The Effects of Medical Marijuana Laws on Utilization of Prescribed Opioids and Other Prescription Drugs

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Abstract

More than half of the US population lives in a state that has adopted medical marijuana laws (MMLs). Studies show that most medical marijuana patients use marijuana for managing their pain with the overwhelming majority of them preferring it to opioids. Despite ongoing pro-marijuana policies and the growing trend of public acceptance, the evidence on how people change their prescription use due to the availability of marijuana as an alternative treatment is limited. Using the variations across state MMLs between 1996 and 2014 of Medical Expenditure Panel Survey (MEPS) this paper estimates the effects of MMLs on prescription drug utilization, with a focus on opioids. I find that MMLs lead to a $2.47 decrease in per person prescribed opioid spending among young adults (ages 18-39) over a year. Most of this decrease results from the intensive margin of use and MML states that allow home cultivation experience even larger decreases. Furthermore, the decreasing effects are persistent over time and they get stronger following the years of implementation. MMLs also decrease the number of opioid pill use among young adults. I do not find any discernible impact on older populations' opioid utilization. I then investigate the effects on other prescriptions for which marijuana can be a potential substitute and find the allowance of dispensaries is generally associated with decreases, although the effects depend on the the type of MML, the margin of use and age.

Keywords: marijuana, opioids, prescription drugs
JEL Classification: I12, I18

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1 Introduction

Between 1996 and 2017, 29 states and the District of Columbia enacted laws that legalize the medical use of marijuana. Eight states and D.C. legalized recreational use and 19 states and D.C. have operating dispensaries. The total estimated value of legal marijuana sales in the United States was $5.7 billion in 2015 and $7.1 billion in 2016 (Arcview, 2017). The market is projected to grow as more than half of the U.S population now lives in a state where marijuana is legalized either medically or recreationally. Understanding the consequences of legalizing marijuana as a medicine is important as more states are discussing new medical marijuana laws (MMLs) in the near future. However, all these ongoing pro-marijuana policies are founded on limited scientific evidence on marijuana's effects on health due to the federal government's classification of marijuana as a Schedule 1 substance, which imposes significant barriers to conducting randomized controlled trials with human subjects to study marijuana's effects.

Despite the limitations, there is some evidence suggesting that marijuana can improve several health conditions and symptoms like nausea and vomiting, loss of appetite, depression, anxiety, chronic pain, and muscle spasms, as well as regulate sleep.[1] Prior studies generally find that the most reported reason for using medical marijuana among medical marijuana patients is the relief of pain, and most of those who use it for pain relief use it together with their opioid-based prescriptions.[2] According to a recent survey from a database of medical marijuana patients conducted by Reiman et al. 2017, 63% of participants reported using marijuana for pain-related conditions. 30% reported using an opioid-based drug and of those 61% reported using it with marijuana. In addition, more than 97% of their sample agreed they were able to decrease the amount of opioids they consume when they also used marijuana. 53% of their participants were between 20 and 39 years old.

Allowing marijuana as an option to treat pain and other symptoms can have two opposing effects on people's prescription opioid and other drug utilization. First, it can reduce utilization by inducing people to substitute away from prescriptions to marijuana. Second, MMLs can act like direct-to-consumer prescription drug advertising, inducing people seek medical help for their conditions, which in turn increases demand for prescriptions.

This paper examines if MMLs influence prescription drug utilization with a particular focus on opioids; a category of powerful pain-reducing medicines with severe risks of addiction, abuse, overdose and death.[3] Using Medical Expenditure Panel Survey (MEPS)

[1] Whiting et al. 2015; Borgelt et al. 2013; Jensen et al. 2015; Institute of Medicine 1999, Amar 2006, National Academies, 2017.

[2] Reinerman et al. 2011, Reiman et al. 2017.

[3] According to Centers for Disease Control (CDC), half of all U.S. opioid deaths involve a prescription opioid and 91 Americans die from opioid overdose every day. Deaths from prescription opioids and the sales of these prescriptions drugs have quadrupled from 1999. National Institute on Drug Abuse reports

household and prescribed medicine files, I estimate the effects of MML implementation and its provisions on utilization of prescribed opioids by exploiting the variations in MMLs across states over time. For my main analysis, I show results from two-part models, jointly estimating the extensive and intensive margins of prescribed opioid expenditures and their effects on each part of the model separately. I then examine MMLs' effects on utilization of other categories of drugs for which medical marijuana is a plausible substitute. Studying the effects on these other prescriptions is also important because they make up a large portion of overall healthcare expenditures.

My main results indicate that MMLs significantly decrease expenditures on opioids among young adults (ages 18-39) by $2.47 per person over a year. This decreasing effect results from the significant decrease on the intensive margin, implying that rather than quitting opioids altogether, young adults continue to use them with marijuana. States allowing home cultivation of marijuana experience even larger decreases in opioid expenditures. Furthermore, these decreasing effects of MMLs on opioid expenditures are persistent over time and they get stronger following the years of MML implementation. The results are similar when we consider the effects on the total amount of prescribed opioid pills. Namely, implementation of a MML decreases the total amount of prescription opioid pills by 2.16 pills per person over a year among young adults. I find no discernible effect of MMLs on the opioid utilization of older populations.

I then estimate MML's effects on utilization of other prescription drugs and find that MML states which allow retail dispensaries generally experience decreases on spending for the drugs which marijuana can substitute among young adults. MML is also associated with significant decreases in sedatives among elderly population (ages 65+). The results from other prescription drugs mostly depend on age and the level of access MMLs provide to marijuana.

Based on my findings MMLs can potentially alleviate the problems associated with opioid misuse in younger adults, the biggest abusers of prescription opioids. MMLs with looser restrictions, especially those that allow greater access by legalizing dispensaries and allowing home cultivation can reduce excess medical costs associated with adverse drug events[4], which cause more than 1 million emergency department visits and cost $3.5 billion each year (Aspden et al. 2007). The third reason why MMLs can be useful is because it can reduce the costs on the insurance pool. Medical marijuana is not covered by insurance like prescription drugs. If people switch to marijuana they pay it out of pocket. If MMLs turn a public healthcare cost into a private cost this can be welfare

young adults (age 18 to 25) are the biggest abusers of prescription opioid pain relievers and in 2014 more than 1,700 died from prescription drug (mainly opioid) overdoses-more than died from overdoses of any other drug, including heroin and cocaine combined. https://www.drugabuse.gov/related-topics/trends-statistics/infographics/abuse-prescription-rx-drugs-affects-young-adults-most.

[4]An adverse drug event (ADE) is an injury resulting from medical intervention related to a drug. This includes medication errors, adverse drug reactions, allergic reactions, and overdoses. (Office of Disease Prevention and Health Promotion). https://health.gov/hcq/ade.asp

increasing by internalizing an externality.

The paper proceeds as follows. Section 2 summarizes the existing literature and provides background information on prevalence of marijuana on health and the evidence on its substitutability with opioids. Section 3 outlines the theoretical framework by laying out a simple patient-physician interaction in an MML state and gives some testable implications. Section 4 describes the data, variable measurement, and identification strategy. Section 5 shows primary results of the effects of MML on opioids and Section 6 presents sensitivity analyses and examines effects on other prescriptions. I conclude with a summary of my findings and implications for future medical marijuana policy design in Section 7.

2 Background

2.1 Medical uses of marijuana and substitutability with opioids

The National Sciences report 2017 systemically reviewed the most recently published studies since 2011 that were "fair-and-good quality" in reaching conclusions on the health effects of cannabis.[5] The report finds: 1) conclusive evidence that cannabis is effective in reducing chronic pain in adults, cancer-induced nausea and vomiting and patient-reported spasticity symptoms 2) moderate evidence that cannabis is effective in improving short-term sleep outcomes 3) limited evidence that cannabis is effective in improving symptoms of anxiety and post-traumatic stress disorder.

Whiting et al. 2015 did a meta-analysis from a total of 79 trials (6462 participants) and report the following findings: 1) moderate-quality evidence to suggest cannabis was beneficial for the treatment of chronic neuropathic or cancer pain and spasticity due to multiple sclerosis 2) low-quality evidence to suggest cannabis was associated with improvements in cancer-induced nausea and vomiting, weight gain in HIV and sleep disorders 3) very low-quality evidence to suggest cannabis was associated with improvement in anxiety.

Given the risks and problems associated with opioid use and the widespread acceptance of using marijuana as a medicine it is natural to ask two questions: 1) Can marijuana be a substitute for opioid-based medicines and if so 2) do people really substitute away from opioids to marijuana? The literature from clinical studies and with selected samples from medical marijuana patients suggests that medical marijuana patient may substitute opioids for marijuana.

Abrams et al. 2011 study the cannabis-opioid interaction drawing evidence from 21 patients with chronic pain. They conclude that cannabis augments the pain relieving

[5]Scientific literature refers to marijuana as cannabis. I use the terms "marijuana" and "cannabis" interchangeably in this paper.

effects of opioids and their combination may allow for opioid treatment at lower doses with fewer side effects. Drawing evidence from an open-label clinical research trial, Haroutounian et al. 2016 found treatment of chronic pain with medicinal cannabis resulted in improved pain outcomes and significant reduction in opioid use.

In addition to the clinical results above, there is suggestive evidence that medical marijuana patients change their opioid use in response to medical marijuana use. Studies involving surveys of medical marijuana patients report that the most common reason patients citing for using medical marijuana was the relief of pain (Reinerman et al. 2011; Reiman et al. 2017). Reinerman et al. 2011 find 79.3% of the medical marijuana patients reported having tried other medicines presented by their physicians and almost half of them were opioids. Reiman et al. 2017 find 30% of their sample reported using an opioid-based medication currently or in the past six months and out of those 61% reported using it with cannabis. More strikingly, they report that 92% of the sample "strongly agreed/agreed" that they prefer cannabis to opioids and 93% "strongly agreed/agreed" that they would be more likely to choose cannabis for opioids to treat their condition. Boehnke et al. 2017 find medical cannabis use was associated with a 64% decrease in opioid use among medical marijuana patients with chronic pain between 2013 and 2015 in Michigan.

Although there is some evidence that availability of marijuana decreases the use of opioids, it is hard to extrapolate these results from the above studies to wider populations since their conclusions are based on small and selected samples that rely on self-reported outcomes.

2.2 Effects of MMLs and contribution of this study

Although the literature on MMLs is rich the effects studied are mostly focused on the unintended consequences. The effects of MMLs on recreational marijuana use, alcohol consumption, initiation by youth, drunk driving, cigarettes and other substance use are studied by prior literature. Lynne-Landsman et al. 2013 show no effects of MMLs on adolescent marijuana use in the first few years after their enactment using the National Youth Risk Behavioral Surveys (YRBS). Anderson et al. 2015 revisit the relationship using data from the national and state YRBS, Treatment Episode dataset, and National Longitudinal Survey of Youth 1997. They find MMLs were not associated with an increase in marijuana use among teenagers. Anderson et al. 2013 found a significant and negative relationship between MML and traffic fatalities, especially for those involving alcohol. Pacula et al. 2015 re-examine the effects of MMLs on recreational marijuana use by adult and youth population and they also examine different provisions of MMLs. They report that treating MMLs as one dichotomous variable hide the effects of different provisions of MMLs. They show that not all MMLs are the same and the provisions of the law matter.

In particular, they find that the MMLs that legally protect dispensaries can increase recreational marijuana use and abuse among adults and youth compared to MMLs that do not protect this supply source. Wen et al. 2015 show estimates from the National Survey on Drug Use and Health (NSDUH) and report that MMLs increase marijuana use and abuse among people who are 21 and older and initiation in younger populations. They also find MMLs increase binge drinking for 21 and above but have no effect on psychoactive substance use in either age group.

The MML literature on problematic opioid use is less comprehensive. Bauchhuber et al. 2014 examined state-level death certificates in the U.S. between 1999 and 2010 and found that states with MMLs had lower mean annual opioid overdose mortality rates compared with states without them. Powell et al. 2015 studied the effects of MML on problematic opioid use and found that broader access to marijuana reduced the abuse of highly addictive painkillers. Smart 2015 finds that growth in the supply of medical marijuana decreases opioid poisonings for adults between 45 and 64 by 12-16%. Yuan 2017 finds MMLs were associated with 23% and 13% reductions in hospitalization related to opioid abuse and overdose respectively. These studies all involve outcomes of people on the margins of abusive and possibly non-medical use. In this paper, I will show the effects on outcomes involving prescribed opioid use from a population which represent the U.S population more broadly, and not necessarily from a population of opioid abusers.

The literature examining the effects on prescription drug use more broadly is very limited. Bradford and Bradford 2016 examined data on all prescription drugs filled by physicians for the Medicare Part D enrollees from 2010 to 2013. They find that MML implementation led to significant reductions in daily doses filled per physician in seven drug categories that marijuana can serve as an alternative. These conditions include anxiety, depression, nausea, pain, psychosis, seizures and sleep disorders. In another paper Bradford and Bradford 2017 find significant negative associations between the presence of MML and quarterly logged average prescription units filled for the aforementioned drug categories among the Medicaid population from 2007 to 2014.

I extend the studies from the Bradford and Bradford articles in several ways. First, my analyses span years from 1996 to 2014, giving me a richer source of policy variation. During those 19 years, 23 states and D.C implemented MMLs and this relatively longer time horizon also enables me to estimate the long run effects of MMLs. Second, my observations are representative of the U.S population instead of consisting of patients on Medicaid and Medicare with positive spending. I will show the effects of MMLs on the extensive and intensive margins separately. It is plausible that MMLs affect prescription use differently on these two margins since the decisions on the probability of use and amount of use are decided by different agents. Third, this paper will investigate isolated effects of different MML provisions. Prior research suggests heterogeneity in MMLs lead to different effects which indicates that the design of these laws is essential in analyzing

the costs and benefits of MMLs. Lastly, I focus explicitly on the utilization of opioids, defining utilization in terms of expenditures and pills both. Knowing how MMLs change the utilization of prescribed opioids and other prescription drugs is not only important for the analysis of MMLs but also important within the context of the growing trend of prescription drug costs and the costs associated with their misuse, such as the recent epidemic of opioid abuse.

3 Theoretical Framework

There are many mechanisms through which MMLs and their provisions can affect the demand of prescription drugs for which marijuana can be a substitute. The first and most obvious effect would be that patients with these conditions will seek their physicians' recommendation to substitute their prescriptions with marijuana. However, having a MML in place may also encourage a fraction of people who also had the conditions/symptoms but for some reason did not visit a physician before a MML was enacted. Enactment of a MML may serve to inform these people about their existing conditions and to seek medical help just like how direct-to-consumer advertising of prescription drugs would. Due to information asymmetry, the physician is the agent of the patient and she will make the decision whether to and if so, how much to prescribe/recommend an FDA-approved prescription or medical marijuana. Given marijuana's classification as a Schedule 1 drug, and the resulting absence of scientific evidence and incentives that the physician would have if she prescribed prescriptions supplied by the pharmaceutical firm (low cost of information due to heavy advertising/detailing/scientific evidence/habit formation, less risk), some physicians will be reluctant to substitute it.

Following Brekke et al. 2006 I assume there is a continuum of patients with a condition in a therapeutic drug market which marijuana can have a potential to treat on the line segment [0, 1]. The location of the patient x $\in$ [0,1] is associated with his condition and personal characteristics. They all need either a prescription drug (Rx=0) or medical marijuana (m=1). Rx and m are located at the either ends of a unit interval [0, 1] and are indexed as i. This classification of 0 and 1 only reflect their chemical compounds and the treatment effects. I assume the patient's utility takes the following linear form when he takes the treatment i:

$$U^{patient}(x, i) = \upsilon - \tau|x - i| - C_i \tag{1}$$

where the parameter υ represents the effectiveness of drug i. I assume that both treatments Rx and m have the same effectiveness but they differ in their treatment effects to a given x. τ represents the weight given to the utility loss that is realized due to the mismatch between the condition x and the treatment choice (the distance between the

condition and the treatment choice). These can be thought of as side effects. I assume that υ and τ are both positive. C_i represents the out-of-pocket cost for the treatment.

Consider a population of people who have a condition and let $z \in [0,1]$ be the fraction of patients who already saw a doctor related with their condition and (1-z) the fraction of patients who have the condition but did not see a doctor yet (potential patients). When states adopt MMLs this can serve as a marijuana advertisement inducing some of these potential patients to be aware of their conditions and encourage them to go to the doctor's office. Let $\phi \in [0,1]$ be the fraction of patients who receive information about the legalization of medical marijuana in their state. I assume all patients need a treatment, whether medical marijuana or a prescription drug. Only potential patients who have not heard about MMLs will not go to a doctor's office. The fraction of patients who go to the doctor's office for treatment is then N=z+(1-z)ϕ.

I assume all physicians face the same distribution of patients. Once the patient goes to the physician, the physician asks questions to determine the patient's type; his location $x \in [0,1]$. After observing the patient's type the physicians can either recommend medical marijuana or prescribe a drug. I assume there are two type of physicians: 1) Physicians who will not recommend medical marijuana no matter how much the patient insists; I call them "Type 1 physician" and denote their share as θ 2) Physicians who are willing to recommend marijuana if the patient insists, I call them "Type 2 physicians" and their share is (1-θ).

Consider a type 1 physician who will not recommend marijuana at all costs. I assume her utility function takes the linear form below;

$$U^{physician}(x, Rx) = b_{Rx} + \gamma U^{patient} \tag{2}$$

where b_{Rx} denotes the private benefit she receives from prescribing the prescription drug and γ denotes the weight she puts on her patient's utility. Plugging the patient's utility given in equation (1) type 1 physician will prescribe Rx to the patient x only if the following is true;

$$U^{physician}(x, Rx) \geq 0 \iff b_{Rx} + \gamma\upsilon - \gamma\tau x - \gamma C_{Rx} \geq 0 \tag{3}$$

If $U^{physician}(.)<0$, then the physician will recommend a different treatment or no treatment at all. Consider a type 1 physician who is indifferent between prescribing and not prescribing. Solving (3) we get;

$$\tilde{x} = \frac{b_{Rx} + \gamma\upsilon - \gamma C_{Rx}}{\gamma\tau} \tag{4}$$

She will prescribe the drug if the patient x is on the interval $[0,\tilde{x}]$ and not prescribe if the patient is between $[\tilde{x},1]$.

Now consider a type 2 physician who considers marijuana as an alternative to Rx. She will recommend marijuana (m) instead of Rx only if the following condition holds;

$$\begin{aligned} U^{physician}(x,m) \geq U^{physician}(x,Rx) \iff & b_m + \gamma(\upsilon - \tau(1-x) - C_m) \\ & \geq b_{Rx} + \gamma(\upsilon - \tau x - C_{Rx}) \end{aligned} \tag{5}$$

where b_m denotes the private benefit (or cost – e.g., her time cost of searching for information about marijuana or the cost of writing a recommendation letter) the physician gets from recommending medical marijuana and C_m denotes the financial cost of medical marijuana to the patient. Let $\tilde{x}$ denote the patient whom the physician is indifferent in recommending m vs. prescribing Rx. By solving (4) we get;

$$\hat{x} = \frac{1}{2} - (\frac{\gamma(C_{Rx} - C_m) + b_m - b_{Rx}}{2\gamma\tau})$$

This means the physician will recommend marijuana if the patient x is located on [$\hat{x}$,1] and prescribe Rx if he is on [0,$\hat{x}$]. Since the physician will not recommend m or prescribe Rx if her utility is not positive the condition

$$b_m + \gamma(\upsilon - \tau(1-\hat{x}) - C_m) = b_{Rx} + \gamma(\upsilon - \tau\hat{x} - C_{Rx}) \geq 0$$

must hold. This is satisfied when $\tilde{x} \geq \hat{x}$.

Proposition 1 *Entrance of medical marijuana as another treatment option will decrease the 'mismatch' between a given therapeutic condition and the prescription drug substituting marijuana with prescription drugs.*

Proposition 2 *Substitution effect; $\tilde{x}$-$\hat{x} \geq 0$ will be higher for more expensive drugs and/or for drugs which treat conditions that are not a good match with the prescription drug (or drugs with more severe side effects).*

Proposition 3 *In states where the patient's cost of obtaining marijuana is lower (small C_m) and physician's benefit of recommending it is higher (or lower cost of recommending, high b_m) more prescription drugs will be substituted.*

From the physician's choices above we can derive the shares of patients who get Rx and m respectively,

$$\begin{aligned} M_{Rx} &= [z + (1-z)\phi] * [\theta\tilde{x} + (1-\theta)\hat{x}] \text{ and,} \\ M_m &= [z + (1-z)\phi] * [(1-\theta)(1-\hat{x})]. \end{aligned}$$

If a MML was not enacted the share of the patients who would be on Rx would simply be $z\tilde{x}$. The difference between the share of prescription drugs after and before

the MML then would be $\tilde{x}[\theta\phi(1\text{-}z)+z(\theta\text{-}1)]+\hat{x}(1\text{-}\theta)[z+(1\text{-}z)\phi]$. A high enough $\theta\phi$ (the fraction of new patients who visit the type 1 physician) could increase the prescription drug shares after the MML.

Proposition 4 *If the share of new patients that visit the type 1 physician ($\theta\phi$) is high enough prescription drug utilization can increase after the MML.*

Proposition 5 *For prescription drugs which are already a good match with a given condition (less severe side effects), utilization can increase after the MML.*

4 Estimation

To determine the effects of MMLs on prescription drug spending I use prescribed medicine event-level data linked to person level data from the Medical Expenditure Panel Survey (MEPS) spanning 1996 to 2014. Starting from 1996, MEPS collects detailed information for each person in selected households. This information includes demographic characteristics, health insurance coverage and income. MEPS Prescribed Medicine Files contain pharmacy-provided information on names of prescribed medicines obtained, their therapeutic class and sub-class, total amount paid for the prescribed medicines and source of their payments for each time a prescription drug was purchased.

The MEPS is a nationally representative panel survey and it has an overlapping panel design. A new panel of sample households is selected each year and they are surveyed for two years. I acquired the unrestricted version of MEPS with state identifiers and merged the state-and year-level MML variables. As seen in Table 1.1, 23 states and D.C implemented MMLs during the study period.

Since the literature suggests that there is relatively stronger evidence of marijuana as a painkiller and the fact that the majority of medical marijuana patients use it for their pain, specifically preferring it to opioid-based painkillers, I choose the main outcome variable as the total amount of dollars spent on opioid-based medicines. Focusing on opioids is also important from a policy perspective considering the costs associated with opioid misuse.

The key independent variables are indicators for MML implementation (effective dates) in a given state and year and its individual components. As noted by Pacula et al. 2015, MML states differ highly in how they allow medical marijuana and ignoring the heterogeneities in these policy dimensions that exist both across time and states can mask their heterogeneous effects and the mechanisms through which MMLs affect utilization. Following Pacula et al. 2015 and Wen et al. 2015, I analyze the effects of four key components that can lead to heterogeneity in prescription drug utilization: i) "Retail dispensary" provision, an indicator of whether the state's MML explicitly allows/protects dispensaries to dispense marijuana to medical marijuana patients ii) "home cultivation"

provision, an indicator of whether a state's MML allows the medical marijuana patient to cultivate a certain amount of marijuana iii) "non-specific pain" provision, an indicator of whether the state's MML lists any chronic pain or intractable pain in the eligible conditions for medical marijuana instead of specifically listing the conditions associated with the pain iv) "patient registry" provision, an indicator for whether a state's MML requires the patient registry. These provisions can directly determine both the monetary and search costs of obtaining medical marijuana of the patient as well as marijuana's perceived risk and appropriateness for recommendation from the physician's view.

I control for individual and state level factors that are correlated with prescription drug spending and with state decisions about MMLs. Individual-level covariates include a rich set of sociodemographic and economic characteristics. State-level covariates include four time-varying measures reflecting the variations in state economic conditions between 1996 and 2014: i) state unemployment rate ii) state median household income iii) state average personal income iv) state uninsured rate. I include two policy variations during the study period that can affect prescription drug spending and MML implementation. These state-level policy variables include i) indicator for operational prescription drug monitoring programs (PDMPs) in a state ii) indicator for the implementation of a marijuana decriminalization/depenalization in a state.

After pooling all the year, collapsing the prescribed opioid transactions at the year- and person-level and excluding people under the age of 18, I have a sample of 435,035 person level observations. Tables 1.2 and 1.3 show the summary statistics for dependent and independent variables.

4.1 Data characteristics and two-part model

Like the other healthcare utilization data, prescription drug utilization distributions tend to be skewed because 1) there cannot be negative spending 2) there is a mass at point zero for non-users 3) patients with more severe conditions use substantially more on prescription drugs than those with less severe conditions 4) there can be a small number of patients with astronomical spending due to catastrophic health conditions. Health economists often use log-transformed models to deal with these types of skewed outcomes. Other approaches include more flexible methods of conditional density estimation or estimation with GLM. Certain transformations such as logging are not appropriate, especially when there is a large mass of zeros. First, adding an arbitrary constant to observations is not recommended, and second, using one-part models implicitly assume that observations with zero outcomes are similarly affected by covariates as nonzero outcomes. These models are shown to behave poorly compared to multi-part models (Duan et al. 1983; Mihaylova et al. 2011).

Due to the presence of the zero mass of non-users in the data, I use a two-part

model approach. The two-part model splits the prescription spending into two parts and applies the basic rule of probability in estimating the parameters in the conditional mean function $E(y|x)=Pr(y>0|x)\times E(y|y>0,x)$.

Figure 1.1 shows the nonlinearities in the distribution of opioid spending. There is a large mass of non-users (approximately 90%), and the spending from users is skewed to the right even after logging.

Since health care utilization data show heteroscedasticity, a re-transformation that assumes homoscedastic, normally distributed log-scale error terms will give biased results. Due to the complications that can arise with estimating the correct form of heteroscedasticity, I avoid using OLS on logged outcomes with heteroscedastic retransformation and use GLM for consistent estimation instead. The advantages of using GLM compared to models with transformations are more broadly discussed in Manning and Mullahy 2001 and Jones 2000.

GLM extends the classical linear models in two ways. First, it allows the dependent variable to be distributed with any exponential family. Second, it allows for any monotonic differentiable function of the dependent variable to vary linearly with the covariates (the link function), rather than requiring the dependent variable itself to respond linearly (McCullagh and Nelder 1989). Another advantage of using GLM is that it gives predictions on the raw scale since it does not transform data and it also allows for heteroscedasticity. Modeling health care utilization and costs with GLM is a common approach in the literature (e.g. Goda et al. 2011; Chandra et al. 2014; Strumpf et al. 2017).

For the baseline model, I use probit estimation, shown below, to estimate the probability of being a prescription drug user:

$$Pr(Y_{iast} > 0 \mid X) = \Phi(X\beta)$$

where Y_{iast} is the binary variable equal to one if the consumption for a person i living in state s in year t for the drug category a is positive and zero otherwise. X is a vector of explanatory variables including all the control variables in Table 3, state and year fixed effects and state-specific linear time trends to capture the state-level factors that evolve over time at a constant rate.

For the intensive margin, I use GLM models with log-link and gamma family to estimate the amount of spending conditional on being a user as shown below:

$$E(Y_{iast} \mid Y_{iast} > 0, X) = \exp(X\gamma)$$

where Y_{iast} denotes the prescription drug spending for person i for the drug category a, in state s and year t, X denote the same vector of covariates as in the first part.

As suggested by Manning and Mullahy 2001, I used modified Park tests to determine the relationship between the conditional variance and the conditional mean functions, namely the parameter δ in $Var[Y_{iast}|Y_{iast}>0,X]=\alpha[E(Y_{iast} \mid Y_{iast} > 0, X)]^{\delta}$. In all drug cases, $\hat{\delta}$ was closest to 2 implying the gamma family.

Standard errors in all regressions are robust to heteroscedasticity and they are clustered at the state level to correct for serial correlation. The clustered standard errors allow the errors to be correlated within states while allowing them to be independent across states (Bertrand et al. 2004).

As the main results, I report the combined marginal effects from both parts of the model[6]

$$E(Y_{iast} \mid X) = Pr(Y_{iast} \mid X > 0) \times E(Y_{iast} \mid Y_{iast} > 0, X)$$

This setup models the difference in difference in utilization on the original scale of the dependent variable (dollar amount) yielding estimates that are readily interpretable. It also allows for heteroscedasticity where *Var(Expenditure|X)* depends on the mean level of conditional expenditures, *E(Expenditure|X).*

I also report the results from probability of use and amount of use separately. It is possible that MMLs (and their provisions) have opposite effects on each margin of use, especially if they act as an advertisement and encourage people to visit doctors who then prescribe them drugs, increasing the probability of utilization, while decreasing the amount of utilization by the users that are already on these drugs. If MMLs have opposite signs in different parts, then it would be possible for the marginal effect to be significant in isolated parts of the model along with the combined marginal effect being insignificant.

According to the CDC, prescription drug utilization is highest for people age 65 and older, and there are substantial differences in utilization based on age. I stratified the sample into three age groups because prescription drug utilization varies largely depending on age, and lumping everyone in the same sample obscures this heterogeneity (Kantor et al. 2015). The samples are ages 18-39 (N=186,144), 40-64 (N=180,723) and 65 and older (N=68,168). Because there are stricter barriers for minors to obtain medical marijuana and the fact that they are much less likely to have the conditions for which marijuana can be beneficial, I exclude people younger than 18 from the sample.

5 Primary Results

Table 2 presents the means of the main outcome variable of opioid spending along with the drug categories that marijuana can potentially replace for the full sample. Both the

[6]I used STATA's twopm command developed by Belotti et al. 2015 to obtain the combined marginal effects and their standard errors.

probability of any spending and the amount of spending conditional on positive spending on opioids and other potentially marijuana substitutable prescriptions are lower in MML states compared to control states.

To determine whether these differences are driven by MMLs, I estimate two different models. First, I show results from the models that only include any MML, and in the second I report the results from the model which only include its provisions. I also report a model that simultaneously estimates all provisions and MML, but due to collinearity when the fixed effects are included, I do not report these results as main findings.[7]

For my analyses I show results from two-part models instead of OLS on the whole sample for three reasons. First, many people in these samples do not use these prescription drugs, and two-part models explicitly model this large mass of non-users. Second, the two-part model yields lower Akaike information criterion. Third, the two-part model gave better out-of-sample predictions compared to OLS. I also run joint significance tests where the null hypothesis is the coefficients from the four provisions of MMLs are jointly equal to zero and report their p-values. I perform these tests for the models that include indicators for all provisions and an indicator for existence of any MML. The motivation is to test whether these provisions jointly explain variations which are not captured by a generic MML indicator.

Tables 4 through 6 show the effects of a MML and its provisions on the different margins of opioid spending among different age groups. According to the results in Table 4, a MML has no discernible effect on the probability of using opioids in young adults (ages 18-39). Although the coefficient on "any MML" is positive, it is insignificant. Similarly, none of the provisions show any discernible effects. However, there is a significant decrease in opioid spending on the intensive margin. Namely, among young adult users of opioids there is a decrease of \$37.46 per person over a year associated with passing of MML which translates as a 53.7% decrease from the baseline mean of opioid expenditures. Looking at the model which includes its provisions we can see that "home cultivation" is the main driver of this decrease with an even larger and significantly negative effect. Although "retail dispensary" has negative effects its coefficient is not precisely estimated. The last two columns in Table 4 report the combined effects of MML and its provisions on the overall population bringing the two parts together. Implementation of a MML significantly lowers opioid spending in the overall population of young adults by \$2.47 per person over a year. Focusing on the effects of individual provisions in states where home cultivation is allowed young adults use \$4 less on opioids per person holding all other provisions constant. The "home cultivation" provision appears to be the main driver of the decreasing effect of MML on opioids among young adults and these effects result from the intensive margin of use. Tables 5 and 6 show there is not much evidence

[7] Also, the interpretation of "any MML" becomes difficult in this model. These results are available upon request.

that a MML and its provisions significantly change opioid spending among middle age (ages 40-64) and elderly people (ages 65+). The only significant effect is found among middle age people. Namely, in states where the law allows retail dispensaries there is a 1.4 % point drop in the probability of using opioids among this group when we hold the other provisions fixed (a 14% decrease from the baseline mean). As pointed out by earlier literature, most medical marijuana patients are younger so it makes sense that we see a significant drop in opioid spending among younger populations and almost no effect among older people.

The above analyses show independent effects of the four provisions, but states have combinations of these provisions. Table 7 shows linear combinations of the marginal effects from various combinations of the four provisions for each age group on the overall spending of opioids consisting of both parts. First, I examine the linear combinations of the marginal effects of "home cultivation," "non-specific pain" and "retail dispensary" provisions. California is a state with this type of MML. California's type of MML is effective in reducing opioid spending among young adults by $3.86 per person over a year and has no effect on older populations. Second, I examine the effects of "retail dispensary," "home cultivation," "non-specific pain" and "patient registry" provisions. Colorado is an example of a state with such a MML. Colorado's type of MML is effective in reducing opioid spending among young adults by $3.27 per person over a year. Next, I examine the combined effects of "retail dispensary," "non-specific pain" and "patient registry" provisions (New Jersey-type) and combined effects of "home cultivation," "non-specific pain" and "patient registry" (Alaska-type). Both New Jersey's and Alaska's types of MML are not associated with any significant decreases in reducing opioid spending.

A California-type MML which allows home cultivation, legalizes and protects dispensaries, and imposes no restrictions such as having a specific type of pain to be eligible or requiring a registry of the patient is one of the least strict type of MML.[8] It is also the type of MML that reduces opioid spending the most among young adults, as measured by the amount of dollar reduction in this study. Although not as loose as California's MML, Colorado's type of MML is also one of the loosest models and associated with decreases in opioid spending comparable to California's.

These results from the combined effects of provisions indicate the effects of MML are not uniform but depend on the different combinations of provisions consistent with Pacula et al. 2015. The types of MMLs with the most generous provisions which include the protection and allowance of dispensaries with home cultivation seem to be the most effective types of MMLs in decreasing spending on opioid prescriptions.

[8] I also check whether the overall reductions in opioids were driven by California alone. The estimates from models excluding California show similar and even slightly larger estimates in magnitude. These results are available upon request.

6 Additional Analyses

Up to this point I have shown that the response of total prescription opioid expenditures to MMLs depends on the age of the users and the margin of use. The point estimates from combined marginal effects point decreases in spending on prescription opioids associated with MMLs among young adults. To further assess the validity of this finding, I perform two types of sensitivity and two other additional analyses by exploring (i) the timing of the policy implementation and policy endogeneity, (ii) the effects of MMLs on the number of total opioid pills acquired instead of expenditures, (iii) the effects of MMLs and their provisions on spending on other prescription drugs for which marijuana can potentially be used as a substitute and (iv) the effects of MMLs and their provisions on prescription drugs for which MMLs are not supposed to have any effect.

6.1 Event studies

Here I replicate my baseline specification with two-part models for expenditures on opioids adding lead and lag indicators. This flexible event study approach enables me to investigate whether there are any pre-existing trends in opioid expenditures which are endogenous to MML adoption. Furthermore, it shows if the law has differential effects over time after a MML is adopted. I exclude the indicator for the last year prior to MML adoption and set it equal to zero for normalization.

Figure 2 shows the estimated average marginal effects of the timing of the intervention within four or more years before and after for each age group. The results for young adults indicate there is a drop in prescription opioid expenditures after a year following the MML adoption (relative to the year prior to adoption). The decreasing effect of a MML becomes statistically significant after two years following the year it takes effect and continues to be significantly negative even after four years or more, with its magnitude reaching its maximum after three years. The decreasing impact of MML on opioids among young adults is persistent over time with the long run difference being even larger than its instantenous effect. There is not evidence of pre-existing trends: prior to intervention the effect of a MML is indistinguishable from zero.

Turning to middle age and elderly populations there is not much evidence supporting the hypothesis that a MML changes prescribed opioid expenditures over time. Among the elderly population, a MML increases the opioid utilization after the first year of its adoption (relative to the year prior to adoption), but this estimate is barely significant and it dissipates the following years. There is not evidence of pre-trends before MML implementation in either of these age groups.

These results from event study analyses support the main findings that MML implementation decreases the spending of prescription opioids among young adults but does not have any discernible effect on older populations.

6.2 Effects on total number of opioid pills

So far, all the analyses were concerned with the expenditure outcomes for prescription opioids. Although total expenditure is an important outcome from a government budget spending perspective, it is not the only or the most complete measure of utilization. To investigate whether the spending decreases in opioids associated with MMLs are attributed to use rather than heterogeneous prescription drug prices, I perform analyses on total number of prescribed opioid pills purchased using MEPS prescribed medicine files. Despite being an imperfect measure of utilization, total number of prescribed opioid pills obtained can provide some insights for the mechanisms of the effects found in main results.

Table 8 shows the average marginal effects of MMLs from two-part models on total opioid pills for the same age groups. Turning to results for the young adults on Table 8, the decreasing effect of "any MML" on opioid utilization remains. Namely, the mere adoption of MML decreases the number of prescription opioid pills in young population by 2.16 pills per person over a year, which is a 27% decrease from the baseline mean. We can see that decreases from "any MML" on opioids among young adults mainly result from the effects from "home cultivation" and "retail dispensary" provisions. The effects of MML and its provisions are null among the older populations when the outcome variable is number of pills instead of total expenditures.

Comparing these results we see that the effects of MMLs found on opioid pills support the primary results found on the opioid expenditures: implementation of MML decreases opioid utilization among young adults.

6.3 Effects on the utilization of other prescription drugs

Although majority of medical marijuana patients report using marijuana for pain, there exists suggestive evidence on marijuana's effects on other health conditions. Furthermore, Reinerman et al. 2011 report the other common reasons patients cite for using medical marijuana were muscle spasms, headache and anxiety. Reiman et al. 2017 report mental health conditions were the second most common reason for using medical marijuana after pain. In the light of these findings I study the effects of MMLs on other prescription drugs for which marijuana can be a potential substitute.

The non-opioid prescription drugs I examine fall under four major groups: non-opioid painkillers, antidepressants, anticonvulsants and sedatives. These categories of drugs are commonly prescribed and they treat the conditions medical marijuana states render eligible. They are also examined by earlier studies (Bradford and Bradford 2016 and 2017). If MMLs are causing people to switch from their prescriptions to medical marijuana, utilization of these drugs must show the biggest change. However, Bradford and Bradford 2016 and 2017 analyses only include Medicaid and Medicare recipients who

incurred positive expenditures of prescriptions. Here, l extend the analyses to a broader population.

Tables 9 through 11 show the combined marginal effects of "any MML" and MMLs' four main provisions on expenditures for other marijuana-substitutable prescriptions for each age group. The mere implementation of a MML has no impact on other drugs, except a barely significant spending decrease in sedatives among young adults by $1.47 per person over a year and a significant decrease in sedatives among the elderly by $6.75 per person over a year.

Focusing on the effects of the four main provisions of MMLs, "retail dispensary" and "home cultivation" provisions are generally associated with significant decreases on antidepressant and anticonvulsant expenditures among young adults and the elderly. Having a "non-specific pain" provision in a state's MML is associated with a significant increase in sedative spending among young adults. This increase in sedative spending results from the increase in the extensive margin: having a "non-specific pain" provision increases the probability of sedative use significantly. This could be attributed to "non-specific pain" provision's creation of ambiguities in eligibility criteria and extension of the patient base to people with relatively milder pain (or no pain), who later end up being prescribed other prescriptions upon seeing the physician. In fact, a "non-specific pain" provision also significantly increases the probability of using antidepressants and anticonvulsants among young adults.[9]

Having a "patient registry" provision offsets the increasing effects of a "non-specific pain" provision in young adults' sedative spending by decreasing it by $4.51 per person over a year. It also decreases the elderly's sedative spending by $10.18 per person over a year. The decreasing effect of a "patient registry" provision seems odd at first, but it could be due to three reasons. First, requiring the registration of the patient could make the recommendation of marijuana less risky from the physician's viewpoint, decreasing her cost of recommending it. Similarly, being registered by the state and having a medical marijuana patient identification card can decrease the patient's risk of arrest from carrying marijuana. Looking at tables 9 and 11, it is natural to ask why sedatives are the drug category that is most sensitive to these provisions in young adults and elderly. As pointed out in Proposition 5 MMLs' effects depend on the "mismatch" (or side effects) associated with a prescription drug class and the health condition it treats. Sedatives along with opioids are reported to be a class of drugs with the most severe side effects.[10] Furthermore, mental health conditions and anxiety are found to be the second most commonly reported reason for using medical marijuana among medical marijuana patients (Reinerman et al. 2011 and Reiman et al. 2017). Therefore, a MML and its provisions can decrease sedative

[9]These results from extensive margin of use from other prescriptions are in Appendix Table 1A.

[10]According to the CDC, sedatives were involved in 31.7% of drug-poisoning ER visits between 2008 and 2011. Hampton et al. 2014 find sedatives made up most of the adverse drug event related ER visits between 2009 and 2011 compared to all other psychiatric medications.

utilization more relative to other categories of drugs with less severe side effects for which marijuana can substitute.

6.4 Placebo tests

Here, I check the effects of MMLs on drug classes for which marijuana has no potential to substitute. I perform these analyses to demonstrate that negative effects of MML only exist for the drug classes for which marijuana can be a substitute and not for the other drugs. Tables 12 through 14 show results for some of the other commonly prescribed drugs on which MMLs should not have any negative effect. The commonly prescribed placebo drugs include hormones, hypertension drugs, cardiovascular agents and acid reducers. The results generally support the hypothesis that MMLs and their provisions do not decrease expenditures on other drugs, although there are some statistically significant increases, especially with middle age and elderly people. "Patient registry" is linked with decreasing spending in one of the test although it is only marginally significant at the 10% significance level.

7 Conclusion

This paper shows that implementation of a MML by itself decreases opioid utilization among young adults significantly, whether utilization is defined as spending or the number of pills. Most of these reductions result from the intensive margin of utilization. The decreasing effects of MMLs on opioids among young adults are persistent over time. They continue to decrease opioid spending among young adults even four or more years after the year of their implementation. The decreasing effects of MMLs are only observed among young adults except for the allowance of retail dispensaries which decreases the probability of use among middle age adults. MMLs also decrease sedative spending among the elderly. Given that opioids and sedatives are the drug classes associated with the most severe cases of addiction and adverse drug events, MMLs can be useful in alleviating the problematic use of these prescriptions. Consistent with the prior literature, ignoring the heterogeneity in MMLs can mask important effects of their individual provisions. States with the loosest MMLs experience the biggest reductions in opioid utilization.

Despite growing trends of pro-marijuana policies, there remains a lack of scientific evidence and consensus as to what extent marijuana affects health in the short and long terms. Unlike prescription drugs there are almost no guidelines on how to use marijuana for medicinal purposes regarding its dosage, type, frequency and the method of its consumption. Although states have been experimenting with different MMLs since 1996, conducting randomized controlled experiments on marijuana with human subjects remains challenging given its Schedule 1 categorization by the federal government.

There are several policy implications from this study. First, non-MML states with high rates of opioid abuse and adverse drug events especially stemming from young adults should look more carefully into adopting MMLs. Second, MML states should consider the consequences of having different provisions since MMLs with restrictive supply channels are less likely to experience utilization reductions in prescribed opioids or other prescription drugs, while less restrictive supply policies increase recreational use and abuse as found by Pacula et al. 2015. This implies states should weigh the pros and cons of different provisions when they design their MMLs according to their needs. Lastly, more research is needed to inform policy makers on identifying the characteristics of medical marijuana patients and why and how they use and substitute it. More randomized clinical trials are also needed to assess the effects of marijuana on health so that physicians and patients are more clear on how to use it effectively.

References

Abrams, DI, P Couey, SB Shade, ME Kelly, and NL Benowitz. 2011. "Cannabinoid–opioid interaction in chronic pain." *Clinical Pharmacology & Therapeutics* 90 (6):844–851.

Albert M, Uddin S., McCaig LF. 2015. "Emergency department visits for drug poisoning: United States, 2008-2011." Tech. rep., National Center for Health Statistics.

Amar, Mohamed Ben. 2006. "Cannabinoids in medicine: A review of their therapeutic potential." *Journal of ethnopharmacology* 105 (1):1–25.

Anderson, Hansen Benjamin, Mark. and Daniel Rees. 2013. "Medical marijuana laws, traffic fatalities, and alcohol consumption." *The Journal of Law and Economics* 56 (2):333–369.

———. 2015. "Medical marijuana laws and teen marijuana use." *American Law and Economics Review* 17 (2):495–528.

Arcview. 2017. "The State of Legal Marijuana Markets: 5th Edition." Tech. rep., The ArcView Group, Inc.

Aspden, Philip, Julie A Wolcott, J Lyle Bootman, Linda R Cronenwett et al. 2007. *Preventing medication errors*. National Acad. Press.

Bachhuber, Marcus A, Brendan Saloner, Chinazo O Cunningham, and Colleen L Barry. 2014. "Medical cannabis laws and opioid analgesic overdose mortality in the United States, 1999-2010." *JAMA internal medicine* 174 (10):1668–1673.

Belotti, Federico, Partha Deb, Willard G Manning, Edward C Norton et al. 2015. "twopm: Two-part models." *Stata Journal* 15 (1):3–20.

Benson Jr, John A, Stanley J Watson Jr, Janet E Joy et al. 1999. *Marijuana and medicine: assessing the science base*. National Academies Press.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How much should we trust differences-in-differences estimates?" *The Quarterly journal of economics* 119 (1):249–275.

Boehnke, Kevin F, Evangelos Litinas, and Daniel J Clauw. 2016. "Medical cannabis use is associated with decreased opiate medication use in a retrospective cross-sectional survey of patients with chronic pain." *The Journal of Pain* 17 (6):739–744.

Borgelt, Laura M, Kari L Franson, Abraham M Nussbaum, and George S Wang. 2013. "The pharmacologic and clinical effects of medical cannabis." *Pharmacotherapy: The Journal of Human Pharmacology and Drug Therapy* 33 (2):195–209.

Bradford, Ashley C and W David Bradford. 2016. "Medical marijuana laws reduce prescription medication use in medicare part D." *Health Affairs* 35 (7):1230–1236.

———. 2017. "Medical marijuana laws may be associated with a decline in the number of prescriptions for medicaid enrollees." *Health Affairs* :10–1377.

Brekke, Kurt R and Michael Kuhn. 2006. "Direct to consumer advertising in pharmaceutical markets." *Journal of health Economics* 25 (1):102–130.

Buntin, Melinda Beeuwkes and Alan M Zaslavsky. 2004. "Too much ado about two-part models and transformation?: Comparing methods of modeling Medicare expenditures." *Journal of health economics* 23 (3):525–542.

Chandra, Amitabh, Jonathan Gruber, and Robin McKnight. 2014. "The impact of patient cost-sharing on low-income populations: evidence from Massachusetts." *Journal of health economics* 33:57–66.

Duan, Naihua, Willard G Manning, Carl N Morris, and Joseph P Newhouse. 1983. "A comparison of alternative models for the demand for medical care." *Journal of business & economic statistics* 1 (2):115–126.

for Health Statistics, National Center. 2016. "Health, United States, 2015: with special feature on racial and ethnic health disparities."

Goda, Gopi Shah, Ezra Golberstein, and David C Grabowski. 2011. "Income and the utilization of long-term care services: Evidence from the Social Security benefit notch." *Journal of health economics* 30 (4):719–729.

Hampton, Lee M, Matthew Daubresse, Hsien-Yen Chang, G Caleb Alexander, and Daniel S Budnitz. 2014. "Emergency department visits by adults for psychiatric medication adverse events." *JAMA psychiatry* 71 (9):1006–1014.

Haroutounian, Simon, Yael Ratz, Yehuda Ginosar, Karina Furmanov, Fayez Saifi, Ronit Meidan, and Elyad Davidson. 2016. "The Effect of Medicinal Cannabis on Pain and Quality-of-Life Outcomes in Chronic Pain: A Prospective Open-label Study." *The Clinical journal of pain* 32 (12):1036–1043.

Jensen, Bjorn, Jeffrey Chen, Tim Furnish, and Mark Wallace. 2015. "Medical marijuana and chronic pain: a review of basic science and clinical evidence." *Current pain and headache reports* 19 (10):50.

Jones, Andrew M et al. 2010. *Models for health care*. University of York., Centre for Health Economics.

Kantor, Elizabeth D, Colin D Rehm, Jennifer S Haas, Andrew T Chan, and Edward L Giovannucci. 2015. "Trends in prescription drug use among adults in the United States from 1999-2012." *Jama* 314 (17):1818–1830.

Lynne-Landsman, Sarah D, Melvin D Livingston, and Alexander C Wagenaar. 2013. "Effects of state medical marijuana laws on adolescent marijuana use." *American journal of public health* 103 (8):1500–1506.

Manning, Willard G. 1998. "The logged dependent variable, heteroscedasticity, and the retransformation problem." *Journal of health economics* 17 (3):283–295.

Manning, Willard G and John Mullahy. 2001. "Estimating log models: to transform or not to transform?" *Journal of health economics* 20 (4):461–494.

McCullagh, Peter and James A Nelder. 1989. "Generalized Linear Models, no. 37 in Monograph on Statistics and Applied Probability."

Mihaylova, Borislava, Andrew Briggs, Anthony O'hagan, and Simon G Thompson. 2011. "Review of statistical methods for analysing healthcare resources and costs." *Health economics* 20 (8):897–916.

Mullahy, John. 1998. "Much ado about two: reconsidering retransformation and the two-part model in health econometrics." *Journal of health economics* 17 (3):247–281.

National Academies of Sciences, Engineering, Medicine et al. 2017. *The health effects of cannabis and cannabinoids: the current state of evidence and recommendations for research*. National Academies Press.

of Health, US Department and Human Services. 2014. "National action plan for adverse drug event prevention." *Washington (DC): Author* 56.

Pacula, Rosalie L, David Powell, Paul Heaton, and Eric L Sevigny. 2015. "Assessing the effects of medical marijuana laws on marijuana use: the devil is in the details." *Journal of Policy Analysis and Management* 34 (1):7–31.

Powell, David, Rosalie Liccardo Pacula, and Mireille Jacobson. 2015. "Do medical marijuana laws reduce addictions and deaths related to pain killers?" Tech. rep., National Bureau of Economic Research.

Reiman, Amanda, Mark Welty, and Perry Solomon. 2017. "Cannabis as a substitute for opioid-based pain medication: patient self-report." *Cannabis and Cannabinoid Research* 2 (1):160–166.

Reinarman, Craig, Helen Nunberg, Fran Lanthier, and Tom Heddleston. 2011. "Who are medical marijuana patients? Population characteristics from nine California assessment clinics." *Journal of psychoactive drugs* 43 (2):128–135.

Shi, Yuyan. 2017. "Medical marijuana policies and hospitalizations related to marijuana and opioid pain reliever." *Drug and alcohol dependence* 173:144–150.

Smart, Rosanna. 2015. "The kids aren't alright but older adults are just fine: Effects of medical marijuana market growth on substance use and abuse." *Browser Download This Paper* .

Strumpf, Erin, Mehdi Ammi, Mamadou Diop, Julie Fiset-Laniel, and Pierre Tousignant. 2017. "The impact of team-based primary care on health care services utilization and costs: Quebec's family medicine groups." *Journal of Health Economics* .

Wen, Hefei, Jason M Hockenberry, and Janet R Cummings. 2015. "The effect of medical marijuana laws on adolescent and adult use of marijuana, alcohol, and other substances." *Journal of health economics* 42:64–80.

Whiting, Penny F, Robert F Wolff, Sohan Deshpande, Marcello Di Nisio, Steven Duffy, Adrian V Hernandez, J Christiaan Keurentjes, Shona Lang, Kate Misso, Steve Ryder et al. 2015. "Cannabinoids for medical use: a systematic review and meta-analysis." *Jama* 313 (24):2456–2473.

8 Figures and Tables

Figure 1: Distribution of opioid expenditures - Ages 18+

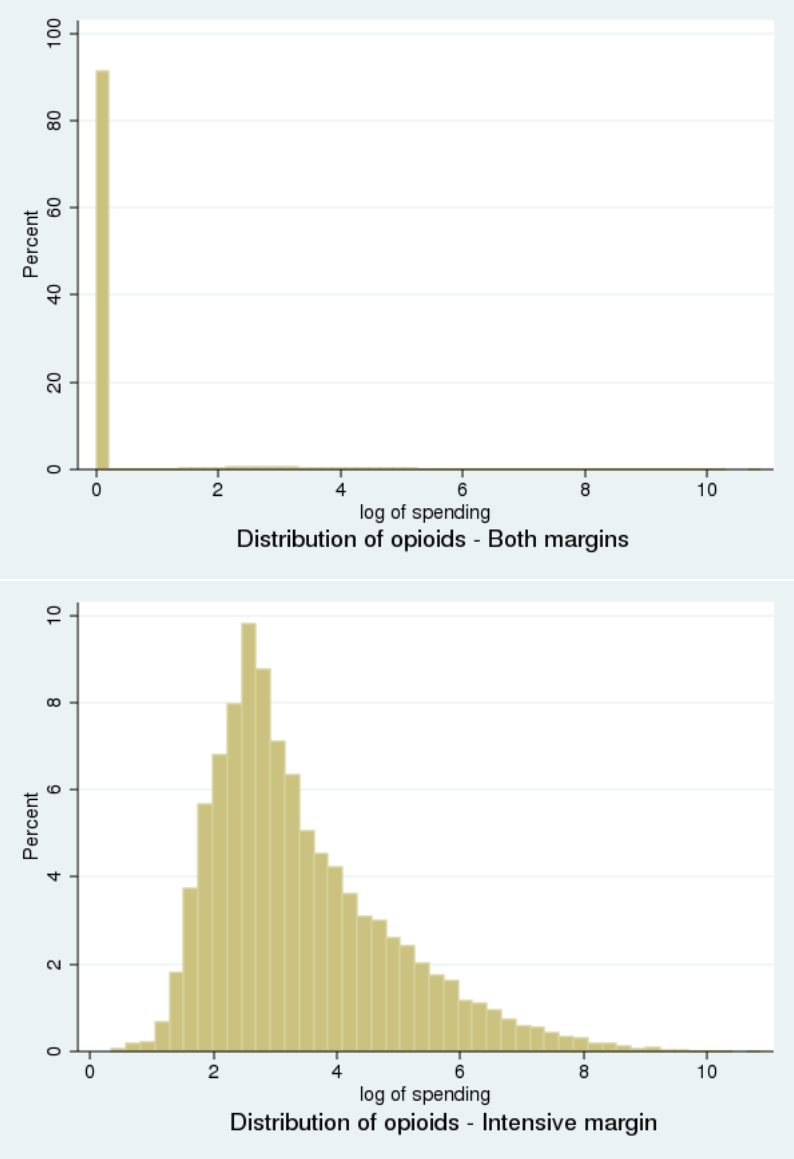
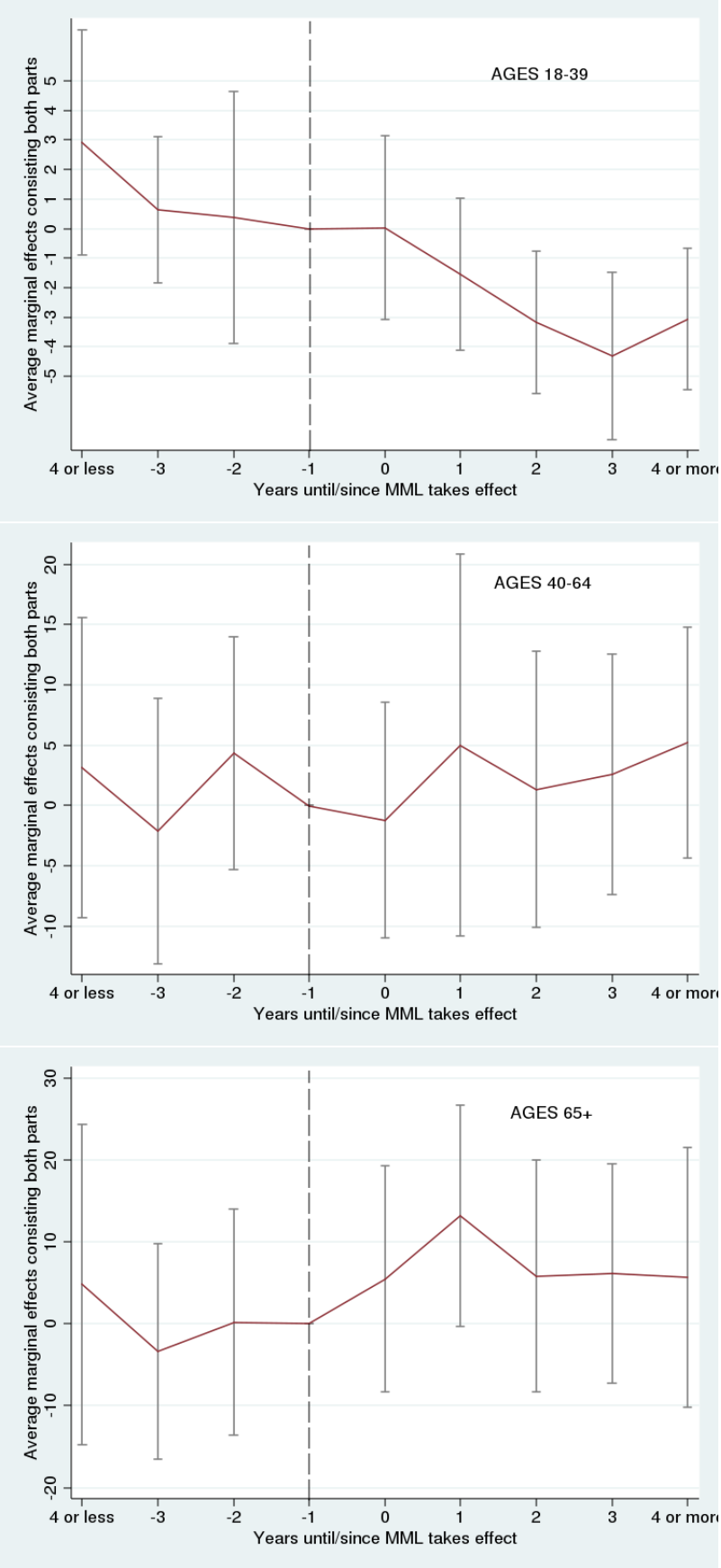


Figure 2: Results from event study analyses on opioid expenditures



The year MML takes effect is represented by 0. The pre-adoption year is set to zero for normalization and excluded from the regression. The coefficients are estimates from the two-part models with probit in the first and GLM (with a log link and gamma family) in the second part.

Table 1: Medical marijuana laws and provisions by state, 1996-2014

State	Effective date	Retail dispensary	Home cultivation	Non-specific pain	Patient registry
California	1996	1996	1996	1996	-
Colorado	2001	2001	2001	2001	2001
Montana	2004	-	2004	2004	-
Michigan	2008	-	2008	2008	-
Oregon	1998	-	1998	1998	2007
Washington	1998	-	-	1998	-
Alaska	1999	-	1999	1999	1999
Arizona	2011	2011	2011	2011	2011
Connecticut	2012	-	-	-	2012
District of Columbia	2010	2010	-	-	2010
Delaware	2011	2011	-	2011	2011
Hawaii	2000	-	2000	2000	2000
Iliinois	2014	2014	-	-	2014
Maine	1999	2009	1999	-	2009
Maryland	2014	2014	-	2014	2014
New Jersey	2010	2010	-	2010	2010
New Mexico	2007	2007	2007	-	2007
New York	2014	2016	-	2014	2014
Nevada	2001	-	2001	2001	2001
Rhode Island	2006	2009	2006	2006	2006
Vermont	2004	-	2004	2007	2004

Sources: Effective dates of MMLs and provisions are taken from Wen et al. 2015 and http://medicalmarijuana.procon.org/view.resource.php?resourceID=000881

Table 2: Summary statistics for outcome variables

	Control states		MML states	
	mean	**s.d**	**mean**	**s.d**
Opioids				
Participation	0.0919	0.289	0.0838	0.277
Spending	14.73	210.1	12.28	266.2
Non-opioid painkillers				
Participation	0.202	0.416	0.173	0.378
Spending	40.54	229.77	30.91	339.57
Antidepressants				
Participation	0.101	0.301	0.0815	0.274
Spending	48.17	263.7	38.02	236.3
Anticonvulsants				
Participation	0.0591	0.236	0.0456	0.209
Spending	30.35	278.5	23.48	255.1
Sedatives				
Participation	0.0822	0.275	0.0608	0.239
Spending	17.86	153.0	12.02	114.4
Number of observations	233,010		202,025	

Table 3: Summary statistics for control variables

	Control states		MML states	
	mean	**s.d**	**mean**	**s.d**
Individual-level controls				
Demographic controls				
Age dummies: Ages 18-24 (ref.)				
Ages 25-29	0.0922	0.289	0.0973	0.296
Ages 30-34	0.0947	0.293	0.0988	0.298
Ages 35-39	0.0952	0.293	0.101	0.301
Ages 40-44	0.0952	0.293	0.101	0.301
Ages 45-49	0.0938	0.292	0.0953	0.294
Ages 50-54	0.0886	0.284	0.0890	0.285
Ages 55-59	0.0771	0.267	0.0720	0.258
Ages 60-64	0.0617	0.241	0.0573	0.232
Ages 65-69	0.0508	0.220	0.0453	0.208
Ages 70-74	0.0408	0.198	0.0358	0.186
Ages 75-79	0.0323	0.177	0.0290	0.168
Ages 80-84	0.0229	0.149	0.0204	0.141
Ages 85-90	0.0180	0.133	0.0170	0.129
Male	0.459	0.498	0.467	0.499
Race dummies: Other (ref.)				
White	0.564	0.496	0.477	0.499
Black	0.217	0.412	0.117	0.322
Hispanic	0.178	0.383	0.303	0.460
Married	0.534	0.499	0.529	0.499
Living in an MSA	0.758	0.428	0.903	0.297
Economic controls				
Education dummies: Less than high school (ref.)				
High school graduate	0.419	0.493	0.380	0.485
College graduate	0.264	0.441	0.304	0.460
Unemployed	0.398	0.498	0.392	0.488
Student	0.0538	0.226	0.0625	0.242
Family income as % of poverty line: Poor (ref)				
Near poor	0.370	0.483	0.350	0.477
Low income	0.164	0.371	0.156	0.363
Middle income	0.311	0.463	0.296	0.456
High income	0.289	0.453	0.340	0.474
Health insurance dummies: Uninsured (ref.)				
Publicly insured	0.180	0.384	0.208	0.406
Privately insured	0.617	0.486	0.611	0.487
State-level controls				
% Unemployment rate	5.896	1.883	6.706	2.220
% Uninsured rate	15.70	4.967	14.46	4.023
$ Average personal income	33,840	6,997	39,448	8,539
$ Average household income	43,911	7,641	50,208	7,681
Decriminalization law	0.157	0.363	0.552	0.497
Prescription drug monitoring law	0.566	0.496	0.774	0.418

Table 4: Ages 18-39 - Average marginal effects on opioid spending

	Extensive margin		Intensive margin		Combined	
Any MML	0.00105		-37.46***		-2.473***	
	(0.00361)		(12.64)		(0.884)	
Retail dispensary		-0.00499		-13.23		-1.205
		(0.00430)		(15.23)		(1.067)
Home cultivation		-0.00363		-56.29**		-4.042**
		(0.00632)		(26.09)		(1.818)
Non-specific pain		0.00855		12.65		1.384
		(0.00620)		(25.02)		(1.741)
Patient registry		0.00255		6.415		0.592
		(0.00409)		(24.20)		(1.661)
N	186,144	186,144	12,894	12,894	186,144	186,144
Baseline means of outcomes	0.0693	0.0693	69.68	69.68	4.827	4.827

Standard errors in parentheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Ages 40-64 - Average marginal effects on opioid spending

	Extensive margin		Intensive margin		Combined	
Any MML	-0.000389		6.531		0.572	
	(0.00401)		(44.99)		(4.474)	
Retail dispensary		-0.014**		12.85		-0.646
		(0.00446)		(32.32)		(3.281)
Home cultivation		-0.00569		61.41		4.964
		(0.0105)		(73.70)		(7.508)
Non-specific pain		0.00885		-45.15		-2.803
		(0.0109)		(66.74)		(6.776)
Patient registry		0.00167		-15.18		-1.174
		(0.00756)		(57.06)		(5.771)
N	180,723	180,723	18,220	18,220	180,723	180,723
Baseline means of outcomes	0.101	0.101	207.1	207.1	20.88	20.88

Standard errors in parentheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Ages 65+ - Average marginal effects on opioid spending

	Extensive margin		Intensive margin		Combined	
Any MML	-0.000999		75.82		7.917	
	(0.00895)		(50.39)		(5.591)	
Retail dispensary		0.00539		2.214		1.153
		(0.0116)		(42.50)		(4.948)
Home cultivation		0.00190		145.9		15.88
		(0.0183)		(90.90)		(10.19)
Non-specific pain		0.00329		-75.92		-7.535
		(0.0169)		(99.42)		(10.98)
Patient registry		-0.00897		48.30		3.625
		(0.0138)		(94.74)		(10.37)
N	68,168	68,168	7,227	7,227	68,168	68,168
Baseline means of outcomes	0.106	0.106	171.8	171.8	18.22	18.22

Standard errors in parentheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effects of different policy combinations on opioid expenditures

	18-39	40-64	65+
home+dispensary+nsp	-3.863***	1.514	9.500
(California)	(1.373)	(6.199)	(11.71)
home+dispensary+nsp+reg	-3.271**	0.341	13.12
(Colorado)	(1.332)	(7.982)	(8.190)
dispensary+nsp+reg	0.771	-4.623	-2.757
(New Jersey)	(2.140)	(7.621)	(11.50)
home+nsp+reg	-2.066	0.987	11.97
(Alaska)	(1.820)	(8.157)	(8.921)
N	184,144	180,723	68,168

Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1. nsp and reg mean non-pain specification and patient registry respectively.

Table 8: Average marginal effects on opioid pills

	18-39		40-64		65+	
Any MML	-2.160**		1.310		0.979	
	(0.869)		(2.753)		(4.650)	
Retail dispensary		-1.440*		-0.153		2.722
		(0.847)		(3.941)		(6.773)
Home cultivation		-3.166		3.382		-2.562
		(2.088)		(4.680)		(13.60)
Non-specific pain		1.157		-6.588		-0.722
		(2.123)		(4.904)		(13.94)
Patient registry		0.0881		5.282		6.178
		(1.410)		(4.997)		(9.927)
N	184,144	186,144	180,723	180,723	68,168	68,168
Baseline means of outcomes	7.965	7.965	24.92	24.92	27.07	27.07

Standard errors in parentheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Other medicines Ages 18-39

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	3.096		-0.128		1.474		-1.468*	
	(2.215)		(3.768)		(4.310)		(0.356)	
Retail dispensary		-3.337		-4.910**		-6.062**		1.139
		(2.315)		(2.351)		(2.775)		(0.792)
Home cultivation		3.720		4.726		-0.648		-1.936
		(4.192)		(7.166)		(6.064)		(1.332)
Non-specific pain		0.778		-3.249		-5.301		2.516**
		(4.544)		(7.350)		(5.963)		(1.255)
Patient registry		3.620		1.328		10.09*		-4.514***
		(3.438)		(4.712)		(6.117)		(1.064)
N	186,144	186,144	186,144	186,144	186,144	186,144		
Baseline means of outcomes	13.13	13.13	22.57	22.57	15.31	15.31	6.119	6.119

Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Other medicines Ages 40-64

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	-3.501		5.781		-3.017		-2.848	
	(4.360)		(6.036)		(4.986)		(4.571)	
Retail dispensary		-5.356		3.033		-0.273		-3.702
		(6.839)		(4.272)		(8.870)		(3.068)
Home cultivation		-10.97		-4.213		-10.97*		7.176
		(7.130)		(12.47)		(6.334)		(5.834)
Non-specific pain		8.460		7.957		10.20*		-4.428
		(6.158)		(12.84)		(5.614)		(5.551)
Patient registry		-0.718		0.587		-4.547		-4.640
		(9.110)		(7.502)		(12.12)		(4.778)
N	180,723	180,723	180,723	180,723	180,723	180,723		
Baseline means of outcomes	48.10	48.10	61.0	61.0	36.7	36.7	21.74	21.74

Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Other medicines Ages 65+

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	-5.075		-1.094		-1.083		-6.747**	
	(9.742)		(9.286)		(10.63)		(3.205)	
Retail dispensary		4.217		-4.523		-18.86***		4.973*
		(7.993)		(8.185)		(6.963)		(2.712)
Home cultivation		-3.039		-33.42***		-18.55		-3.732
		(17.60)		(11.22)		(18.43)		(5.538)
Non-specific pain		-30.13*		15.93		10.70		-2.138
		(17.17)		(11.15)		(15.87)		(4.861)
Patient registry		15.89		15.67		11.51		-10.18**
		(13.16)		(11.61)		(11.80)		(4.147)
N	68,168	68,168	68,168	68,168	68,168	68,168		
Baseline means of outcomes	66.81	66.81	53.98	53.98	34.22	34.22	22.34	22.34

Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Placebo Test Ages 18-39

	Hormones		Hypertension drugs		Cardiovascular agents		Acid reducers	
Any MML	-3.286		-		-		0.271	
	(2.484)						(0.372)	
Retail dispensary		-2.030		-		-		0.842*
		(2.949)						(0.446)
Home cultivation		-6.508		-		-		0.409
		(5.089)						(1.274)
Non-specific pain		9.356*		-		-		-0.118
		(4.963)						(1.247)
Patient registry		-6.056*		-		-		-0.713
		(3.096)						(0.746)
N	186,144	186,144	186,144	186,144	186,144	186,144		

Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1. There are not enough users of hypertension drugs and cardiovascular agents in this sample.

Table 13: Placebo Test Ages 40-64

	Hormones		Hypertension drugs		Cardiovascular agents		Acid reducers	
Any MML	-2.573		1.043		-0.164		-0.568	
	(3.995)		(2.944)		(1.275)		(2.319)	
Retail dispensary		4.297***		12.15***		7.013**		-2.738
		(2.070)		(4.502)		(3.520)		(1.676)
Home cultivation		-4.527		-7.535		-2.283		4.660
		(9.959)		(8.398)		(2.589)		(3.024)
Non-specific pain		-2.416		5.586		2.032		-2.280
		(9.775)		(7.745)		(2.238)		(2.659)
Patient registry		-1.570		-10.89		-7.095*		1.105
		(3.935)		(5.647)		(3.847)		(2.867)
N	180,723	180,723	180,723	180,723	180,723	180,723	180,723	180,723

Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Placebo Test Ages 65+

	Hormones		Hypertension drugs		Cardiovascular agents		Acid reducers	
Any MML	2.474		-4.601		-0.999		8.719**	
	(3.918)		(8.103)		(4.212)		(3.726)	
Retail dispensary		-0.0800		-13.30		-2.180		-3.721
		(2.930)		(8.464)		(3.903)		(3.077)
Home cultivation		11.80		10.38		-0.809		-6.720
		(12.11)		(16.35)		(6.702)		(7.435)
Non-specific pain		-6.614		3.028		-6.906		14.43**
		(11.92)		(14.66)		(5.452)		(6.952)
Patient registry		-0.714		-6.701		8.236		3.752
		(6.701)		(11.36)		(5.842)		(6.213)
N	68,186	68,186	68,186	68,186	68,186	68,186	68,186	68,186

Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table 1A: Other medicines Ages 18-39 (Extensive margin)

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	0.00330		0.00537		0.00446*		0.00443	
	(0.00741)		(0.00354)	(0.00266)		(0.00326)		
Retail dispensary		0.00885*		-0.000818		-0.000414		0.00928***
		(0.00503)		(0.00311)		(0.00233)		(0.00240)
Home cultivation		0.0159		0.00195		-0.00288		-0.00490
		(0.0107)		(0.00335)		(0.00327)		(0.00636)
Non-specific pain		-0.0116		0.00678**		0.00648**		0.0141**
		(0.000806)		(0.00346)		(0.00329)		(0.00649)
Patient registry		0.000806		-0.00339		0.00126		-0.0133***
		(0.00578)		(0.00494)		(0.00401)		(0.00286)
N	186,144	186,144	186,144	186,144	186,144	186,144	186,144	186,144
Baseline means of outcomes	0.131	0.131	0.0531	0.0531	0.0261	0.0261	0.0411	0.0411

Coefficients are average marginal effects from probit. Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 2A: Other medicines Ages 40-64 (Extensive margin)

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	0.000403		-0.00296		0.00377		-0.00650	
	(0.00501)		(0.00652)		(0.00443)		(0.00527)	
Retail dispensary		-0.00754		0.00113		-0.0104***		0.00661*
		(0.00475)		(0.00547)		(0.00327)		(0.00368)
Home cultivation		-0.000335		-0.00363		0.0169***		-0.0185**
		(0.00876)		(0.00990)		(0.00455)		(0.00835)
Non-specific pain		-0.00157		0.0167*		0.00103		0.00616
		(0.00732)		(0.00980)		(0.00470)		(0.00789)
Patient registry		0.00714		-0.0130		-0.00448		-0.00735
		(0.00658)		(0.00857)		(0.00465)		(0.00581)
N	180,723	180,723	180,723	180,723	180,723	180,723	180,723	180,723
Baseline means of outcomes	0.214	0.214	0.118	0.118	0.0656	0.0656	0.0932	0.0932

Coefficients are average marginal effects from probit. Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 3A: Other medicines Ages 65+ (Extensive margin)

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	-0.00427		-0.000350		0.0116		-0.0130	
	(0.0161)		(0.00971)		(0.0129)		(0.00800)	
Retail dispensary		0.0336***		-0.00293		-0.00920		0.00536
		(0.0116)		(0.00849)		(0.00729)		(0.00461)
Home cultivation		0.0125		-0.00440		-0.0159		-0.00448
		(0.0245)		(0.0166)		(0.0163)		(0.0108)
Non-specific pain		-0.0498*		-0.00466		0.0350**		-0.0189**
		(0.0269)		(0.0148)		(0.0136)		(0.00820)
Patient registry		0.0102		0.0190		0.00331		0.00228
		(0.0172)		(0.0175)		(0.0145)		(0.00811)
N	68,168	68,168	68,168	68,168	68,168	68,168	68,168	68,168
Baseline means of outcomes	0.278	0.278	0.129	0.129	0.0921	0.0921	0.102	0.102

Coefficients are average marginal effects from probit. Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 4A: Other medicines Ages 18-39 (Intensive margin)

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	21.13		-43.84		-40.78		-51.58***	
	(15.93)		(65.38)		(147.3)		(17.98)	
Retail dispensary		-31.88*		-85.83**		-223.5**		-3.666
		(17.17)		(36.74)		(93.73)		(17.85)
Home cultivation		16.67		72.80		37.45		-31.14
		(30.88)		(133.1)		(221.2)		(24.77)
Non-specific pain		14.38		-112.9		-344.0		13.75
		(33.90)		(136.6)		(216.8)		(21.99)
Patient registry		26.97		51.59		359.6*		-66.01***
		(25.79)		(79.91)		(216.3)		(24.60)
N	24,466	24,466	9,890	9,890	4,859	4,859	7,655	7,655
Baseline means of outcomes	99.93	99.93	424.8	424.8	586.6	586.6	148.8	148.8

Coefficients are average marginal effects from GLM with a log link and gamma family. Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 5A: Other medicines Ages 40-64 (Intensive margin)

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	-16.83		61.54		-76.96		-15.30	
	(19.73)		(43.36)		(68.35)		(47.77)	
Retail dispensary		-17.46		21.07		79.66		-55.76*
		(31.66)		(28.20)		(134.5)		(31.94)
Home cultivation		-50.85		-20.52		-305.7***		121.3**
		(32.16)		(97.30)		(91.13)		(59.62)
Non-specific pain		41.11		-2.468		149.3*		-62.28
		(27.86)		(100.9)		(78.26)		(56.84)
Patient registry		-10.54		59.52		-34.29		-32.54
		(42.12)		(52.72)		(183.7)		(49.76)
N	38,681	38,681	21,299	21,299	11,851	11,851	16,837	16,837
Baseline means of outcomes	224.7	224.7	517.6	517.6	559.6	559.6	233.3	233.3

Coefficients are average marginal effects from GLM with a log link and gamma family. Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.

Table 6A: Other medicines Ages 65+ (Intensive margin)

	Non-opioid painkillers		Antidepressants		Anticonvulsants		Sedatives	
Any MML	-14.71		-7.324		-57.67		-38.28	
	(32.29)		(64.61)		(65.80)		(26.38)	
Retail dispensary		-13.45		-25.56		-113.8**		37.24
		(27.00)		(57.09)		(47.11)		(24.69)
Home cultivation		-21.64		-243.9***		-83.10		-26.97
		(59.78)		(68.39)		(128.3)		(49.07)
Non-specific pain		-66.02		137.7*		-60.90		19.46
		(57.38)		(72.04)		(115.4)		(44.32)
Patient registry		48.37		60.54		79.17		-104.6***
		(45.09)		(70.11)		(70.68)		(36.78)
N	18,959	18,959	8,822	8,822	6,280	6,280	6,931	6,931
Baseline means of outcomes	240.2	240.2	417.1	417.1	371.5	371.5	219.7	219.7

Coefficients are average marginal effects from GLM with a log link and gamma family. Standard errors in parantheses are clustered at the state level. Controls include state and year fixed effects, state-specific linear time trends, and all the controls listed in Table 3. *** p<0.01, ** p<0.05, * p<0.1.