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The Impact of Cannabis Access Laws on Opioid Prescribing

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WORKING PAPER

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Abstract

While recent research has shown that cannabis access laws can reduce the use of prescription opioids, the effect of these laws on opioid use is not well understood for all dimensions of use and for the general United States population. Analyzing a dataset of over 1.3 billion individual opioid prescriptions between 2011 and 2017, which were aggregated to the individual provider-year level, we find that recreational and medical cannabis access laws reduce the number of morphine milligram equivalents prescribed each year by 6.9 and 6.1 percent, respectively. These laws also reduce the total days supply of opioids prescribed, the total number of patients receiving opioids, and the probability a provider prescribes any opioids net of any offsetting effects. Additionally, we find consistent evidence that cannabis access laws have different effects across types of providers and physician specialties.

Keywords: Cannabis, Marijuana, Opioids

JEL Codes: I18, K19

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Introduction

As health care providers began to recognize pain as a "fifth vital sign" and began to treat it more aggressively, the number of opioid prescriptions quadrupled in the first fifteen years of the new millennium (Dart et al., 2015; Merboth and Barnason, 2000; Rudd et al., 2016; Tompkins et al., 2017; Von Korff and Franklin, 2016). Opioids are used to treat both chronic and acute pain, though their efficacy in treating chronic, non-cancer pain is limited (Boudreau et al., 2009; Chou et al., 2015, 2009). However, as prescription opioid use increased, so did opioid-related mortality, leading to the ongoing opioid crisis (Mattson et al., 2017; Pacula and Powell, 2018). While state governments have enacted various policies to curtail opioid prescriptions, e.g., prescription drug monitoring programs, many of these policies simply limit access to opioids and may push individuals already dependent on prescription opioids to more dangerous drugs, such as heroin. Thus, policies that reduce opioid prescriptions without leading individuals to substitute more dangerous drugs may be preferable to policies that simply restrict opioid prescriptions.

One policy option that has the potential to reduce opioid prescriptions and opioid-related deaths is the passage of cannabis access laws. These state laws facilitate access to cannabis by removing state legal barriers—though possession of cannabis remains illegal under federal law. Recreational cannabis laws (RCLs) allow adults over 21 to possess and consume a limited amount of cannabis. Medical cannabis laws (MCLs) allow patients with eligible conditions, which are listed in the law and often include some form of intractable pain, to obtain cannabis upon the recommendation or certification of a healthcare provider.

The National Academies of Sciences, Engineering, and Medicine concluded after a comprehensive review of the clinical literature that "[t]here is conclusive . . . evidence that cannabis . . . [is] effective . . . [f]or the treatment of chronic pain in adults," i.e., the condition that was one of the motivating factors behind the initial increase in opioid prescriptions (National Academies of Sciences, Engineering, and Medicine, 2017). Similarly, conducting a meta-analysis of the clinical literature, Whiting et al. (2015) find evidence that cannabis is effective in the treatment of chronic neuropathic pain and cancer pain. And clinical evidence suggests that cannabis can effectively substitute for opioids in the treatment of pain. For example, Haroutounian et al. (2016) examine the effect of cannabis treatment on pain and functional outcomes of 274 participants and finds statistically significant improvements in various measures of pain and a 44 percent decrease in opioid consumption.

Given the ability of cannabis to substitute for opioids in the treatment of pain and the more moderate side effects associated with cannabis relative to opioids, several studies have examined the potential of RCLs and MCLs to reduce opioid consumption and ameliorate the ongoing opioid crisis. For example, Bradford et al. (2018) find that opioid use among Medicare beneficiaries declines by 8.5 percent following the passage of an MCL. Examining state-level Medicaid data, Wen and Hockenberry (2018) conclude that MCLs and RCLs reduce opioid prescribing by 5.9 percent and 6.4 percent, respectively. While these and other studies provide important evidence on the potential of cannabis access laws to reduce opioid use, prior work has generally been limited to examining specific populations (such as Medicaid or Medicare beneficiaries), survey evidence, and outcomes defined at the state level.

We extended the scope of the results in the existing literature by analyzing a dataset of over 1.3 billion individual opioid prescriptions, which represent approximately 90 percent of all prescription opioids filled by outpatient pharmacies over the time period we examine. We aggregate these prescription data to the individual-provider level and calculate highly specific measures of opioid prescriptions, including morphine milligram equivalents (MMEs), to examine changes in provider opioid prescribing patterns caused by cannabis access laws. Thus, we examine the effect of RCLs and MCLs using more granular information and more specific measures of prescribing behavior than has previously been available. Additionally, because we observe prescriptions at the provider level, we are able to analyze changes in opioid prescribing across different types of providers controlling for provider-specific fixed effects. We also explore differences by physician specialties.

In general, we find consistent evidence that both RCLs and MCLs reduce the use of prescription opioids. These laws reduce the amount of annual MMEs prescribed by individual providers by 6.9 and 6.1 percent, respectively. However, our results are not unique to the MME measure of opioid prescriptions, and both types of cannabis access laws similarly reduce the total days supply of opioids, the number of patients to whom providers prescribe opioids, and the probability that a provider prescribes any opioids. Interestingly, while we find evidence that RCLs and MCLs reduce opioid use across a wide array of medical (and other) specialties, the magnitude of this reduction is not uniform across specialties. The five largest physician specialties (in terms of practitioners) are slightly more sensitive to RCLs and slightly less sensitive to MCLs. These laws reduce the MMEs prescribed by the five largest specialties by 9 percent and 3.1 percent, respectively. The five specialties that have the highest prescribing rates, as measured by MMEs, reduce their opioid use by 20.2 percent when an RCL is passed and 7.1 percent when an MCL is passed.

The evidence reported here presents the most accurate picture of the effect of cannabis access laws on prescription opioid use to date and can therefore inform the ongoing state and national debates over the legality of cannabis as well as other policy options to combat the opioid epidemic. Our analysis of a comprehensive national database on a diverse set of measures of opioid use provides an estimate of the overall net impact of cannabis laws. There has been some concern in the literature that cannabis may serve as a "gateway" drug and eventually increase the use of opioids (Secades-Villa et al., 2015; Wilkinson et al., 2016), though recent empirical work found no evidence that cocaine and heroin usage increase following the passage of MCLs (Chu, 2015). While there may be a gateway effect for some individuals, our results take any such offsetting impacts into account. On balance, cannabis access laws reduce overall opioid usage measured by total MMEs, total days of opioid supply, number of opioid patients, and whether the provider prescribed opioids. By analyzing data at the provider level and estimating separate effects by specialty, our results also provide policymakers with how to target policies to have the most impact.

Background and Institutional Framework

Given the severity of the ongoing opioid crisis—the Centers for Disease Control and Prevention estimated in 2017 that over forty people die from prescription opioid overdoses each day (Mattson et al., 2017)—policymakers have begun searching for solutions. Perhaps the most popular policy to date has been the increased use of prescription drug monitoring programs (PDMPs), which give providers and others (including law enforcement in some states) access to a central repository of information on prescription drugs. These programs can be effective in reducing opioid-related overdoses (Buchmueller and Carey, 2018; Patrick et al., 2016), though some work suggests they do not reduce opioid use (Brady et al., 2014). However, to the extent these programs are effective, they can be costly to implement and may (intentionally or unintentionally) reduce the ability of individuals suffering from pain to obtain treatment. Reductions in the availability of prescription opioids—as a result of PDMPs or for other reasons—

may also encourage individuals to increase their consumption of illicit (and dangerous) substitutes, such as heroin (Alpert et al., 2017).

Cannabis access laws, on the other hand, have the potential to both reduce the use of opioids and provide an alternative treatment for individuals suffering from pain (Corroon et al., 2017) by allowing individuals to substitute away from opioids to cannabis—these laws do not directly reduce the availability of opioids as other policies do. In particular, several studies have found that cannabis access laws are associated with a substitution from prescription opioids to cannabis. Surveying almost 3,000 patients, Corroon et al. (2017) finds that nearly 50 percent of patients substitute cannabis for prescription drugs and that the most commonly substituted drugs are prescription opioids. Sexton et al. (2016) similarly find that almost 60 percent of patients surveyed report substituting cannabis for prescription drugs. They further find that 25 percent of patients substitute cannabis for pain medication, including prescription opioids. Examining opioid use among users of medical cannabis, Boehnke et al. (2016) conclude that use of medical cannabis is associated with an approximately 60 percent decrease in prescription opioid use. Reiman et al. (2017) find an even stronger association, with over 95 percent of medical cannabis users reporting a decrease in their use of prescription opioids. As one might expect, cannabis laws also lead to an uptick in the use of cannabis (Wen et al., 2015; Williams and Bretteville-Jensen, 2014). Collectively, this evidence is consistent with the conclusion of the National Academies of Sciences, Engineering, and Medicine that cannabis can effectively treat chronic pain in adults and further suggests that the use of cannabis can decrease the use of prescription opioids.

Several studies have examined the next logical step of whether laws facilitating access to cannabis reduce the use of prescription drugs generally, prescription opioids in particular, and the issues that accompany the overuse of prescription opioids. Early work investigated the potential of MCLs to reduce individuals' reliance on prescription drugs. Bradford and Bradford (2016) analyze a dataset of Medicare prescriptions between 2010 and 2013 and conclude that MCLs decrease the use of prescription drugs for which cannabis can serve as a clinical substitute. Based on their results, Bradford and Bradford (2016) estimate that MCLs could reduce Medicare spending by over $150 million. Following up on this analysis, Bradford and Bradford (2017) examine the impact of MCLs on Medicaid prescriptions between 2007 and 2014. Consistent with their earlier analysis, they find that MCLs reduce the use of prescription drugs among Medicaid beneficiaries across five different clinical areas. Their results suggest that, if all states had passed an MCL in 2014, fee-for-service Medicaid would have saved over $1 billion.

While these two studies by Bradford and Bradford shed light on important effects of MCLs, they are not specific to prescription opioids. In a third study, however, Bradford et al. (2018) estimate the impact of MCLs on opioid prescriptions among the Medicare population between 2010 and 2015. Examining MCLs generally as well as different types of MCLs—e.g., those that provide for the operation of dispensaries—they find statistically significant decreases of between 8 percent and 21 percent in prescription rates for a group of six different types of opioids among Medicare beneficiaries. Focusing on Medicaid beneficiaries, Wen and Hockenberry (2018) examine the effect of both MCLs and RCLs on opioid prescription rates between 2011 and 2016. They conclude that MCLs and RCLs decrease the rate of opioid prescribing by 5.88 percent and 6.38 percent, respectively. In addition to Wen and Hockenberry (2018), only one other study has examined the effect of RCLs on prescription opioid use. Livingston et al. (2017) find evidence that Colorado's legalization of recreational cannabis reduced the number of opioid-related deaths. Finally, only one study has examined the role of cannabis access laws in prescription opioid use among the general population (Ozluk, 2017). Analyzing the Medical Expenditure Panel Survey, Ozluk (2017) finds that MCLs decrease annual spending on prescription opioids (per person prescribed) by $2.47.

Both because detailed information on opioid prescribing is difficult to obtain and because the negative effects of opioid use are important, a number or studies have investigated the ability of cannabis access laws to reduce these negative effects. Kim et al. (2016) find that drivers in fatal car accidents are less likely to test positive for opioids following those accidents in states that have MCLs. However, Hansen et al. (2018) find no increase in cannabis related traffic fatality rates in Washington and Colorado when those states passed RCLs. Bachhuber et al. (2014) conclude that, relative to states without MCLs, states with MCLs have nearly 25 percent lower opioid-related mortality rates, suggesting that MCLs are associated with lower prescription-opioid overdose deaths. Similarly, Powell et al. (2018) examine state-level prescription opioid deaths over a fourteen-year period beginning in 1999 and find that the number of deaths decreased in states allowing access to medical cannabis. They also examine admissions to treatment facilities for prescription opioid abuse, which proxies for opioid addiction. Consistent with the reduction in opioid-related deaths, treatment facility admissions decline when states allow access to medical cannabis. Along the same lines, (Shi, 2017) examines the association between MCLs and hospital admissions. MCLs are associated with a 23 percent decrease in admissions for opioid use disorder and a 13 percent decrease in admissions related to prescription-opioid overdose. Interestingly, Shi (2017) does not find evidence that hospital admissions related to cannabis use increase, suggesting that, to the extent individuals substitute cannabis for prescription opioids, they experience a decrease in the risk of events serious enough to warrant hospitalizations. This, in turn, suggests that cannabis may be a safer alternative to prescription opioids.

Existing studies provide important evidence on the role of cannabis access laws in the ongoing opioid crisis. However, these studies have salient limitations that prevent them from providing broad-ranging evidence. For example, many studies are based on survey evidence (see, e.g., Corroon et al., 2017; Sexton et al., 2016). Other studies lack granular data, which can prevent the analysis of nuanced effects or the inclusion of controls for provider-specific influences. For example, Wen and Hockenberry (2018) are limited to using state-level data. While some studies analyze more granular data, they still lack information on individual prescriptions, which is necessary to calculate specific measures of prescription opioid use. For example, Bradford and Bradford (2016) analyze physician-level information but are limited to the number of daily doses of different drugs. Additionally, the studies that have provided the most specific information to date—Bradford and Bradford (2016), Bradford and Bradford (2017), Bradford et al. (2018), and Wen and Hockenberry (2018)—have been limited to studying either the Medicare or Medicaid population, thereby omitting from their analysis a large proportion of individuals across the country. Ozluk (2017) addresses some of these issues, but that study nonetheless lacks the data necessary to calculate specific measures of opioid use.

In this study, we focus on the direct link between cannabis access laws and the opioid crisis—opioid prescriptions—as opposed to the downstream effects of opioid use. And we extend the existing literature in three important ways. First, we examine all opioid prescriptions—not just those written for Medicare or Medicaid beneficiaries. In doing so, we provide a more complete picture of the net effects of RCLs and MCLs on prescription opioid use. Second, we analyze more granular data than has been available to date. These data are described in the next section and include information on individual prescriptions that allow us to analyze highly specific measures of prescription opioid use. Prior work has explicitly listed as a limitation the inability to examine opioid use in terms of morphine milligram equivalents (MMEs) (see, e.g., Wen and Hockenberry, 2018), and we address this limitation by analyzing this measure of opioid use. This measure, along with the other measures considered here, allows us to conduct a more detailed analysis than has previously been possible. Finally, we analyze data at the individual provider level, which allows us to estimate the effect of RCLs and MCLs across different provider specialties. In doing so, we elucidate where cannabis access laws have the greatest impact.

Data

Cannabis Access Laws

While cannabis remains a schedule I controlled substance under the Controlled Substances Act, meaning it is illegal to possess under federal law, a number of states have nonetheless sought to increase access to cannabis by passing cannabis access laws at the state level.[1] These laws, while having no effect on federal law, remove state-level legal barriers to obtaining and possessing cannabis. In general, cannabis access laws can be classified into two groups. First, RCLs allow an individual to possess some amount of cannabis. Second, MCLs allow an individual to possess cannabis for a medical reason. For our analysis, we constructed a comprehensive list of all cannabis access laws.

Initial information on cannabis access laws came from previous research (Bradford et al., 2018; Wen and Hockenberry, 2018). We then conducted a search of primary legal documentation using the Westlaw database to identify individual statutes and other primary sources of law providing the legal basis for each cannabis access law used in this study. We classified any law

[1] While federal authorities retain the ability to enforce federal law despite the permissibility of possessing cannabis under state law, these authorities have, so far, taken a "hands off" approach by not stepping up enforcement of federal laws in states with cannabis access laws.

allowing access to cannabis for the purpose of treating a medical condition as an MCL. These laws generally (but not always) require the recommendation or certification of a healthcare provider and registration in a patient database prior to obtaining cannabis for the purpose of treating a medical condition. The list and definitions of medical conditions that allow a patient to access cannabis under an MCL vary but generally include some form of intractable pain as a condition. We classified any law allowing access to cannabis without limiting that access to medical reasons as an RCL. These laws allow adults 21 years or older to access cannabis. Where there was a legal question as to the exact date that a law became effective, we followed previous research in resolving the dispute in favor of the earlier date (Bradford et al., 2018). Different resolutions of disputed dates do not meaningfully affect the results reported below.

Table 1 provides a comprehensive list of all the cannabis access laws used in our study, and it includes both the year of enactment and the statutory citation for each law. To date, 9 states and the District of Columbia (DC) have passed RCLs, and 29 states and DC have passed MCLs. Of these laws, 9 RCLs and 14 MCLs were passed during our study period. Prior work has distinguished between different types of MCLs (Bradford et al., 2018; Pacula et al., 2015), and we analyze different types of MCLs as part of a series of robustness checks.[2]

[2] The results from this analysis are consistent with the main analysis.

Table 1: List of Cannabis Access Laws

State	Year of Enactment	Type	Citation	Notes
Alaska	2015	RCL	ALASKA STAT. ANN. § 17.38.020	MCL (1998)
Arizona	2010	MCL	ARIZ. REV. STAT. ANN. § 36-2801	
Arkansas	2016	MCL	ARK. CONST. AMEND. XCVIII, § 3	
California	2016	RCL	CAL. HEALTH & SAFETY CODE § 11362.1	MCL (1996)
Colorado	2012	RCL	COLO. CONST. ART. XVIII, § 16	MCL (2000)
Connecticut	2012	MCL	CONN. GEN. STAT. ANN. § 21A-408	
Delaware	2011	MCL	DEL. CODE ANN. TIT. 16, § 4903A	
Florida	2016	MCL	FLA. STAT. ANN. § 381.986	
Hawaii	2000	MCL	HAW. REV. STAT. ANN. § 329D-2	
Illinois	2013	MCL	410 ILL. COMP. STAT. ANN. 130/195	
Maine	2016	RCL	ME. REV. STAT. TIT. 7, § 2452	MCL (1999)
Maryland	2014	MCL	MD. CODE ANN., CRIM. LAW § 5-601(C)	
Massachusetts	2016	RCL	MASS. GEN. LAWS ANN. CH. 94G, § 7	MCL (2012)
Michigan	2008	MCL	MICH. COMP. LAWS ANN. § 333.26424	
Minnesota	2014	MCL	MINN. STAT. ANN. § 152.22–37	
Montana	2004	MCL	MONT. CODE ANN. § 50-46-302	
Nevada	2016	RCL	NEV. REV. STAT. ANN. § 453D.110	MCL (2000)
New Hampshire	2013	MCL	N.H. REV. STAT. ANN. § 126-X:2	
New Jersey	2010	MCL	N.J. STAT. ANN. § 24:6I-6	
New Mexico	2007	MCL	N.M. STAT. ANN. § 26-2B-2	
New York	2014	MCL	N.Y. PUB. HEALTH LAW § 3362	
North Dakota	2016	MCL	N.D. CENT. CODE ANN. § 19-24.1-02	
Ohio	2016	MCL	OHIO REV. CODE ANN. § 3796.02	
Oregon	1998	RCL	OR. REV. STAT. ANN. § 475B.005	MCL (1998)
Pennsylvania	2016	MCL	35 PA. STAT. ANN. § 10231.102	
Rhode Island	2006	MCL	21 R.I. GEN. LAWS ANN. § 21-28.6-4	
Vermont	2018	RCL	2018 VERMONT LAWS NO. 86 (H. 511)	MCL(2004); Vermont's 2018 RCL is not included in our analysis.
Washington	2012	RCL	Initiative 502	MCL (1998)
District of Columbia	2015	RCL	D.C. CODE ANN. § 48-904.01	MCL(2010)
West Virginia	2017	MCL	W. VA. CODE ANN. § 16A-3-2	

Prescription Opioid Data

Information on opioid prescriptions comes from Symphony Health's IDV® (Integrated Dataverse) dataset. This dataset includes information on individual prescriptions filled by patients at outpatient pharmacies between 2011 and 2017. The data were collected by combining health insurance claims data (from both private and public payers) with information from non-retail invoices and point-of-sale data collected from individual pharmacies. The dataset includes approximately 90% of all prescriptions filled at outpatient pharmacies in the United States between 2011 and 2017. Importantly, the dataset includes prescriptions regardless of payer, including prescriptions paid for in cash. In total, approximately 1.3 billion individual opioid prescriptions appear in the dataset.

Each observation includes the year the prescription was filled, the eleven-digit national drug code (NDC) for the prescription, the total days supply for the prescription, the quantity of drugs, an encrypted patient identifier, and an encrypted healthcare provider identifier. The provider identifier, which remains constant throughout the dataset, includes the provider's full taxonomy from the National Plan and Provider Enumeration System (NPPES) and the provider's state of practice. We define state for the purposes of assigning cannabis access laws as the provider's practice state. The data do not include information on the state of the patient or pharmacy, and while prescriptions may be transferred across state lines, the provider's state ultimately determines the ability of the provider to recommend cannabis.

From these data on individual prescriptions, we aggregate the data to the individual provider-year level and calculate the following outcomes for use in our analysis: (1) the total number of MMEs prescribed by each provider, (2) the total days supply prescribed by each provider, (3) the number of unique patients to whom each provider prescribed opioids, and (4) whether a provider prescribed any opioids. First, to calculate the MME of each opioid prescription, we use data compiled by the Prescription Drug Monitoring Program Training and Technical Assistance Center (PDMPTTAC). This dataset is organized by 11-digit NDC and includes both the strength per unit and MME conversion factor for all oral opioid medications. However, while buprenorphine/naloxone does, technically, have an MME conversion factor, the PDMPTTAC dataset codes this conversion factor as zero. We maintain this coding in our analysis because this drug is used in the treatment of opioid addiction. Using the NDCs in the prescription and PDMPTTAC datasets, we match the strength per unit and conversion factor information for all prescription opioids appearing in the prescription data.

With the information on days supply and quantity from the prescription data matched with the drug strength and MME conversion factor information from the PDMPTTAC data, we calculate the MME for every opioid prescription as:

$$MME = \frac{(Drug\ Strength) \cdot (Drug\ Quantity) \cdot (MME\ Conversion\ Factor)}{Days\ Supply}.$$

Using the MME for each individual prescription, we calculate the total MMEs prescribed by each provider in each year of our study using the encrypted provider identifiers. We then apply a logarithmic transformation to the total annual MMEs for each provider in each year. [3]

Second, to calculate total days supply prescribed by each provider in each year, we add the days supply for all opioid prescriptions associated with each provider in each year. We then apply a logarithmic transformation. Third, we calculate the total number of unique opioid patients associated with each provider in each year. To do so, we count the number of different patient identifiers (which are associated with the same patients throughout the entire dataset) associated

[3] Here and throughout our analysis, we add one to each observation before applying a logarithmic transformation.

with each provider's identifier in each year. We then apply a logarithmic transformation to the total number of unique opioid patients. If a patient obtains opioids from multiple providers, this patient is counted as a unique patient for each of these providers. Finally, we calculate an indicator variable for whether an individual provider prescribed any opioids in a given year. This variable equals one in years that the provider wrote at least one opioid prescription and zero otherwise.

These variables are more specific measures of opioid prescribing than has previously been examined (Bradford et al., 2018; Wen and Hockenberry, 2018). Instead of defining the total number of prescriptions at the state level, we are able to measure both the number and intensity of prescriptions via a conversion to MMEs at the individual provider level. Similarly, the other three outcome variables we examine provide a clearer picture of opioid prescribing than has been available in previous studies.

We limit our analysis to individual providers for whom the dataset includes at least one prescription for any medication (not only opioids) in at least two of the years between 2011 and 2017. Based on the Medicare definition of "physician" and the ability of other providers to prescribe opioids, we include the following types of providers in the analysis: MD- and DO-prepared physicians,[4] dentists, podiatrists, optometrists, advanced practice registered nurses, and physician assistants. We identify these providers using the NPPES taxonomies accompanying the provider identifiers. We also assign individual providers' specialties using these taxonomies.

For physicians, we separate each provider into the broadest specialty class provided by the primary taxonomy codes. For example, we include an internal medicine specialty but do not further distinguish between internists. For the other providers included in our analysis, we do not

[4] While we differentiate physicians based on the specialty listed in the NPPES, we do not differentiate between physicians who received a Doctor of Medicine degree from an allopathic medical school and those who received a Doctor of Osteopathy degree from an osteopathic medical school.

disaggregate them into specialties. For example, all physician assistants are classified simply as physician assistants. We do include separate categories for different types of advanced practice registered nurses but do not distinguish between specialties within a given type of advanced practice registered nurse (e.g., there are separate categories for nurse practitioners and certified nurse midwives but nurse practitioners are not further disaggregated based on specialty).

In our primary analysis, we consider all providers, and to present a more complete picture of the effects of RCLs and MCLs, we also examine two general subsets. First, we examine the five largest physician specialties as measured by the number of provider-years. This group includes emergency medicine, family medicine, internal medicine, pediatrics, and psychology and neurology. Second, we examine the five specialties with the highest mean annual MMEs. This group includes oral and maxillofacial surgery, orthopaedic surgery, pain medicine, physical medicine and rehabilitation, and sports medicine. In the appendix, we present results at the individual specialty level.

Summary Statistics

Figure 1 reports the mean number of MMEs prescribed each year by members of the ten largest specialties in our dataset. Family physicians prescribe, on average, the equivalent of more than 15 kilograms of morphine each year, which is more than any other large specialty. Though not included in Figure 1, pain medicine specialists prescribe the most MMEs on average among all specialties, prescribing the equivalent of over 172 kilograms of morphine each year. Similar information is available for all other specialties in the appendix.

Figure 1: Mean MMEs Prescribed by the Ten Largest Specialties

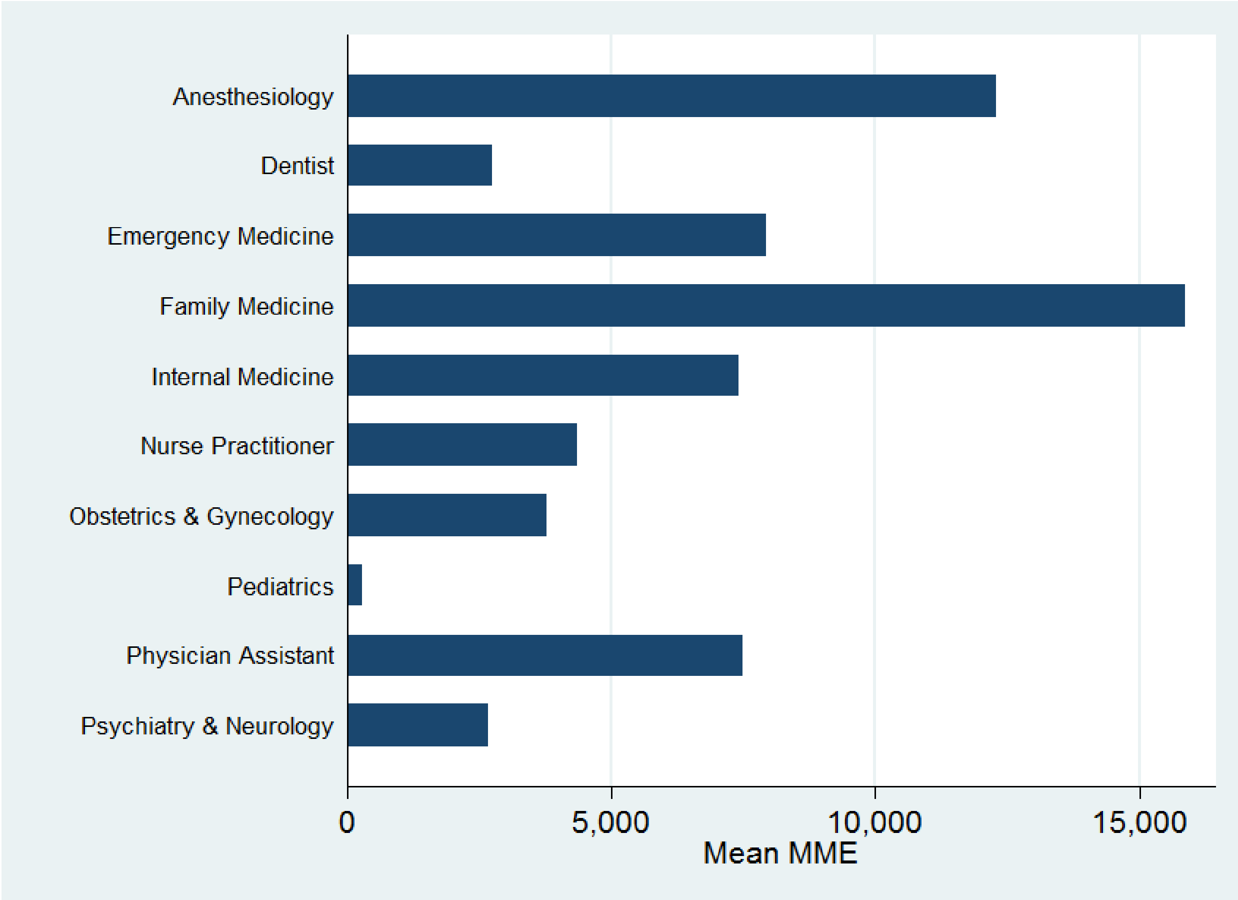


Table 2 reports the mean of each outcome variable across three different groups of providers: all providers, the five largest specialties, and the specialties with the highest mean MMEs. Table 2 also reports these means across different cannabis legal regimes. For all providers included in the analysis, the average annual number of MMEs is 6,540, while the average annual total days supply of opioids and unique opioid patients are 2,204 and 58, respectively. On average, 72% of providers prescribe at least one opioid in a year.

Table 2: Summary Statistics

Panel A: All Providers and Providers Not Subject to Any Cannabis Access Law

	All Providers				No Cannabis Access Law			
Group	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids
All Providers	6,540	2,204	58	72	7,352	2,555	68	74
Top 5 Size	7,720	3,129	61	75	8,737	3,699	74	79
Top 5 MME	35,608	10,564	191	90	41,269	12,789	227	92

Panel B: Providers Subject to Cannabis Access Laws

	Medical Cannabis Law				Recreational Cannabis Law			
Group	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids
All Providers	5,715	1,929	49	69	5,334	1,711	46	69
Top 5 Size	6,666	2,678	50	72	6,040	2,309	44	69
Top 5 MME	32,465	9,375	166	89	22,209	5,805	128	87

The mean annual MMEs is highest in states without a cannabis access law and decreases monotonically as states progress from MCLs to RCLs. The same general pattern is present across the three other outcomes we consider—total days supply, opioid patients, and whether a provider prescribes any opioids. Similarly, the same pattern persists within the five largest specialties and the five specialties with the highest mean annual MMEs. Across all measures, opioid use is highest in states that have no cannabis access law, lower in states with an MCL, and lowest in states with an RCL. In the appendix, we provide similar summary statistics for each individual specialty.

Empirical Strategy

General Model Specification

To examine the effect of cannabis access laws on opioid prescriptions, we estimate a series of difference-in-differences models, exploiting the staggered adoption of cannabis access laws over time. We estimate separate ordinary least squares models for each of our four outcome variables using the following general specification:

$$Y_{ist} = \beta_1 RCL_{st} + \beta_2 MCL_{st} + X_{st} + \delta_i + \tau_t + \varepsilon_{ist}.$$

In this model, i indexes individual providers, s indexes states, and t indexes years. The dependent variable, Y_{ist} is either the natural logarithm of MMEs prescribed by provider i, the natural logarithm of the total days supply of all opioids prescribed by provider i, the natural logarithm of the number of unique patients receiving opioids from provider i, or an indicator for whether provider i prescribes any opioids in year t.

The independent variables of interest, RCL_{st} and MCL_{st}, are indicator variables that equal one beginning the year that a given state enacts an RCL or MCL, respectively, and every year thereafter. In a series of robustness checks, which are described below, we change the definition of cannabis access laws to ensure that our results are not unique to the definition of these laws used in the primary analysis. The vector X_{st} includes control variables. In the primary analysis, we follow Bradford et al. (2018) and include an indicator that equals one if a state has an operational prescription drug monitoring program in year t, as these programs have been shown to affect opioid prescribing (Bradford et al., 2018; Patrick et al., 2016). In a series of robustness checks discussed below, we include additional control variables in X_{st}.

Importantly, every model includes a full set of individual-provider fixed effects, δ_i, and year fixed effects, τ_t. Provider fixed effects control for observed and unobserved characteristics of providers and their patient mix, and year fixed effects control for any linear or nonlinear trends in opioid prescriptions over time. The provider fixed effects absorb much of the heterogeneity present in opioid prescribing and allow the models to isolate the role of cannabis access laws from any idiosyncratic factors present at the provider level. The inclusion of these fixed effects obviates the need for many control variables, including state-level fixed effects, since provider fixed effects better control for confounding factors than traditional state- or county-level variables.

Throughout the analysis, we calculate two-way clustered standard errors at the state and provider level to correct for serial autocorrelation. As described in detail in the appendix, we test our data for parallel trends between providers in states that adopted cannabis access laws and those in states that did not. We are unable to reject the null hypothesis of parallel trends, which supports the use of difference-in-differences models. The primary models include all providers, with a total of 9,341,532 provider-years. This study was exempt from institutional review board review.

Model Choice

The criterion for inclusion in the analysis for each provider is the prescription of at least one medication (not necessarily an opioid) in two separate years of our study period (2011–2017). Thus, we include providers who prescribed no opioids in some years in our analysis, and approximately 28% of the provider-years we consider involve no opioid prescriptions. While this procedure results in the inclusion of many provider-years with zero opioid prescriptions in our analysis, we estimate OLS models instead of more complex models. As Angrist and Pischke (2009) note, the marginal effects of variables from OLS models are accurate despite the inclusion of zeros, and more complex models involve imposing specific distributional assumptions on the data that may not be warranted. Additionally, these more complex models cannot accommodate individual-level fixed effects for both theoretical (e.g., the incidental parameters problem) and computational feasibility reasons.

Specialty-Specific Models

In supplementary analyses, we separately estimate models specific to different specialties, and these are reported in the appendix. Because of the number of individual specialty-specific models we estimate, we report the results from these models in a condensed form. Only specialties with at least 2,000 provider-years are included in the appendix.

Results

Table 3 reports the results of our primary analysis. Because we estimate log-linear models, each coefficient can be interpreted as the percent change in the dependent variable that results from passing the relevant law.[5] As reported in column (1), RCLs reduce MMEs by approximately 6.9 percent, and MCLs reduce them by approximately 6.1 percent. Given a baseline mean annual MMEs of 7,352 in states without any cannabis access law, these effects represent decreases of 504 and 451 MMEs, respectively.[6] In other words, cannabis access laws reduce the average provider's opioid prescriptions by the equivalent of half a kilogram of morphine.

[5] Because the dependent variable is in logarithmic form, the marginal effect of an indicator variable with coefficient β is approximately $((\exp(\beta) - 1)(100))$ percent (Halvorsen and Palmquist, 1980).
[6] These effects are not statistically significantly different from one another (p = .1081).

Table 3: Regression Results for the Effect of Cannabis Access Laws on Opioid Prescribing

Variables	(1) ln(MME total)	(2) ln(total days supply)	(3) ln(number of opioid patients)	(4) I(provider prescribed any opioids)
Recreational (RCL)	-0.071**	-0.057**	-0.030**	-0.007**
	(0.004)	(0.003)	(0.002)	(0.001)
Medical (MCL)	-0.063**	-0.080**	-0.041**	-0.013**
	(0.003)	(0.003)	(0.002)	(0.000)
Observations	9,341,532	9,341,532	9,341,532	9,341,532
R-squared	0.820	0.836	0.862	0.649

Notes: The dependent variable in each model is reported at the top of each column. All specifications include an indicator variable for whether a state had an operational prescription drug monitoring program and a series of individual provider fixed effects and year fixed effects. Standard errors clustered at the provider and state levels are reported in parentheses.
* significant at the p < 0.01 level
** significant at the p < 0.001 level

In column (2), RCLs and MCLs reduce the total days supply of opioids by approximately 5.5 and 7.7 percent, respectively.[7] These decreases account for a total of 142 and 195 fewer days of opioids supplied to patients by each provider. Next, RCLs and MCLs reduce the number of patients receiving opioids by approximately 2.9 and 4 percent, respectively.[8] As reported in column (4), RCLs reduce the probability that a provider prescribes opioids in a given year by 0.7 percentage points, while MCLs reduce this probability by 1.3 percentage points, from a baseline of 74%.[9] Whereas RCLs have a greater effect than MCLs on total MMEs, MCLs have a larger effect in reducing total days of opioid supply, the number of patients taking opioids, and the probability that the provider prescribed opioids. Thus, MCLs are comparatively more effective in reducing the three measures of the scope of opioid use, but RCLs are more effective in reducing

[7] These effects are statistically significantly different from one another (p < 0.001).
[8] These effects are statistically significantly different from one another (p < 0.001).
[9] These effects are statistically significantly different from one another (p < 0.001).

the total MME quantity. Across all four measures of opioid prescriptions, we find a consistent, statistically significant, negative effect of both RCLs and MCLs in decreasing opioid use.

To further examine the role of cannabis access laws, we estimate a series of models limited to two groups of specialists—the five largest specialties and the highest-prescribing specialties (as measured by mean annual MMEs). Beyond limiting the models to specific specialties, the regressions are identical to those discussed above. Results for the largest and highest-prescribing specialties are reported in Panels A and B of Table 4, respectively. In both sets of models, RCLs and MCLs maintain their statistically significant and negative effects across all measures of opioid prescribing. Interestingly, for both groups of specialists and all measures of opioid use, RCLs reduce opioid prescribing to a greater extent than MCLs.

Table 4: Regression Results for the Effect of Cannabis Access Laws on Opioid Prescribing for Selected Specialties

Panel A: Top 5 Physician Specialties by Size

Variables	(1) ln(MME total)	(2) ln(total days supply)	(3) ln(number of opioid patients)	(4) I(provider prescribed any opioids)
Recreational (RCL)	-0.094**	-0.068**	-0.032**	-0.012**
	(0.007)	(0.006)	(0.003)	(0.001)
Medical (MCL)	-0.031**	-0.048**	-0.019**	-0.011**
	(0.005)	(0.004)	(0.002)	(0.001)
Observations	3,735,174	3,735,174	3,735,174	3,735,174
R-squared	0.817	0.841	0.871	0.601

Panel B: Top 5 Specialties by Mean MMEs

Variables	(1) ln(MME total)	(2) ln(total days supply)	(3) ln(number of opioid patients)	(4) I(provider prescribed any opioids)
Recreational (RCL)	-0.225**	-0.230**	-0.120**	-0.012**
	(0.025)	(0.022)	(0.014)	(0.003)
Medical (MCL)	-0.073**	-0.111**	-0.074**	-0.008**
	(0.019)	(0.017)	(0.011)	(0.002)
Observations	291,380	291,380	291,380	291,380
R-squared	0.795	0.802	0.821	0.604

Notes: The dependent variable in each model is reported at the top of each column. All specifications include an indicator variable for whether a state had an operational prescription drug monitoring program and a series of individual provider fixed effects and year fixed effects. Standard errors clustered at the provider and state levels are reported in parentheses.
* significant at the $p < 0.01$ level
** significant at the $p < 0.001$ level

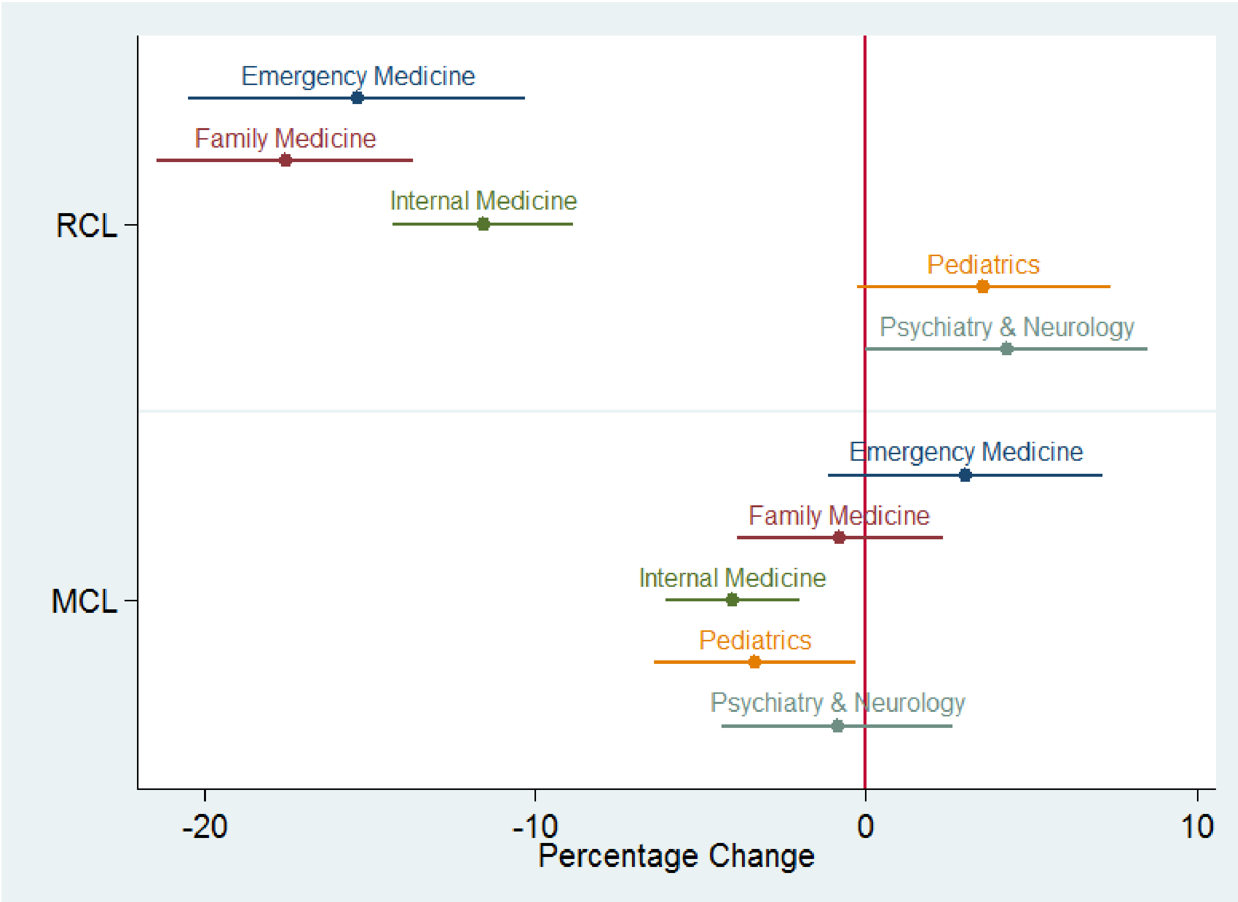
For example, RCLs and MCLs reduce the MMEs prescribed by 9 percent and 3.1 percent, respectively, among the largest five specialties. Among the highest-prescribing specialties, the magnitudes of these decreases increase to 20.2 percent and 7.1 percent. And these effects highlight another important pattern. While the largest and highest-prescribing specialties are each affected to a greater extent than all providers, the highest-prescribing specialties exhibit the largest decreases. This pattern is present across all measures of prescription opioid use we consider and suggests that the physicians who prescribe the most opioids (based on any of the four measures) are most affected by the greater availability of cannabis that comes with RCLs and MCLs. While this result is not particularly surprising, it does provide an important plausibility check for the estimates derived throughout our analysis, as we would expect that physicians who rely more heavily on prescription opioids to be more affected by laws increasing the availability of a potential substitute for those drugs.

Figure 2 reports results for the individual specialties that are included in the two groups in Table 4. These specialty-specific results illustrate that, while RCLs and MCLs generally reduce all measures of opioid prescriptions, the impacts of these laws are not consistent across specialties. For example, in the results in Panel A, the effects of RCLs are both greater and more likely to be statistically significant than the effects of MCLs. The largest effects for RCLs are for family medicine, emergency medicine, and internal medicine. For MCLs, the two statistically significant effects are the negative impacts for internal medicine and pediatrics.

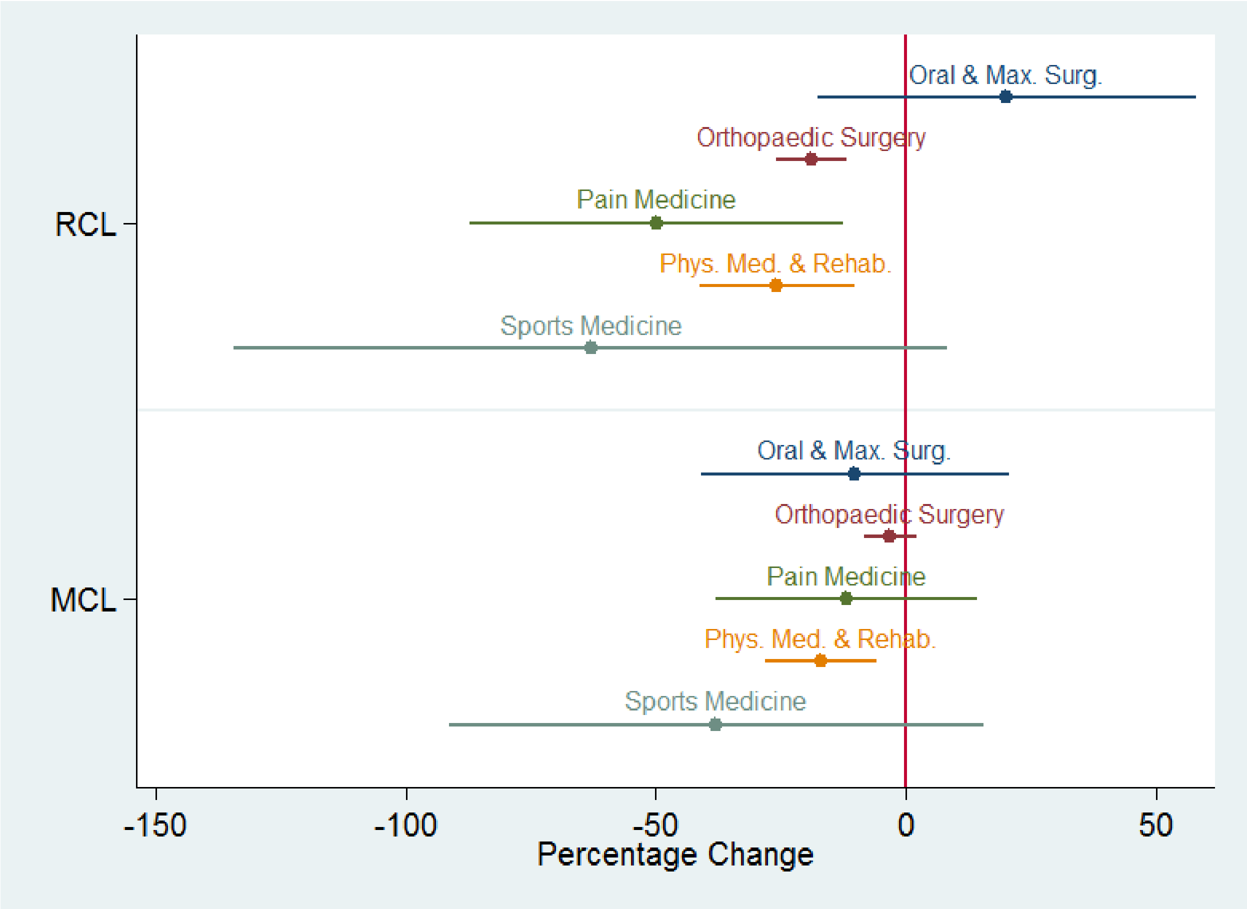
The results in Panel B of Figure 2 for the highest-prescribing specialties also show more frequent statistically significant negative effects for RCLs than for MCLs. RCLs reduce MMEs for sports medicine, pain medicine, and physical medicine and rehabilitation. The only top-five prescribing specialty that exhibits a statistically significant decline with respect to MCLs is physical medicine and rehabilitation. Results for other individual specialties are provided in the appendix.

Figure 2: Effect of Cannabis Access Laws on Opioid Prescribing for Selected Specialties

Panel A: Top 5 Physician Specialties by Size



Panel B: Top 5 Specialties by Mean MME



Notes: Individual points represent the marginal effects. Bars represent 99% confidence intervals. The appendix provides full results from the individual models reported in this figure.

Discussion

In general, we find consistent evidence that both RCLs and MCLs decrease opioid prescribing, and the sizes of the estimated reductions are in line with previous estimates derived from more limited populations (Bradford et al., 2018; Wen and Hockenberry, 2018). Thus, the evidence presented here suggests that cannabis access laws could be a useful tool in combatting the prescription opioid epidemic. The evidence also suggests that, while RCLs and MCLs reduce the use of prescription opioids, these reductions are not uniform across different types of providers.

These heterogeneous effects across different specialties can inform future policies related to both cannabis and opioids.

For example, policymakers may wish to target specialties that both prescribe large amounts of opioids and are strongly affected by cannabis access laws. These large, negative, and statistically significant effects may suggest that certain specialties could decrease their use of opioids with relatively little harm to patients, as patients may be able to substitute cannabis for prescription opioids relatively easily. While future work should investigate these relationships and potential policy solutions in more detail, the results of this study can highlight which specialties should be targeted first for investigation and (potentially) intervention.

The specialty-specific results also suggest a potential mechanism by which RCLs and MCLs may impact opioid prescribing. While future research should investigate specific mechanisms in more detail, the results here are consistent with cannabis substituting for opioids in the treatment of pain. In general, if cannabis access laws allow providers to better treat pain without the use of prescription opioids, then RCLs and MCLs should reduce the use of prescription opioids among specialties which routinely treat pain to a greater extent than other specialties. Examining the relative sizes of the negative effects reported in panels A and B of Table 4, the results suggest that cannabis access laws have larger effects on specialties that regularly treat pain (panel B) relative to specialties that do not (panel A). While our data do not allow us to test this potential mechanism explicitly, our results are consistent with a substitution of cannabis for prescription opioids in the treatment of pain and suggest future work on this mechanism could be useful.

In addition to elucidating which specialties are most affected by cannabis access laws, the specialty-specific results also provide a plausibility test of our results. In particular, the results for pediatricians suggest that the effects described in this study comport with the legal functioning of

RCLs and MCLs. Generally, pediatricians should not regularly treat individuals who are eligible to obtain cannabis pursuant to RCLs, as these laws allow possession only by adults. However, pediatric patients could benefit from MCLs (Ananth et al., 2018). Our results demonstrate that, while RCLs have no statistically significant effect on the opioid prescribing patterns of pediatricians, MCLs have a statistically significant and negative effect on the MMEs prescribed by pediatricians.

Robustness

All of the primary models include general RCL and MCL variables; however, not all cannabis access laws are written in exactly the same way. In particular, prior work has disaggregated MCL laws based on (1) the definition of pain that will allow a patient to access medical cannabis and (2) whether states allow medical cannabis dispensaries (Bradford et al., 2018; Ozluk, 2017; Powell et al., 2018). Table 5 reports results from regression specifications that are similar to our primary models but replace our general MCL variable with an indicator variable that equals one if a state law specifically includes a provision allowing access to medical cannabis for intractable pain with no limitations on the origins of that pain (e.g., a specific type of disease) (see Ozluk 2017). Table 6 reports regression results similar to our primary models but replaces the MCL variable with an indicator variable that equals one if a state law both allows access to medical cannabis and allows medical cannabis dispensaries. The results reported in Tables 5 and 6, while not identical to, are consistent with the results from our primary models.

Table 5: Regression Results with Pain-Specific MCLs

Variables	(1) ln(MME total)	(2) ln(total days supply)	(3) ln(number of opioid patients)	(4) I(provider prescribed any opioids)
Recreational (RCL)	-0.068**	-0.053**	-0.028**	-0.006**
	(0.004)	(0.003)	(0.002)	(0.001)
Medical (MCL – Pain)	-0.077**	-0.095**	-0.053**	-0.014**
	(0.004)	(0.004)	(0.002)	(0.001)
Observations	9,341,532	9,341,532	9,341,532	9,341,532
R-squared	0.820	0.836	0.862	0.649

Notes: The dependent variable in each model is reported at the top of each column. All specifications include an indicator variable for whether a state had an operational prescription drug monitoring program and a series of individual provider fixed effects and year fixed effects. Standard errors clustered at the provider and state levels are reported in parentheses.
* significant at the p < 0.01 level
** significant at the p < 0.001 level

Table 6: Regression Results with Dispensary-Specific MCLs

Variables	(1) ln(MME total)	(2) ln(total days supply)	(3) ln(number of opioid patients)	(4) I(provider prescribed any opioids)
Recreational (RCL)	-0.060**	-0.043**	-0.022**	-0.005**
	(0.004)	(0.003)	(0.002)	(0.001)
Medical (MCL – Dispensary)	-0.028**	-0.035**	-0.017**	-0.008**
	(0.003)	(0.003)	(0.002)	(0.001)
Observations	9,341,532	9,341,532	9,341,532	9,341,532
R-squared	0.820	0.836	0.862	0.649

Notes: The dependent variable in each model is reported at the top of each column. All specifications include an indicator variable for whether a state had an operational prescription drug monitoring program and a series of individual provider fixed effects and year fixed effects. Standard errors clustered at the provider and state levels are reported in parentheses.
* significant at the p < 0.01 level
** significant at the p < 0.001 level

Next, our primary models include a control variable for whether a state had an operational prescription drug monitoring program (PDMP) in place. Prior work has shown these programs can affect opioid prescribing (Patrick et al., 2016). To further control for the roles PDMPs play, the models reported in Table 7 include, in addition to an indicator variable for whether a state has an operational PDMP, an indicator variable for whether a state has enacted a law mandating a PDMP (regardless of whether one was operational). The models in Table 7 also include an indicator variable that equals one in states that expanded Medicaid following that expansion. Prior work has shown that consumption of healthcare increased following Medicaid expansion (Nikpay et al., 2017), and this increase in consumption may extend to prescription opioids. In general, including these additional control variables results in only small changes in the estimated coefficients for RCLs and MCLs.

Table 7: Regression Results with Additional Controls

Variables	(1) ln(MME total)	(2) ln(total days supply)	(3) ln(number of opioid patients)	(4) I(provider prescribed any opioids)
Recreational (RCL)	-0.071**	-0.056**	-0.028**	-0.008**
	(0.004)	(0.003)	(0.002)	(0.001)
Medical (MCL)	-0.064**	-0.080**	-0.040**	-0.014**
	(0.003)	(0.003)	(0.002)	(0.001)
Observations	9,341,532	9,341,532	9,341,532	9,341,532
R-squared	0.820	0.836	0.862	0.649

Notes: The dependent variable in each model is reported at the top of each column. All specifications include an indicator variable for whether a state had an operational prescription drug monitoring program, an indicator variable for whether a state had passed a law mandating a prescription drug monitoring program, and an indicator for whether a state had expanded Medicaid under the Affordable Care Act. Each specification also includes a series of individual provider fixed effects and year fixed effects. Standard errors clustered at the provider and state levels are reported in parentheses.
* significant at the $p < 0.01$ level
** significant at the $p < 0.001$ level

In addition to the robustness checks reported here, the appendix provides a thorough test of the parallel trends assumption that underlies every difference-in-differences empirical strategy. As with previous work (Bradford et al., 2018; Wen and Hockenberry, 2018), we find no evidence that pre-trends are affecting our results.

Conclusion

The results of this study suggest that passing cannabis access laws reduces the use of prescription opioids across four separate measures of opioid prescriptions pertaining to total MME, total days supply, number of opioid patients, and whether the health care provider prescribed opioids. These empirical effects are net impacts on each of these measures of usage, including both increases and decreases that may have occurred for any individual patient. While cannabis may be a gateway drug that encourages use of opioids in some patients, on balance for the population generally both recreational and medical marijuana laws decrease opioid use. Thus, the passage of an RCL or MCL may be a valid policy option for combating the ongoing opioid epidemic, even if these laws were not originally conceived for that purpose. While the results here do not suggest that cannabis access laws are the only tool to address prescription opioid use, they do suggest that cannabis access laws could play a meaningful role in addressing the opioid epidemic.

References

Alpert, A., Powell, D., Pacula, R.L., 2017. Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids, NBER Working Paper 23031.

Ananth, P., Ma, C., Al-Sayegh, H., Kroon, L., Klein, V., Wharton, C., Hallez, E., Braun, I., Michelson, K., Rosenberg, A.R., London, W., Wolfe, J., 2018. Provider Perspectives on Use of Medical Marijuana in Children With Cancer. Pediatrics 141, e20170559. https://doi.org/10.1542/peds.2017-0559

Bachhuber, M.A., Saloner, B., Cunningham, C.O., Barry, C.L., 2014. Medical Cannabis Laws and Opioid Analgesic Overdose Mortality in the United States, 1999-2010. JAMA Internal Medicine 174, 1668. https://doi.org/10.1001/jamainternmed.2014.4005

Boehnke, K.F., Litinas, E., Clauw, D.J., 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, 739–744. https://doi.org/10.1016/j.jpain.2016.03.002

Boudreau, D., Von Korff, M., Rutter, C.M., Saunders, K., Ray, G.T., Sullivan, M.D., Campbell, C.I., Merrill, J.O., Silverberg, M.J., Banta-Green, C., Weisner, C., 2009. Trends in long-term opioid therapy for chronic non-cancer pain. Pharmacoepidemiol Drug Saf 18, 1166–1175. https://doi.org/10.1002/pds.1833

Bradford, A.C., Bradford, W.D., 2017. Medical Marijuana Laws May Be Associated With A Decline In The Number Of Prescriptions For Medicaid Enrollees. Health Aff (Millwood) 36, 945–951. https://doi.org/10.1377/hlthaff.2016.1135

Bradford, A.C., Bradford, W.D., 2016. Medical Marijuana Laws Reduce Prescription Medication Use In Medicare Part D. Health Aff (Millwood) 35, 1230–1236. https://doi.org/10.1377/hlthaff.2015.1661

Bradford, A.C., Bradford, W.D., Abraham, A., Bagwell Adams, G., 2018. Association Between US State Medical Cannabis Laws and Opioid Prescribing in the Medicare Part D Population. JAMA Internal Medicine 178, 667. https://doi.org/10.1001/jamainternmed.2018.0266

Brady, J.E., Wunsch, H., DiMaggio, C., Lang, B.H., Giglio, J., Li, G., 2014. Prescription drug monitoring and dispensing of prescription opioids. Public Health Rep 129, 139–147. https://doi.org/10.1177/003335491412900207

Buchmueller, T.C., Carey, C., 2018. The Effect of Prescription Drug Monitoring Programs on Opioid Utilization in Medicare. American Economic Journal: Economic Policy 10, 77–112. https://doi.org/10.1257/pol.20160094

Chou, R., Fanciullo, G.J., Fine, P.G., Adler, J.A., Ballantyne, J.C., Davies, P., Donovan, M.I., Fishbain, D.A., Foley, K.M., Fudin, J., Gilson, A.M., Kelter, A., Mauskop, A., O'Connor, P.G., Passik, S.D., Pasternak, G.W., Portenoy, R.K., Rich, B.A., Roberts, R.G., Todd, K.H., Miaskowski, C., American Pain Society-American Academy of Pain Medicine Opioids Guidelines Panel, 2009. Clinical guidelines for the use of chronic opioid therapy in chronic noncancer pain. J Pain 10, 113–130. https://doi.org/10.1016/j.jpain.2008.10.008

Chou, R., Turner, J.A., Devine, E.B., Hansen, R.N., Sullivan, S.D., Blazina, I., Dana, T., Bougatsos, C., Deyo, R.A., 2015. The effectiveness and risks of long-term opioid therapy for chronic pain: a systematic review for a National Institutes of Health Pathways to Prevention Workshop. Ann. Intern. Med. 162, 276–286. https://doi.org/10.7326/M14-2559

Chu, Y.-W.L., 2015. Do Medical Marijuana Laws Increase Hard-Drug Use? The Journal of Law and Economics 58, 481–517. https://doi.org/10.1086/684043

Corroon, J.M., Mischley, L.K., Sexton, M., 2017. Cannabis as a substitute for prescription drugs - a cross-sectional study. J Pain Res 10, 989–998. https://doi.org/10.2147/JPR.S134330

Dart, R.C., Surratt, H.L., Cicero, T.J., Parrino, M.W., Severtson, S.G., Bucher-Bartelson, B., Green, J.L., 2015. Trends in Opioid Analgesic Abuse and Mortality in the United States. New England Journal of Medicine 372, 241–248. https://doi.org/10.1056/NEJMsa1406143

Halvorsen, R., Palmquist, R., 1980. The Interpretation of Dummy Variables in Semilogarithmic Equations. American Economic Review 70, 474–475.

Hansen, B., Miller, K.S., Weber, C., 2018. Early Evidence on Recreational Marijuana Legalization and Traffic Fatalities.

Haroutounian, S., Ratz, Y., Ginosar, Y., Furmanov, K., Saifi, F., Meidan, R., Davidson, E., 2016. The Effect of Medicinal Cannabis on Pain and Quality-of-Life Outcomes in Chronic Pain: A Prospective Open-label Study. Clin J Pain 32, 1036–1043. https://doi.org/10.1097/AJP.0000000000000364

Kim, J.H., Santaella-Tenorio, J., Mauro, C., Wrobel, J., Cerdà, M., Keyes, K.M., Hasin, D., Martins, S.S., Li, G., 2016. State Medical Marijuana Laws and the Prevalence of Opioids Detected Among Fatally Injured Drivers. Am J Public Health 106, 2032–2037. https://doi.org/10.2105/AJPH.2016.303426

Livingston, M.D., Barnett, T.E., Delcher, C., Wagenaar, A.C., 2017. Recreational Cannabis Legalization and Opioid-Related Deaths in Colorado, 2000-2015. Am J Public Health 107, 1827–1829. https://doi.org/10.2105/AJPH.2017.304059

Mattson, C.L., Schieber, L., Scholl, L., Rudd, R.A., Seth, P., Xu, L., Wilson, N.O., Paulozzi, L., 2017. Annual Surveillance Report of Drug-Related and Outcomes. Centers for Disease Control and Prevention, Atlanta, GA.

Merboth, M.K., Barnason, S., 2000. Managing pain: the fifth vital sign. Nurs. Clin. North Am. 35, 375–383.

National Academies of Sciences, Engineering, and Medicine, 2017. The Health Effects of Cannabis and Cannabinoids: The Current State of Evidence and Recommendations for Research. https://doi.org/10.17226/24625

Nikpay, S., Freedman, S., Levy, H., Buchmueller, T., 2017. Effect of the Affordable Care Act Medicaid Expansion on Emergency Department Visits: Evidence From State-Level Emergency Department Databases. Ann Emerg Med 70, 215-225.e6. https://doi.org/10.1016/j.annemergmed.2017.03.023

Ozluk, P., 2017. The Effects of Medical Marijuana Laws on Utilization of Prescribed Opioids and Other Prescription Drugs (SSRN Scholarly Paper No. 3056791). Social Science Research Network, Rochester, NY.

Pacula, R.L., Powell, D., 2018. A Supply-Side Perspective on the Opioid Crisis. Journal of Policy Analysis and Management 37, 438–446. https://doi.org/10.1002/pam.22049

Pacula, R.L., Powell, D., Heaton, P., Sevigny, E.L., 2015. Assessing the effects of medical marijuana laws on marijuana use: the devil is in the details. J Policy Anal Manage 34, 7–31.

Patrick, S.W., Fry, C.E., Jones, T.F., Buntin, M.B., 2016. Implementation Of Prescription Drug Monitoring Programs Associated With Reductions In Opioid-Related Death Rates. Health Aff (Millwood) 35, 1324–1332. https://doi.org/10.1377/hlthaff.2015.1496

Powell, D., Pacula, R.L., Jacobson, M., 2018. Do medical marijuana laws reduce addictions and deaths related to pain killers? Journal of Health Economics 58, 29–42. https://doi.org/10.1016/j.jhealeco.2017.12.007

Reiman, A., Welty, M., Solomon, P., 2017. Cannabis as a Substitute for Opioid-Based Pain Medication: Patient Self-Report. Cannabis and Cannabinoid Research 2, 160–166. https://doi.org/10.1089/can.2017.0012

Rudd, R.A., Aleshire, N., Zibbell, J.E., Gladden, M., 2016. Increases in Drug and Opioid Overdose Deaths — United States, 2000–2014 [WWW Document]. URL https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6450a3.htm (accessed 5.27.18).

Secades-Villa, R., Garcia-Rodríguez, O., Jin, C.J., Wang, S., Blanco, C., 2015. Probability and predictors of the cannabis gateway effect: a national study. Int. J. Drug Policy 26, 135–142. https://doi.org/10.1016/j.drugpo.2014.07.011

Sexton, M., Cuttler, C., Finnell, J.S., Mischley, L.K., 2016. A Cross-Sectional Survey of Medical Cannabis Users: Patterns of Use and Perceived Efficacy. Cannabis and Cannabinoid Research 1, 131–138. https://doi.org/10.1089/can.2016.0007

Shi, Y., 2017. Medical marijuana policies and hospitalizations related to marijuana and opioid pain reliever. Drug and Alcohol Dependence 173, 144–150. https://doi.org/10.1016/j.drugalcdep.2017.01.006

Tompkins, D.A., Hobelmann, J.G., Compton, P., 2017. Providing chronic pain management in the "Fifth Vital Sign" Era: Historical and treatment perspectives on a modern-day medical dilemma. Drug and Alcohol Dependence 173, S11–S21. https://doi.org/10.1016/j.drugalcdep.2016.12.002

Von Korff, M.R., Franklin, G., 2016. Responding to America's Iatrogenic Epidemic of Prescription Opioid Addiction and Overdose: Medical Care 54, 426–429. https://doi.org/10.1097/MLR.0000000000000537

Wen, H., Hockenberry, J.M., 2018. Association of Medical and Adult-Use Marijuana Laws With Opioid Prescribing for Medicaid Enrollees. JAMA Internal Medicine 178, 673. https://doi.org/10.1001/jamainternmed.2018.1007

Wen, H., Hockenberry, J.M., Cummings, J.R., 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. https://doi.org/10.1016/j.jhealeco.2015.03.007

Whiting, P.F., Wolff, R.F., Deshpande, S., Di Nisio, M., Duffy, S., Hernandez, A.V., Keurentjes, J.C., Lang, S., Misso, K., Ryder, S., Schmidlkofer, S., Westwood, M., Kleijnen, J., 2015. Cannabinoids for Medical Use: A Systematic Review and Meta-analysis. JAMA 313, 2456. https://doi.org/10.1001/jama.2015.6358

Wilkinson, S.T., Yarnell, S., Radhakrishnan, R., Ball, S.A., D'Souza, D.C., 2016. Marijuana Legalization: Impact on Physicians and Public Health. Annu. Rev. Med. 67, 453–466. https://doi.org/10.1146/annurev-med-050214-013454

Williams, J., Bretteville-Jensen, A.L., 2014. Does liberalizing cannabis laws increase cannabis use? Journal of Health Economics 36, 20–32. https://doi.org/10.1016/j.jhealeco.2014.03.006

APPENDIX A

To Accompany

The Impact of Cannabis Access Laws on Opioid Prescribing

Additional Summary Statistics

Table A1 reports the means of each of our outcome variables across different cannabis legal regimes for all specialties for which we have at least 2,000 provider-year observations. This table mirrors the format of Table 2 in the main text but provides specialty-specific information.

Specialty-Specific Models

Because of the number of individual specialty-specific models we estimate, we include the results in Appendix B. This separate appendix (which is provided as a Microsoft Excel file for convenience) includes a series of models for the specialties that were used throughout the main analysis—defined at the primary taxonomy code level for physicians and defined as the type of provider for other providers. For each specialty, we report the marginal effects of each cannabis access law, the 99% confidence intervals, and the P-values for each marginal effect. Also included in the same row as the name of the specialty is the number of individual provider-years included in the models. We adopt this reporting format, which is common in medical journals, in order to provide the results in the most condensed form possible. Only specialties with at least 2,000 provider-years are included in Appendix B. This restriction is necessary to maintain confidentiality.

Parallel Trends Analysis

A key assumption in any difference-in-differences model is that the pre-treatment trends in the outcome of interest in the treated and untreated groups were parallel. The specific assumption underlying our models is that opioid prescribing trends in states that never adopted a cannabis access law and those that did were parallel. If these trends are not parallel, then providers in non-adopting states are not an appropriate comparison group for those in states that adopted a cannabis access law.

To test whether the trends in adopting and non-adopting states were parallel prior to adoption, we follow the approaches of Wen et al. (2018) and Bradford et al. (2018). As in those studies, we find no evidence of a violation of the parallel trends assumption. We first simply graph the mean of our different outcome variables in states that adopted and those that did not adopt. Figure A1 includes the mean of our MME outcome variable across the entire study period for states that never adopted an MCL and states that adopted an MCL during our study period. States that adopted an MCL prior to our study period were excluded from these graphs. Panel A of Figure A1 includes the comparison group of never-adopting states and states that adopted an MCL in 2012. Panels B, C, and D repeat this comparison for states that adopted an MCL in 2013, 2014, and 2016, respectively. In the interest of succinctness and based on the absence of a "post" period, we do not include a graph with states that enacted cannabis access laws in 2017. Visually, nothing suggests that the pre-treatment trends in our MME variable differed across adopting and non-adopting states. In the interest of succinctness, we do not include graphs of our other outcome variables, but visual inspection of those graphs similarly reveals no discernible differences in pre-treatment trends.

Figure A2 repeats Figure A1, replacing the MCL comparison with an RCL comparison. Across all three panels of Figure A2, there is little evidence of a divergence in the pre-adoption trends in our MME variable. As with the MCL comparisons, we do not report the graphs for our other outcome variables in the interest of succinctness. Though not all of the laws presented in Figures A1 and A2 have a substantial number of pre-enactment years for comparison purposes, most legal changes have at least a two-year pre-enactment period. And all of the graphs reported in Figures A1 and A2 provide strong evidence of pre-enactment parallel trends.

While visual inspection of Figures A1 and A2 supports our assumption of parallel trends in the pre-treatment periods, we further test this assumption in a series of regression models. We first examine the potential of differential pre-trends with respect to MCLs. Starting from the general model specification provided in the main text, we replace the independent variables of interest with a time trend and an interaction between this time trend and an indicator variable for whether a given state would enact an MCL in the future. We then estimate this model using observations on provider-years in states that never adopted an MCL and states that would adopt an MCL during our study period, excluding observations in these adopting states following adoption.

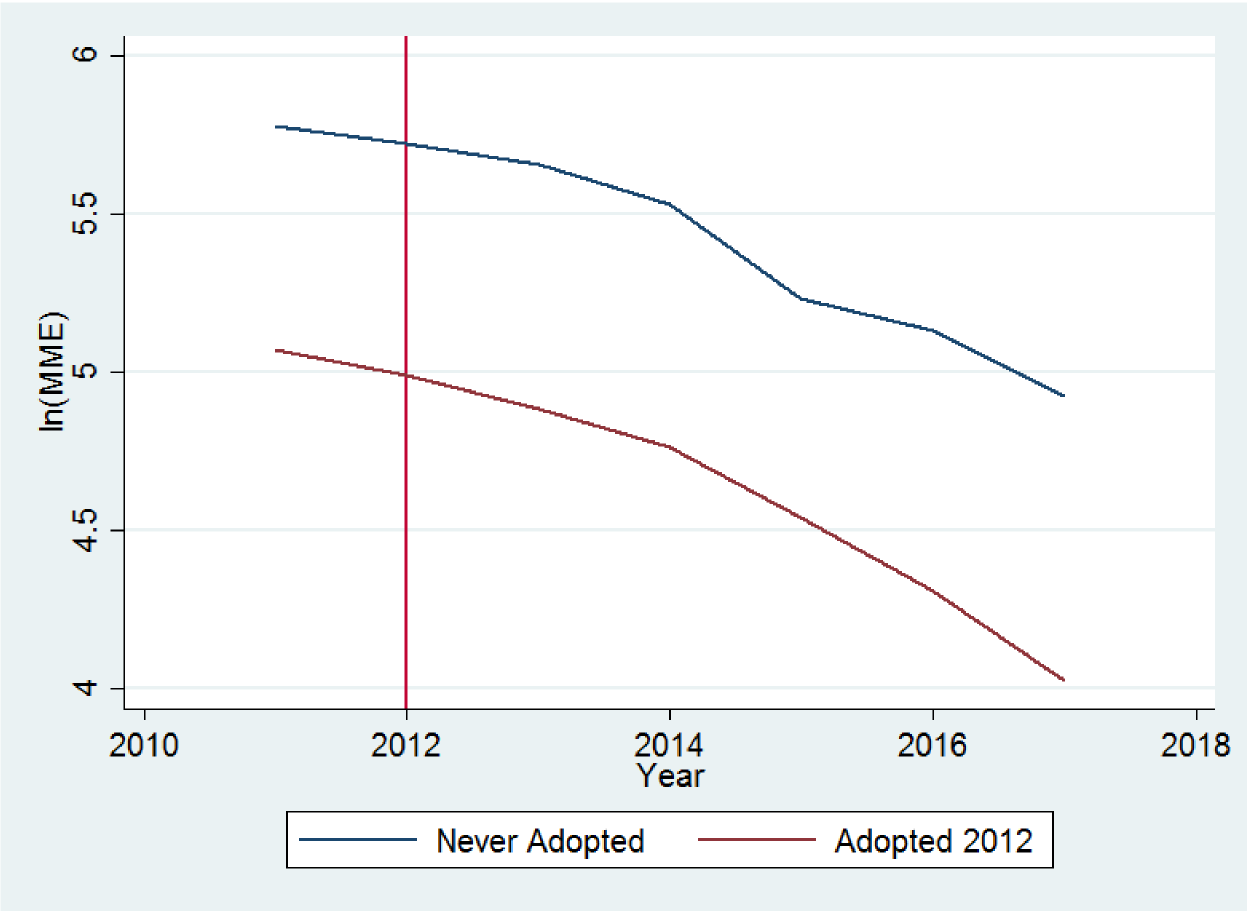
Table A2 reports the coefficient estimates for the interaction term between the time trend and the indicator variable for whether a state would adopt an MCL during the study period. Each row represents a different model for our four different outcome variables. Statistically significant coefficients would imply a statistically significant difference in time trends in states that adopt MCLs relative to states that do not. However, none of the reported coefficients is statistically significant, meaning we are unable to reject the null hypothesis that the pre-adoption trends in adopting and non-adopting states are the same.

Table A3 reports the coefficient estimates for a similar analysis with respect to RCLs. As with MCLs, we are unable to reject the null hypothesis that the pre-adoption trends in adopting and non-adopting states are the same. Thus, we do not find statistically significant evidence to suggest that the pre-adoption paths of states adopting cannabis access laws and those not adopting such laws are different. The results in Tables A2 and A3 support the use of difference-in-differences models in our primary analysis.

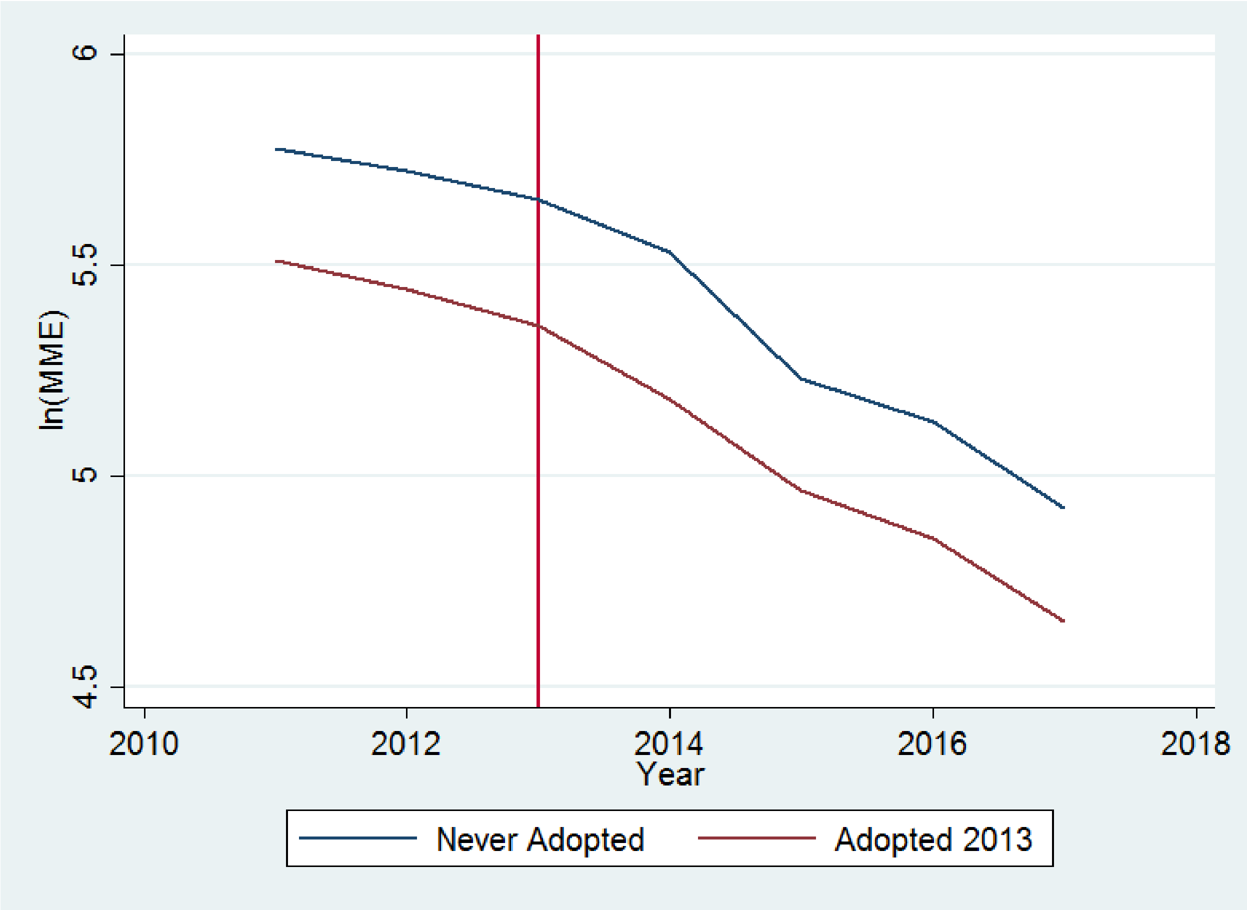
Tables and Figures

Figure A1: MCL Parallel Trends

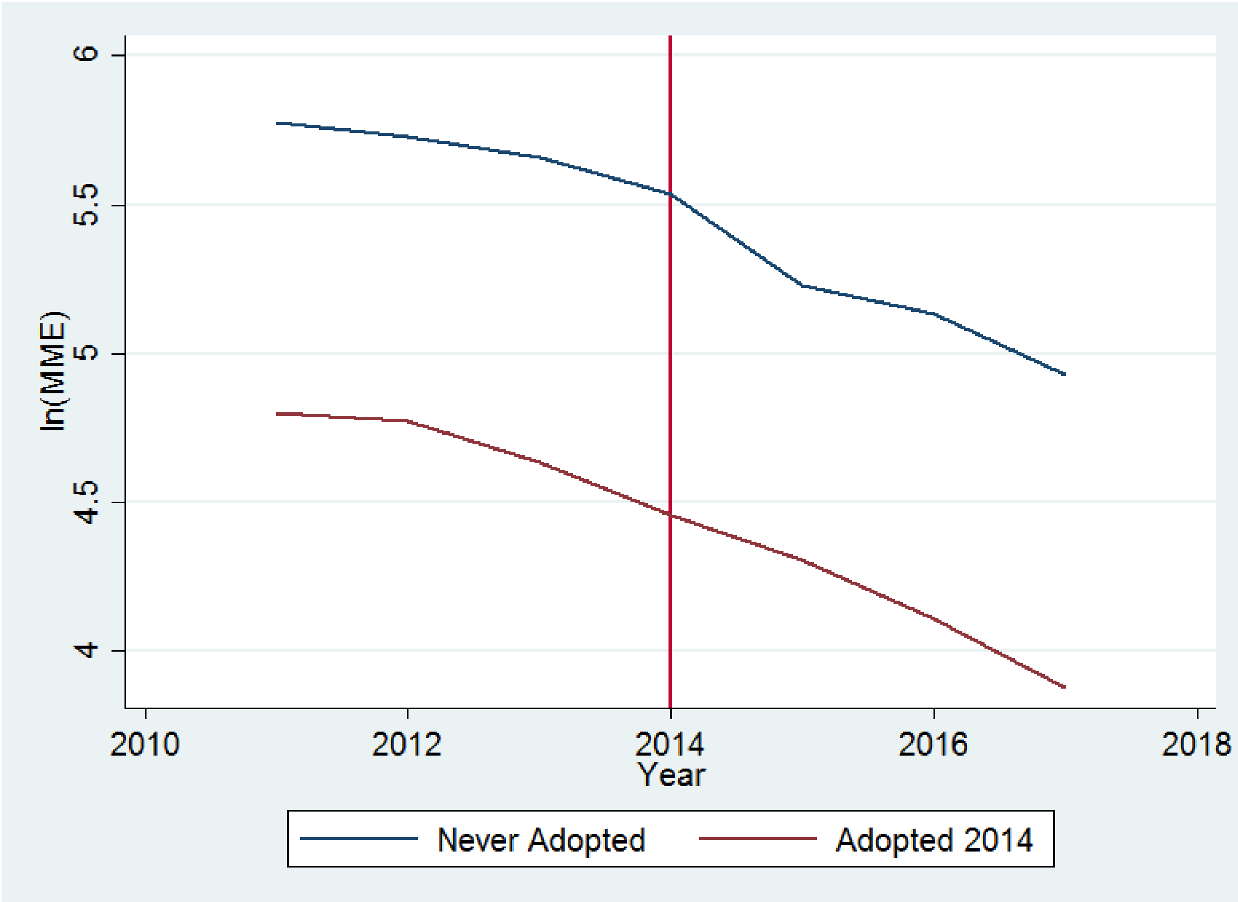
Panel A: States Adopting in 2012



Panel B: States Adopting in 2013



Panel C: States Adopting in 2014



Panel D: States Adopting in 2016

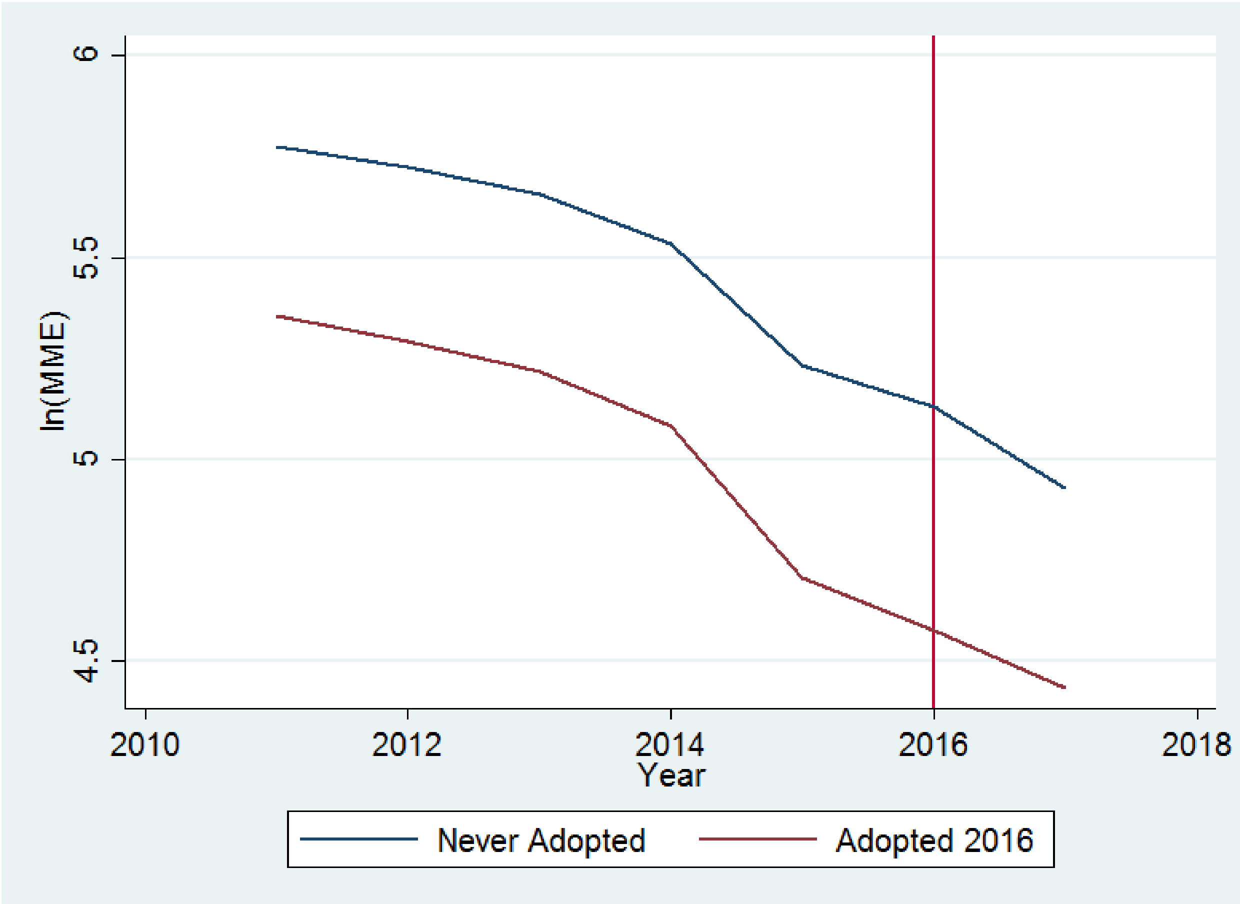
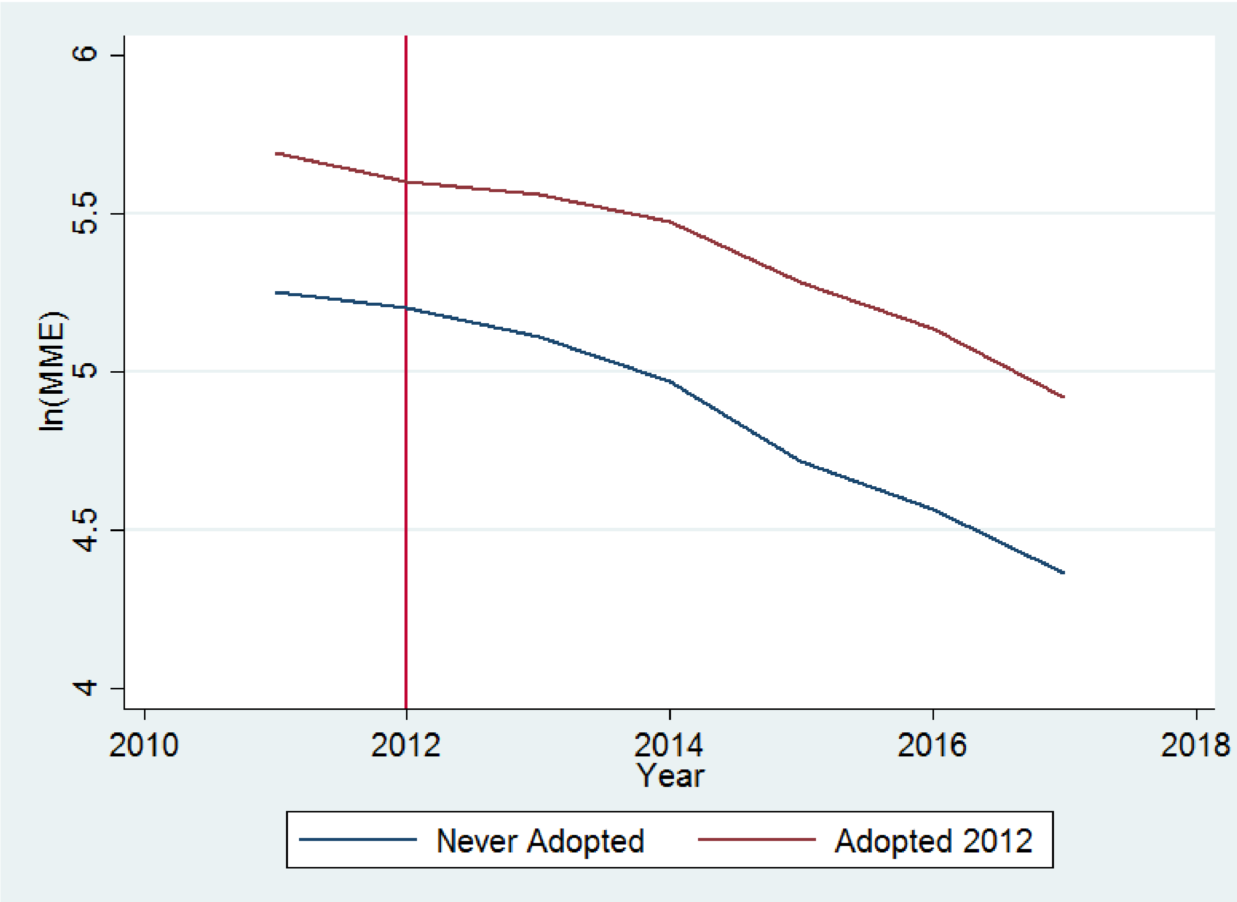
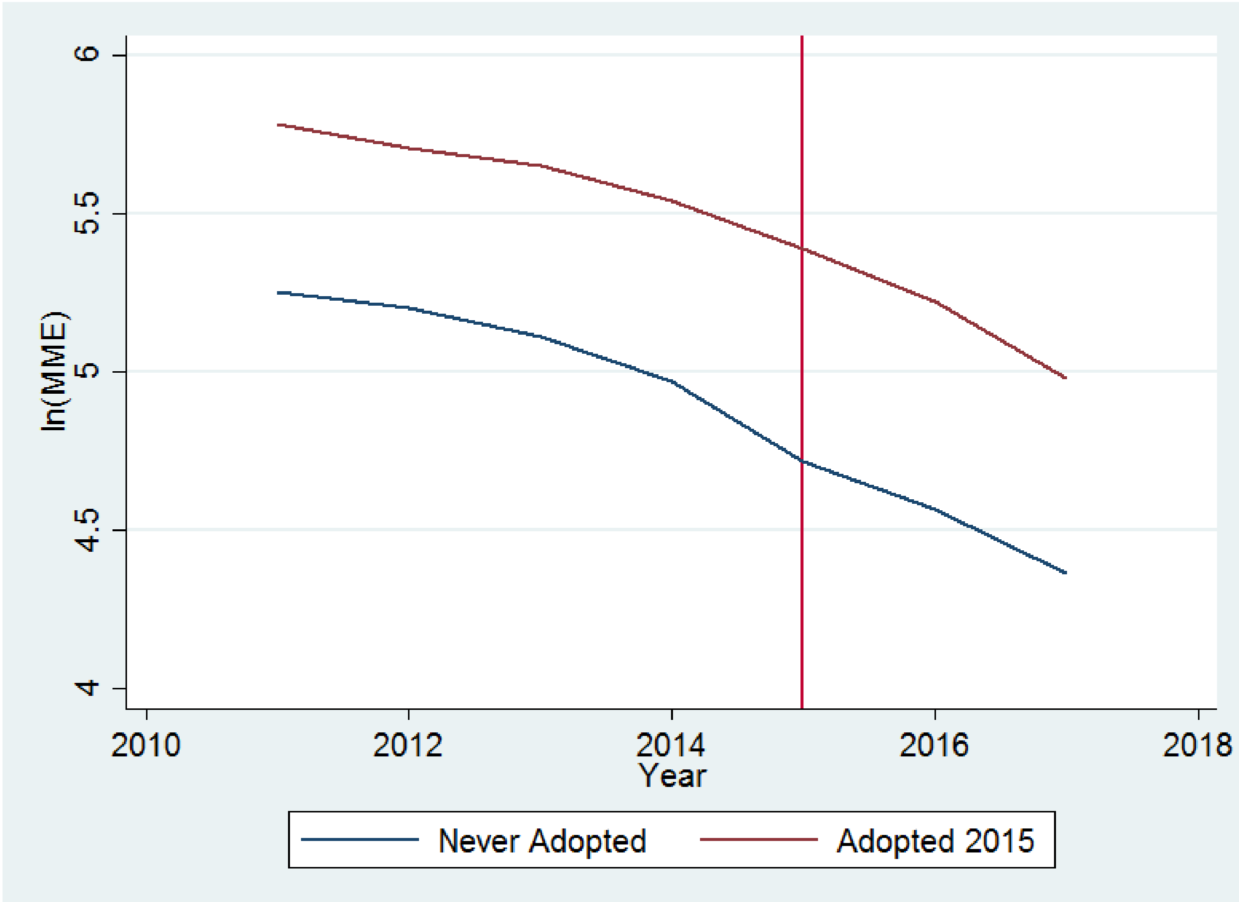


Figure A2: RCL Parallel Trends

Panel A: States Adopting in 2012



Panel B: States Adopting in 2015



Panel C: States Adopting in 2016

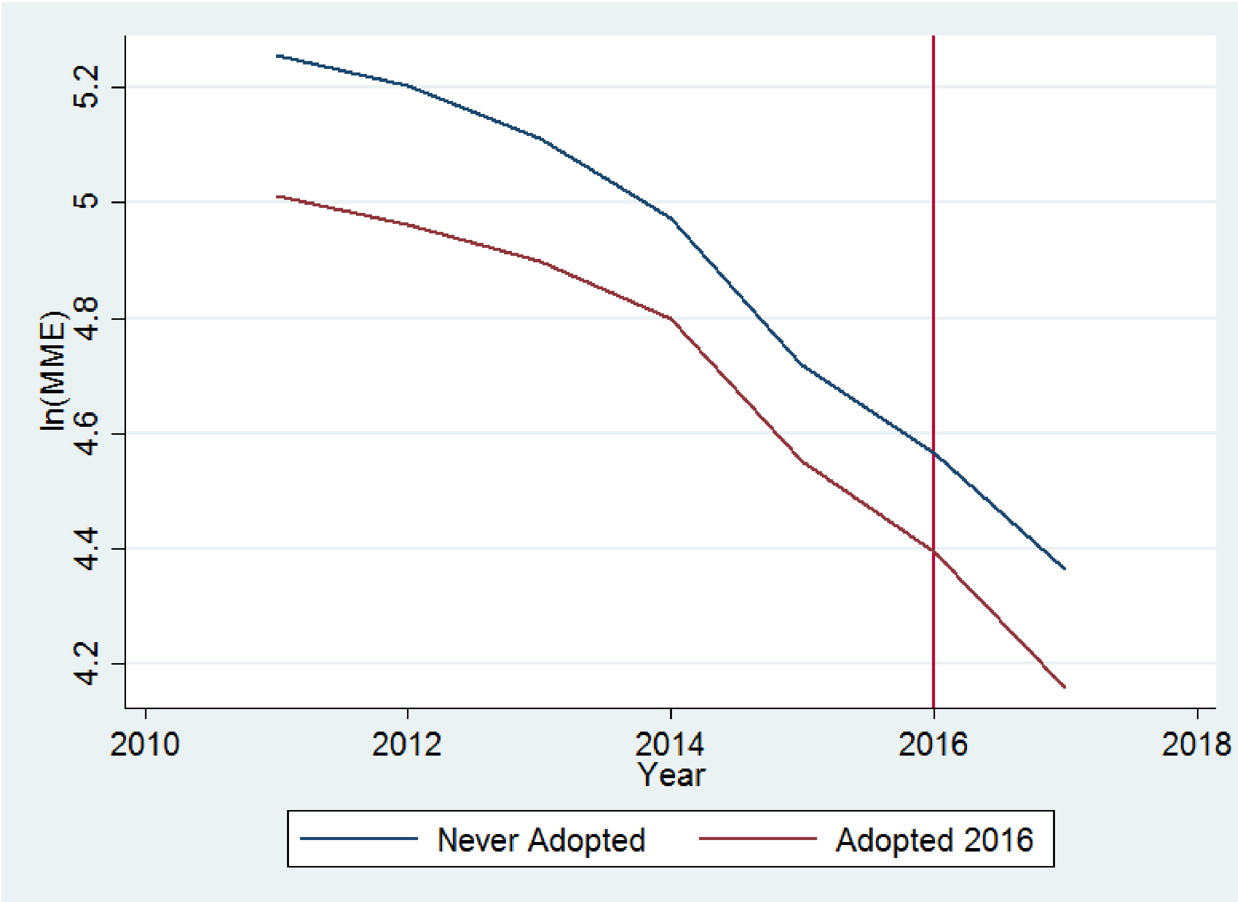


Table A1: Summary Statistics by Specialty

Panel A: All Providers and Providers Not Subject to Any Cannabis Access Law

	All Providers				No Cannabis Access Law			
Specialty	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids
Advanced Practice Midwife	547	79	11	62	633	97	12	61
Allergy & Immunology	466	195	4	50	537	213	5	56
Anesthesiologist Assistant	254	122	6	27	340	173	8	28
Anesthesiology	12,285	4,373	33	34	14,812	5,470	40	37
Clinical Nurse Specialist	2,793	815	17	45	2,405	848	17	46
Clinical Pharmacology	117	54	1	28	189	63	2	36
Colon & Rectal Surgery	7,380	915	95	92	8,763	1,064	108	94
Dentist	2,749	270	63	85	3,531	330	78	87
Dermatology	750	107	19	70	964	137	25	75
Electrodiagnostic Medicine	1,585	431	17	68	2,551	739	23	68
Emergency Medicine	7,947	956	204	92	9,645	1,189	250	93
Family Medicine	15,852	6,943	101	89	16,994	7,826	117	90
General Practice	9,668	3,900	57	65	10,992	4,469	66	68
Hospitalist	2,397	578	33	88	2,807	730	37	90
Independent Medical Examiner	1,236	333	18	34	1,801	515	25	39
Internal Medicine	7,424	3,289	44	80	8,111	3,804	51	82
Legal Medicine	172	26	3	20	282	43	6	24
Medical Genetics	726	131	3	23	893	75	3	27
Neurological Surgery	10,256	2,838	80	87	13,208	3,712	103	89
Neuromusculoskeletal Medicine & OMM	10,321	3,415	33	75	15,187	5,383	51	76
Neuromusculoskeletal Medicine, Sports Medicine	33,311	6,630	95	77	43,339	8,470	109	77
Nuclear Medicine	461	190	4	28	516	257	6	33
Nurse Anesthetist, Certified Registered	283	83	2	16	127	39	1	16
Nurse Practitioner	4,357	1,681	36	62	4,152	1,698	38	63
Obstetrics & Gynecology	3,777	488	65	86	4,695	606	79	89
Ophthalmology	598	82	13	66	711	94	15	72
Optometrist	40	10	1	16	51	12	1	20
Oral & Maxillofacial Surgery	17,298	1,574	368	95	19,806	1,745	407	96
Orthopaedic Surgery	19,854	4,173	187	92	23,681	5,061	220	93
Otolaryngology	3,973	526	69	88	4,420	595	78	90
Pain Medicine	172,593	61,794	418	93	184,158	70,894	476	94
Pathology	146	38	1	15	158	37	1	16
Pediatrics	289	86	4	53	325	97	5	58
Phlebology	2,028	432	38	77	2,481	474	50	80
Physical Medicine & Rehabilitation	47,551	16,787	133	84	54,227	20,274	160	86
Physician Assistant	7,489	2,323	82	79	6,637	2,093	80	77
Plastic Surgery	7,641	799	102	91	8,998	939	114	93

Podiatrist	3,533	721	46	84	4,271	866	55	86
Preventive Medicine	3,200	1,084	27	58	3,874	1,240	31	59
Psychiatry & Neurology	2,673	942	9	52	3,611	1,278	13	58
Radiology	577	118	5	39	683	136	6	41
Surgery	5,385	682	82	87	6,382	802	96	89
Thoracic Surgery (Cardiothoracic Vascular Surgery)	2,255	369	33	80	2,838	450	42	83
Transplant Surgery	1,414	239	23	85	1,566	272	25	87
Urology	5,592	675	93	88	6,826	810	109	89

Panel B: Providers Subject to Cannabis Access Laws

	Medical Cannabis Law				Recreational Cannabis Law			
Specialty	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids	Mean MME	Mean TDS	Mean Op Pts	Pct Any Opioids
Advanced Practice Midwife	439	62	9	62	541	72	11	66
Allergy & Immunology	336	183	4	45	396	154	3	35
Anesthesiologist Assistant	55	10	2	23	8	1	0	19
Anesthesiology	10,324	3,762	29	30	7,622	2,516	19	25
Clinical Nurse Specialist	2,906	752	17	45	5,504	1,092	15	42
Clinical Pharmacology	58	36	1	19	26	36	0	13
Colon & Rectal Surgery	5,538	717	79	91	6,579	791	85	88
Dentist	2,162	223	54	81	2,115	215	50	82
Dermatology	551	80	13	64	590	69	15	62
Electrodiagnostic Medicine	421	142	9	68	521	23	10	58
Emergency Medicine	6,038	735	158	91	5,457	588	142	90
Family Medicine	14,595	6,320	85	87	12,612	5,115	72	87
General Practice	8,662	3,465	48	61	5,992	2,493	38	60
Hospitalist	1,911	413	30	87	1,914	366	25	86
Independent Medical Examiner	420	52	8	25	406	99	8	19
Internal Medicine	6,693	2,882	38	77	5,962	2,464	32	73
Legal Medicine	3	0	0	8	4	4	0	6
Medical Genetics	1,078	363	5	19	169	23	2	19
Neurological Surgery	6,579	1,977	59	85	6,684	1,375	44	79
Neuromusculoskeletal Medicine & OMM	7,549	2,865	28	73	6,245	2,271	22	69
Neuromusculoskeletal Medicine, Sports Medicine	32,220	5,793	92	77	10,574	3,225	59	70
Nuclear Medicine	429	131	3	24	589	247	4	22
Nurse Anesthetist, Certified Registered	607	177	2	16	497	214	2	16
Nurse Practitioner	4,390	1,615	31	59	5,148	1,910	36	64
Obstetrics & Gynecology	2,578	342	47	83	3,022	367	51	81
Ophthalmology	393	54	9	60	640	83	11	59

Optometrist	27	7	0	11	15	3	0	10
Oral & Maxillofacial Surgery	15,740	1,516	366	94	14,539	1,279	311	94
Orthopaedic Surgery	15,492	3,351	163	91	12,825	2,285	128	89
Otolaryngology	3,569	487	63	87	3,546	408	61	84
Pain Medicine	184,093	57,663	395	93	106,525	34,264	235	92
Pathology	141	37	1	12	174	73	1	10
Pediatrics	267	81	3	46	180	55	3	44
Phlebology	1,192	310	22	74	306	77	9	57
Physical Medicine & Rehabilitation	42,176	14,314	113	83	34,913	11,232	91	81
Physician Assistant	6,821	2,146	77	77	9,630	3,099	93	84
Plastic Surgery	6,207	668	94	90	6,841	643	91	88
Podiatrist	2,539	545	35	80	3,825	684	45	84
Preventive Medicine	2,535	863	21	55	2,319	1,083	23	55
Psychiatry & Neurology	2,249	816	8	48	1,059	398	4	39
Radiology	484	110	4	35	428	84	4	35
Surgery	4,149	570	68	84	4,355	497	68	84
Thoracic Surgery (Cardiothoracic Vascular Surgery)	1,713	316	25	77	1,029	170	17	71
Transplant Surgery	1,275	201	21	84	998	149	17	79
Urology	4,279	546	78	86	4,071	458	71	83

Table A2: MCL Parallel Trends Tests

Model	(1) Coefficient on Parallel Trend	(2) Standard Error	(3) T-Test Statistic	(4) P Value
ln(MME)	0.004	0.020	0.227	0.822
ln(TDS)	-0.008	0.018	-0.427	0.672
ln(op pts)	-0.001	0.010	-0.023	0.982
I(any opioids)	-0.002	0.002	-0.826	0.415

Notes: Each reported coefficient and associated statistics come from an interaction between the time trend and an indicator variable for whether the state will adopt an MCL in a regression with the variable on the left as the dependent variable.

Table A3: RCL Parallel Trends Tests

Model	(1) Coefficient on Parallel Trend	(2) Standard Error	(3) T-Test Statistic	(4) P Value
ln(MME)	-0.025	0.026	-0.976	0.338
ln(TDS)	-0.018	0.021	-0.884	0.384
ln(op pts)	-0.014	0.015	-0.973	0.339
I(any opioids)	-0.001	0.002	-0.125	0.901

Notes: Each reported coefficient and associated statistics come from an interaction between the time trend and an indicator variable for whether the state will adopt an RCL in a regression with the variable on the left as the dependent variable.