuse (Montastruc et al., 2016). This study finds a reduction of such risky behaviors through recreational drugs and implies a better public health through this avenue. In addition, better academic records can be served as singling, in which attribute to positive effect on employment selection process, especially in the public sector and eventually lead to more desired labor outcomes as it is widely studied in education and labor economics literatures (Velasco et al., 2012).

I acknowledge the limitations in the study. First, since schools do not participate in the Healthy

[4] I computed the dollar amount from expected service utilization saved with the reduction of marijuana and cocaine consumption based on the results found in this paper and the total fall enrollment in degree–granting postsecondary institutions provided by National Center for Education Statistics.

[5] See https://www.leafly.com/news/industry/leaflys-state-by-state-guide-to-cannabis-testing-regulations for individual state's testing regulations

Minds Survey every year, there exists missing data for some schools and states for certain years. Second, a common problem of survey data applies to this study as well. Respondents of the survey do not truly represent the proportion of the gender differences in reality. For instance, most respondents in the survey have a proportion of female (74 percent) than the national average of 60 percent. Third, underreporting drug use is a widely recognized concern in survey data (McGregor et al., 2003; Chen et al., 2006; de Beaurepaire et al., 2007) due to the legality status of the drugs. Individuals' underreporting is however relatively constant from year to year, so it is reasonable to presume of the constancy of downward bias. Fourth, I do not observe medical marijuana use among students. Although I have information of prescription drugs use and recreational drug use of different substances, including marijuana, there is no way to tell from the survey whether or not students actually use provisioned medical marijuana. The findings in this study suggest that introducing a new option of medicine through medical marijuana laws lead to a substitution effect among prescription drugs and recreational drugs as well as contributing to better academic outcomes. As the U.S. is liberalizing marijuana policies, its impact on mental health outcomes is yet to be disentangled. Policy makers are advised to study both the direct and spillover effects when moving forward with their agenda regarding marijuana legalization.

Table 1.1: Effective Dates of Medical Marijuana Laws and Recreational Marijuana Laws, 1990–2020 *

	Effective Date of MMLs	Effective Date of RMLs
Alaska	March 4, 1999	February 24, 2015
Arizona	November 2, 2010	
Arkansas	November 9, 2016	
California	November 6, 1996	November 9, 2016
Colorado	June 1, 2001	January 1, 2014
Connecticut	October 1, 2012	
Delaware	July 1, 2011	
District of Columbia	July 27, 2010	February 26, 2015
Florida	January 3, 2017	
Hawaii	December 28, 2000	
Illinois	August 1, 2013	January 1, 2020
Louisiana	August 6, 2019	
Maine	December 22, 1999	December 18, 2016
Maryland	June 1, 2014	
Massachusetts	January 1, 2013	December 15, 2016
Michigan	December 4, 2008	December 6, 2018
Minnesota	May 20, 2014	
Missouri	December 6, 2018	
Montana	November 2, 2004	
Nevada	October 1, 2001	January 1, 2017
New Hampshire	July 23, 2013	
New Jersey	October 1, 2010	
New Mexico	July 1, 2007	
New York	July 5, 2014	
North Dakota	November 8, 2016	
Ohio	September 8, 2016	
Oklahoma	November 6, 2018	
Oregon	December 3, 1998	October 1, 2015
Pennsylvania	April 17, 2016	
Rhode Island	January 3, 2006	
Utah	November 6, 2018	
Vermont	July 1, 2004	July 1, 2018
Washington	November 3, 1998	July 8, 2014
West Virginia	April 19, 2017	

* This table is up to the date of January 1, 2020.

Table 1.2: Summary Statistics

	(1) No Marijuana Laws		(2) MMLs only		(3) All Non–RMLs	
Demographic characteristics						
Age	22.35	(5.179)	23.09	(5.895)	22.72	(5.561)
Female	0.65	(0.475)	0.66	(0.473)	0.66	(0.474)
White	0.78	(0.415)	0.70	(0.458)	0.74	(0.439)
Black	0.06	(0.241)	0.07	(0.251)	0.06	(0.246)
Hispanic	0.07	(0.254)	0.10	(0.302)	0.09	(0.279)
Asian	0.11	(0.315)	0.15	(0.357)	0.13	(0.337)
International students	0.07	(0.252)	0.10	(0.297)	0.08	(0.276)
Single	0.52	(0.500)	0.50	(0.500)	0.51	(0.500)
In a relationship	0.37	(0.483)	0.38	(0.485)	0.37	(0.484)
Sexual orientation minority	0.10	(0.301)	0.14	(0.347)	0.12	(0.325)
Undergraduate	0.73	(0.442)	0.70	(0.459)	0.72	(0.451)
Live on campus	0.36	(0.481)	0.27	(0.442)	0.32	(0.465)
Financial struggle	0.23	(0.418)	0.29	(0.452)	0.26	(0.436)
No any health insurance	0.04	(0.206)	0.04	(0.185)	0.04	(0.196)
Prescription and recreational drug use						
Any prescription medications in the past 12 months	0.09	(0.280)	0.06	(0.240)	0.07	(0.261)
Binge drinking in the past 14 days	0.53	(0.499)	0.51	(0.500)	0.52	(0.500)
Any cigarettes in the past 30 days	0.15	(0.360)	0.15	(0.360)	0.15	(0.360)
Any marijuana use in the past 30 days	0.14	(0.350)	0.17	(0.374)	0.16	(0.362)
Mental health outcomes						
Raw Patient Health Questionnaire (PHQ–9) score	6.48	(5.272)	7.38	(5.694)	6.94	(5.509)
Any screening of panic and/or anxiety disorder	0.18	(0.380)	0.23	(0.424)	0.21	(0.405)
Any screening of severe depression	0.18	(0.388)	0.17	(0.374)	0.18	(0.381)
Any suicidal ideation in the past year	0.09	(0.280)	0.10	(0.298)	0.09	(0.289)
Any diagnosed depression by professionals	0.17	(0.380)	0.19	(0.391)	0.18	(0.385)
Any diagnosed anxiety disorder by professionals	0.17	(0.377)	0.19	(0.389)	0.18	(0.383)
N	80556		80819		161640	

Mean coefficients; standard deviations in parentheses

Table 1.3: Impact of MMLs on PHQ–9 scores and Depression

	(1)	(2)	(3)
	PHQ-9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.414**	0.0374	-0.140
	(0.172)	(0.201)	(0.546)
N	80743	80743	87772

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Impact of MMLs on Moderately Severe to Severe Depression Screening

	(1)	(2)	(3)	(4)	(5)	(6)
	Severe Depression			*Mod.Sev. Depression*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0150	-0.319	-0.0206	0.0135	-0.0122	-0.000755
	(0.108)	(0.782)	(0.0505)	(0.0114)	(0.266)	(0.0165)
N	93879	84440	84440	93206	83745	83745

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Impact of MMLs on Moderate Depression Screening

	(1)	(2)	(3)
	Moderate Depression		
	OLS	Logit	Logit AME
mml	0.00156	-0.0547	-0.00377
	(0.00992)	(0.197)	(0.0136)
N	93206	83729	83729

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Impact of MMLs on Mild to No Depression Screening

	(1) *Mild Depression* OLS	(2) Logit	(3) Logit AME	(4) *No Depression* OLS	(5) Logit	(6) Logit AME
mml	-0.0500	0.266	0.0560	0.0465	0.185	0.0392
	(0.0451)	(0.213)	(0.0449)	(0.0399)	(0.230)	(0.0487)
N	93206	142645	142645	93206	83767	83767

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Impact of MMLs on Anxiety Screening and Suicidal Ideation

	(1) *Anxiety* OLS	(2) Logit	(3) Logit AME	(4) *Suicidal Ideation* OLS	(5) Logit	(6) Logit AME
mml	-0.00756	-0.136	-0.0203	0.00146	-0.0594	-0.00474
	(0.0182)	(0.0846)	(0.0126)	(0.00984)	(0.110)	(0.00876)
N	73784	73784	73784	91340	91340	91340

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: Impact of MMLs on Psychiatric Prescription Drugs Consumption

	(1) *Prescription Drugs* OLS	(2) Logit	(3) Logit AME
mml	-0.0314	-0.706***	-0.0889***
	(0.0252)	(0.0826)	(0.0104)
N	92732	42407	42407

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons)

	(1)	(2)	(3)	(4)	(5)	(6)
	Marijuana			*Cocaine*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0534**	-0.388**	-0.0481**	-0.00734***	-0.549***	-0.00845***
	(0.0221)	(0.159)	(0.0197)	(0.00264)	(0.138)	(0.00213)
N	93554	89234	89234	93384	87168	87168

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: Impact of MMLs on Binge Drinking and Cigarettes Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.00725	0.0263	0.00562	-0.0182	-0.137	-0.0161
	(0.0235)	(0.108)	(0.0231)	(0.0201)	(0.143)	(0.0169)
N	67207	67199	67199	86575	86566	86566

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: Impact of MMLs on Students' Time Spent on Study

	(1)
	Time Spent on Study
	Ordered Logit
mml	0.0113
	(0.0902)
N	93879

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.12: Impact of MMLs on Students Academic Outcomes

	(1) *GPA* Ordered Logit
mml	0.266**
	(0.107)
N	93879

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Relationship between Legal Access to Medical and Recreational Marijuana and Motor Vehicle Fatalities in the U.S.

2.1 Introduction

According to the National Highway Traffic Safety Administration of the Department of Transportation, since 1990 approximately 2 million people have been injured and over 30,000 died from motor vehicle accidents annually in the United States. In the effort to minimize traffic accidents and fatalities, states periodically implement and update the traffic codes, such as 0.08 percent blood alcohol content, primary and secondary seat belt laws, texting ban, graduate driver licensing systems, drug per se laws and many others. Researchers in the past have focused on the effectiveness of specific motor vehicle codes on the reduction of traffic fatalities: seat belt laws (Cohen & Einav, 2003), graduated driver licensing (Dee et al., 2005), drug per se laws (Anderson & Rees, 2015). On the other hand, some studies have estimated the indirect effect of policy changes to traffic fatalities such as minimum legal drinking age and beer taxes (Ruhm, 1996; Ponicki et al., 2007), and highway speed limits (Farmer et al., 1999; Ossiander & Cummings, 2002). There exists some economics literature regarding the legalization of alcohol and cigarettes, and the relationship of each to motor vehicle accidents. Yet, only a few have studied the legalization of marijuana laws, such as Anderson et al. (2013), in recent years. In 1996, California became the first state to legalize marijuana for medical purposes. In 2012, Colorado Amendment 64 legalized the sale and possession of marijuana for non–medical uses. Since then, more states have enacted similar laws allowing citizens to consume marijuana for medical and/or recreational purposes.

In this chapter, I focus on the policy change of marijuana laws in the past 20 years and estimate the effect of these changes to traffic fatalities. The history of marijuana laws can be categorized in four periods over the course of 100 years in the United States: prohibition laws began in the early 1900s, decriminalization laws began in the 1970s, legalization of medical marijuana began in the 1990s, and legalization of recreational marijuana began in the 2010s. For the past few decades, possession and usage of cannabis was illegal and prohibited in most parts of the United States. In Anderson et al. (2013), it was mentioned that California passed the first marijuana prohibition law aimed at recreational use in 1913; by 1936 the remaining 47 states had followed. The Marijuana Tax Act in 1937 has further restricted the usage even for medical purposes. Marijuana was then classified as a Schedule I drug in 1970. Later, in 1973, Oregon became the first state to decriminalize the possession of cannabis. By 1978, there were a total of eleven states that decriminalized marijuana. Yet, the use, possession, sale, cultivation, and transportation of marijuana has remained illegal under federal law in the United States. A few studies such as Serrano et al. (2008); Hill (2015) have suggested that intake of cannabinoid, an ingredient of cannabis or using marijuana as a medical treatment, a chemical in cannabis may have beneficial effects on treating certain symptoms and diseases. In 1996, California became the first state to enact medical marijuana laws (MMLs). Up to February, 2018, 29 states and the District of Columbia have legalized marijuana for medical purposes. Although qualifying conditions to consume medical marijuana vary among different states, they include the treatment of the following illnesses: cancer, HIV/AIDS, seizures, PTSD, epilepsy, glaucoma, Wasting syndrome and many others. Meanwhile, at the state–level, eleven states and the District of Columbia have legalized marijuana use for recreational purposes since Colorado passed the recreational marijuana laws in 2012[1]. This means persons who are 21 years old or above in those states and D.C. may possess small amounts of marijuana and consume it under several circumstances, such as consuming such related–substances in one's own property, in bars, lounges, and restaurants with special permits from certain cities and states, etc. Again, specific conditions for the recreational marijuana laws vary as they were for medical purposes across

[1]Laws became effective on January 1, 2014

states. A summary of the dates of legalization of MMLs and RMLs are provided in Table 1.1.

Since legalization of marijuana have been a controversial topic, some epidemiological research has been done to determine the effect of cannabis to human body. Some suggest that Tetrahydrocannabinol (THC), the main psychoactive ingredient in cannabis, impairs cognition and psychomotor performance such as hand–eye coordination, vigilance, time and distance perception Khiabani et al. (2006). Hence, it would be interesting to estimate if there is correlation between the legalization of marijuana and traffic fatalities. This is also one of the motivations behind this study. The objective of this paper is to estimate whether or not there is a change in the number of traffic accident fatalities that is contributed to the legalization of either or both MMLs and RMLs. More specifically, given the fact that numbers of states have passed both medical and recreational marijuana laws in the past few years, this paper contributes to the existing literature by extending the analysis to both MMLs and RMLs simultaneously using the most recent data. Thus, it aims to examine the relationship between the traffic fatality rate and increasing legalization of marijuana access in the United States over the past 27 years (1990–2016).

2.2 Data

The data used in this study comes from the Fatality Analysis Reporting System (FARS), which is regulated by the Department of Transportation. FARS contains information about crash characteristics and environmental conditions at the time of the accident. The dataset comprises the 50 states and the District of Columbia, as well as many other characteristics of the people who are involved in the accidents, the conditions of the vehicles, the road and weather conditions. In addition, FARS consists of information regarding the location down to the county level as well as the exact date and time of the accidents to the unit of hour and minute. The data contain details of all of the traffic accidents, time of the accident, the number of fatalities, speed limit of the location, as well as some general information about people involved in the accident. For the purposes of this study, data were aggregated on a monthly state level to constitute a panel, dating from January, 1990 until December, 2016. After aggregating the data at a monthly level, the panel contains 324 time periods for 50 states plus the District of Columbia, constituting 16,524 observations.

In addition, the data of economic conditions and policies are extracted from various sources. First, the variable *Speed* 70 was constructed using the FAR accident files. For seat belt laws, see Insurance Institute for Highway Safety and Highway Loss Data Institute. Freeman (2007) provided a detailed reference for the blood alcohol content laws (BAC). Information on vehicle miles driven per licensed driver is computed using Highway Statistics (U.S. Department of Transportation 1990– 2016). In addition, data of the control variables such as *Income* come from the U.S. Census and data of state unemployment rate comes from the Bureau of Labor Statistics (BLS).

On Panel A, it shows the summary statistics for some relevant variables when comparing control states and treatment states with MMLs. Likewise, Panel B shows the summary statistics for the variables when comparing control states and treatment states with RMLs. Lastly, Panel C shows the summary statistics for the variables when comparing control states and treatment states with both MMLs and RMLs.

Table 2.1: Summary Statistics for Relevant Variables

Panel A - Medical Marijuana Laws

	Control states	Treatment states: All months	Treatment states: Pre–MML months	Treatment states: Post–MML months
Number of fatalities	77.154	54.121	55.275	51.593
Population (annually)	5,424,690	5,865,225	5,671,528	6,279,369
Unemployment rate (monthly)	5.624	5.701	5.568	5.796
Miles driven per driver (in thousands)	15.849	13.257	13.405	12.901
Sample Size	7,452	9,072	6,158	2,564

Panel B - Recreational Marijuana Laws

	Control states	Treatment states: All months	Treatment states: Pre–RML months	Treatment states: Post–RML months
Number of fatalities	64.512	64.622	66.297	33.56
Population (annually)	5,373,790	7,240,146	7,397,251	4,272,712
Unemployment rate (monthly)	5.766	5.131	5.156	4.718
Miles driven per driver (in thousands)	14.843	12.181	12.216	134
Sample Size	13,932	2,592	2,452	146

Panel C - Medical and Recreational Marijuana Laws

	Control states	Treatment states: All months	Treatment states: Months of Pre–MML & RML	Treatment states: Months of Post–MML & RML
Number of fatalities	77.154	64.622	56.421	33.565
Population (annually)	5,424,690	7,240,146	5,671,528	4,272,271
Unemployment rate (monthly)	5.624	5.132	5.658	4.718
Miles driven per driver (in thousands)	15.849	12.181	13.405	11.146
Sample Size	7,452	2,592	6,189	134

2.3 Empirical Model

In order to explore the relationship between legalization of marijuana and traffic fatalities, I employ difference–in–differences model with the following baseline equations. Equation 2.1 estimates the effect on fatalities with the enactment of medical marijuana laws.

$$ln(FatalitiesTotal_{st}) = \beta_0 + \beta_1 MML_{st} + X_{st}\beta_2 + v_s + w_t + \varepsilon_{st} \tag{2.1}$$

where s indexes states and t indexes months. β_1, represents the effect of legalizing medical marijuana. On the other hand, Equation 2.2 estimates the effect on fatalities with the enactment of recreational marijuana laws.

$$ln(FatalitiesTotal_{st}) = \beta_0 + \beta_1 RML_{st} + X_{st}\beta_2 + v_s + w_t + \varepsilon_{st} \tag{2.2}$$

In Equation 2.3, the variable RML_s is added to Equation 2.1 to estimate the effects on fatalities with the enactment of both medical and recreational marijuana laws as trying to explore the joint effect of medical and recreational marijuana on traffic fatalities.

$$ln(FatalitiesTotal_{st}) = \beta_0 + \beta_1 MML_{st} + \beta_2 RML_{st} + X_{st}\beta_3 + v_s + w_t + \varepsilon_{st} \tag{2.3}$$

The vector X_{st} is composed of the controls (independent variables). State fixed effects, represented by v_s, control for time–invariant unobservable factors at the state level; month–specific fixed effects is represented by w_t. The vector X_{st} includes the following independent variables: MML – Equals one if a state had a medical marijuana law in a given month and zero otherwise; RML – Equals one if a state had a recreational marijuana law in a given month and zero otherwise; $Unemployment$ – Natural logarithm of monthly state unemployment rate; $Income$ – Natural logarithm of state annual real income per capita; $MilesDriven$ – Vehicle miles driven per licensed driver (thousands

Table 2.2: Independent Variables for the Fatality Analysis Reporting System Analysis

Independent Variable	Mean	Description
MML	.174 (.379)	Equals one if a state had a medical marijuana law in a given month and zero otherwise
RML	.00828 (.0902)	Equals one if a state had a recreational marijuana law in a given month and zero otherwise
Unemployment (monthly)	5.667 (1.870)	State unemployment rate
Income (annually)	4.493 (.144)	Natural logarithm of state income per capita
Miles Driven	14.426 (2.548)	Vehicle miles driven per licensed driver (thousands of miles)
Decriminalized	.227 (.419)	Equals one if a state had a marijuana decriminalization law in a given month and zero otherwise
Drug Per Se	.176 (.381)	Equals on if a state had a drug per se law in a given month and zero otherwise
GDL	.565 (.491)	Equals one if a state had a graduated driver–licensing law with an intermediate phase in a given year and zero otherwise
Primary Seat Belt	.402 (.490)	Equals one if a state had a primary seat belt law in a given month and zero otherwise
Secondary Seat Belt	.770 (.421)	Equals one if a state had a secondary seat belt law in a given month and zero otherwise
BAC .08	.604 (.489)	Equals one if a state had a .08 BAC law in a given month and zero otherwise
ALR	.769 (.421)	Equals one if a state had an administrative license revocation law in a given year and zero otherwise
Zero Tolerance	.800 (.399)	Equals one if a state had a zero–tolerance drunk–driving law in a given month and zero otherwise
Speed 70	.488 (.500)	Equals one if a state had a speed limit of 70 mph or greater in a given month and zero otherwise
Texting Ban	.199 (.392)	Equals one if a state had a cell phone texting ban in a given month and zero otherwise
Hands Free	.0392 (.194)	Equals one if a state had a hands–free cell phone law in a given month and zero otherwise

The data are based on the FARS state–level panel for 1990–2016. Standard deviations are in parentheses.

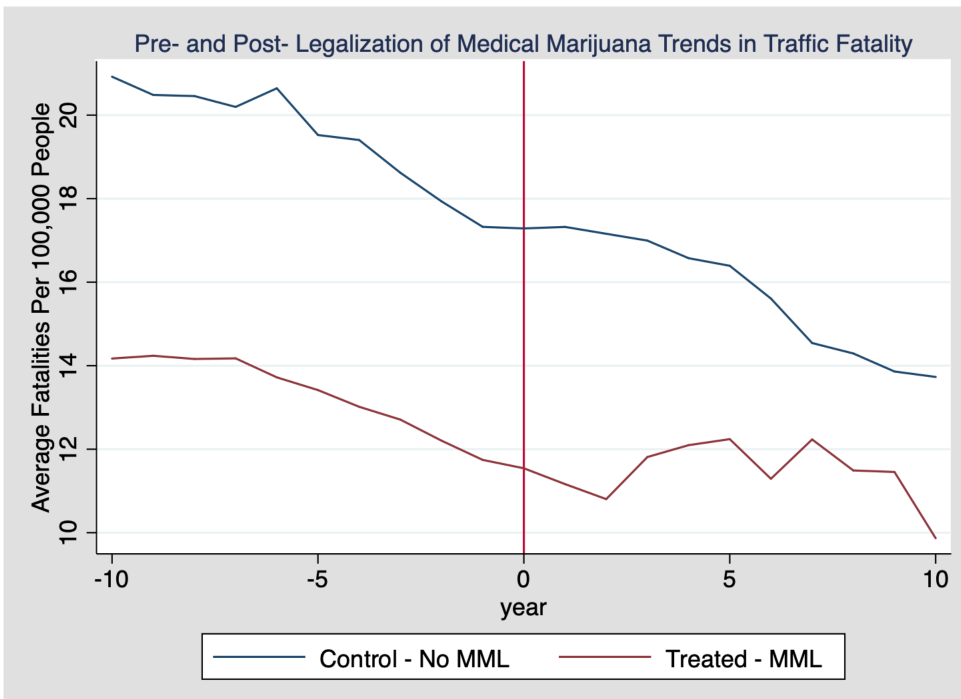
of miles); *Decriminalized* – Equals one if a state has had a marijuana decriminalization law in a given month and zero otherwise; *DrugPerSe* – Equals one if a state had a drug per se law in a given month and zero otherwise; *GDL* – Equals one if a state had a graduated driver–licensing law with an intermediate phase in a given year and zero otherwise; *PrimarySeatBelt* – Equals one if a state had a primary seat belt law in a given month and zero otherwise; *SecondarySeatBelt* – Equals one if a state had a secondary seat belt law in a given month and zero otherwise; *BAC*.08 – Equals one if a state had a .08 BAC law in a given month and zero otherwise; *ZeroTolerance* – Equals one if a state had a zero–tolerance drunk–driving law in a given month and zero otherwise; *Speed*70 – Equals one if a speed limit of 70 mph or greater in a given month and zero otherwise; *TextingBan* – Equals one if a state had a cell phone texting ban in a given month and zero otherwise; *HandsFree* – Equals one if a state had a hands–free cell phone law in a given month and zero otherwise. A detailed summary statistics of the control variables are shown on Table 2.2.

These variables are chosen because previous studies have provided evidence that various state–level policies can impact traffic fatalities, such as stricter seat belt laws are associated with fewer traffic fatalities (Cohen & Einav, 2003). Also, some studies have examined the effect of cell phone ban (Kolko, 2009) and BAC laws (Dee, 2001; Young & Bielinska-Kwapisz, 2006; Freeman, 2007) to the traffic fatality. Additionally, marijuana decriminalization was used as an indicator of policy change that may possibly have a direct impact on the usage of marijuana.

2.4 Results

In order to show the validity of the difference–in–differences results, the pre– and post– legalization of medical marijuana and recreational marijuana trends are shown in Figure 2.1 and Figure 2.2 in the appendix. Table 2.3 presents the results of the first regression model with data from 1990–2016, where the error terms were clustered within state level. The first column reports the standard ordinary least squares (OLS) estimates of the relationship between MMLs and traffic fatalities. The baseline estimate suggests that the legalization of medical marijuana leads to a decrease in the fatality rate. When the state fixed effect is included in the regression in the second column, the magnitude of the effect slightly dropped yet remains statistically significant. The coefficient of interest, which displays in the third column, includes month fixed effect as well as the state effect. At 95% confidence level, it suggests that there will be an approximate 6.8% drop in traffic fatalities after the MMLs have been passed. The results in this study are consistent with the ones from Anderson et al. (2013) – medical marijuana legalization leads to decrease in the fatality rate.

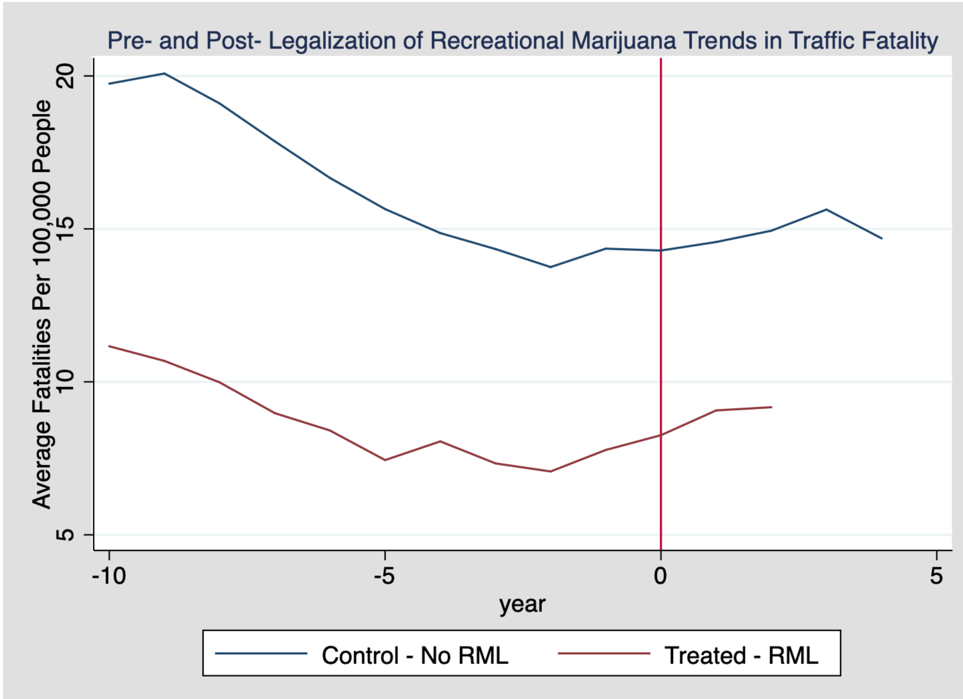
Figure 2.1: Pre– and Post– Legalization of Medical Marijuana Trends in Traffic Fatality



In the second model in Table 2.4 , the coefficient of interest is negative and statistically significant in the base model when clustering the standard errors at the state level. With the incorporation of month and state fixed effect, the coefficient switched positive and became statistically insignificant. This suggests that regressing traffic fatalities on RMLs alone does not give us a conclusive estimated effect.

Table 2.5 presents the third model of this paper. It attempts to explore the joint impact of MMLs and RMLs. On the first column, it shows that the coefficient of interest for MML is –0.0834.

Figure 2.2: Pre– and Post– Legalization of Recreational Marijuana Trends in Traffic Fatality



While the statistical significance and the sign remain, the magnitude has dropped to –0.0685 after incorporating both month and state fixed effects. On the other hand, RML has a positive yet a statistically insignificant value when controlling for month fixed effect. Hence, the model suggests that legalization of medical marijuana laws are associated with a decrease in traffic fatalities by 6.8 percent, and states with the legalization of recreational marijuana were not statistically different from the states without RMLs, which agrees with the findings from Aydelotte et al. (2017).

Next, instead of estimating the effect of the total number of traffic fatalities, the estimation of the relationship among MMLs, RMLs, and traffic fatalities are broken down by day and time of the accidents. Referring to Table 2.6 , the first column represents fatalities that occurred during the weekdays; the second column represents fatalities that occurred during the weekends; the third column represents fatalities that occurred during the daytime; while the fourth column represents fatalities that occurred during the nighttime. All four regressions in each column are using the specification of model (3). The results are consistent with the previous findings: states with MMLs have an approximately 5.5 to 7.5 precent decrease in traffic fatalities as opposed to states without them. In addition, the effect of RMLs on traffic fatalities remains statistically insignificant during different days and times according to the findings.

Lastly, unlike previous models, regressions are ran using the yearly–level data. Model (3) specifications again are employed here. From Table 2.7, it appears that results are aligned with the previous findings in the paper. Traffic fatalities decrease by about 6.8 percent in the states with MMLs, while no statistically significant difference is observed between states with or without RMLs.

Table 2.3: Model (1): Medical Marijuana Laws and Traffic Fatalities 1990–2016

	(a)	(b)	(c)
MML	-.0811**	-.0723***	-.0685**
	(.0351)	(.0201)	(.0276)
R^2	.9021	.9428	.9624
State fixed effect	No	Yes	Yes
Month fixed effect	No	No	Yes
State covariates	Yes	Yes	Yes

Reported are coefficients from weighted least squares regressions, weighted by state population size for 50 states and D.C. over 324 months. The dependent variable is the natural logarithm of the number of fatalities. Standard errors are in parentheses and are clustered to allow for nonindependence of observations from the same state. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2.4: Model (2): Recreational Marijuana Laws and Traffic Fatalities 1990–2016

	(a)	(b)	(c)
RML	-.136**	.0833***	.000614
	(.964)	(.0288)	(.0288)
R^2	.9195	.9425	.9622
State fixed effect	No	Yes	Yes
Month fixed effect	No	No	Yes
State covariates	Yes	Yes	Yes

Reported are coefficients from weighted least squares regressions, weighted by state population size for 50 states and D.C. over 324 months. The dependent variable is the natural logarithm of the number of fatalities. Standard errors are in parentheses and are clustered to allow for nonindependence of observations from the same state. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2.5: Model (3): Medical and Recreational Marijuana Laws and Traffic Fatalities 1990–2016

	(a)	(b)	(c)
MML	-.0834**	-.0730***	-.0685**
	(.034)	(.0202)	(.0276)
RML	.164***	.0924***	.00875
	(.0553)	(.507)	(.762)
R^2	.9203	.9428	.9624
State fixed effect	No	Yes	Yes
Month fixed effect	No	No	Yes
State covariates	Yes	Yes	Yes

Reported are coefficients from weighted least squares regressions, weighted by state population size for 50 states and D.C. over 324 months. The dependent variable is the natural logarithm of the number of fatalities. Standard errors are in parentheses and are clustered to allow for nonindependence of observations from the same state. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 2.6: MMLs, RMLs and Traffic Fatalities by Day and Time

	Fatals Weekdays	Fatals Weekends	Fatals Daytime	Fatals Nighttime
MML	-.0739**	-.0570**	-.0729**	-0.0628**
	(.0295)	(.0277)	(.0285)	(.0301)
RML	.00573	.00355	-.0592	.08759
	(.0339)	(.0376)	(.0554)	(.0367)
R^2	.950	.9171	.9422	.9278
State fixed effect	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
State covariates	Yes	Yes	Yes	Yes

The dependent variable is equal to the natural log of fatalities. Regressions are weighted using state populations. Standard errors, corrected for clustering at the state level, are in parentheses. Month fixed effects and state fixed effects are included in all specifications. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

2.5 Discussion and Next Steps

State legalization of both medical and recreational marijuana has been a trend the past 20 years in the U.S. This study explored the relationship between the legal access through RMLs and MMLs and the traffic fatalities. The findings showed that there is approximately a 6.8 percent decrease in traffic fatalities when states have medical marijuana laws in effect. On the other hand, the

Table 2.7: MMLs, RML, and Total Traffic Fatalities 1990–2016, yearly–aggregated data

	(1)	(2)	(3)
MML	-.0692		-.0680**
	(.0122)		(.0285)
RML		.0607	-.0484
		(.0329)	(.0326)
R^2	.756	.750	.756
State fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
State covariates	Yes	Yes	Yes

The dependent variable is equal to the natural log of fatalities per 100,000 people. Standard errors, corrected for clustering at the state level, are in parentheses. Year fixed effects and state fixed effects are included in all specifications. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

effect of recreational marijuana laws on traffic fatalities was not statistically significant. Since more states passed MMLs and RMLs in recent years, it has notably expanded the treatment groups size. Furthermore, using the most recently available dataset, the results in this study aligned and emphasized the findings from previous literature regarding both effects of both MMLs and RMLs on traffic fatalities. I intend to further expand analyses and contribute to previous research by examining relative rates of cannabis usage and traffic accident by age groups, demographics such as sex as men and women have different rates of usage (Jacobi & Sovinsky, 2016). In addition, further analyses such as synthetic control as well as other sensitivity tests will be performed.

Chapter 3

Marijuana Decriminalization, Medical Marijuana Laws, and Fatal Traffic Crashes in U.S. Cities, 2010–2017[1]

Marijuana is federally prohibited in the United States. However, since 1996, 33 states and Washington, DC, have passed laws legalizing medical marijuana. Of those 33 states, 21 enacted medical marijuana laws (MMLs) after a 2009 federal memorandum stated that federal funds would not be used to prosecute those in compliance with state MMLs. Following the 2009 Ogden Memorandum, the number of medical marijuana patients and dispensaries increased exponentially and the number of fatal crashes in which marijuana was detected in a driver increased by approximately 50%.(Smart, 2015; Smith, 2020). Although increased drug testing likely contributed to greater marijuana detection in drivers, recent studies found that MMLs are associated with a lower perceived risk of marijuana use among adults (Schuermeyer et al., 2014; Wen et al., 2019).

For states that have not enacted an MML, marijuana remains illegal. However, select municipalities in states without MMLs recently began reducing the criminal penalty for marijuana possession. Although many decriminalization laws were passed following years, the Controlled Substances Act of 1970 and well before states began enacting MMLs, recent decriminalization laws are viewed as a middle ground between prohibition and legalization. Decriminalization became more common within non–MML adopting states after the issuance of Ogden Memorandum in 2009, and allows cities to reduce penalties for possession of small amounts of marijuana without contradicting the prohibitive laws at the state and federal levels. Because the severity of

[1]This is a co–authored paper with Amanda C. Cook, Department of Economics, Bowling Green State University, and Rhet A. Smith, Department of Economics and Finance, University of Arkansas at Little Rock.The chapter is published in the American Journal of Public Health 110, no. 3 (March 1, 2020): pp. 363–369.

punishment is a cost associated with consumption Becker (1968), decriminalization will reduce the nonpecuniary costs associated with cannabis use. Studies examining early decriminalization laws found a positive relationship between cannabis decriminalization and marijuana consumption among young adults (Chaloupka et al., 1999a; DeSimone, 2002).

Marijuana is the most commonly used illicit substance in the United States (Sevigny et al., 2014) and is the most frequently detected non–alcohol substance in traffic crashes (National Institute of Drug Abuse, 2019). It has been shown to impair the cognitive and psycho–motor skills associated with driver–related functions (Kelly et al., 2004; Ramaekers et al., 2004; Sewell et al., 2009), and acute usage significantly increases the risk of motor vehicle collisions (Asbridge et al., 2012; Hartman & Huestis, 2013). Therefore, as more states legalize the use of cannabis for medicinal purposes and municipalities reduce the severity of punishment of cannabis possession, traffic safety may be adversely affected from increased driver impairment.

Even so, recent research examining the impact of marijuana legalization found that MMLs are associated with fewer traffic fatalities in those aged 15–24 or 25–44 years (Santaella-Tenorio et al., 2017). An earlier study found quantitatively similar results and argued the negative relationship is driven by changes in alcohol–related traffic deaths (Anderson et al., 2013). This suggests a substitutability between alcohol and marijuana. However, while MMLs reduce the legal costs associated with cannabis and provide legal protection to consumers, the laws also include stipulations that restrict marijuana consumption to a private residence. Thus, the incentives to travel concurrently or shortly after consuming marijuana are diminished, and it is not clear whether consumers are substituting away from other substances (e.g. alcohol) or away from travel.

Because decriminalization reduces the severity and probability of punishment without directly affecting consumer incentives to travel, we examined and compared the heterogeneous effects of marijuana decriminalization and medical marijuana legalization on fatal traffic crashes. Although there is evidence to suggest individuals are not fully aware of the extent of punishment for marijuana possession (MacCoun et al., 2009), earlier research examining the period after the first wave of state–level marijuana decriminalization bills in the 1970s found that individuals in decriminalized states were aware of their state marijuana laws (Johnston et al., 1981). Moreover, recent municipality–level decriminalization laws attracted attention from local and national media as well as state–level legislatures whose laws now differed from the local municipality, increasing the likelihood that citizens were aware of the reduced penalty associated with marijuana consumption.

By examining the impact of both decriminalization and MMLs, we were able to disentangle the channels through which marijuana policies and traffic safety are related. We also explored how this relationship varied by age and gender. Because traffic fatality rates and illicit drug use are highest among young drivers, and men are more likely than are women to drive under the influence of drugs or alcohol (Tefft, 2017; Center for Behavioral Health Statistics and Quality, 2018), we expected these demographics to be more responsive to changes in marijuana–related policies. Similarly, because drug and alcohol use is highest on weekend nights (Berning et al., 2015), we examined changes in fatal crashes by time of day. This last specification also validated our approach because statistically significant changes in weekday daytime crashes when drug and alcohol use is low are evidence of omitted variables confounding our results.

Last, a significant amount of the literature argues the potential substitutability or complementarity between alcohol and marijuana (Miller & Seo, 2018). Recent articles argued that the substitutability between substances is the mechanism through which traffic safety improves following MML enactment (Anderson et al., 2013; Santaella-Tenorio et al., 2017). We contribute to this discussion by examining the impact of the different marijuana–liberalizing policies on fatal crashes involving a drunk driver (blood alcohol concentration $\geq$ 0.08).

3.1 Methods

We obtained traffic fatality data from the Fatality Analysis Reporting System (FARS). The FARS is a census of all fatal motor vehicle crashes that occur on public roads and it includes driver information, crash location, and drug or alcohol presence in drivers. Our outcomes of interest included all fatal traffic crashes by age and gender. Because drug and alcohol use varies over the week, we also considered crashes that occurred on weekend nights and during the day on weekdays. We totaled individual crashes semiannually and aggregated them to the city level. Our sample included all cities with a 2017 population greater than 100 000 that are located in states that had not enacted MMLs or decriminalized marijuana by 2010. Our estimation strategy was to exploit the variation in the reduction of criminal penalties associated with marijuana to examine the impact of marijuana liberalization on fatal crashes. Therefore, we constructed our sample of cities so that all cities in the sample began the period with similar prohibitive laws before cities and states implemented measures to relax these legal constraints. The complete list of cities in our sample is provided in Tables A.42 and A.43 in the Appendix.

Because the U.S. marijuana market changed significantly following the 2009 Ogden Memorandum, we limited our analysis to the years 2010 through 2017 (n = 2496 semiannual city–level observations) to focus on the post–expansion relationship between marijuana liberalization and traffic safety to provide more relevant information to policymakers.

3.1.1 City Decriminalization Laws

Decriminalization of cannabis often occurs within states at the city or county level. To capture the impact of a city decriminalizing marijuana on fatal crashes, we omitted cities that had been previously exposed to state–level decriminalization policies. Table 3.1 provides the cities and dates of marijuana decriminalization that occurred within our sample period. We obtained state–level MML enactment dates from ProCon.org (2019).

3.1.2 Other Variables

Following previous research (Anderson et al., 2013), we controlled for time–varying local characteristics and changes in state legislation to isolate the effect of marijuana policies on fatal crashes. We included state–level traffic safety laws in the analysis, and these consisted of driver–texting laws, administrative license revocation laws, and per se drugged–driving laws. We obtained law enactment dates from the National Organization for the Reform of Marijuana Laws, Insurance Institute for Highway Safety, Governors Highway Safety Association, and previous literature (Abouk

Table 3.1: Cities with Decriminalization Laws with No Prior Medical Marijuana Laws: United States, 2010–2017

City	Date of Decriminalization
Chicago, IL	August, 2012
Springfield, MO	August, 2012
St. Louis, MO	June, 2013
Milwaukee, WI	June, 2015
Miami, FL*	July, 2015
Hialeah, FL*	July, 2015
Miami Gardens, FL*	July, 2015
Pembroke Pines, FL*	November, 2015
Hollywood, FL*	November, 2015
Miramar, FL*	November, 2015
Pompano Beach, FL*	November, 2015
Davie, FL*	November, 2015
West Palm Beach, FL*	December, 2015
Tampa, FL	April, 2016
New Orleans, LA	June, 2016
Orlando, FL	October, 2016
Garland, TX*	December, 2017
Pasadena, TX*	March, 2017
Houston, TX*	March, 2017
Dallas, TX*	December, 2017
Kansas City, MO	April, 2017
Atlanta, GA	October, 2017
Mesquite, TX*	December, 2017
Garland, TX*	December, 2017

Decriminalization dates describe the month when cities in the sample decriminalized marijuana. A city was considered to have decriminalized marijuana if the provisions were in place for the entire calendar month.

* City decriminalization results from county decriminalization laws

& Adams, 2013; Anderson & Rees, 2015), and we verified these dates through Thomson Reuters Westlaw and the National Conference of State Legislatures. We collected population and demographic characteristics from intercensal estimates of the U.S. Census Bureau. We obtained city unemployment rates from the Bureau of Labor Statistics. We included state–level per gallon beer tax rates from the Brewers' Almanac to control for the relative price of alcohol, as it may be a complement to or substitute for cannabis.

3.2 Model

To estimate the effect of marijuana decriminalization and medical marijuana legalization on fatal traffic crashes, we exploited the temporal and geographic variation in policy changes at the city and state levels using a difference–in–differences approach. The de- pendent variable was a count of fatal crashes that occurred in a city aggregated semiannually. We included 6–month periods with zero fatal crashes; these constituted approximately 7% of the city–half–year observations in our sample. Because the outcomes were positively skewed, we estimated a Poisson model

$$F_{cst} = exp(\beta_1 Decrim \times post_{cst} + \beta_2 MML \times post_{st} + X'_{cst}\theta + \alpha_c + \gamma_t + \ln(pop_{ct})) \quad (3.1)$$

where F_{cst} is a count of fatal crashes in city c in state s in half–year t. We standardized the number of crashes to per capita rates by constraining the coefficient on the natural log of the affected population to 1 (Osgood, 2000). This technique is common in Poisson–based regressions and we carried it out using the offset option in Stata version 15 (StataCorp LLC, College Station, TX). We also estimated Equation 1 using a negative binomial approach. Our results are not sensitive to this alternative specification and are available in Table A.44. City fixed effects were represented by α_c and controlled for time–invariant unobservable city characteristics. We included half–year fixed effects (γ_t) to control for unobservable variables that were constant across cities but varied over time. It is worth noting, the Poisson regression does not require the mean be equal to the variance (Silva

& Tenreyro, 2006), and the fixed effects Poisson model does not suffer from incidental parameters (Fernández-Val & Weidner, 2016). The vector X'_{cst} included city–level unemployment rates to control for macroeconomic conditions, state–level per gallon beer tax to control for the relative price of alcohol, and state–level traffic laws that could affect traffic safety. $Decrim \times post_{cst}$ is equal to 1 if a city decriminalizes marijuana and is equal to zero otherwise. Similarly, $MML \times post_{st}$ is equal to 1 if a state enacts an MML. We did not consider the 6–month period in which MML enactment or decriminalization occurred "treated" in our analysis. We clustered standard errors by city (Bertrand et al., 2004).

3.3 Results

We present the estimated impact of marijuana decriminalization and medical marijuana legalization on fatal crashes by age and gender in Table 3.2. Table 3.2 provides the Poisson–estimated incidence rate ratios (IRRs) on fatal crashes involving 15– to 24– year–old drivers, describes the relationship for crashes involving 25– to 44–year–old drivers, and provides the IRRs for all fatal crashes. The percentage change in fatal crashes is equal to (IRR – 1) · 100. An estimate was statistically significant at the 95% confidence level if 1 does not fall within the upper and lower bounds provided in parentheses. To quantify the magnitude of the percentage changes, the pretreated mean of fatal crash rates for each demographic group is provided under the estimated IRRs.

The results in Table 3.2 indicate that state–level MMLs were associated with fewer fatal crashes. Cities, on average, experienced a 9% reduction in fatal crashes following the implementation of an MML in their state (IRR = 0.91; 95% confidence interval [CI] = 0.84, 0.98). Although males were involved in more fatal crashes, the results suggested similar decreases in crashes involving male and female drivers. MMLs were also associated with fewer fatal crashes among young drivers (IRR = 0.86; 95% CI = 0.77, 0.97). However, the impact on fatal crashes involving young female drivers was no longer statistically significant. Unlike the reduction in fatal crashes following MML enactment, there was no evidence of a similar relative decrease in fatal crashes following marijuana decriminalization. In fact, a city experienced a 13% increase in fatal crashes involving young male drivers after a city decriminalized marijuana (IRR = 1.13; 95% CI = 1.01, 1.25). However, the relative increase in fatal crashes following marijuana decriminalization was not statistically significant overall for any other subgroup. We examined whether the differential effects observed across MMLs and marijuana decriminalization stemmed from differences in alcohol–related crashes. Consistent with state–level studies (Anderson et al., 2013; Leung, 2018), we found that MMLs were associated with fewer alcohol–related crashes. However, the estimated IRRs associated with marijuana decriminalization were not statistically significant for alcohol–related crashes of any demographic group.

Table 3.2: Poisson–Estimated Incident Rate Ratios (IRRs) of the Effect of Marijuana Policy Changes on Fatal Traffic Crashes by Age and Gender: United States, 2010–2017s

	(1) Male		(2) Female		(3) All		(4) BAC$\geq$ 0.08	
Panel A: Ages 15-24								
Decriminalization	1.125	(1.014,1.249)	0.892	(0.692,1.150)	0.966	(0.872,1.070)	1.013	(0.769, 1.333)
State MML	0.884	(0.783,0.998)	0.876	(0.683,1.123)	0.859	(0.765,0.965)	0.741	(0.524, 1.049)
pre-treated mean†	28.044		10.513		19.292		1.658	
Panel B: Ages 25-44								
Decriminalization	0.972	(0.879,1.075)	0.961	(0.803,1.150)	1.038	(0.909,1.185)	0.953	(0.780,1.165)
State MML	0.864	(0.794,0.939)	0.849	(0.703,1.026)	0.881	(0.765,1.014)	0.721	(0.597,0.872)
pre-treated mean†	20.317		9.764		14.910		1.394	
Panel C: All Ages								
Decriminalization	1.017	(0.940,1.099)	1.004	(0.905,1.113)	1.021	(0.947,1.102)	0.953	(0.794, 1.145)
State MML	0.905	(0.840,0.976)	0.892	(0.807,0.986)	0.907	(0.843,0.976)	0.718	(0.584, 0.882)
pre-treated mean†	10.559		5.914		5.327		0.903	

Table includes Poisson-estimated incidence rate ratios and corresponding 95% confidence intervals of the effect of marijuana policy changes on fatal crashes by age and gender. Each specification includes city and half-year fixed effects, state-level traffic safety laws, and city-level semi-annual average unemployment rates. Standard errors are clustered at the city level.

†- Pre-treated mean of rate of fatal crashes per 100,000 people within the demographic category.

3.3.1 Fatal Crashes by Day and Time

Because drivers are more likely to test positive for alcohol or marijuana on weekend nights (Berning et al., 2015), the effects of marijuana policies on fatal crashes should be most evident this time of the week. Moreover, significant effects of marijuana–related policies on weekday day–time crashes would be evidence of omitted variables confounding our results. Therefore, we estimated the effects of MMLs and marijuana decriminalization on fatal crashes by day and time of the week.

The results are presented in Table 3.3. For each demographic group, we did not find any evidence that marijuana decriminalization or MMLs affect fatal daytime crashes on weekdays. For weekend nights, however, we found that cities experienced fewer fatal crashes following MML enactment. Conversely, we found that marijuana decriminalization was associated with a relative increase in fatal crashes involving males and young drivers. Decriminalization effects were not statistically significant for female–related crashes of any age group. These results were consistent with the results in Table 3.2 and suggest MMLs are generally associated with fewer fatal crashes, whereas fatal crashes among young and male drivers increased following marijuana decriminalization.

Table 3.3: Poisson-Estimated Incidence Rate Ratios (IRRs) of the Effect of Marijuana Policy Changes on Fatal Crashes by Age, Gender, and Time of Week: United States, 2010–2017

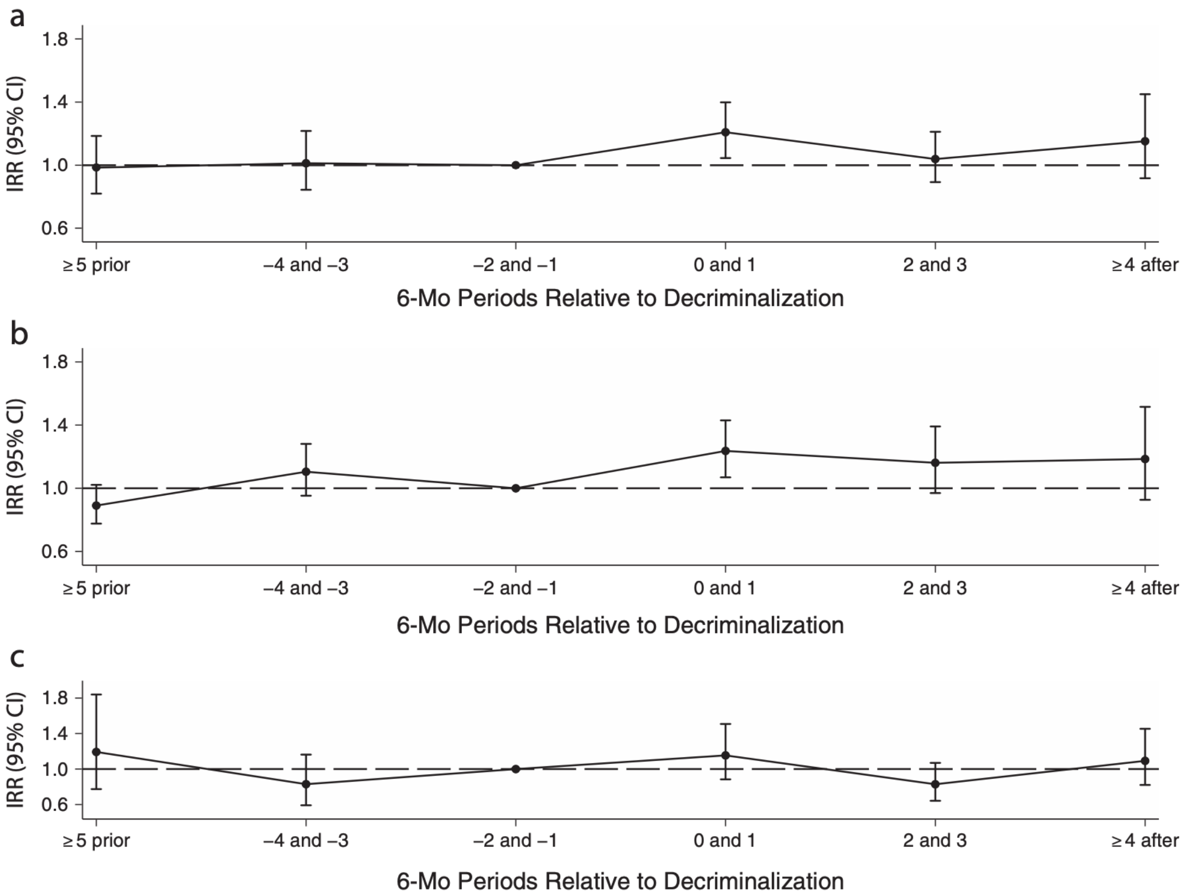
	(1) Male		(2) Female		(3) All	
Panel A: Ages 15-24	Changes in Weekday Crashes					
Decriminalization	1.061	(0.900,1.251)	0.892	(0.692,1.150)	0.990	(0.852,1.152)
State MML	0.873	(0.685,1.113)	0.876	(0.683,1.123)	0.886	(0.677,1.159)
	Changes in Weekend Night Crashes					
Decriminalization	1.428	(1.107,1.842)	1.294	(0.976,1.715)	1.372	(1.087,1.730)
State MML	0.762	(0.615,0.944)	0.758	(0.594,0.968)	0.763	(0.632,0.920)
Panel B: Ages 25-44	Changes in Weekday Crashes					
Decriminalization	0.907	(0.749,1.099)	0.931	(0.707,1.225)	0.915	(0.749,1.117)
State MML	0.818	(0.658,1.015)	0.831	(0.605,1.140)	0.825	(0.649,1.047)
	Changes in Weekend Night Crashes					
Decriminalization	1.262	(1.018,1.564)	1.048	(0.792,1.385)	1.178	(0.949,1.463)
State MML	0.781	(0.660,0.923)	0.819	(0.657,1.020)	0.794	(0.668,0.944)
Panel C: All Ages	Changes in Weekday Crashes					
Decriminalization	0.883	(0.765,1.019)	0.851	(0.659,1.098)	0.869	(0.742,1.018)
State MML	0.853	(0.687,1.059)	1.019	(0.743,1.398)	0.912	(0.709,1.171)
	Changes in Weekend Night Crashes					
Decriminalization	1.247	(1.018,1.528)	1.173	(0.897,1.536)	1.219	(0.992,1.499)
State MML	0.743	(0.633,0.872)	0.850	(0.720,1.003)	0.781	(0.671,0.908)

Table includes Poisson-estimated incidence rate ratios and corresponding 95% confidence intervals of the effect of marijuana policy changes on fatal crashes by age and gender. Each specification includes city and half-year fixed effects, state-level traffic safety laws, and city-level semi-annual average unemployment rates. Standard errors are clustered at the city level.

3.3.2 Marijuana Decriminalization Over Time

To examine the time–varying effects of marijuana decriminalization and ensure that the previous estimated effects on young drivers were not driven by poor comparability between treated and untreated cities before decriminalization, we implemented an event study approach common in policy analysis. The estimated IRRs (and corresponding 95% CIs) on fatal crashes involving young drivers for each period relative to cannabis decriminalization are described in Figure 1. The 12 months before decriminalization are normalized to 1 and each point along the x–axis corresponds to two 6–month periods relative to a city decriminalizing marijuana. For each subgroup, there were no obvious violations to the parallel trends assumption our difference–in–differences strategy relied on. There were no trends in the pre–decriminalization IRRs and no point estimate was statistically significant. In the period in which a city decriminalized marijuana, however, there was a temporary increase in fatal crashes involving young male drivers that attenuated to become non–statistically significant after 6 months of decriminalization. There was no evidence of marijuana decriminalization affecting crashes involving young female drivers and the attenuation was more severe when examining the impact on fatal crashes involving all young drivers.

Figure 3.1: City-Level Time-Varying Marijuana Decriminalization Effects on Fatalities Among Drivers Aged 15–24 Years by (a) All, (b) Males, and (c) Females: United States, 2010–2017



CI = confidence interval; IRR = incidence rate ratios (Poisson estimated). The coefficient on the 12–month period before a city decriminalizing marijuana is normalized to 1. Period 0 indicates a city decriminalizes marijuana, and period 1 is the first full 6–mo period of treatment. The 95% CIs are displayed at each point. Periods greater than 2.5 years before or 2 years after decriminalization are combined into bins at –5 periods and +4 periods, respectively.

3.4 Discussion

Using a census of fatal traffic crashes aggregated to the city level, we found that cities that are located in states that enacted MMLs experienced fewer fatal crashes following medical marijuana legalization. The relative decline was strongest for 15– to 24–year–old drivers, a demographic group with the highest fatal crash rate among all age cohorts (younger than 80 years) and most likely to operate a vehicle under the influence of alcohol or marijuana (Tefft, 2017; Center for Behavioral Health Statistics and Quality, 2018). On average, fatal crashes involving drivers of this age group decreased by 14% following MML enactment. Relative to the pretreated average rate of fatal crashes, this decrease equates to approximately 2.7 fewer fatal crashes per 100 000 15– to 24–year–old people following state–level medical marijuana legalization. Although our study differs by level of observation and time period, these results are consistent with previous studies (Anderson et al., 2013; Santaella-Tenorio et al., 2017; Leung, 2018).

Second, we found that the impact of marijuana decriminalization on fatal crashes differed from that of medical legalization. On average, a city experienced 13% more fatal crashes involving 15– to 24–year–old male drivers following city–level marijuana decriminalization (an average of approximately 3.5 more fatal crashes per 100 000 15– to 24– year–old males). However, there was no evidence of changes in fatal crashes among females or older drivers, suggesting that young males responded to marijuana de– criminalization differently than did other populations. The increase in fatal crashes involving young drivers was most pronounced immediately after decriminalization before attenuating to non–significance in later periods of decriminalization.

The temporary effect on fatal crashes is comparable to the short–term accident reductions following anti–texting laws (Abouk & Adams, 2013). Similarly, although not statistically significant at conventional levels, Washington State experienced a temporary increase in traffic fatalities after legalizing recreational marijuana (Hansen et al., 2020). Most similar to our article, Santaella-Tenorio et al. (2017) found an immediate relative decrease in traffic fatality rates among those aged 15 to 24 years after MML enactment that was not evident in later years of legalization. Thus, the temporary effects observed here and in related traffic safety literature suggest drivers may initially react to the announcement of city decriminalization laws before reverting back to previous behaviors.

Third, we did not find evidence that either marijuana–related policy affects fatal crashes that occur during the day on weekdays. These null results suggest that our findings are not being confounded by omitted variables. Instead, the effects on fatal crashes are most evident on weekend nights, when drug and alcohol use is highest among drivers (Berning et al., 2015).

Fourth, we found that MMLs and marijuana decriminalization had heterogeneous effects on alcohol–related fatal crashes. Although the relative decrease in alcohol–related fatal crashes following medical marijuana legalization was consistent with a substitutability between substances, we did not find evidence of a similar effect following marijuana decriminalization. Because MMLs and decriminalization both reduce the non–pecuniary costs associated with marijuana, the effects of each policy should be qualitatively similar if the results are attributable to changes in alcohol consumption.

Although we cannot eliminate the possibility that the relationship between alcohol and cannabis may differ across decriminalized and conditionally legal environments, the heterogeneous effects on alcohol–related traffic crashes and fatal crashes overall suggest that changes in consumer travel behavior may be the mechanism driving the differing outcomes. Specifically, MMLs dictate that consumption occur in a private residence. Thus, marijuana consumers in MML states, while facing lower costs to consume marijuana (relative to a prohibitive state), now have lower incentives to travel after consumption. Although previous research argues that a substitution away from alcohol is occurring and improving traffic safety (Anderson et al., 2013), the reduced incentives to travel will also lessen the probability of a crash occurring. It is difficult for researchers to disentangle the mechanisms through which traffic safety is improving.

In a decriminalized environment, however, the legality of the drug has not changed. Instead, decriminalization reduces the severity and probability of punishment without directly affecting consumer incentives to travel. Although MMLs are associated with fewer fatal crashes, the relative reduction in fatal crashes is not evident after marijuana decriminalization. Rather, we found that marijuana decriminalization was associated with increased fatal crashes involving younger drivers, for whom driving under the influence of marijuana or alcohol is more common (Center for Behavioral Health Statistics and Quality, 2018).

3.4.1 Limitations

The FARS documents all fatal crashes that occur on public roads. However, the data set has limitations. First, fatal crashes constitute a small percentage of total crashes. Therefore, we cannot comment on the relationship between marijuana laws and less severe traffic outcomes. This outcome should be explored in future research.

We also did not examine whether these laws affected marijuana presence in drivers. Although these data are available in the FARS, drug detection does not imply driver impairment. In addition, because testing procedures vary by state and over time, it is not reliable in examining changes in marijuana–related impairment in drivers. We addressed this limitation by focusing on total fatal crashes and total crashes that occurred on weekend nights, when substance use is highest.

A second limitation of our study was that we did not explore the impacts of various aspects of marijuana laws. MMLs differ by qualifying medical conditions, restrictions regarding consumption, and quantities of cannabis a person may possess (Pacula et al., 2015; Smith, 2020). Similarly, marijuana decriminalization is not uniform and can be defined as the de–prioritization of marijuana–related law enforcement or by significantly reducing the penalty associated with marijuana possession. Our analysis relied on the assumption that the relationship between alcohol and cannabis is consistent across legal status. Put differently, we could not rule out changes in alcohol consumption if alcohol is complementary to cannabis in decriminalized marijuana regions but a substitute for cannabis in MML states. However, we only observed alcohol consumption after a fatal crash occurred and cannot directly comment on a possible heterogeneous alcohol–marijuana relationship that differs by the legal status of marijuana.

Third, we used city–level observations because many within–state changes in marijuana policies occur in metropolitan areas, and comparing cities with rural areas could bias the estimates. It is possible that rural areas may be affected differently by changes in marijuana policies than urban areas. We leave this as an avenue for future research.

3.4.2 Public Health Implications

The marijuana market in the United States changed significantly over the past 10 years. As more states continue to implement marijuana–liberalizing polices, understanding the unintended consequences of such policies is becoming increasingly important. Although recent research focuses on the implications of legalized medical and recreational marijuana (Kim et al., 2016; Hansen et al., 2020), the effects of marijuana decriminalization in states where marijuana use is still prohibited is largely ignored by the literature. Although our findings of fewer fatal traffic crashes following MML enactment are consistent with previous studies (Anderson et al., 2013; Santaella-Tenorio et al., 2017; Leung, 2018), we provide evidence that marijuana decriminalization has the opposite effect on fatal crashes involving young male drivers that is most pronounced immediately following decriminalization.

Marijuana decriminalization and MMLs relax the prohibitive market constraints and are associated with greater marijuana use (Chaloupka et al., 1999a; Chu, 2014). Although decriminalization is often argued as a compromise between prohibition and medical marijuana legalization, the 2 marijuana policies do not have similar effects on traffic safety. Thus, from a public health perspective, we must be careful not to assume that the impact of decriminalization will be some intermediate impact between criminalization and medical marijuana legalization or we will miss a critical opportunity to inform policy. Moreover, the heterogeneous effects on traffic safety across marijuana decriminalization and MMLs emphasize a need for caution from generalizing spillover effects from MMLs to recreational use environments. Our findings suggest that reducing the non–pecuniary costs of marijuana through decriminalization without explicitly affecting travel behaviors will have adverse effects on traffic safety. As the United States becomes more permissive toward marijuana, policies should be crafted to discourage travel and limit this effect.

Chapter 4

Profits from Sins: The Substitution (Complementarity) of State Revenue from Alcohol, Tobacco and Marijuana Taxation[1]

4.1 Introduction

A consistent source of revenue for state governments has been the taxation of “sins”, or taxes on goods and services considered detrimental for ones’ well–being or society. Such “sins” often include the consumption of alcohol, tobacco, gambling and even sugar–sweetened beverages (Fletcher et al., 2010). Increasing the price to consume “sinful” behaviors through taxation acts to both reduce consumer demand and to redeem “sins” by re–distributing taxes to other public services. Recently, some U.S. states have begun to experiment with a new source of “sin" taxation, marijuana.

While still classified as a Schedule I drug under federal law, medicinal use of marijuana has been accepted in the majority of U.S. states as an alternative treatment for health conditions such as acute chronic pain management or terminal illness. As of December 2018, 33 states and the District of Columbia have passed medical marijuana laws (MMLs). The legalization of marijuana for recreational use has been more controversial. Recreational marijuana laws (RMLs) allow any person 21 and older to purchase and possess marijuana for personal consumption and 10 states and D.C. (see Table 4.1) have passed RMLs. [2]

This paper examines the effect of the recent enactment of RMLs on state–level “sin" tax rev-

[1]This is a co-authored paper with Scott Dallman, Department of Applied Economics, University of Minnesota

[2]The District of Columbia has also passed medical and recreational marijuana laws but has not allowed sale of marijuana due to its unique relationship with the federal government

Table 4.1: Recreational Marijuana Laws, 2014-2018

	Date of Legalization
Colorado	January 1, 2014
Washington	July 8, 2014
Alaska	February 24, 2015
District of Columbia*	February 26, 2015
Oregon	October 1, 2015
California	November 9, 2016
Massachusetts	December 15, 2016
Maine	December 18, 2016
Nevada	January 1, 2017
Vermont	July 1, 2018
Michigan	December 16, 2018

*D.C. does not allow sale of marijuana due to its unique relationship with the federal government.

enues for potential substitute or complementary "sin" goods, specifically alcohol and tobacco products.

Although U.S. marijuana-related studies are quickly proliferating with the passage of RMLs in several states, much of the current interest in RMLs is focused on individuals' behavioral response to increased accessibility and the exploitation of illicit inter–state arbitrage opportunities. A major concern of RML opponents is its potential negative impact on driving and traffic fatalities (HIDTA, 2017; Hansen et al., 2020). Another concern is the spillover effects of RMLs on marijuana consumption and possession in nearby states. Working papers by Hansen et al. (2017a) on inter–state consumer–level marijuana trafficking as well Hao & Cowan (2017) which estimates the effect of RMLs in Washington and Colorado on rates of marijuana possession–related arrests. They found that RMLs significantly increased rates of marijuana possession–related sales and arrests in the bordering non–RML counties. Using enactments of state–level MMLs, (Wen et al., 2015) found similar effects on marijuana use in bordering states. Another study by Anderson et al. (2015) found evidence of increased teen marijuana use following the passage of MMLs.

On the other hand, a large amount of research has been conducted at the individual–level correlations between substance abuse of alcohol, tobacco and marijuana with prices as well as each other with contradictory conclusions. Using several survey data sources, some economists suggested that marijuana and alcohol are economic complements rather than substitutes and increased taxation of alcohol would potentially reduce consumption of both goods (Chaloupka et al., 1999b; Pacula, 1998a,b; Farrelly et al., 1999; Williams et al., 2004). In addition, using National Housing Survey on Drug Abuse, Farrelly et al. (2001) found that both higher fines for marijuana possession and increased probability of arrest decrease the the likelihood of young adult marijuana use. Higher cigarette taxes suggestively decreases the intensity and likelihood of marijuana use. However, related work by DiNardo & Lemieux (2001) on the effect of increasing the legal minimum drinking age found that it had the unintended consequence of slightly increasing the prevalence of marijuana consumption due to substitution away from alcohol.

There is extensive economics literature on the optimal taxation of goods and services in order to raise government revenue, distort consumer behaviors and provides incentives to guide economic investment and research (Hines Jr, 2007). Some study the effects of "sin" taxation, largely legal alcohol and tobacco, and intersect these traditional economic analyses of optimal taxation with additional insights from rational addiction theory and behavioral economics (Becker & Murphy, 1988; Chaloupka et al., 1999b; O'Donoghue & Rabin, 2003, 2006).

From a paternalistic aspect, many economists believe that while consumers may derive utility from "sin" tax consumption, their decisions are short–sighted, not factoring in negative spillover effects of "sin" consumption on their health and others' welfare. Therefore, there is a public impetus to try and reduce the level of "sin" consumption through prices in order to reduce potential externalities such as declining health and premature death (Becker et al., 1990, 1991; Grossman et al., 1993; Cook & Moore, 1994; Moore, 1995; Gruber, 2002; Pacula & Lundberg, 2013; Anderson & Rees, 2014). However, since the passage of RMLs are relatively recent, little is known about how legal marijuana consumption interacts with alcohol and tobacco consumption at the aggregate level.

Our contribution to the academic literature is two–fold. First, this study provides a descriptive overview of recent trends in state–level "sin" tax revenues as well as state–level comparisons of recreational marijuana tax revenues for those which have enacted RMLs. Although tax revenue from the sale of medical marijuana is small or non–existent since states impose little or no tax on pharmacutical goods, the regulation and sale of recreational marijuana products presents a lucrative opportunity for state tax agencies (Caputo & Ostrom, 1994). By broadening the potential tax base of marijuana users to all individuals 21 and older, creating state–exclusive production and sales restrictions and leveraging social mores to impose large excise "sin" taxes on marijuana, states with longstanding RMLs such as California, Colorado, Washington and Oregon have collected substantial tax revenue from marijuana and appropriated the proceeds towards other public interests.

Second, to the authors' knowledge, no recent academic study has investigated the fiscal implications of RMLs for the aggregate consumption of other "sin" goods. Therefore, an important empirical question to ask policy makers as well as public health advocates is "how does marijuana legality complement the consumption of other 'sins' (tobacco/alcohol)?" or "does passage of state RMLs reflect a rising trend in the substitution of demand from other 'sins' like tobacco, which has declined due to intensive anti–smoking and anti–tobacco campaigns, or alcohol, one of the leading indirect causes of death in the U.S.(Grossman et al., 1993; Cutler et al., 2002; Gruber, 2002)?" If marijuana is complementary to alcohol and/or tobacco use, the legalization of recreational marijuana provide states the benefit of the regulation and taxation of marijuana as well as increased tax revenues from other "sin" goods at the potential cost of increasing public health concerns. However, if marijuana use is a substitute for potentially more risky health behaviors (alcohol/tobacco), then the net tax revenue benefits of RMLs may be less than what is collected in sales tax revenues with less certain consequences for public health.

To empirically estimate the causal impact of RMLs on aggregate state "sin" (alcohol, tobacco and marijuana) tax revenues, we conduct a difference–in–differences analysis using quarterly state–level tax revenue data for alcohol, tobacco and marijuana (for states which have enacted RMLs) as well as demographics from 2010–2018 and normalizing the start of the treatment period by the effective state RML enactment date.

Preliminary results show that RMLs have no statistically significant impact on aggregated state tobacco tax revenue. However, RMLs are found to have a statistically significant negative impact on state alcohol tax revenue. Although it is difficult to disentangle the substitution/complementary effects between recreational marijuana and tobacco taxation, the results suggest that a substitution of state revenue (aggregate state consumption) from alcohol to marijuana products.

4.2 U.S. Marijuana Legislation Over the Last Century

The last 100 years of U.S. marijuana laws can be separated into four distinct periods: prohibition beginning in the early 1900s, decriminalization in the 1970s, legalization of medical marijuana (MMLs) in the 1990s, and legalization of recreational marijuana (RMLs) in the 2010s. A summary of the dates of legalization of MMLs and RMLs are provided in Table 1.1 . In 1913, California passed the first marijuana prohibition law aimed at recreational use, and by 1936 the remaining 47 states had enacted similar legislation (Anderson et al., 2013). The federal Marihuana Tax Act in 1937 further restricted marijuana for medicinal use. In 1970, marijuana was classified as a Schedule I drug.[3]

However in 1973, Oregon became the first state to decriminalize the possession of cannabis. By 1978, there were a total of eleven states that decriminalized marijuana. In 1996, California became the first state to enact medical marijuana laws (MMLs). Up until December, 2018, 33 states and the District of Columbia have legalized marijuana for medical purposes. A few studies such as Serrano et al. (2008) and Hill (2015) have suggested that the intake of cannabinoids, an organic compound found in cannabis, may have medicinal benefits for treating certain symptoms and diseases.

While the use, possession, sale, cultivation, and transportation of marijuana continues to remain illegal under federal U.S. law, 11 states and the District of Columbia have legalized marijuana use for recreational purposes starting with Colorado in 2012. In states that have enacted RMLs, any

[3]According to the Controlled Substance Act, a Schedule I drug must have a “high potential for abuse” and “no currently accepted medical use in treatment in the United States”

person 21 or older may possess as well as consume small amounts of marijuana on one's private property or in licensed public bars, lounges, and restaurants.

4.3 Data on Recreational Marijuana Tax Revenue

Data was collected from several different sources for the period 2010–2018. Information on quarterly state–level tax revenue was collected from the Quarterly Summary of State and Local Tax Revenue (QTAX). QTAX is a survey conducted by the U.S. Census Bureau of detailed tax revenue data for individual state governments. The survey population includes all 50 state governments and tax authorities that report tax revenues. The survey is a complete enumeration of all state government imposers and therefore does not have any tax revenue sampling error. Each state government provides the Census with administrative accounting records. These administrative records are unique to each state as each state is legally organized differently.

In order to harmonize tax revenue statistics across state governments, the Census Bureau conducts two major procedures. First, the Census defines the term "state government" as referring "not only to the executive, legislative, and judicial branches of a given state, but it also includes agencies, institutions, commissions, and public authorities that operate separately or somewhat autonomously from the central state government but where the state government maintains administrative or fiscal control over their activities as defined by the Census Bureau." Therefore, state–level QTAX data from the Census may differ from published state government data because of a potential difference in definition.

Second, the Census Bureau constructs uniform tax categories for more than 25 types of taxes including personal income, sales and corporate income taxes. In the context of the survey, "taxes" are defined as "all compulsory contributions exacted by a government for public purposes, except employer and employee assessments for retirement and social insurance purposes." All receipts from licenses and compulsory fees, including those that are imposed for regulatory purposes, as well as those designated to provide revenue are also included.[4]

[4] Quarterly Summary of State and Local Government Tax Revenue Survey Methodology

State–level marijuana tax revenue data were collected from each state which had passed a RML and began marijuana–related tax collection until 2018. Over the study period Q1 2010 – Q4 2018, 9 states enacted RMLs: Alaska, California, Colorado, Maine, Massachusetts, Nevada, Oregon, Vermont, and Washington.[5]

While medical marijuana is exempted from state sales tax since it is classified as a pharmaceutical good in most states, MMLs and other state–level drug policies which remove penalties for marijuana possession may affect illicit consumption behaviors (Pacula et al., 2014). In general, the other legislation which reduces consequences for possession would affect illicit marijuana use confounding the affect of RMLs. Therefore, we also collect information regarding whether states have enacted RMLs as well as MMLs, drug per se laws or have decriminalized the possession of marijuana.

Additional geographic variation which may affect rates of alcohol, tobacco and marijuana consumption are controlled for using one–year U.S. American Community Survey (ACS) estimates available from IPUMS–USA. Demographic characteristics controlled for include state population counts, age, race, education, percent single female households, per capita income, as well as unemployment and poverty rates.

Descriptive statistics for the entire study period, 2010–2018 are presented in Table 4.2. The first column presents mean values for all 50 states. The second and third columns decompose mean values by RML and Control states for those states which passed RMLs by Q4 2016 (AK, CO, OR, WA). Figure 4.3 shows time trends in marijuana tax revenues for those states which passed RMLs by Q4 2018.

All treated states also have MMLs (row 5) prior to the legalization of marijuana for recreational use. This shows a pattern and path of state liberalization of marijuana. In general, control states tend to have a higher quarterly tobacco and alcohol tax revenue. This could likely be due to differences in sizes of the states. Control states include the most populous states in the U.S. such as California, Texas, Florida and New York and this could drive up the total average population as

[5]The District of Columbia has also passed medical and recreational marijuana laws but has not allowed sale of marijuana for recreational purposes due to its unique relationship with the federal government.

Table 4.2: Summary Statistics

Variables	N= 1800 (1) All States	N=324 (2) RML States	N= 1476 (3) Control States
	Mean	Mean	Mean
Quarterly Tobacco Tax Revenue (in Millions $)	85.87	80.72	87.00
Quarterly Alcohol Tax Revenue (in Millions $)	29.70	25.40	30.61
Quarterly Tobacco Tax Revenue per 18+ ($)	21.05	22.96	20.63
Quarterly Alcohol Tax Revenue per 21+ ($)	6.62	6.61	6.41
State Medical Marijuana Laws	41.61%	100%	29.60%
State Drug Per Se Law	33.00%	14.20%	37.10%
State Marijuana Decriminalization Laws	9.94%	22.50%	7.18%
Annual Income per capita (in thousands $)	26.81	28.56	26.43
Population (in millions)	6.26	7.39	6.01
Unemployment Rate	6.63 %	7.39%	6.51%
Poverty	13.22%	11.97%	13.49%
Food Stamp	12.29%	16.27%	12.44%
Age	38.04	38.23	37.99
Female	50.89%	50.44%	50.99%
White	70.12%	70.28%	70.08%
Black	10.09%	3.85%	11.46%
Other Race	8.51%	14.42%	7.86%
Education – Bachelors	56.01%	58.87%	55.38%
Education – High School	29.72%	27.87%	30.12%
Education – Less than High School	14.27%	13.26%	14.50%

well as the likelihood of having a higher number of tobacco and alcohol customers. On average, states which have enacted RMLs have a significantly smaller population, about $2/3$ of the national average and the subgroup of control states.

When we adjust the tax revenue by population (rows 3-4), the means become objectively similar across the states with and without RMLs. The remaining control variables are also reasonably comparable. Figures 4.1–4.3 show the recent trend of the RML states' average alcohol tax revenue per age of 21+, average tobacco tax revenue per age of 18+, and RML marijuana sales tax collection over the study period from 2010–2018. The breakdown of individual states' alcohol tax revenue are shown from A.9–A.15, tobacco tax revenue are shown from A.16–A.22, and marijuana tax revenue are shown from A.24–A.28.

Figure 4.1: RML States Average Alcohol Tax Revenue Per Age 21+

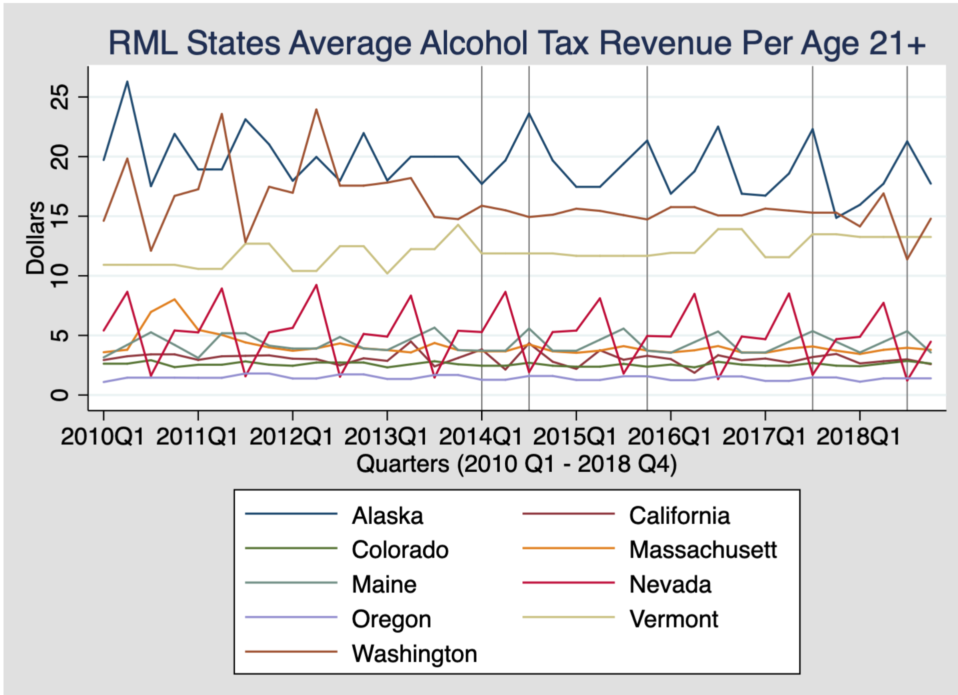


Figure 4.2: RML Average Tobacco Tax Revenue Per Age 18+

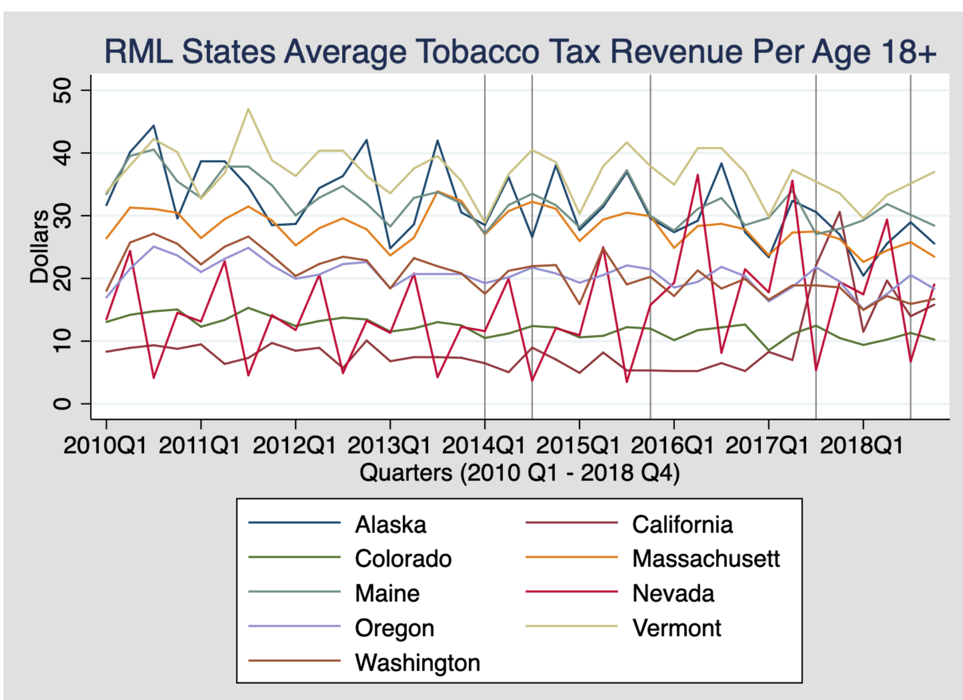
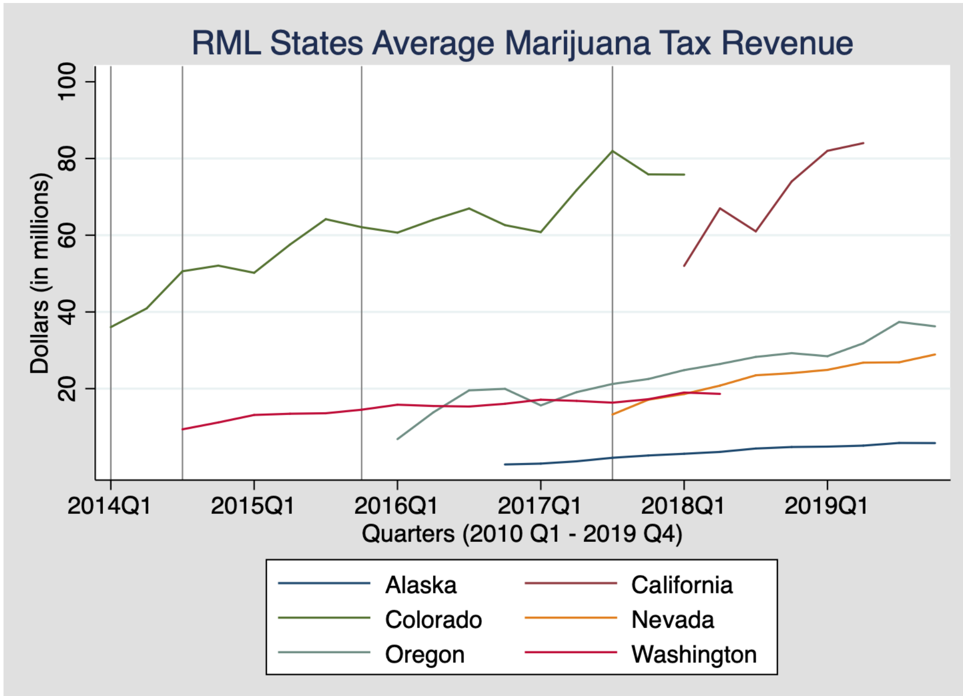


Figure 4.3: RML States Average Marijuana Tax Revenue



4.4 Estimating the Effect of RMLs on Other "Sins"

Using a difference–in–differences framework to examine whether the recreational legalization of marijuana has contributed to the tax revenue of other sin goods, specifically alcohol and cigarettes from 2010–2016. While normalizing the effective dates of RMLs, we merge it with the state–level administrative tax revenue data. The dependent variables in the models are the specific "sin" tax revenue, which include tobacco and alcohol tax revenue. Our difference-in-difference variable, RML_{st} is constructed by interacting the treatment states and the quarter posted the implement of the RML.The vector X_{st} is composed of the controls (independent variables). State fixed effect, represented by δ_s, control for time-invariant unobservable factors at the state level and quarter fixed effect are represented by τ_t.

Effect of RMLs on Total State Tax Revenues : Difference–in–Difference

$$TobaccoTaxRevenue_{it} = \alpha_0 + \beta_1 RML_{st} + \beta_2 OtherDrugPolicies_{it} + \beta_3 X_{it} + \delta_i + \tau_t + \varepsilon_{it} \quad (4.1)$$

$$AlocoholTaxRevenue_{it} = \alpha_0 + \beta_1 RML_{st} + \beta_2 OtherDrugPolicies_{it} + \beta_3 X_{it} + \delta_i + \tau_t + \varepsilon_{it} \quad (4.2)$$

RML_{st}: $RMLTreat_i \times RMLPost_t$

$Treat_i$: State that passed/Implemented RML

$Post_t$: Quarter after passing RML

δ_i, τ_t : State, Quarter–FEs

One assumption we need when employing difference–in–difference model is the exhibition of a parallel trend between the treatment and control prior to the policy change. In the context of sensitivity analysis, we assess the impact on tax revenue due to the RMLs with an event study approach. Using the event study model, it is suggestive that both alcohol and tobacco tax revenue exhibit parallel pre–trends, as shown in Figures 4.4 and 4.5.

Figure 4.4: Event Study: Effect of RMLs on Average Alcohol Tax Revenue Per Age 21+

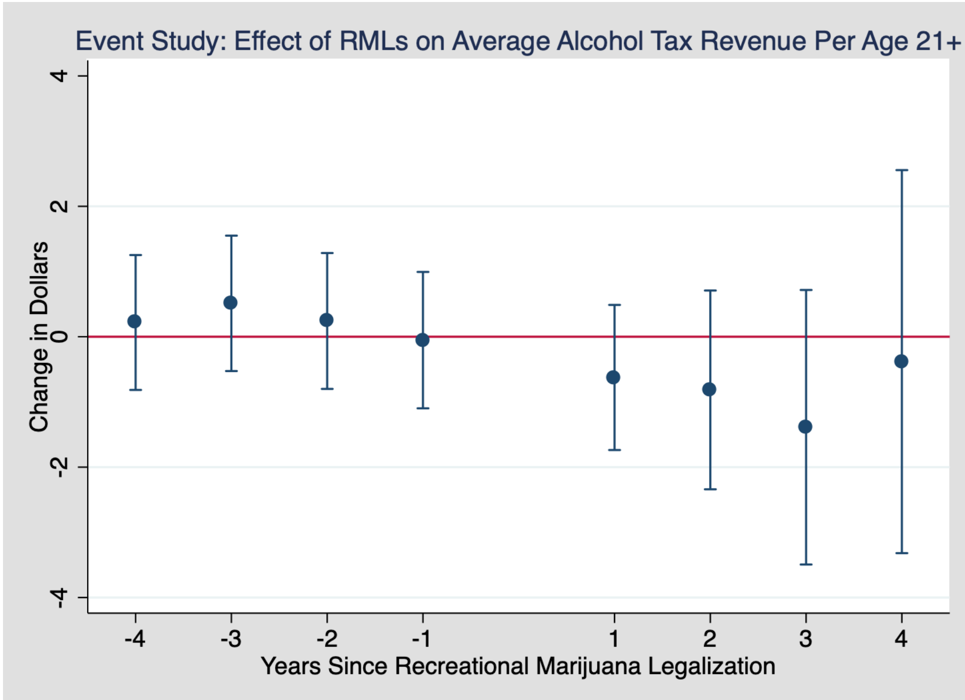
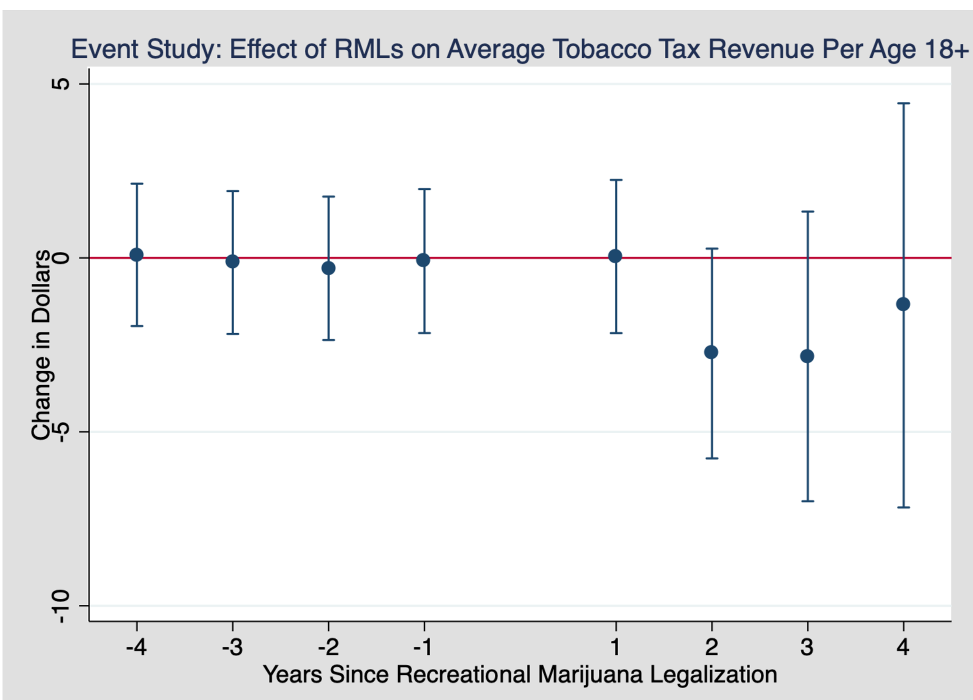


Figure 4.5: Event Study: Effect of RMLs on Average Tobacco Tax Revenue Per Age 18+



4.5 Results

From the specification described in the last section, we see that RMLs have no statistically significant impact on aggregated state tobacco tax revenue. Meanwhile, it is statistically significant that RMLs may have a negative impact on state alcohol tax revenue (See Table 4.3). Specifically, with the passage of RML, on average, the leads to a \$.61 decrease in alcohol tax revenue per age 21–and–up customer per quarter. This suggests that although it is ambiguous to conclude the relationship between recreational marijuana and tobacco taxation, the results might have potentially revealed the substitution of state revenue from the "sin" good taxation regarding the alcohol and marijuana.

MMLs may have also significantly affected on state–level collection of tax revenues for additional "sins". However due to restricted access under MMLs and therefore a smaller tax–base, it is also possible they had little effect on overall and other "sin" tax revenue. Current state–level RMLs place very few qualification restrictions on individuals and the effect that RMLs may have on marijuana consumption by lowering the social costs to marijuana use (e.g. reduced legal consequences (social stigma) of production, possession, consumption; increased access to marijuana), potentially creating a significantly larger consumer base and source for state tax revenue. Furthermore, we employ the synthetic control method (Abadie et al., 2010) to validate our results. We chose Colorado due to its longest post–treatment periods compared with other RML states. From Figures 4.6 and 4.7, we see that the synthetic Colorado and the actual Colorado generally have similar pre–trends. Figure 4.6 provides evidence that Colorado has a significant decrease in alcohol tax revenue per age 21–and–up when comparing to the synthetic Colorado where RML was not implemented. However, tobacco tax revenue per age 18–and–up is not significantly distinguishable whether recreational marijuana was legalized as shown in Figure 4.7. These results are aligned with the findings from Table 4.3.

Table 4.3: RML, Tobacco and Alcohol Tax Revenues, 2010-2018

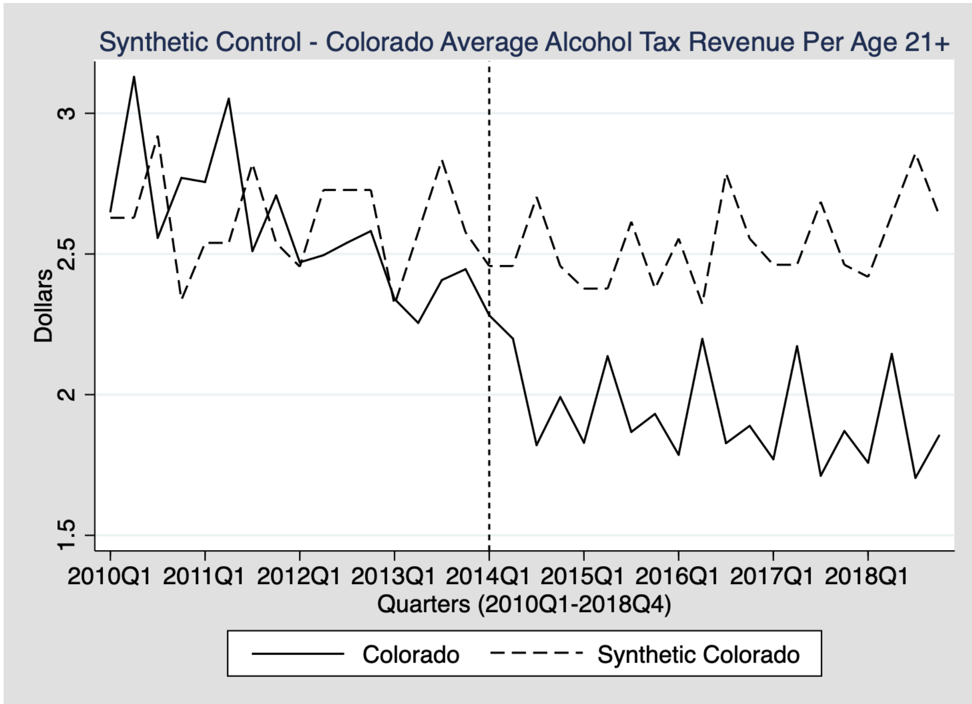
	(1)	(2)	(3)	(4)	(5)	(6)
	Tobacco Tax Rev. per 18+			Alcohol Tax Rev. per 21+		
RML	.241	.210	-.605	-.671*	-.757**	-.605*
	(1.445)	(1.333)	(.893)	(.399)	(.659)	(.318)
MML		-.0139	-1.713*		-.659	-.788
		(1.452)	(.951)		(.421)	(.431)
State decriminalization		-2.072**	-.825		.0249	.296
		(.819)	(.547)		(.395)	(374)
Drug per se law		-1.714*	-1.131		-.0808	-.0620
		(.881)	9.7370		(.350)	(.360)
Cigarette tax rate			6.073***			.425
			(1.021)			(.248)
Beer tax rate			-1.660			1.601**
			(1.198)			(.712)
Drug policies	No	Yes	Yes	No	Yes	Yes
Tax rates	No	No	Yes	No	No	Yes
Other state covariates	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.867	.875	.880	.821	.822	.819
N	1800	1800	1800	1800	1800	1800

Standard errors, corrected for clustering at the state level, are in parentheses. Quarter fixed effects and state fixed effects are included in all specifications. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

4.6 Discussion

Although this study sought to provide additional evidence of the effects that recreational marijuana legalization has had on state–level sales tax revenue (an indirect measure for aggregate consumption) for alcohol and tobacco as well as marijuana itself, we admit there are several limitations to the current empirical strategy and analysis. One potential shortcoming of our study is its reliance on state–level tax data collected and harmonized by the Census Bureau. Through the harmonization

Figure 4.6: Synthetic Control of Colorado – Alcohol Tax Revenue Per Age 21+

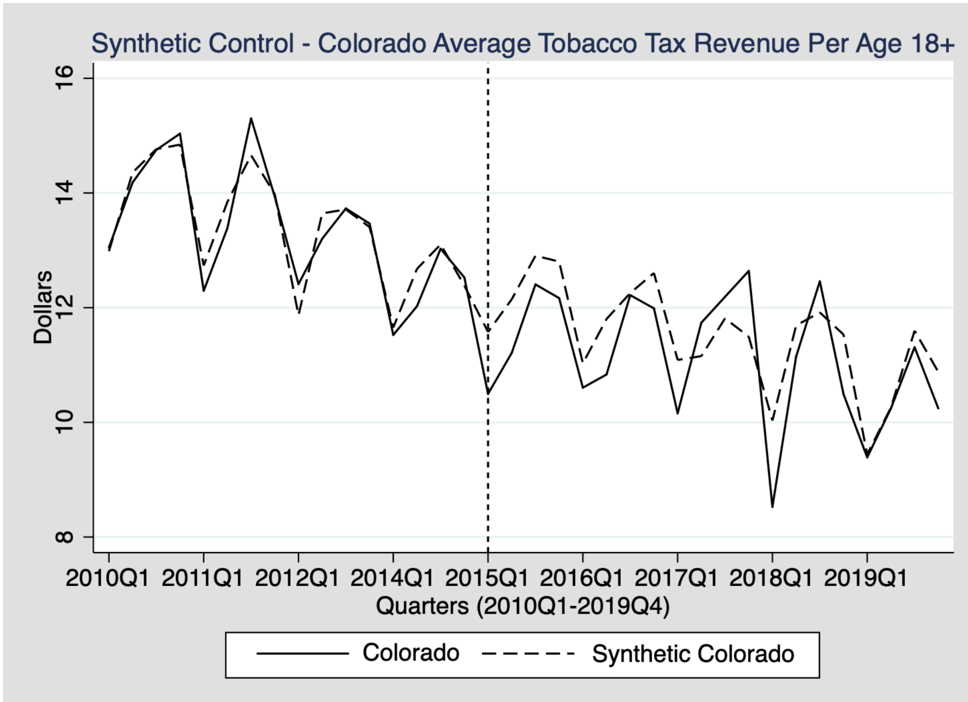


process, important information regarding the impact of RMLs on underlying tax revenue source may be less explicit due to the aggregation of state–level tax categories for consistency.

As well, while the enactment of RMLs may be viewed as an exogenous shock to consumer demand and sales tax revenue, state's choice to legalize possession and use of marijuana is not. Since proposition of many recent RMLs is due to popular referendum, the likelihood of RML enactment as well as the marijuana and related drug consumption habits of the adult public is undoubtedly associated with the demographic characteristics of the state. While we attempt to control for this endogenous relationship it is possible that unobservable characteristics of the adult populations in these states are driving consumption results.

Further, our study of state–level "sin" tax revenues focuses on the aggregate tax and consumption effects of the enactment of RMLs rather than the distributional effects of marijuana consumption throughout the population. Ideally, to analyze the effect of RMLs and marijuana sales taxes with tobacco, alcohol and other consumption taxes the data would also include information on quantities sold and micro–level information on quantities sold for each good of interest. Then

Figure 4.7: Synthetic Control of Colorado – Tobacco Tax Revenue Per Age 18+



using a system of demand, it would be possible to more accurately estimate the economic complementarity/substitutability of marijuana taxation with all other consumption taxes. With additional information on the distribution of individual consumption patterns with states, we would extend results to include counterfactual welfare analyses and distributional effects of RMLs and changes to tax regimes (Deaton & Muellbauer, 1980; Banks et al., 1996; Ayyagari et al., 2009). Further, without accounting for individual–level correlations of consumption across goods and services, it is uncertain if there are common observable or unobservable characteristics of individuals which drive marijuana consumption and the disproportional (regressive) effects it may have on heavy versus casual marijuana users.

Finally, while the black market and illicit sales/possession/use of marijuana within and across states is a potential large externality of reducing the penalties for marijuana and increasing production, the results of this study are confined to the legal sales of marijuana, alcohol and tobacco. Given the potential for increased firm profits in black markets, the actual sale and use of marijuana, and therefore effects on sales taxes may be much higher than what is legally reported.

In recent, years many states have come up short in the collection of public revenues in order to provide many public services. As tobacco use continues to decrease, its important to monitor consumers' substitution of marijuana and therefore its "sin" taxation which may replace tax losses from tobacco sales. Importantly, public costs should not outweigh the benefits associated with recreational marijuana legalization. RMLs may reduce the cost of marijuana crime enforcement as well as provide tax revenue for states. However, increased access to marijuana may also cause higher rates of marijuana–related hospitalization and other public health concerns.

While controversial, it is also important to assess if marijuana consumption is less harmful for the individual and has less social costs than tobacco or alcohol use. If the "sin" of marijuana is less than that of alcohol and tobacco use, this is an important implication for optimal taxation. A greater investigation into these "net social effects" of recreational marijuana legalization in both the short– and long–run should be further studied. Furthermore, although laws to legalize and regulate of marijuana may seek to decrease illicit activities surrounding marijuana in the U.S., inter–state as well as international tax avoidance may become a greater issue with higher tax rates. Thus an important question for policymakers is how do we optimally tax marijuana?

State governments must also weigh short–term benefits of greater tax from marijuana versus potential long–term benefits of fostering the economic growth of the marijuana production industry. While high taxation of marijuana may deter consumption demand while creating short–term revenue to provide public goods, tax wedge distortions may hinder production or growth of the marijuana industry. A recent study by Hansen et al. (2017b) of the Washington marijuana production industry found that gross receipts tax collected at every step of production provided strong incentives for vertical integration. This decreases industrial competition and potentially consumer welfare due to the ability of rent collections by large marijuana producers.

There is still limited information on the re–distribution of revenue collected from the recreational marijuana industry by states towards other public goods and the social benefit created by additional funding. Additional research is necessary to answer questions such as, "what types of public good provisions have tax revenues from the marijuana industry benefited directly?" and “who benefits from these additional public services?”

Finally, additional research on the association between social demographics and the likelihood of recreational marijuana legalization should be undertaken. It appears that there is a growing movement towards the legalization throughout the U.S. and internationally as well (e.g. Canada’s and Uruguay’s national legalization of recreational marijuana). While the demographic characteristics of voters who passed RMLs is important to understand for future policies, the (potential) enactment of RMLs may also have significant effects on inter–state migration. Tiebout (1956) suggests that individuals “vote with their feet” by migrating to localities where local public good expenditures best match their own utility preference, since “At the central level the preferences of the consumer-voter are given, and the government tries to adjust to the pattern of these preferences, whereas at the local level various governments have their revenue and expenditure patterns more or less set.” Thus, the impact that RMLs have had demographic changes across U.S. states in the U.S should also be studied further.

While the recreational legalization of marijuana is still very recent, it is crucial to understand the social implications that recreational marijuana use has for the U.S. public. Akin to the prohibition of alcohol, the prohibition of marijuana has begun to be overturned in several states due to popular demand and changing social norms towards marijuana, tobacco and alcohol. As with alcohol prohibition, its likely that many localities in the U.S. will continue to view marijuana as a socially–unacceptable practice and will choose to not serve, sell or produce marijuana. However, additional empirical work is necessary to best inform U.S. policymakers regarding the negative and potentially positive direct and spillover effects of marijuana on the U.S. public.

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Appendix A

Figures

Figure A.1: States with Marijuana Laws - January 1, 2000

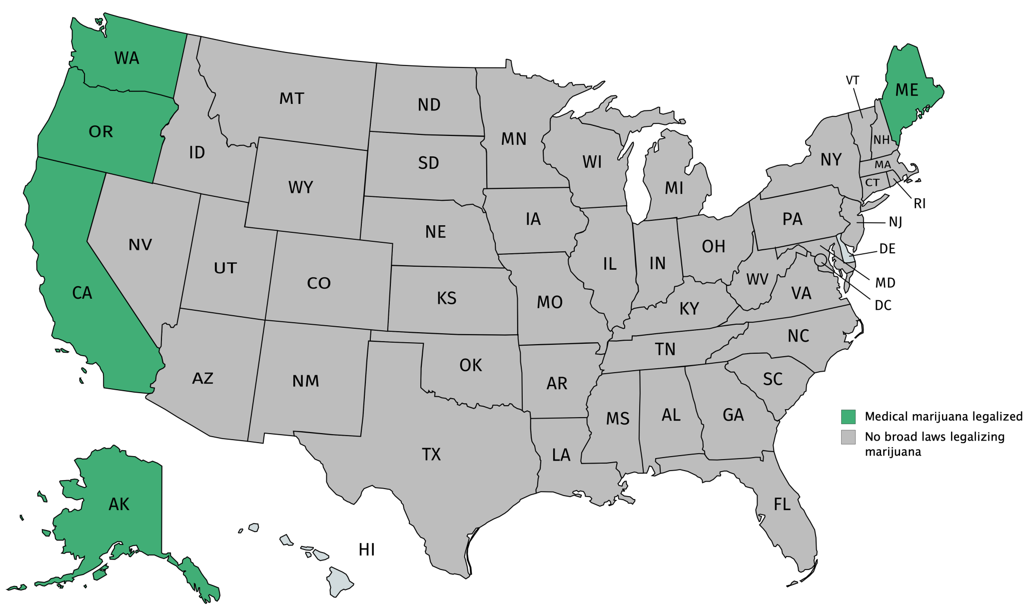


Figure A.2: States with Marijuana Laws - January 1, 2005

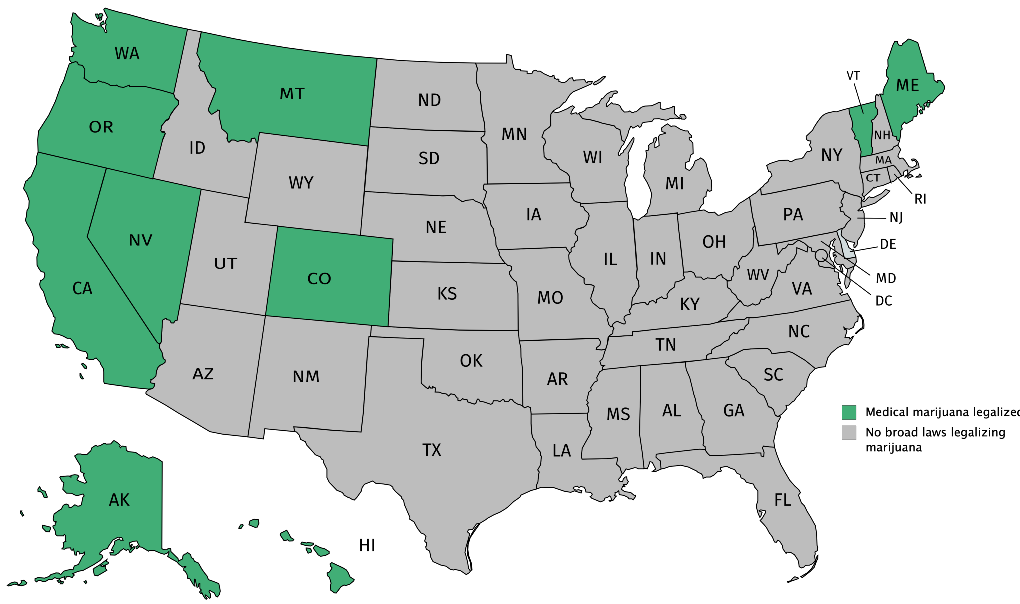


Figure A.3: States with Marijuana Laws - January 1, 2010

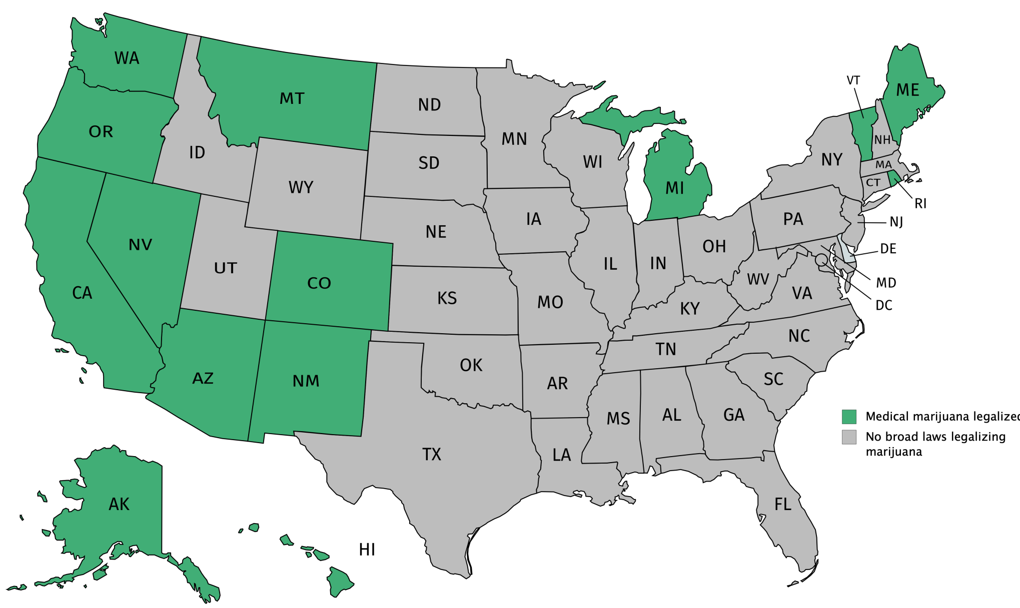


Figure A.4: States with Marijuana Laws - January 1, 2015

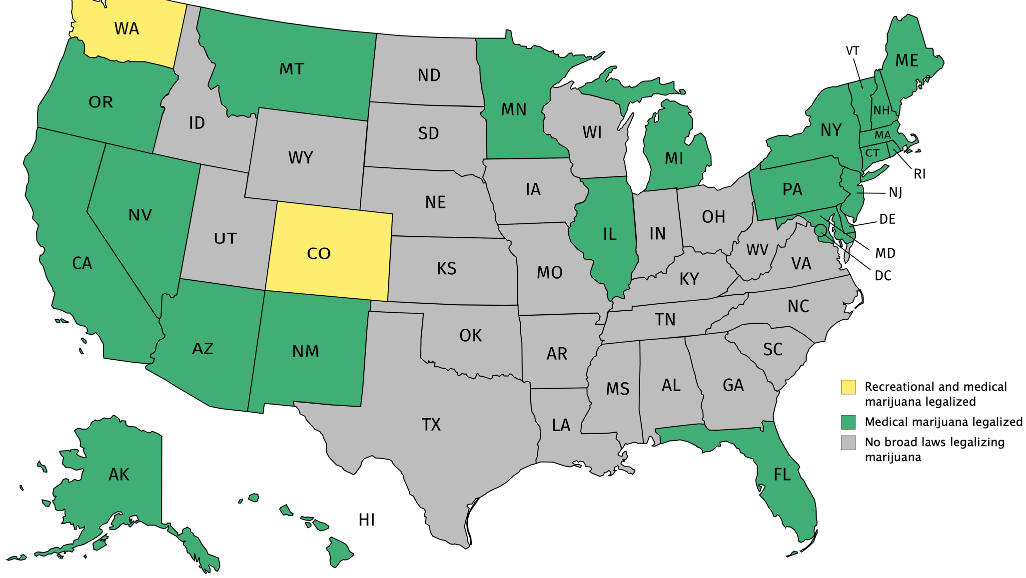


Figure A.5: States with Marijuana Laws - January 1, 2020

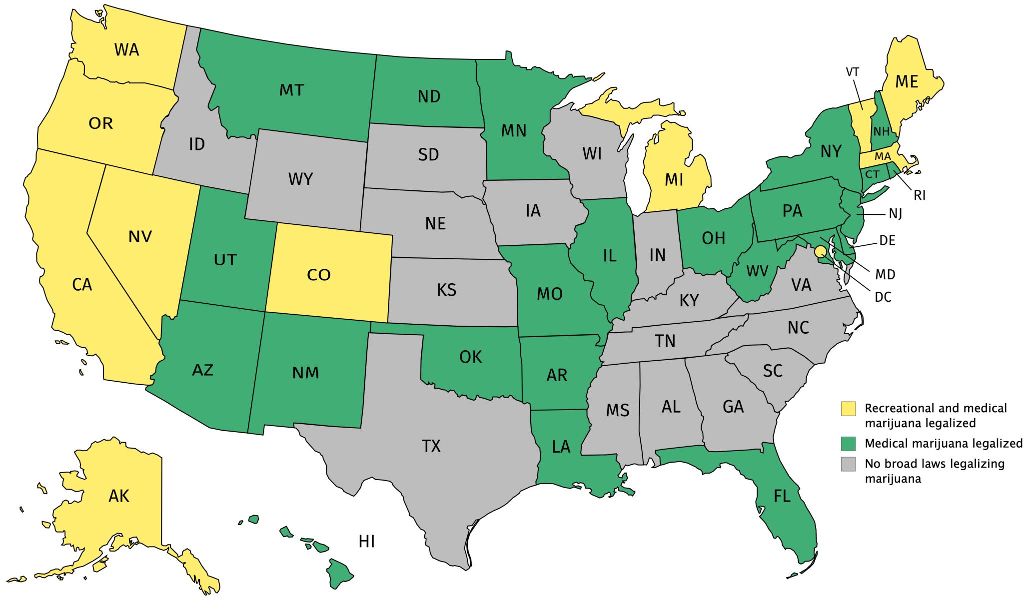


Figure A.6: Locations of Colleges or Universities that have participated in HMS

Figure A.7: Patient Health Questionnaire (PHQ–9)

Over the *last 2 weeks*, how often have you been bothered by any of the following problems?	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual	0	1	2	3
9. Thoughts that you would be better off dead or of hurting yourself in some way	0	1	2	3

(For office coding: Total Score ________ = _________ + __________ + __________)

Figure A.8: Generalized Anxiety Disorder 7–item (GAD–7)

Generalized Anxiety Disorder 7-item (GAD-7) scale

Over the last 2 weeks, how often have you been bothered by the following problems?	Not at all sure	Several days	Over half the days	Nearly every day
1. Feeling nervous, anxious, or on edge	0	1	2	3
2. Not being able to stop or control worrying	0	1	2	3
3. Worrying too much about different things	0	1	2	3
4. Trouble relaxing	0	1	2	3
5. Being so restless that it's hard to sit still	0	1	2	3
6. Becoming easily annoyed or irritable	0	1	2	3
7. Feeling afraid as if something awful might happen	0	1	2	3
Add the score for each column	+	+	+	
Total Score *(add your column scores)* =				

Figure A.9: California Average Alcohol Tax Revenue Per Age 21+

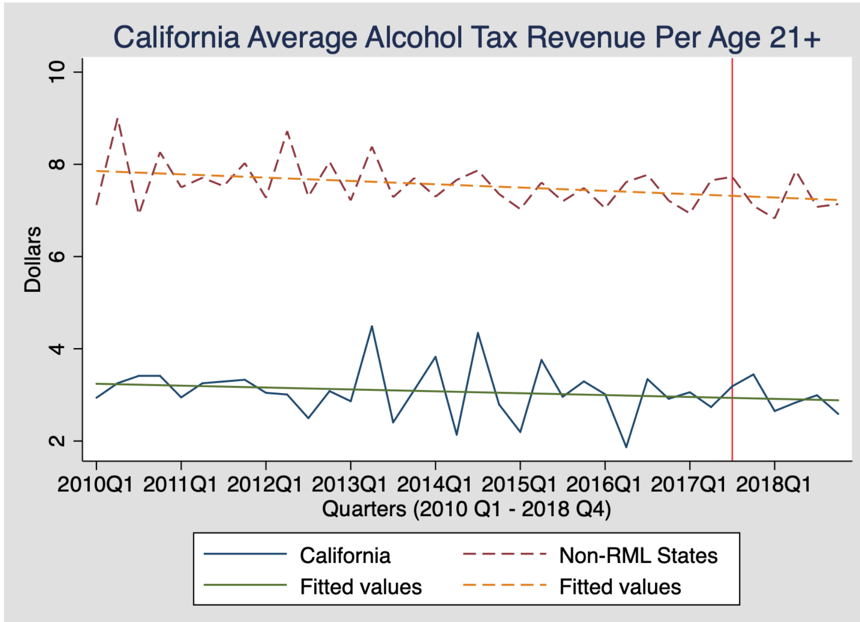


Figure A.10: Colorado Average Alcohol Tax Revenue Per Age 21+

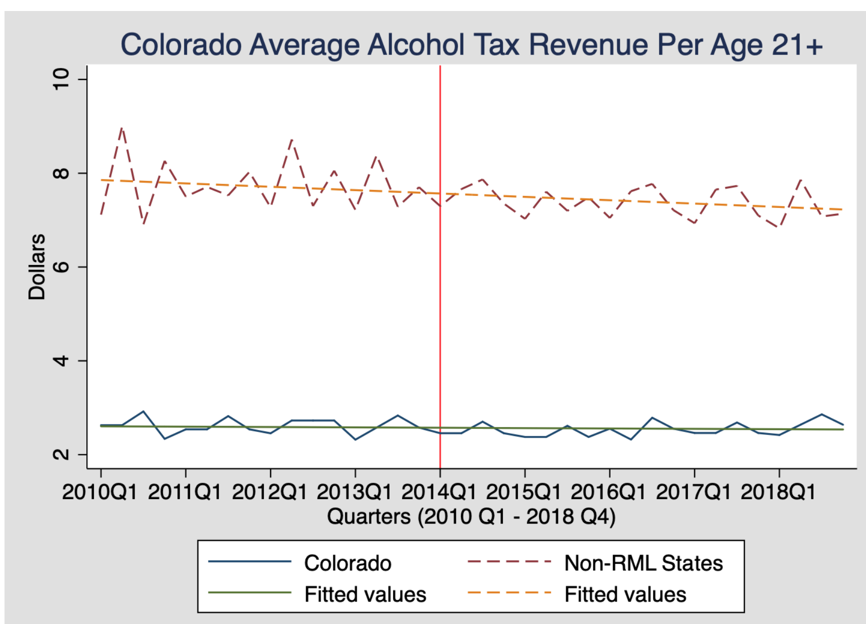


Figure A.11: Massachusetts Average Alcohol Tax Revenue Per Age 21+

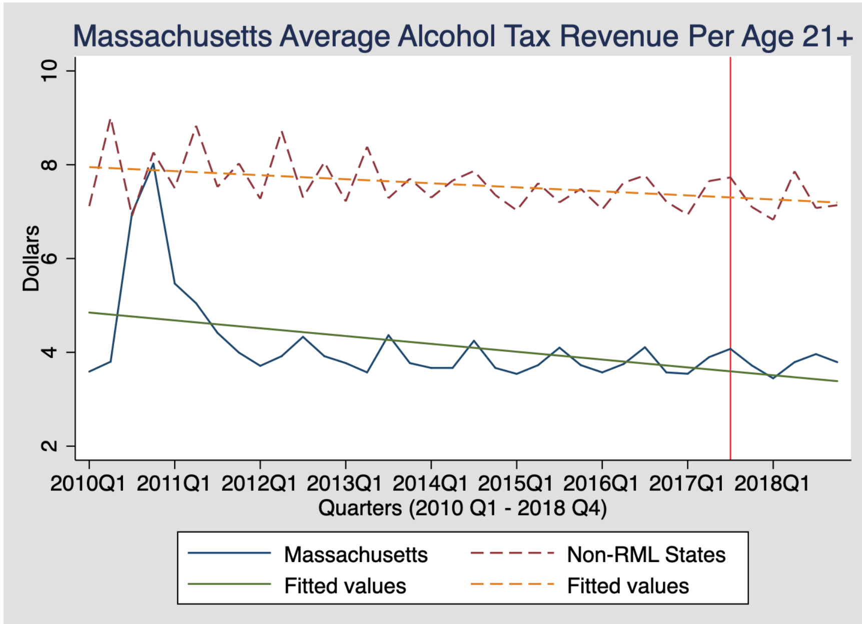


Figure A.12: Maine Average Alcohol Tax Revenue Per Age 21+

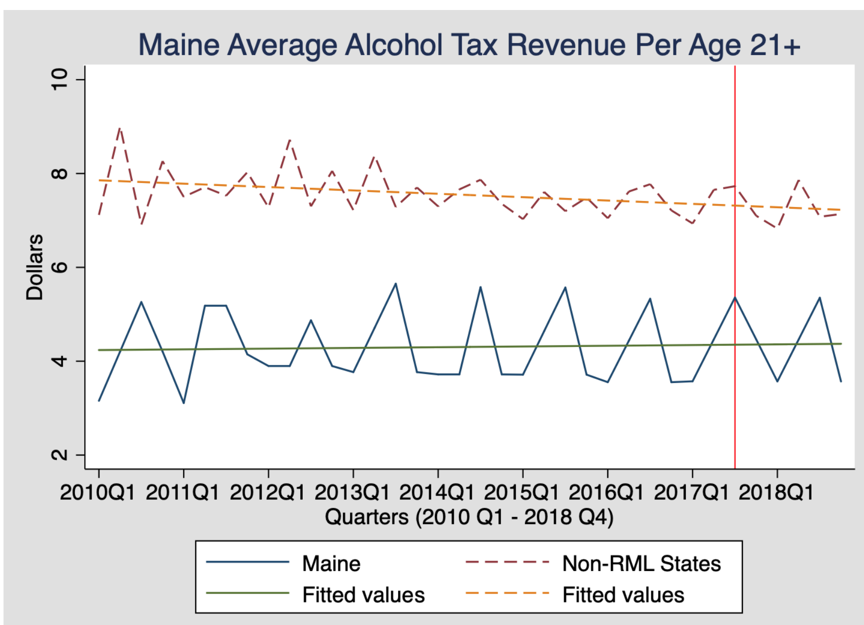


Figure A.13: Nevada Average Alcohol Tax Revenue Per Age 21+

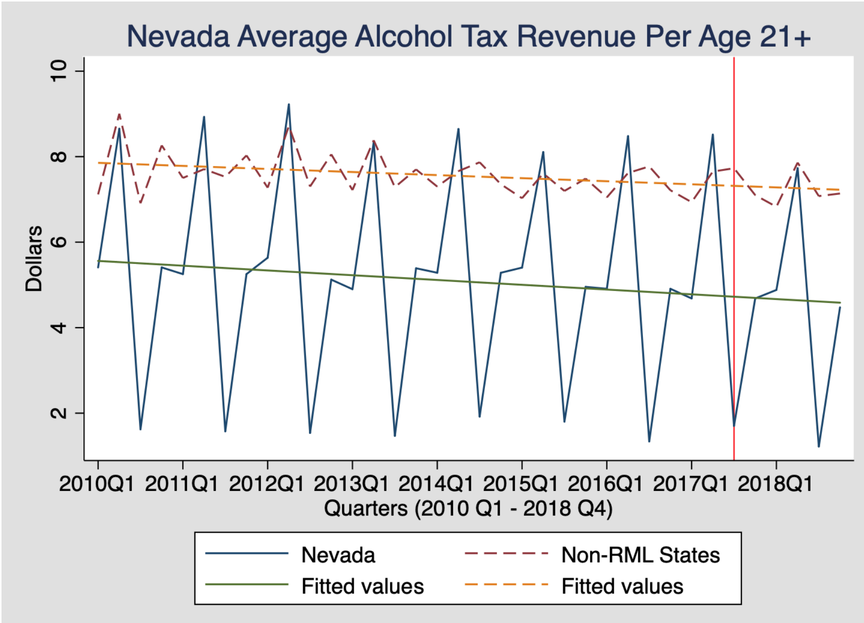


Figure A.14: Oregon Average Alcohol Tax Revenue Per Age 21+

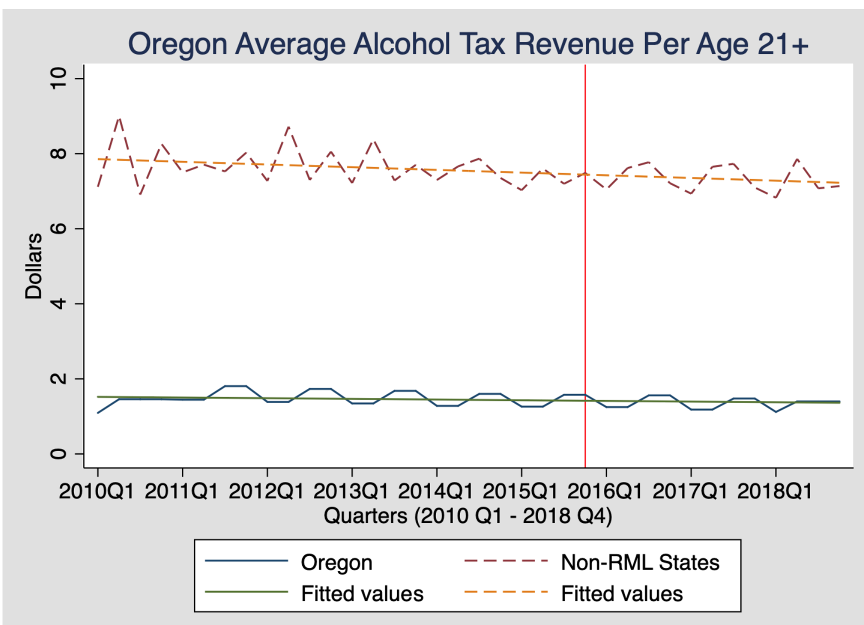


Figure A.15: Washington Average Alcohol Tax Revenue Per Age 21+

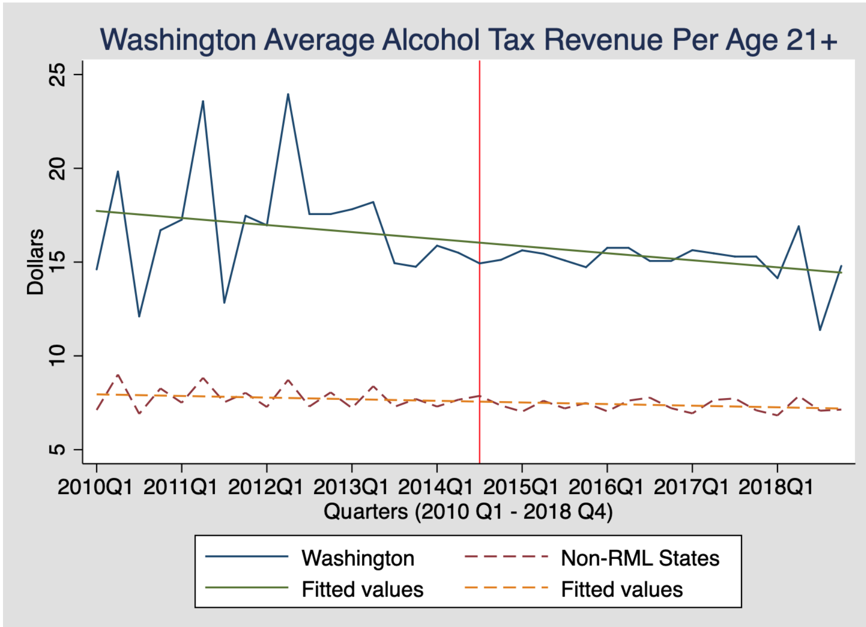


Figure A.16: California Average Tobacco Tax Revenue Per Age 18+

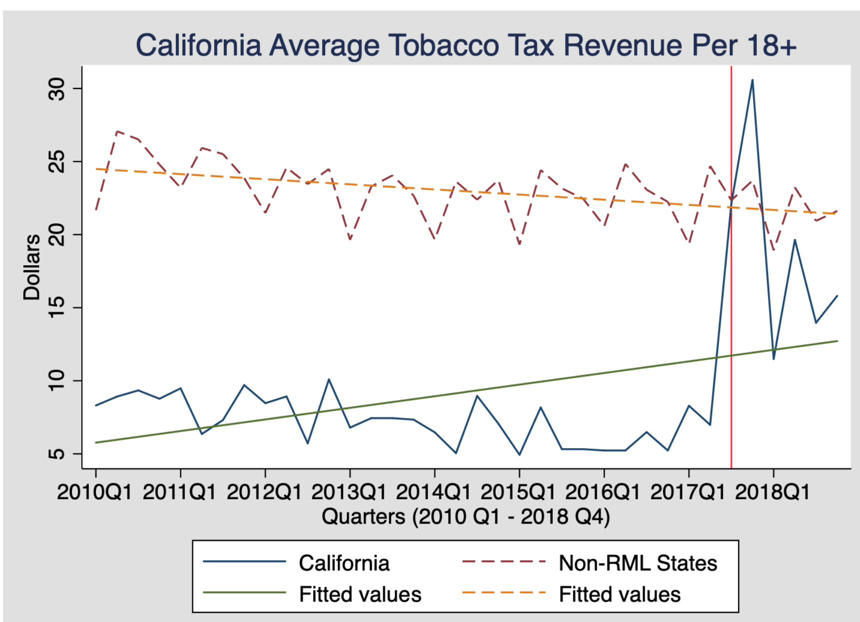


Figure A.17: Colorado Average Tobacco Tax Revenue Per Age 18+

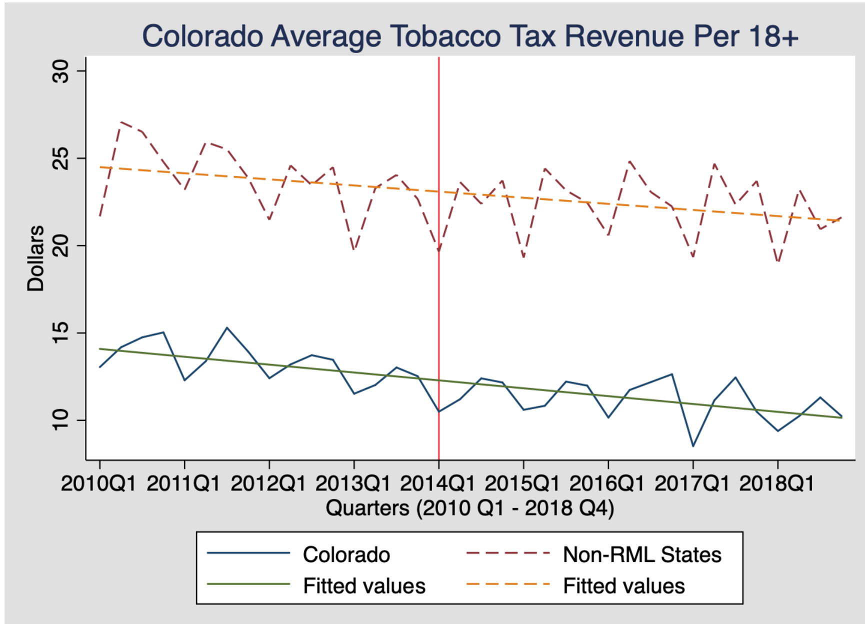


Figure A.18: Massachusetts Average Tobacco Tax Revenue Per Age 18+

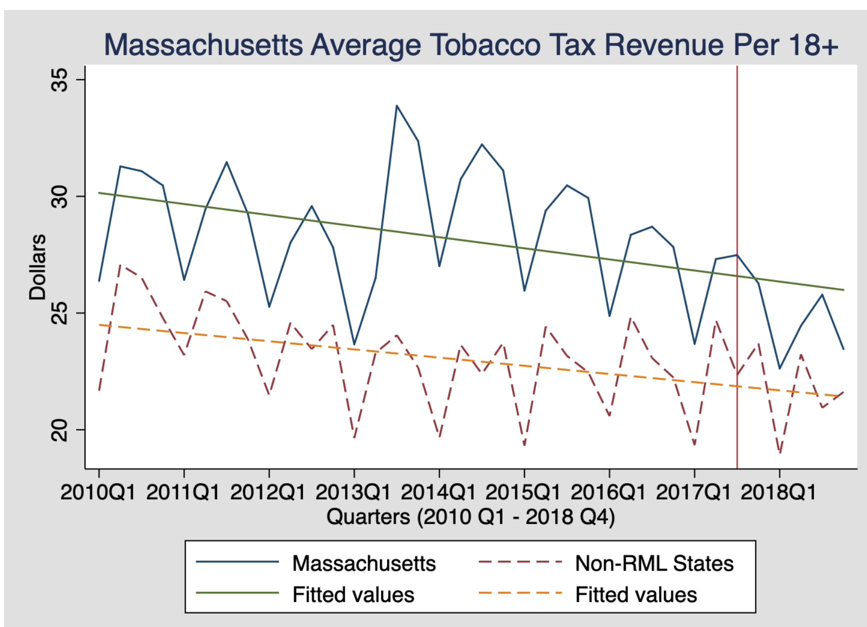


Figure A.19: Maine Average Tobacco Tax Revenue Per Age 18+

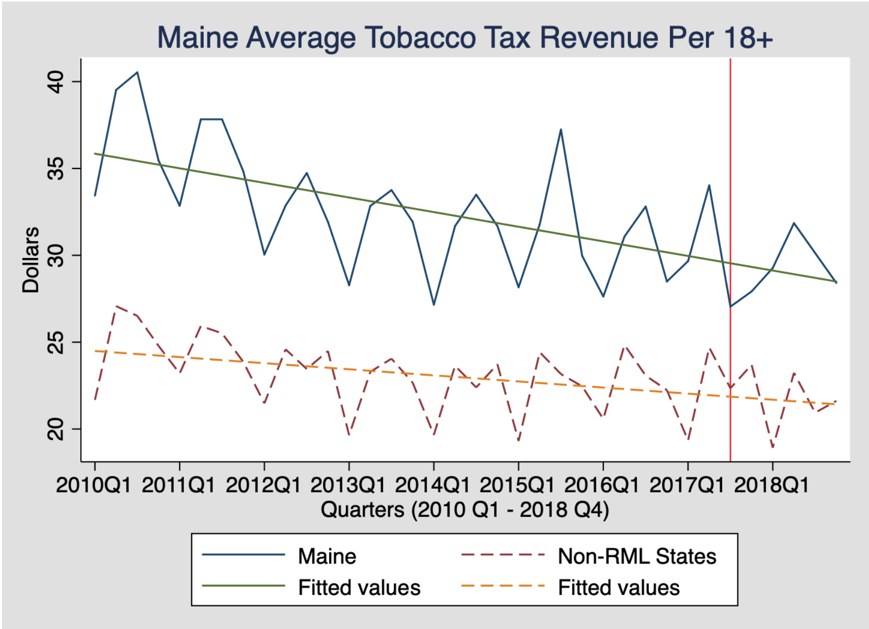


Figure A.20: Nevada Average Tobacco Tax Revenue Per Age 18+

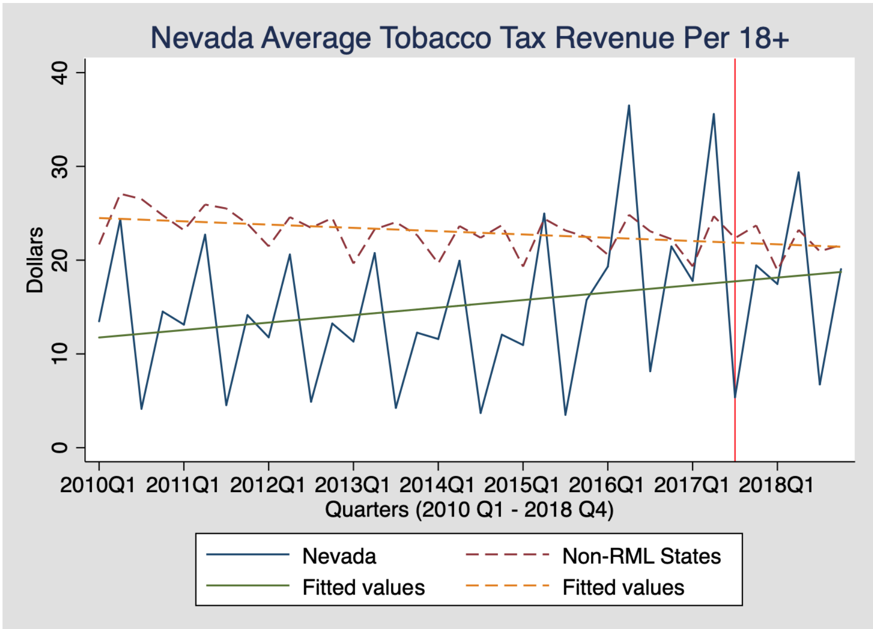


Figure A.21: Oregon Average Tobacco Tax Revenue Per Age 18+

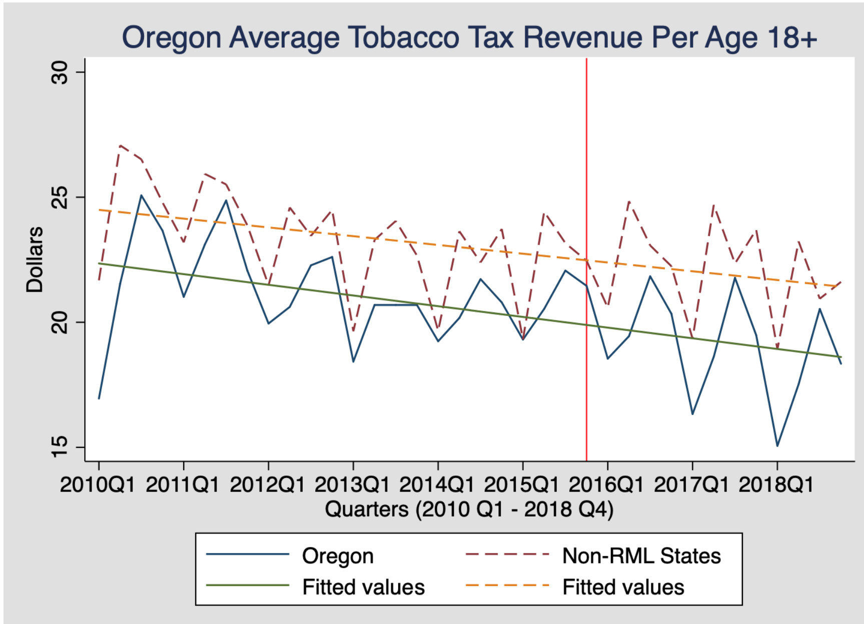


Figure A.22: Washington Average Tobacco Tax Revenue Per Age 18+

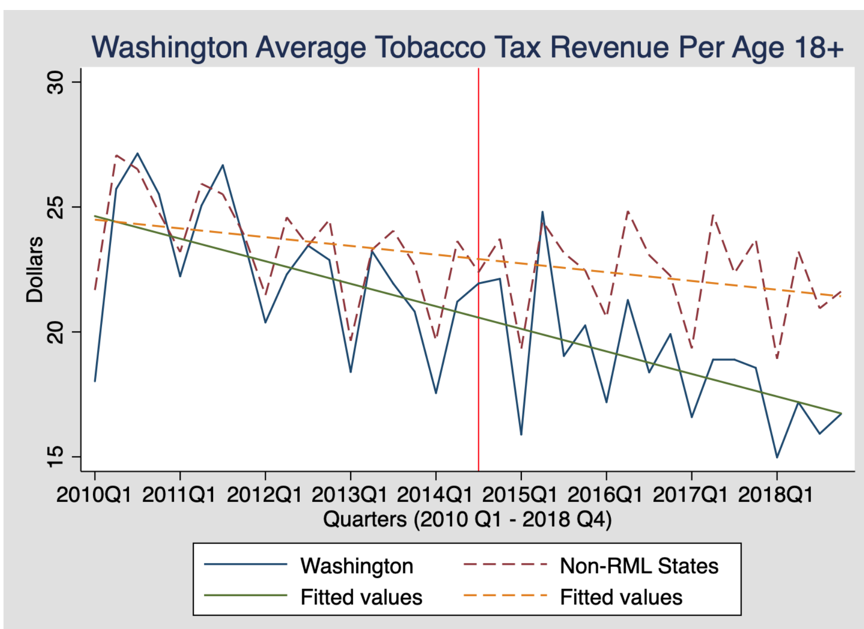


Figure A.23: Alaska Average Marijuana Tax Revenue

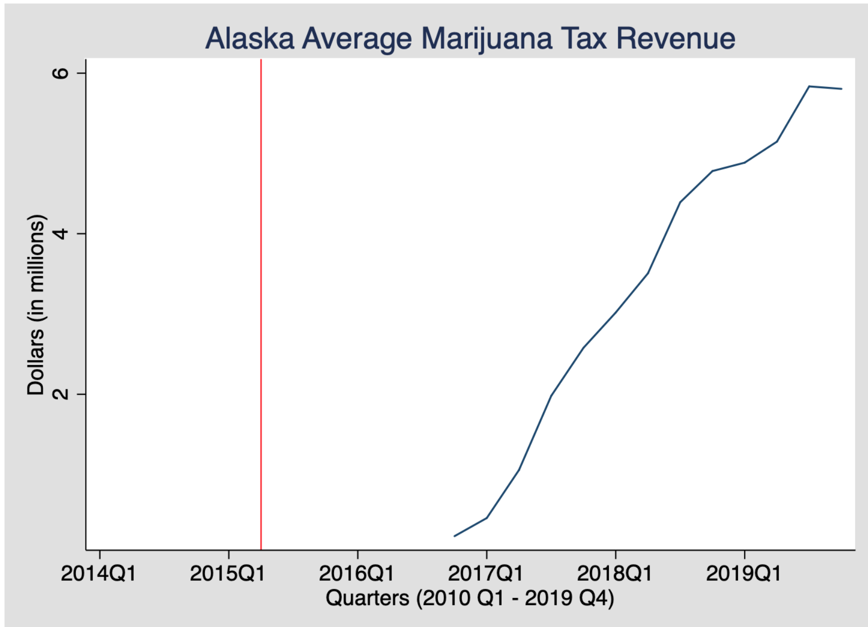


Figure A.24: California Average Marijuana Tax Revenue

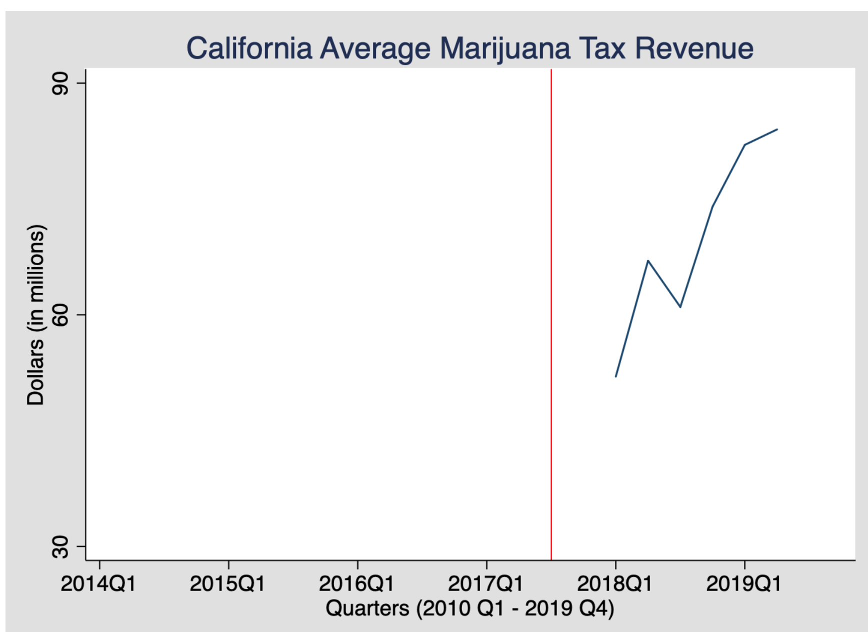


Figure A.25: Colorado Average Marijuana Tax Revenue

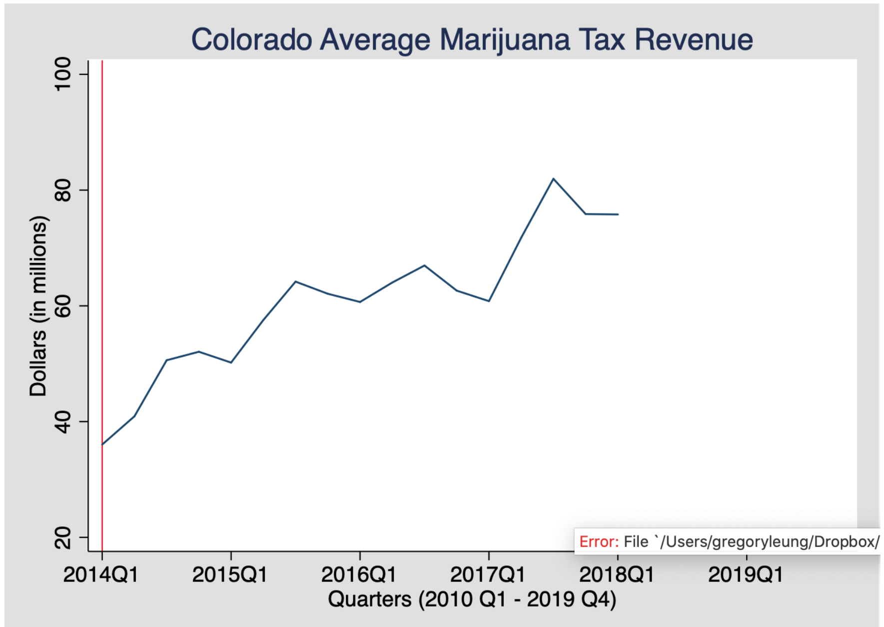


Figure A.26: Nevada Average Marijuana Tax Revenue

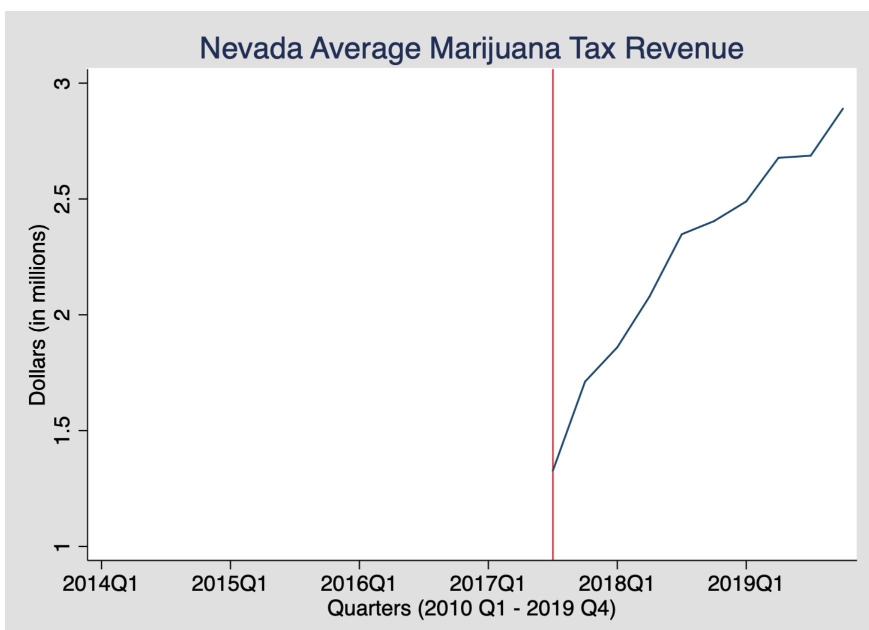


Figure A.27: Oregon Average Marijuana Tax Revenue

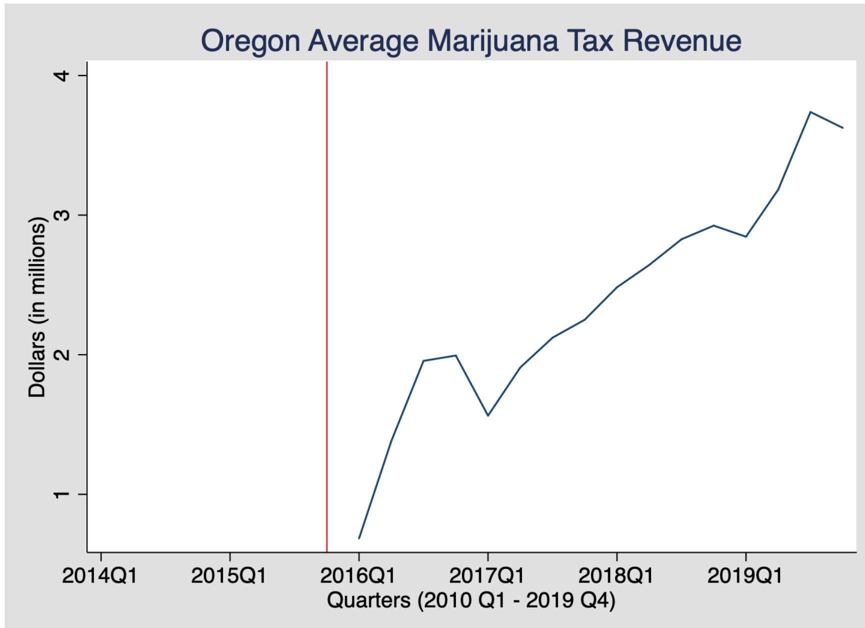
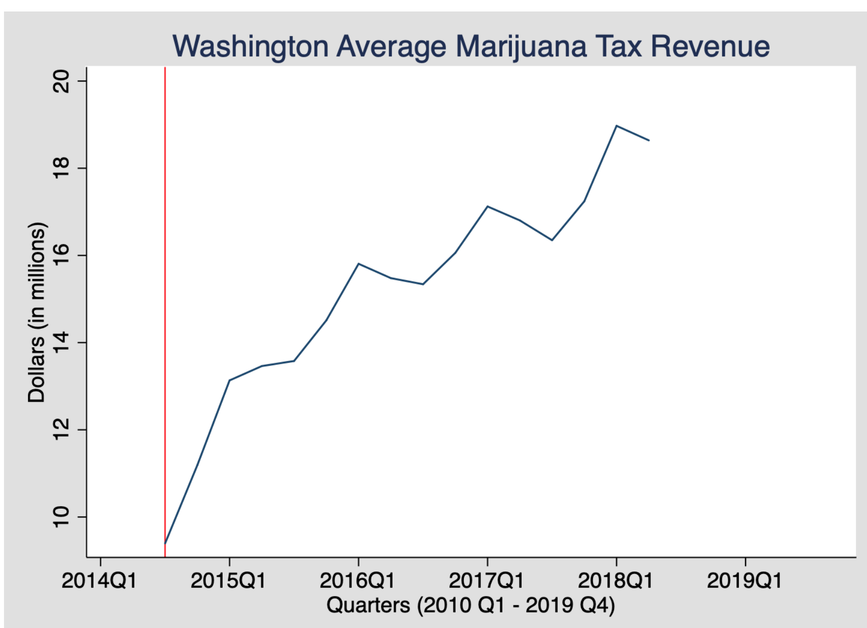


Figure A.28: Washington Average Marijuana Tax Revenue



Tables

Table A.1: List of Colleges or Universities that have participated in HMS

Alberta College of Art and Design	Florida State University
American University of Beirut Medical Center	George Mason University
Appalachian State University	Georgia Institute of Technology
Arizona State University	Goucher College
Art Center College of Design	Grand Rapids Community College
Bard College	Guilford College
Boston University	Hamilton College
Bridgewater College	Harrisburg Area Community College
California Institute of the Arts	Hocking College
California Polytechnic State University, San Luis Obispo	Howard University
California State University - Fresno	Humboldt University
California State University – Chico	Illinois State University
California State University – Fullerton	James Madison University
California State University – Pomona	Kalamazoo College
Carleton College	Kansas City Art Institute
Case Western Reserve University	Kent State University
Central Washington University	Kettering University
Cleveland State University	Lake Washington Institute of Technology
Cleveland Institute of Art	Lake Superior State University
College of Saint Rose	Lakeland Community College
College of William and Mary	Liberty University
College for Creative Studies	Loyola University of Chicago
Colorado College	Marietta College
Colorado Mountain College	Mary Baldwin College

Table A.1: Colleges or University that have participated in the Survey (continue)

Columbus College of Art & Design	Maryland Institute College of Art
Cornish College of the Arts	Marygrove College
Cumberland University	Massachusetts College of Art and Design
CUNY System	Massachusetts Institute of Technology
Cuyahoga Community College: Western Campus Defiance College	Memorial University of Newfoundland
Delgado Community College	Mercyhurst University
Denison College	Merrimack College
Earlham College	Miami Dade College
Eastern Mennonite University	Miami University
Eastern Michigan University	Michigan State University
Emerson College	Minneapolis College of Art and Design
Emmanuel College	Montana State University
Emory & Henry College	Montclair State University
Emory University	Moraine Park Technical College
New Hampshire Institute of Art	Southwestern Oklahoma State University
New Mexico State University	Springfield College
New York University	St John's University
Oakland Community College	Stanford University
Oklahoma City Community College	SUNY College at Old Westbury
Old Dominion University	Texas Christian University
Onondaga Community College	The Cleveland Institute of Art
Oregon State University	The New School
Otis College of Art and Design	The Pennsylvania State University
Owens Community College	The University of Arizona

Table A.1: Colleges or Universities that have participated in the survey (continue)

Pacific Lutheran University	The University of Texas - Pan American
Palo Alto College	Truman State University
Pennsylvania College of Technology	Tufts University
Penn State Altoona	Tulane University
Pomona College	University of Alberta
Pratt Institute	University of Arkansas
Purdue University Calumet	University of Chicago
Qatar University	University of Delaware
Radford University	University of Denver
Randolph – Macon College	University of Detroit Mercy
Redlands Community College	University of Florida
Rhode Island College	University of Illinois – Chicago
Rhode Island School of Design	University of Illinois – Springfield
Richard Stockton College	University of Illinois – Urbana – Champaign
Ringling College of Art and Design	University of Kansas
Roanoke College	University of Lethbridge
Rollins College	University of Maryland
Saint Joseph's University	University of Massachusetts – Boston
Saint Mary's College	University of Michigan – Ann Arbor
San Diego Community College	University of Michigan – Dearborn
San Diego State University	University of Minnesota
School of the Art Institute of Chicago	University of Nevada
Seattle Central College	University of Nevada, Las Vegas
Seattle University	University of Nevada, Reno
Sewanee: The University of the South	University of North Carolina at Chapel Hill
Shawnee State University	University of North Carolina at Greensboro

Table A.1: Colleges or Universities that have participated in the survey (continue)

Shenandoah University	University of North Carolina School of the Arts
Smith College	University of Oregon
Southern Connecticut State University	University of Puget Sound
Southern Nazarene University	University of Richmond
University of the Sciences	University of Wisconsin - Superior Vanderbilt
University of South Carolina	Virginia Commonwealth University Virginia Tech
University of Southern California	Virginia Wesleyan College
University of Tennessee, Knoxville	Wake Forest University
University of Texas Medical Branch	Walsh University
University of Utah	Washington State Community College
University of Virginia	Watkins College of Art, Design, and Film
University of Washington – Seattle	Wayne State University
University of Washington – Botthell	Weill Cornell Medical College in Qatar
University of Washington – Tacoma	West Virginia UniversitY
University of Wisconsin - Eau Claire	Western Carolina University
University of Wisconsin - Parkside	Western Michigan University
University of Wisconsin - River Falls	Western Washington University
University of Wisconsin - Whitewater	Western Wyoming Community College
University of Wisconsin - Lacrosse	Whatcom Community College
University of Wisconsin - Oshkosh	Whitworth University
University of Wisconsin – Madison	Wilmington College
University of Wisconsin- Milwaukee	Worcester Polytechnic Institute
University of Wisconsin - Green Bay	Wright State University
University of Wisconsin - Platteville	Xavier University
University of Wisconsin - Stevens Point	Yeshiva University
University of Wisconsin - Stout	

Table A.2: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression for Undergraduate Students

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.474**	0.200	-0.0685
	(0.188)	(0.264)	(0.599)
N	60763	60763	66231

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression for Graduate Students

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.332*	0.279	-0.338
	(0.188)	(0.264)	(0.599)
N	15948	15948	17654

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression for White Students

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.331	-0.0807	-0.135
	(0.177)	(0.153)	(0.658)
N	60834	60834	21610

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression for Non–white Students

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.615*	0.140	-0.112
	(0.150)	(0.347)	(0.633)
N	23194	23194	25162

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression for Female Students

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.441**	0.0617	-0.134
	(0.172)	(0.153)	(0.579)
N	54025	54025	58007

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression for Male Students

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.242	0.00624	-0.228
	(0.180)	(0.308)	(0.470)
N	25823	25823	28766

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression for Students Aged 25 or under

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.462**	0.248	-0.0351
	(0.180)	(0.247)	(0.526)
N	66781	66781	72641

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Sensitivity Analysis: Impact of MMLs on PHQ–9 scores and Depression Excluding Illinois and New York

	(1)	(2)	(3)
	PHQ–9		*Depression Categories*
	OLS	Fixed Effects	Ordered Logit
mml	0.414*	0.0374	-0.140
	(0.172)	(0.201)	(0.546)
N	80743	80743	87772

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation for Undergraduate Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Anxiety			*Suicidal Ideation*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0126	-0.161	-0.0250	-0.00330	-0.109	-0.00959
	(0.0212)	(0.109)	(0.0169)	(0.0104)	(0.114)	(0.0101)
N	55421	55421	55421	69002	69002	69002

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation for Graduate Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Anxiety			*Suicidal Ideation*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.00756	-0.136	-0.0203	0.00146	-0.0594	-0.00474
	(0.0182)	(0.0846)	(0.0126)	(0.00984)	(0.110)	(0.00876)
N	73784	73784	73784	91340	91340	91340

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation for White Students

	(1) *Anxiety* OLS	(2) Logit	(3) Logit AME	(4) *Suicidal Ideation* OLS	(5) Logit	(6) Logit AME
mml	0.00908	-0.0275	-0.00419	0.0331*	0.397*	0.0322*
	(0.0376)	(0.237)	(0.0361)	(0.0190)	(0.225)	(0.0182)
N	18598	18578	18578	22351	22272	22272

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation for Non–white Students

	(1) *Anxiety* OLS	(2) Logit	(3) Logit AME	(4) *Suicidal Ideation* OLS	(5) Logit	(6) Logit AME
mml	-0.0167	-0.181	-0.0280	0.0302	0.326	0.0279
	(0.0282)	(0.172)	(0.0266)	(0.0213)	(0.225)	(0.0193)
N	21679	21679	21679	26096	26083	26083

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.14: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation for Female Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Anxiety			*Suicidal Ideation*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0318**	-0.246***	-0.0397***	-0.0143	-0.198	-0.0156
	(0.0131)	(0.0689)	(0.0111)	(0.0109)	(0.127)	(0.0100)
N	50174	50174	50174	60668	60668	60668

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.15: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation for Male Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Anxiety			*Suicidal Ideation*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.0292	0.0939	0.0111	0.0249**	0.258**	0.0194**
	(0.0314)	(0.183)	(0.0216)	(0.0102)	(0.109)	(0.00820)
N	22714	22700	22700	29631	29590	29590

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.16: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation for Students Aged 25 or under

	(1)	(2)	(3)	(4)	(5)	(6)
	Anxiety			*Suicidal Ideation*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.00756	-0.136	-0.0203	0.00146	-0.0594	-0.00474
	(0.0182)	(0.0846)	(0.0126)	(0.00984)	(0.110)	(0.00876)
N	73784	73784	73784	91340	91340	91340

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.17: Sensitivity Analysis: Impact of MMLs on Anxiety Screening and Suicidal Ideation Excluding Illinois and New York

	(1)	(2)	(3)	(4)	(5)	(6)
	Anxiety			*Suicidal Ideation*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.00756	-0.136	-0.0203	0.00146	-0.0594	-0.00474
	(0.0182)	(0.0846)	(0.0126)	(0.00984)	(0.110)	(0.00876)
N	73784	73784	73784	91340	91340	91340

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.18: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption for Undergraduate Students

	(1)	(2)	(3)
	Prescription Drugs		
	OLS	Logit	Logit AME
mml	-0.0275	-0.656^{***}	-0.0815^{***}
	(0.0237)	(0.0356)	(0.00448)
N	70133	30954	30954

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.19: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption for Graduate Students

	(1)	(2)	(3)
	Prescription Drugs		
	OLS	Logit	Logit AME
main			
mml	-0.0166	-0.00860	-0.00110
	(0.0245)	(0.265)	(0.0339)
N	18461	7617	7617

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.20: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption for White Students

	(1)	(2)	(3)
	Prescription Drugs		
	OLS	Logit	Logit AME
mml	-0.0256	-1.288***	-0.0901***
	(0.0232)	(0.179)	(0.0124)
N	22901	9590	9590

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.21: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption for Non–white Students

	(1)	(2)	(3)
	Prescription Drugs		
	OLS	Logit	Logit AME
main			
mml	-0.0388*	-1.252***	-0.0992***
	(0.0194)	(0.119)	(0.00941)
N	26673	10879	10879

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.22: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption for Female Students

	(1)	(2)	(3)
	Prescription Drugs OLS	Logit	Logit AME
mml	-0.0379*	-0.677***	-0.0905***
	(0.0222)	(0.113)	(0.0151)
N	61482	28177	28177

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.23: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption for Male Students

	(1)	(2)	(3)
	Prescription Drugs OLS	Logit	Logit AME
mml	-0.00901	-0.751***	-0.0822***
	(0.0288)	(0.0605)	(0.00673)
N	30177	14230	14230

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.24: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption for Students Aged 25 or Under

	(1)	(2)	(3)
	Prescription Drugs		
	OLS	Logit	Logit AME
mml	-0.0366	-0.164	-0.0240
	(0.0284)	(0.730)	(0.107)
N	76839	7035	7035

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.25: Sensitivity Analysis: Impact of MMLs on Psychiatric Prescription Drugs Consumption Excluding Illinois and New York

	(1)	(2)	(3)
	Prescription Drugs		
	OLS	Logit	Logit AME
mml	-0.0314	-0.706***	-0.0889***
	(0.0252)	(0.0826)	(0.0104)
N	92732	42407	42407

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.26: Sensitivity Analysis: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) for Undergraduate Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Marijuana			*Cocaine*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0626**	-0.409***	-0.0555***	-0.0106**	-0.736***	-0.0132***
	(0.0238)	(0.156)	(0.0211)	(0.00406)	(0.255)	(0.00458)
N	70796	67509	67509	70650	64439	64439

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.27: Sensitivity Analysis: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) for Graduate Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Marijuana			*Cocaine*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0566*	-0.532**	-0.0451**	0.00430	1.044	0.0112
	(0.0292)	(0.223)	(0.0189)	(0.00896)	(1.066)	(0.0115)
N	18585	17434	17434	18576	15336	15336

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.28: Sensitivity Analysis: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) for White Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Marijuana			*Cocaine*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0730***	-0.732***	-0.0696***	-0.0157**	-1.711**	-0.0200
	(0.0243)	(0.235)	(0.0222)	(0.00753)	(0.666)	(.)
N	23186	21875	21875	23160	17305	17305

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.29: Sensitivity Analysis: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) for Non–white Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Marijuana			*Cocaine*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.0720**	-0.628**	-0.0669**	-0.00839	-1.109**	-0.0144**
	(0.0276)	(0.268)	(0.0284)	(0.00501)	(0.460)	(0.00597)
N	26994	25465	25465	26967	22068	22068

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.30: Sensitivity Test: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) for Female Studenets

	(1) *Marijuana* OLS	(2) Logit	(3) Logit AME	(4) *Cocaine* OLS	(5) Logit	(6) Logit AME
mml	-0.0718***	-0.570***	-0.0642***	-0.00595	-0.519	-0.00705
	(0.0177)	(0.132)	(0.0148)	(0.00425)	(0.361)	(0.00490)
N	62108	59126	59126	62000	54406	54406

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.31: Sensitivity Analysis: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) for Male Students

	(1) *Marijuana* OLS	(2) Logit	(3) Logit AME	(4) *Cocaine* OLS	(5) Logit	(6) Logit AME
mml	0.000209	0.0108	0.00153	-0.0134**	-1.214**	-0.0263**
	(0.0333)	(0.216)	(0.0308)	(0.00558)	(0.473)	(0.0103)
N	30370	29085	29085	30308	26547	26547

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.32: Sensitivity Analysis: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) for Students Aged 25 or Under

	(1) *Marijuana* OLS	(2) Logit	(3) Logit AME	(4) *Cocaine* OLS	(5) Logit
mml	-0.0619***	-0.185	-0.0145	-0.00993***	0.144
	(0.0213)	(0.304)	(0.0239)	(0.00319)	(0.465)
N	77592	15135	15135	77436	22137

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.33: Sensitivity Analysis: Impact of MMLs on Illicit Drug Use (Non–Medical Reasons) Excluding Illinois and New York

	(1) *Marijuana* OLS	(2) Logit	(3) Logit AME	(4) *Cocaine* OLS	(5) Logit	(6) Logit AME
mml	-0.0534**	-0.388**	-0.0481**	-0.00734***	-0.549***	-0.00845***
	(0.0221)	(0.159)	(0.0197)	(0.00264)	(0.138)	(0.00213)
N	93554	89234	89234	93384	87168	87168

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.34: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption for Undergraduate Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.00439	-0.0177	-0.00371	-0.0173	-0.172	-0.0205
	(0.0209)	(0.104)	(0.0218)	(0.0215)	(0.194)	(0.0231)
N	49741	49733	49733	65310	65301	65301

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.35: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption for Graduate Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.000545	-0.00155	-0.000345	-0.0815**	-0.510***	-0.0549***
	(0.0223)	(0.0981)	(0.0218)	(0.0347)	(0.188)	(0.0202)
N	13483	13468	13468	17147	17057	17057

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.36: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption for White Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.0253	0.120	0.0244	-0.00929	0.116	0.0116
	(0.0463)	(0.211)	(0.0429)	(0.0278)	(0.288)	(0.0287)
N	15007	14996	14996	20934	20858	20858

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.37: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption for Non–white Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.0586	0.269	0.0554	-0.0114	0.103	0.0104
	(0.0449)	(0.209)	(0.0432)	(0.0230)	(0.253)	(0.0255)
N	17722	17713	17713	24434	24348	24348

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.38: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption for Male Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.0205	0.0544	0.0115	-0.0230	-0.186	-0.0260
	(0.0217)	(0.106)	(0.0223)	(0.0346)	(0.171)	(0.0240)
N	21955	21951	21951	28171	28168	28168

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.39: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption for Female Students

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	-0.00625	-0.0248	-0.00530	-0.0161	-0.171	-0.0181
	(0.0265)	(0.123)	(0.0263)	(0.0187)	(0.197)	(0.0209)
N	44784	44779	44779	57451	57445	57445

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.40: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption for Students Aged 25 or Under

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.00817	-0.0786	-0.0171	-0.0162	-0.278**	-0.0378**
	(0.0235)	(0.0733)	(0.0160)	(0.0205)	(0.127)	(0.0172)
N	55680	11512	11512	71619	14903	14903

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.41: Sensitivity Analysis: Impact of MMLs on Binge Drinking and Cigarettes Consumption Excluding Illinois and New York

	(1)	(2)	(3)	(4)	(5)	(6)
	Binge Drinking			*Cigarettes*		
	OLS	Logit	Logit AME	OLS	Logit	Logit AME
mml	0.00725	0.0263	0.00562	-0.0182	-0.137	-0.0161
	(0.0235)	(0.108)	(0.0231)	(0.0201)	(0.143)	(0.0169)
N	67207	67199	67199	86575	86566	86566

Standard errors in parentheses are clustered at the school level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.42: Cities with Population over 100 000 in 2017

City	State	City	State
New York	New York	Raleigh	North Carolina
Los Angeles	California	Colorado Springs	Colorado
Chicago	Illinois	Miami	Florida
Houston	Texas	Virginia Beach	Virginia
Phoenix	Arizona	Oakland	California
Philadelphia	Pennsylvania	Minneapolis	Minnesota
San Antonio	Texas	Tulsa	Oklahoma
San Diego	California	Arlington	Texas
Dallas	Texas	New Orleans	Louisiana
San Jose	California	Wichita	Kansas
Austin	Texas	Cleveland	Ohio
Jacksonville	Florida	Tampa	Florida
San Francisco	California	Bakersfield	California
Columbus	Ohio	Aurora	Colorado
Fort Worth	Texas	Anaheim	California
Indianapolis	Indiana	Honolulu	Hawaii
Charlotte	North Carolina	Santa Ana	California
Seattle	Washington	Riverside	California
Denver	Colorado	Corpus Christi	Texas
Washington	District of Columbia	Lexington	Kentucky
Boston	Massachusetts	Stockton	California
El Paso	Texas	St. Louis	Missouri
Detroit	Michigan	Saint Paul	Minnesota
Nashville	Tennessee	Henderson	Nevada
Memphis	Tennessee	Pittsburgh	Pennsylvania
Portland	Oregon	Cincinnati	Ohio
Oklahoma City	Oklahoma	Anchorage	Alaska
Las Vegas	Nevada	Greensboro	North Carolina
Louisville	Kentucky	Plano	Texas
Baltimore	Maryland	Newark	New Jersey
Milwaukee	Wisconsin	Lincoln	Nebraska
Albuquerque	New Mexico	Orlando	Florida
Tucson	Arizona	Irvine	California
Fresno	California	Toledo	Ohio
Sacramento	California	Jersey City	New Jersey
Mesa	Arizona	Chula Vista	California
Kansas City	Missouri	Durham	North Carolina
Atlanta	Georgia	Fort Wayne	Indiana
Long Beach	California	St. Petersburg	Florida
Omaha	Nebraska	Laredo	Texas

Table A.42: Cities with Population over 100 000 in 2017 (continue)

City	State	City	State
Buffalo	New York	Akron	Ohio
Madison	Wisconsin	Augusta	Georgia
Lubbock	Texas	Huntsville	Alabama
Chandler	Arizona	Columbus	Georgia
Scottsdale	Arizona	Grand Prairie	Texas
Reno	Nevada	Shreveport	Louisiana
Glendale	Arizona	Overland Park	Kansas
Norfolk	Virginia	Tallahassee	Florida
Winston–Salem	North Carolina	Mobile	Alabama
North Las Vegas	Nevada	Port St. Lucie	Florida
Gilbert	Arizona	Knoxville	Tennessee
Chesapeake	Virginia	Worcester	Massachusetts
Irving	Texas	Tempe	Arizona
Hialeah	Florida	Cape Coral	Florida
Garland	Texas	Brownsville	Texas
Fremont	California	McKinney	Texas
Richmond	Virginia	Providence	Rhode Island
Boise	Idaho	Fort Lauderdale	Florida
Baton Rouge	Louisiana	Newport News	Virginia
Des Moines	Iowa	Chattanooga	Tennessee
Spokane	Washington	Rancho Cucamonga	California
San Bernardino	California	Frisco	Texas
Modesto	California	Sioux Falls	South Dakota
Tacoma	Washington	Oceanside	California
Fontana	California	Ontario	California
Santa Clarita	California	Vancouver	Washington
Birmingham	Alabama	Santa Rosa	California
Oxnard	California	Garden Grove	California
Fayetteville	North Carolina	Elk Grove	California
Rochester	New York	Pembroke Pines	Florida
Moreno Valley	California	Salem	Oregon
Glendale	California	Eugene	Oregon
Yonkers	New York	Peoria	Arizona
Huntington Beach	California	Corona	California
Aurora	Illinois	Springfield	Missouri
Salt Lake City	Utah	Jackson	Mississippi
Amarillo	Texas	Cary	North Carolina
Montgomery	Alabama	Fort Collins	Colorado
Grand Rapids	Michigan	Hayward	California
Little Rock	Arkansas	Lancaster	California

Table A.42: Cities with Population over 100 000 in 2017 (continue)

City	State	City	State
Alexandria	Virginia	Charleston	South Carolina
Salinas	California	Hampton	Virginia
Palmdale	California	Surprise	Arizona
Lakewood	Colorado	Columbia	South Carolina
Springfield	Massachusetts	Coral Springs	Florida
Sunnyvale	California	Visalia	California
Hollywood	Florida	Sterling Heights	Michigan
Pasadena	Texas	Gainesville	Florida
Clarksville	Tennessee	Cedar Rapids	Iowa
Pomona	California	New Haven	Connecticut
Kansas City	Kansas	Stamford	Connecticut
Macon	Georgia	Elizabeth	New Jersey
Escondido	California	Concord	California
Paterson	New Jersey	Thousand Oaks	California
Joliet	Illinois	Kent	Washington
Naperville	Illinois	Santa Clara	California
Rockford	Illinois	Simi Valley	California
Torrance	California	Lafayette	Louisiana
Bridgeport	Connecticut	Topeka	Kansas
Savannah	Georgia	Athens	Georgia
Killeen	Texas	Round Rock	Texas
Bellevue	Washington	Hartford	Connecticut
Mesquite	Texas	Norman	Oklahoma
Syracuse	New York	Victorville	California
McAllen	Texas	Fargo	North Dakota
Pasadena	California	Berkeley	California
Orange	California	Vallejo	California
Fullerton	California	Abilene	Texas
Dayton	Ohio	Columbia	Missouri
Miramar	Florida	Ann Arbor	Michigan
Olathe	Kansas	Allentown	Pennsylvania
Thornton	Colorado	Pearland	Texas
Waco	Texas	Beaumont	Texas
Murfreesboro	Tennessee	Wilmington	North Carolina
Denton	Texas	Evansville	Indiana
West Valley City	Utah	Arvada	Colorado
Midland	Texas	Provo	Utah
Carrollton	Texas	Independence	Missouri
Roseville	California	Lansing	Michigan
Warren	Michigan	Odessa	Texas

Table A.42: Cities with Population over 100 000 in 2017 (continue)

City	State	City	State
Richardson	Texas	Broken Arrow	Oklahoma
Fairfield	California	Lakeland	Florida
El Monte	California	West Covina	California
Rochester	Minnesota	Boulder	Colorado
Clearwater	Florida	Daly City	California
Carlsbad	California	Santa Maria	California
Springfield	Illinois	Hillsboro	Oregon
Temecula	California	Sandy Springs	Georgia
West Jordan	Utah	Norwalk	California
Costa Mesa	California	Jurupa Valley	California
Miami Gardens	Florida	Lewisville	Texas
Cambridge	Massachusetts	Greeley	Colorado
College Station	Texas	Davie	Florida
Murrieta	California	Green Bay	Wisconsin
Downey	California	Tyler	Texas
Peoria	Illinois	League City	Texas
Westminster	Colorado	Burbank	California
Elgin	Illinois	San Mateo	California
Antioch	California	Wichita Falls	Texas
Palm Bay	Florida	El Cajon	California
High Point	North Carolina	Rialto	California
Lowell	Massachusetts	Lakewood	New Jersey
Manchester	New Hampshire	Edison	New Jersey
Pueblo	Colorado	Davenport	Iowa
Gresham	Oregon	South Bend	Indiana
North Charleston	South Carolina	Woodbridge	New Jersey
Ventura	California	Las Cruces	New Mexico
Inglewood	California	Vista	California
Pompano Beach	Florida	Renton	Washington
Centennial	Colorado	Sparks	Nevada
West Palm Beach	Florida	Clinton	Michigan
Everett	Washington	Allen	Texas
Richmond	California	Tuscaloosa	Alabama
Clovis	California	San Angelo	Texas
Billings	Montana	Vacaville	California
Waterbury	Connecticut		

Table A.43: Controlled Cities in the Sample

City	State	City	State
Birmingham	Alabama	St. Petersburg	Florida
Huntsville	Alabama	Tallahassee	Florida
Mobile	Alabama	Tampa	Florida
Montgomery	Alabama	West Palm Beach	Florida
Tuscaloosa	Alabama	Athens	Georgia
Anchorage	Alaska	Atlanta	Georgia
Chandler	Arizona	Augusta	Georgia
Gilbert	Arizona	Columbus	Georgia
Glendale	Arizona	Macon	Georgia
Mesa	Arizona	Sandy Springs	Georgia
Peoria	Arizona	Savannah	Georgia
Phoenix	Arizona	Honolulu	Hawaii
Scottsdale	Arizona	Boise	Idaho
Surprise	Arizona	Aurora	Illinois
Tempe	Arizona	Chicago	Illinois
Tucson	Arizona	Elgin	Illinois
Little Rock	Arkansas	Joliet	Illinois
Bridgeport	Connecticut	Naperville	Illinois
Hartford	Connecticut	Peoria	Illinois
New Haven	Connecticut	Rockford	Illinois
Stamford	Connecticut	Springfield	Illinois
Waterbury	Connecticut	Evansville	Indiana
Washington	District of Columbia	Fort Wayne	Indiana
Cape Coral	Florida	Indianapolis	Indiana
Clearwater	Florida	South Bend	Indiana
Coral Springs	Florida	Cedar Rapids	Iowa
Davie	Florida	Davenport	Iowa
Gainesville	Florida	Des Moines	Iowa
Hialeah	Florida	Kansas City	Kansas
Hollywood	Florida	Olathe	Kansas
Jacksonville	Florida	Overland Park	Kansas
Lakeland	Florida	Topeka	Kansas
Miami	Florida	Lexington	Kentucky
Miami Gardens	Florida	Louisville	Kentucky
Miramar	Florida	Baton Rouge	Louisiana
Orlando	Florida	Lafayette	Louisiana
Palm Bay	Florida	New Orleans	Louisiana
Pembroke Pines	Florida	Shreveport	Louisiana
Pompano Beach	Florida	Baltimore	Maryland
Port St. Lucie	Florida	Cambridge	Massachusetts

Table A.43: Controlled Cities in the Sample (continue)

City	State	City	State
Boston	Massachusetts	Providence	Rhode Island
Lowell	Massachusetts	Charleston	South Carolina
Springfield	Massachusetts	Columbia	South Carolina
Worcester	Massachusetts	North Charleston	South Carolina
Ann Arbor	Michigan	Sioux Falls	South Dakota
Clinton	Michigan	Chattanooga	Tennessee
Detroit	Michigan	Clarksville	Tennessee
Grand Rapids	Michigan	Knoxville	Tennessee
Lansing	Michigan	Murfreesboro	Tennessee
Sterling Heights	Michigan	Abilene	Texas
Warren	Michigan	Allen	Texas
Columbia	Missouri	Amarillo	Texas
Kansas City	Missouri	Arlington	Texas
Independence	Missouri	Austin	Texas
St. Louis	Missouri	Beaumont	Texas
Springfield	Missouri	Brownsville	Texas
Billings	Montana	College Station	Texas
Henderson	Nevada	Corpus Christi	Texas
Las Vegas	Nevada	Dallas	Texas
North Las Vegas	Nevada	Denton	Texas
Reno	Nevada	El Paso	Texas
Sparks	Nevada	Fort Worth	Texas
Manchester	New Hampshire	Frisco	Texas
Edison	New Jersey	Garland	Texas
Elizabeth	New Jersey	Grand Prairie	Texas
Jersey City	New Jersey	Houston	Texas
Lakewood	New Jersey	Irving	Texas
Newark	New Jersey	Killeen	Texas
Paterson	New Jersey	Laredo	Texas
Woodbridge	New Jersey	League City	Texas
Albuquerque	New Mexico	Lewisville	Texas
Las Cruces	New Mexico	Lubbock	Texas
Fargo	North Dakota	McAllen	Texas
Broken Arrow	Oklahoma	McKinney	Texas
Norman	Oklahoma	Mesquite	Texas
Oklahoma City	Oklahoma	Midland	Texas
Tulsa	Oklahoma	Odessa	Texas
Allentown	Pennsylvania	Pasadena	Texas
Philadelphia	Pennsylvania	Pearland	Texas
Pittsburgh	Pennsylvania	Plano	Texas

Table A.43: Controlled Cities in the Sample (continue)

City	State	City	State
Richardson	Texas	Norfolk	Virginia
Round Rock	Texas	Richmond	Virginia
San Angelo	Texas	Virginia Beach	Virginia
San Antonio	Texas	Bellevue	Washington
Tyler	Texas	Everett	Washington
Waco	Texas	Kent	Washington
Wichita Falls	Texas	Renton	Washington
Provo	Utah	Seattle	Washington
Salt Lake City	Utah	Spokane	Washington
West Jordan	Utah	Tacoma	Washington
West Valley City	Utah	Vancouver	Washington
Alexandria	Virginia	Green Bay	Wisconsin
Chesapeake	Virginia	Madison	Wisconsin
Hampton	Virginia	Milwaukee	Wisconsin
Newport News	Virginia		

Table A.44: Negative Binomial Estimated Effects of Marijuana Laws on Fatal Traffic Crashes

	(1) Male		(2) Female		(3) All	
Panel A: Ages 15–24						
Decriminalization	1.204	(1.025,1.415)	0.979	(0.748,1.281)	1.113	(0.957,1.295)
State MML	0.935	(0.806,1.085)	0.872	(0.677,1.124)	0.921	(0.798,1.063)
pre–treated mean†	28.044		10.513		19.292	
Panel B: Ages 25–44						
Decriminalization	0.995	(0.891,1.110)	0.953	(0.799,1.136)	0.970	(0.867,1.085)
State MML	0.860	(0.891,1.110)	0.801	(0.674,0.953)	0.855	(0.755,0.953)
pre–treated mean†	20.317		9.764		14.910	
Panel C: All Ages						
Decriminalization	1.020	(0.942,1.104)	1.013	(0.892,1.150)	1.023	(0.949,1.103)
State MML	0.905	(0.839,0.976)	0.904	(0.805,1.015)	0.908	(0.845,0.975)
pre–treated mean†	10.559		5.914		5.327	

Table includes Poisson–estimated incidence rate ratios and corresponding 95% confidence intervals of the effect of marijuana policy changes on fatal crashes by age and gender. Each specification includes city and half–year fixed effects, state–level traffic safety laws, and city–level semi–annual average unemployment rates. Standard errors are clustered at the city level.

† - Pre–treated mean of rate of fatal crashes per 100,000 people within the demographic category.