Journal of Health Economics 69 (2020) 102273

Contents lists available at ScienceDirect

Journal of Health Economics

journal homepage: www.elsevier.com/locate/econbase

The impact of cannabis access laws on opioid prescribing

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ARTICLE INFO

Article history:
Received 5 October 2018
Received in revised form 17 July 2019
Accepted 7 December 2019
Available online 14 December 2019

JEL classification:
I180
K19

Keywords:
Cannabis
Marijuana
Opioids

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 1.5 billion individual opioid prescriptions between 2011 and 2018, 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 11.8 and 4.2 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, physician specialties, and payers.

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

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https://doi.org/10.1016/j.jhealeco.2019.102273
0167-6296/

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 1.5 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 and by the payer responsible for patients' prescriptions.

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 11.8 and 4.2 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. RCLs and MCLs reduce the MMEs prescribed by the five largest physician specialties (in terms of practitioners) by 10.6 percent and 2 percent, respectively. The five specialties that have the highest prescribing rates, as measured by MMEs, reduce their opioid use by 28.3 percent when an RCL is passed and 6.9 percent when an MCL is passed. Similarly, the impact of RCLs and MCLs differs by the patient's payer. RCLs and MCLs reduce opioid prescriptions to those covered by commercial insurance, Medicare, and government assistance programs. However, the results for the effect of RCLs and MCLs on opioid prescriptions to Medicaid and cash-paying patients are more mixed.

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 information on 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. Prior work has found mixed evidence on the effectiveness of these programs. For example, (Patrick et al., 2016) find some evidence that PDMPs can reduce opioid-related overdoses, though their results are sensitive to which states are included in the analysis and how PDMP laws are specified. On the other hand, results reported by (Brady et al., 2014) suggest that PDMPs do not reduce opioid use. Exploring this conflict in the evidence, Buchmueller and Carey (2018) conclude that only PDMPs requiring providers to access them effectively reduce problematic opioid use (such as the number of patients receiving opioids from five or more providers or filling opioid prescriptions at five or more pharmacies). They find no statistically significant evidence that PDMPs which do not require providers to access them reduce questionable opioid use patterns.

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 3000 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. Liang et al. (2018) focus on the Medicaid population and reach somewhat different conclusions. They find that MCLs reduce the use of Schedule III opioids but not the use of Schedule II opioids. They also find that medical cannabis dispensaries were not associated with a reduction in opioid use among Medicaid beneficiaries.

Similarly 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, 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 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, 11 states and the District of Columbia (DC) have passed RCLs, and 33 states and DC have passed MCLs. Of these laws, 11 RCLs and 17 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]

Prescription opioid data

Information on opioid prescriptions comes from Symphony Health's IDV® (Integrated Dataverse) dataset. This

[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.

[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	
Louisiana	2018	MCL	La. Stat. Ann. § 40:1046	
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. 94 G, § 7	MCL (2012)
Michigan	2018	RCL	Mich. Comp. Laws Ann. § 333.27955	MCL (2008)
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	
Oklahoma	2018	MCL	Okla. Stat. Ann. tit. 63, § 420	
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	
Utah	2018	MCL	Utah Code Ann. § 26-61a-101	
Vermont	2018	RCL	2018 Vermont Laws No. 86 (H. 511)	MCL(2004)
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	

Notes: Each year denotes the first year the relevant statute was enacted. Legal citations are to state codes whenever possible. All states that currently have an RCL in place previously enacted an MCL, and the dates of those previously enacted MCLs are provided for each RCL.

dataset includes information on individual prescriptions filled by patients at outpatient pharmacies between 2011 and 2018. 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 2018. Importantly, the dataset includes prescriptions regardless of payer, including prescriptions paid for in cash. In total, approximately 1.5 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, (4) the percentage of a provider's patients receiving any opioids, and (5) 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. 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.[3]

Throughout the analysis, we exclude all drugs containing buprenorphine. Buprenorphine does, technically, have an MME conversion factor. However, the PDMPTTAC

[3] Matching by NDCs is typically quite difficult. However, both the IDV® and PDMPTTAC datasets are well organized and well cleaned. Accordingly, we faced little difficulty in matching by NDCs, and we appreciate the work of the dataset creators in facilitating this matching.

dataset codes the conversion factor for any drug containing buprenorphine as zero because buprenorphine is used in the treatment of opioid addiction. We follow this logic and exclude all buprenorphine drugs from all parts of our analysis.[4]

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. [5]

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 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. Fourth, we calculate the proportion of a provider's patients that receive opioids and apply a logarithmic transformation. 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 four 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 2018. 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,[6] 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 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 Appendix B, we present results at the individual specialty level.

In addition to disaggregating by provider specialty, we also examine the effects of RCLs and MCLs across different payers. To do so, we examine all prescriptions written by a provider that were covered by one of five different payers: commercial insurance, Medicare, Medicaid, other government assistance, and cash (i.e., self-pay).

Summary statistics

Fig. 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 nearly 15 kg of morphine each year, which is more than any other large specialty. Though not included in Fig. 1, pain medicine specialists prescribe the most MMEs on average among all specialties, prescribing the equivalent of over 161 kg of morphine each year. Similar information is available for all other specialties in Appendix A.

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 6,146, while the average annual total days' supply of opioids and

[4] It is necessary to drop all buprenorphine observations because setting the MME conversion factor to zero will only effectively exclude buprenorphine from our MME analysis.

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

[6] 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.

Table 2
Summary statistics.

Panel A: All Providers and providers not subject to any cannabis access law.

Group	All Providers					No Cannabis Access Law				
	Mean MME	Mean Total Days' Supply	Mean Number of Opioid Patients	Mean Pct of Patients Receiving Opioids	Pct Any Opioids	Mean MME	Mean Total Days' Supply	Mean Number of Opioid Patients	Mean Pct of Patients Receiving Opioids	Pct Any Opioids
All Providers	6,146	2110	55	15	70	7,077	2,491	66	16	73
Largest Special-ties	7,245	2,975	58	9	74	8,432	3,599	72	10	78
Highest-Prescribing Special-ties	33,595	10,269	185	48	89	39,804	12,605	224	51	91

Panel B: Providers subject to cannabis access laws.

Group	Medical Cannabis Access Law					Recreational Cannabis Access Law				
	Mean MME	Mean Total Days' Supply	Mean Number of Opioid Patients	Mean Pct of Patients Receiving Opioids	Pct Any Opioids	Mean MME	Mean Total Days' Supply	Mean Number of Opioid Patients	Mean Pct of Patients Receiving Opioids	Pct Any Opioids
All Providers	5,062	1,690	44	12	66	4,680	1,585	42	14	67
Largest Special-ties	5,649	2,217	42	8	69	5,288	2,119	39	8	67
Highest-Prescribing Special-ties	29,149	8,711	156	42	87	20,062	5,680	121	46	86

Notes: Each column reports the mean of the opioid outcome measure listed above for the group listed to the left. Each set of columns represents a different cannabis legal regime, with the first set representing means across all legal regimes. All providers includes all specialties that we examine. The largest specialties are the five physician specialties for which we observe the most provider-years and include: emergency medicine, family medicine, internal medicine, pediatrics, and psychology and neurology. The highest-prescribing specialties are the five specialties with the highest opioid prescribing rates (as measured by mean total annual MMEs) and include: oral and maxillofacial surgery, orthopaedic surgery, pain medicine, physical medicine and rehabilitation, and sports medicine.

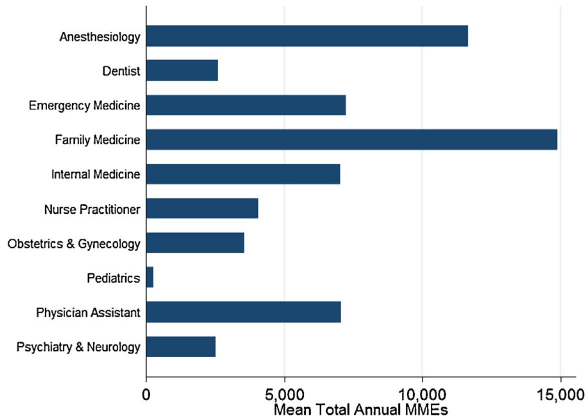

Fig. 1. Mean Total Annual MMEs Prescribed by the Ten Largest Specialties.
Notes: Each bar represents the mean total annual MMEs across all providers for the specialty listed to the left.

unique opioid patients are 2110 and 55, respectively. On average, 15 percent of a provider's patients receive at least one opioid prescription, and 70 percent of providers prescribe at least one opioid in a year.

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 total days' supply, opioid patients, and whether a provider prescribes any opioids. However, providers in states with RCLs prescribe opioids to a higher percentage of patients than providers in states with MCLs. Similar patterns persist within the five largest specialties and the five specialties with the highest mean annual MMEs. In Appendix A, 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.[7] As noted above in Table 1, every state that has enacted an RCL had previously enacted an MCL, and this affects the interpretation of the coefficients on the RCL and MCL variables. The coefficient on the RCL variable does not represent the effect of an RCL relative to no cannabis access law. Instead, it represents the additional impact of an RCL over the impact of an MCL. The full marginal effect of an RCL over no cannabis access law is captured by the sum of the RCL and MCL coefficients.[8] This interpretation stems from both the nature of the variables and from the nature of cannabis access laws themselves. First, because the RCL variable can only take the value one when the MCL variable also equals one, the coefficient on the RCL variable represents the impact of an RCL conditional on an MCL already being in place. Thus, the marginal effect of RCLs relative to no cannabis access law is the sum of the two variables. Second, if a state without an MCL were to enact an RCL, then patients with medical needs could access cannabis, implying that moving from no cannabis access law to an RCL would have the effect of both an MCL and an RCL.[9] Accordingly, the full marginal effect of an RCL relative to no cannabis access law would be both the marginal effect of an MCL and an RCL (conditional on an MCL being in place).

In our primary specifications, the vector X_{st} is empty; however, in a series of robustness checks, we add various control variables. These variables include an indicator for whether a state had expanded Medicaid, whether a state had enacted legislation regulating pain clinics, and whether a state had enacted a PDMP that required providers to access a database of prescriptions when prescribing. Medicaid expansion may improve the ability of individuals to pay for opioids and thereby induce an increase in opioid prescriptions. Pain clinic legislation may facilitate or inhibit the operation of pain clinics, which may affect individuals' access to opioids. Buchmueller and Carey (2018) find consistent evidence that "must-access" PDMPs, i.e., PDMPs that require providers to access the monitoring program/database reduce problematic opioid use.[10] Following Bradford et al. (2018); Buchmueller and Carey (2018) and Patrick et al. (2016), we include controls for all these different legal changes that may impact opioid prescriptions in a series of robustness checks.[11]

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 time-invariant characteristics of providers and their

[7] 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.

[8] Obtaining the marginal effects of and RCL and MCL requires additional transformation in our log-linear models.

[9] Because we do not observe any changes from no cannabis access law to an RCL, we cannot determine this with certainty.

[10] When collecting information on both must-access PDMPs and pain clinic legislation, we follow Buchmueller and Carey (2018) and rely on the information provided by the Prescription Drug Abuse Policy System (pdaps.org).

[11] As with prior work, our information on must-access PDMPs and pain clinic legislation comes primarily from pdaps.org (Buchmueller and Carey, 2018).

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 because provider fixed effects better control for confounding factors than traditional state- or county-level variables. For example, these fixed effects control for the nature of the provider's training (e.g., medical school), personal predilections with respect to opioids, and other time-invariant factors. However, these fixed effects do not control for time-varying factors, and because other state policies may impact opioid prescriptions, we include indicator variables (which vary over time) for these policies in a series of robustness checks.

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 10,884,224 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 (2011–2018). Thus, we include providers who prescribed no opioids in some years in our analysis, and approximately 30 percent 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.

Payer-specific and 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 2000 provider-years are included in the appendix. In addition to the specialty-specific models that include all prescriptions written by members of different specialties, Appendix B also includes specialty-specific models that include only prescriptions covered by a given payer. These specialty-payer models provide more granular information on the impact of RCLs and MCLs than has previously been available.

Results

Results for all providers and payers

Table 3 reports the results of our primary analysis. Here and in all other tables and figures, we report the individual coefficients on the RCL and MCL variables. In the discussion of the effects of these variables, however, we refer to the marginal effects of both MCLs and RCLs relative to no cannabis access law. As noted above, calculating the marginal effect of RCLs relative to no cannabis access law requires adding the RCL and MCL coefficients. Additionally, because we estimate log-linear models, each coefficient (or sum of coefficients) can be interpreted as the percent change in the dependent variable that results from passing the relevant law.[12]

As reported in column (1), MCLs reduce MMEs by approximately 4.2 percent. RCLs reduce MMEs by approximately 11.8 percent. Given baseline mean annual MMEs of 7077 in states without any cannabis access law, these effects represent decreases of 835 and 297 MMEs, respectively. In other words, MCLs reduce opioid prescriptions by the equivalent of nearly 300 mg of morphine, and RCLs reduce opioid use by the equivalent of well over half a kilogram of morphine.

In column (2), RCLs and MCLs reduce the total days' supply of opioids by approximately 12.4 and 6.1 percent, respectively. These decreases account for a total of 294 and 105 fewer days of opioids supplied to patients by each provider. Next, RCLs and MCLs reduce the number of patients receiving opioids by approximately 6.5 and 2.9 percent, respectively. As reported in column (4), RCLs reduce the percentage of a provider's patients receiving opioids by approximately 0.3 percent. However, MCLs increase this percentage by approximately 0.1 percent. In column (5), RCLs reduce the probability that a provider prescribes opioids in a given year by 2.1 percentage points, while MCLs reduce this probability by 1.1 percentage points, from a baseline of 73 percent.

Collectively, the results in Table 3 demonstrate that both RCLs and MCLs reduce the quantity of opioids prescribed. Across columns (1), (2), and (3), RCLs have comparatively larger effects than MCLs. Similarly, the results in columns (4) and (5) imply that RCLs are comparatively more effective at inducing providers to discontinue opioid prescriptions. RCLs have a larger negative effect of on both the probability of a provider prescribing opioids at all and on the percentage of a provider's patients receiving any opioids. While we find that MCLs have a small positive effect on the percentage of a provider's patients receiving opioids, the results in Table 3 are broadly consistent with

[12] Because the dependent variable is in logarithmic form, the marginal effect of an indicator variable with coefficient β is approximately $\left(\left(\exp\left(\beta\right)-1\right)(100)\right)$ percent (Halvorsen and Palmquist, 1980).

Table 3
Regression results for the effect of cannabis access laws on opioid prescribing.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.083**	−0.069**	−0.038**	−0.004**	−0.010**
	(0.004)	(0.003)	(0.002)	(1.706e - 4)	(0.001)
Medical (MCL)	−0.043**	−0.063**	−0.029**	0.001**	−0.011**
	(0.003)	(0.003)	(0.002)	(1.358e - 4)	(4.815e - 4)
Observations	10,884,224	10,884,224	10,884,224	10,884,224	10,884,224
R-squared	0.806	0.822	0.848	0.799	0.634

Notes: The dependent variable in each model is reported at the top of each column. All specifications include 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.

RCLs and MCLs having statistically significant and negative effects on opioid prescribing.

Results by specialty

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 (by number of provider-years) 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 statistical significance and follow the same general pattern of effects reported in Table 3. For both groups of specialists and all measures of opioid use, RCLs reduce opioid prescribing to a greater extent than MCLs.

For example, RCLs and MCLs reduce the MMEs prescribed by 10.6 percent and 2 percent, respectively, among the largest five specialties. Among the highest-prescribing specialties, the magnitudes of these effects increase to 28.3 percent and 6.9 percent. And these effects highlight another important pattern. While the largest and highest-prescribing specialties are generally 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 are most affected by the greater availability of cannabis that comes with RCLs and MCLs. Indeed, unlike all providers and the largest specialties, both RCLs and MCLs reduce the percentage of patients receiving opioids from the highest-prescribing providers. While these results are not particularly surprising, they do 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.

Fig. 2 reports results for the individual specialties that are included in the two groups in Table 4 (results for other individual specialties are provided in the appendix). These specialty-specific results illustrate that, while RCLs and MCLs generally reduce all measures of opioid prescriptions,

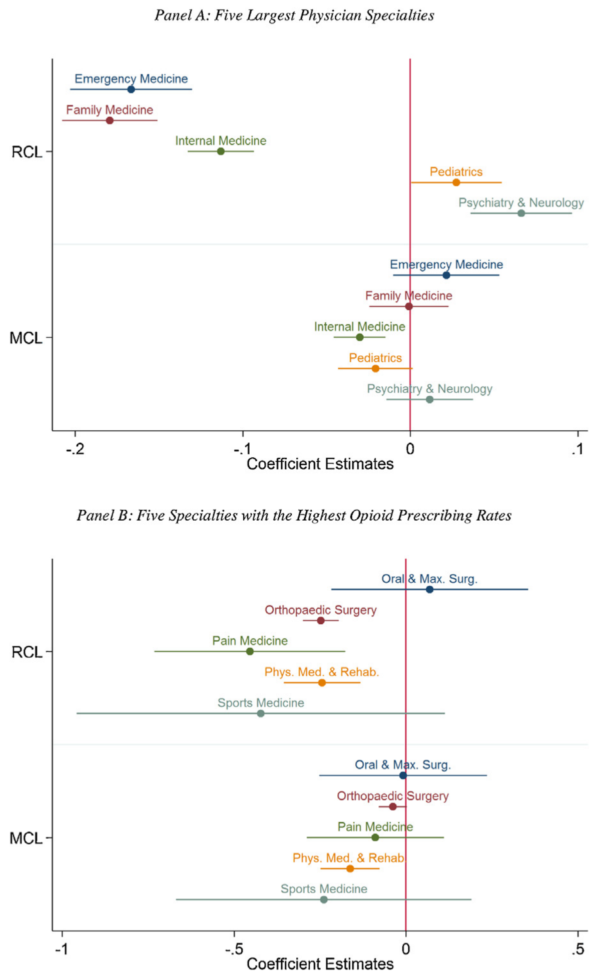

Fig. 2. Effect of Cannabis Access Laws on MMEs for Selected Specialties. *Panel A: Five Largest Physician Specialties. Panel B: Five Specialties with the Highest Opioid Prescribing Rates.* Notes: Individual points represent the marginal effects of the cannabis access laws listed to the left. The RCL and MCL coefficients are estimated in a series of regressions that only include the specialty listed above each point. Bars represent 99% confidence intervals. The appendix provides full results from the individual models reported in this figure.

Table 4
Regression results for the effect of cannabis access laws on opioid prescribing for selected specialties.

Panel A: Five largest physician specialties.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.092**	−0.069**	−0.034**	−0.005**	−0.012**
	(0.006)	(0.005)	(0.003)	(1.954e - 4)	(0.001)
Medical (MCL)	−0.020**	−0.039**	−0.014**	0.001**	−0.009**
	(0.005)	(0.004)	(0.002)	(1.556e - 4)	(0.001)
Observations	4,348,616	4,348,616	4,348,616	4,348,616	4,348,616
R-squared	0.803	0.827	0.857	0.752	0.588

Panel B: Five specialties with the highest opioid prescribing rates.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.262**	−0.253**	−0.142**	−0.011**	−0.017**
	(0.024)	(0.022)	(0.014)	(0.001)	(0.003)
Medical (MCL)	−0.071**	−0.111**	−0.072**	−0.006**	−0.008**
	(0.019)	(0.017)	(0.011)	(0.001)	(0.002)
Observations	341,004	341,004	341,004	341,004	341,004
R-squared	0.774	0.781	0.800	0.748	0.584

Notes: The dependent variable in each model is reported at the top of each column. All specifications include a series of individual provider fixed effects and year fixed effects. Standard errors clustered at the provider and state levels are reported in parentheses. The largest specialties are the five physician specialties for which we observe the most provider-years and include: emergency medicine, family medicine, internal medicine, pediatrics, and psychology and neurology. The highest-prescribing specialties are the five specialties with the highest opioid prescribing rates (as measured by mean total annual MMEs) and include: oral and maxillofacial surgery, orthopaedic surgery, pain medicine, physical medicine and rehabilitation, and sports medicine.
*Significant at the $p < 0.01$ level.
** Significant at the $p < 0.001$ level.

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. MCLs only have a statistically significant effect on internists.

The results in Panel B of Fig. 2 for the highest-prescribing specialties also show more frequent statistically significant negative effects for RCLs than for MCLs. RCLs reduce MMEs for orthopaedics, pain medicine, physical medicine and rehabilitation, and sports medicine.[13] The only top-five prescribing specialty that exhibits a statistically significant decline with respect to MCLs is physical medicine and rehabilitation.

The results in Fig. 2 offer insight into whether RCLs and MCLs have an impact on specialties that generally prescribe opioids within the guidelines set by the CDC and those that historically have prescribed more opioids (Dowell et al., 2016). While the guidelines have not existed long enough to allow a thorough investigation into whether every specialty prescribes in concordance with them, recent work has provided some evidence that certain specialties are more guideline-concordant than others. For example, Jeffery et al. (2018) found that opioid prescriptions written in the emergency department (and likely by emergency physicians) were more likely to accord with CDC guidelines. On the other hand, Nataraj et al. (2019) found that family medicine, internal medicine, and orthopaedics prescribed the highest volume of opioids.

Among these four specialties, Fig. 2 reveals little difference in the impact of RCLs and MCLs. Though prior work has found that emergency medicine is more likely than other specialties to prescribe in concordance with the CDC guidelines (Jeffery et al., 2018), RCLs and MCLs have a similar effect on emergency medicine as family medicine, internal medicine, and orthopaedics. RCLs significantly reduce opioid prescriptions by all four, and MCLs have no statistically significant effect. While it is important to note that our measures of opioid prescriptions are not designed or calibrated to examine concordance with the CDC guidelines, the evidence that RCLs and MCLs have similar effects across specialties with different propensities to prescribe in alignment with those guidelines provides policymakers with important information as they determine which policies to pursue and how those policies may interact (or not) with one another.

Results by payer

In general, the evidence demonstrates that cannabis access laws reduce opioid prescriptions across a variety of measures—with the lone exception that MCLs tend to

[13] The effect of RCLs on MMEs prescribed by sports medicine as calculated by the sum of the coefficients on the RCL and MCL variables is statistically significant, though the coefficient on the RCL variable alone is not statistically significant.

Table 5
Regression results for the effect of cannabis access laws on opioid prescribing by payer.

Panel A: Commercial insurance.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.130**	−0.118**	−0.069**	−0.005**	−0.013**
	(0.004)	(0.003)	(0.002)	(1.813e - 4)	(0.001)
Medical (MCL)	−0.045**	−0.059**	−0.026**	2.268e - 4	−0.011**
	(0.003)	(0.002)	(0.001)	(1.427e - 4)	(4.819e - 4)
Observations	10,002,488	10,002,488	10,002,488	10,002,488	10,002,488
R-squared	0.821	0.835	0.855	0.804	0.681

Panel B: Medicare.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.101**	−0.086**	−0.060**	−0.004**	−0.010**
	(0.004)	(0.003)	(0.002)	(2.257e - 4)	(0.001)
Medical (MCL)	−0.036**	−0.055**	−0.033**	0.001**	−0.010**
	(0.003)	(0.003)	(0.001)	(1.77e - 4)	(4.848e - 4)
Observations	7,640,489	7,640,489	7,640,489	7,640,489	7,640,489
R-squared	0.830	0.839	0.846	0.785	0.745

Panel C: Medicaid.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	0.142**	0.151**	0.127**	−0.008**	−4.12e - 5
	(0.004)	(0.003)	(0.002)	(2.933e - 4)	(6.348e - 4)
Medical (MCL)	−0.054**	−0.068**	−0.027**	−0.004**	−0.009**
	(0.003)	(0.003)	(0.002)	(2.491e - 4)	(0.001)
Observations	4,814,944	4,814,944	4,814,944	4,814,944	4,814,944
R-squared	0.829	0.814	0.787	0.802	0.830

Panel D: Other government assistance.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.143**	−0.140**	−0.091**	−0.009**	−0.009**
	(0.004)	(0.003)	(0.002)	(3.258e - 4)	(0.001)
Medical (MCL)	−0.078**	−0.108**	−0.071**	0.004**	−0.003**
	(0.003)	(0.003)	(0.001)	(2.605e - 4)	(4.9e - 4)
Observations	4,962,583	4,962,583	4,962,583	4,962,583	4,962,583
R-squared	0.855	0.837	0.815	0.793	0.875

Panel E: Cash-paying patients.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	0.023**	0.028**	0.019**	0.004**	−0.008**
	(0.003)	(0.003)	(0.001)	(2.326e - 4)	(0.001)
Medical (MCL)	0.005	−0.016**	0.002	0.003**	−0.009**
	(0.003)	(0.002)	(0.001)	(1.813e - 4)	(4.837e - 4)
Observations	6,855,351	6,855,351	6,855,351	6,855,351	6,855,351
R-squared	0.843	0.829	0.834	0.780	0.812

Notes: The dependent variable in each model is reported at the top of each column. All specifications include a series of individual provider fixed effects and year fixed effects. Standard errors clustered at the provider and state levels are reported in parentheses. The models in each panel include only prescriptions written that were covered by the payer listed above the panel.
*Significant at the p < 0.01 level.
** Significant at the p < 0.001 level.

increase the percentage of providers' patients receiving opioids. To further explore these results, we disaggregate the results by payer. Each prescription in our dataset is associated with one of several payers: commercial,[14] Medicare, Medicaid, other government assistance, and cash.[15] Table 5 reports a series of results from regression models that follow the general specification above but are limited to only prescriptions paid for by a particular payer. To be included in these models, a provider must have written at least one prescription (not necessarily an opioid) to a patient covered by the relevant payer in two separate years between 2011 and 2018.

The models in Panel A of Table 5 are limited to prescriptions paid for by commercial insurance. RCLs and MCLs have stronger effects among the commercially insured than across all individuals. RCLs and MCLs reduce MMEs by 16.1 and 4.4 percent, respectively. Similarly, the effects of RCLs and MCLs across other measures of opioid prescriptions are stronger for the commercially insured than among the general population. The same is generally true for the Medicare population as reported in Panel B. RCLs and MCLs reduce opioid use to a greater extent among Medicare beneficiaries than the general population, but these effects are not as strong as they are among the commercially insured population.

Panel C reports results for Medicaid beneficiaries. For MMEs, total days' supply, and number of unique patients receiving opioids, RCLs have a positive impact on opioid use, but they have a negative impact on the percentage of patients receiving opioids.[16] On the other hand, MCLs have a consistently negative and statistically significant effect on opioid use. The negative effect of MCLs across various measures of opioid prescriptions is consistent with the results of Bradford and Bradford (2017) and Wen and Hockenberry (2018), but the positive effect of RCLs on Medicaid beneficiaries runs counter to the results of Wen and Hockenberry (2018) in addition to the general population results reported above. This difference in effect among the Medicaid population may stem from different prescription drug consumption patterns by Medicaid beneficiaries. Additionally, it is worth noting that Wen and Hockenberry (2018) only find statistically significant and negative effects of RCLs for a subset of opioid prescriptions, only have data that covers only four state-law changes, and are limited to examining state-level prescribing rates.[17]

Panel D reports the results of models limited to prescriptions covered by government assistance. The effects of RCLs and MCLs among this population are similar to the general population and those covered by commercial insurance and Medicare. On the other hand, results for prescriptions paid for in cash are more similar to the Medicaid results in Panel E. While these results are not consistent with the results for the population at large, cash-paying patients may behave differently from those covered by private and government payers.[18]

In general, the results reported in Table 5 demonstrate that RCLs and MCLs have heterogenous effects on opioid prescriptions across payers. Across all payers, MCLs generally reduce opioid prescriptions. However, RCLs reduce opioid prescriptions for the commercially insured, Medicare, and government assistance populations, and increase prescriptions for the Medicaid and cash paying populations. As policymakers continue to grapple with laws around cannabis and prescription opioids, the results reported in Table 5 can provide important context and offer insight into how different laws will affect prescriptions written for different populations.

To provide further context across both payers and specialties, we re-estimate all panels of Table 5 for all specialties. In the interest of succinctness, these results are reported in Appendix B.

Discussion

In general, we find 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. In reducing opioid prescriptions, however, RCLs and MCLs are not created equally. Across the general population, RCLs consistently reduce opioid prescriptions to a greater extent than MCLs. This pattern of effects is consistent with RCLs better enabling patients to access cannabis and substitute it in the treatment of pain (or other conditions). And, by design, RCLs allow greater access to cannabis because patients need not satisfy any medical requirements or obtain the recommendation of a provider.

The pattern of RCLs having a greater impact on opioid prescriptions than MCLs persists across the commercially insured, Medicare, and government assistance populations. However, for Medicaid and cash-paying patients, RCLs increase some measures of opioid prescriptions, while

[14] The data do not include which specific commercial insurance plan paid for a given prescription.

[15] The fact that a particular payer covered some of the prescription cost does not imply that the patient had no co-pay or co-insurance, only that the relevant payer was the primary payer associated with a given observation.

[16] Across the first three columns, adding the RCL and MCL variables results in a positive total effect that is statistically significantly different from zero.

[17] We attempted to replicate the results of Wen and Hockenberry (2018) to the greatest extent practicable in the context of our analysis. Unlike our analysis, which focuses on five separate measures of opioid prescriptions, Wen and Hockenberry (2018) focus on the number of opioid prescriptions for pain management among Medicaid beneficiaries. Estimating the effect of RCLs on the number of prescriptions written for opioids at the individual provider level yields results similar to those reported in the first three columns of Panel C of Table 5. While we have a wealth of information on prescriptions filled by Medicaid beneficiaries, we lack other information that may be present in Medicaid-specific datasets. Future work may explore the discrepancy between our Medicaid results and those of Wen and Hockenberry (2018).

[18] We are not permitted to investigate effects at the patient level. It may be the case that some cash-paying patients were unable to obtain private or government insurance or that cash-paying patients are insured but for some reason have decided to pay for a given prescription out of pocket. Future work may investigate why RCLs and MCLs have different effects on cash-paying patients relative to other patient populations.

MCLs have a more consistent, negative effect on opioid prescriptions. This difference in effect may stem from the greater ability of commercially insured and Medicare patients, who may have greater resources at their disposal, to access recreational cannabis than Medicaid or cash-paying (i.e., self-paying) patients.[19] It may also stem from different drug-consumption behaviors for both cannabis and opioids. While our data do not allow us to test either of these mechanisms directly, future work with patient-specific information or information on cannabis consumption combined with opioid consumption may investigate why RCLs impact Medicaid and cash-paying patients differently.

Beyond highlighting areas for future investigation, the differences in the effects of RCLs and MCLs by payer have important implications for policymakers. As state legislators consider new policies to address the opioid crisis, the results here offer insight into how policies may differ in their impact on different populations. For example, while RCLs may have a larger effect across all patients, MCLs have a more consistent (but smaller) effect across all sub-populations. This information may prove useful as policymakers continue to evaluate new laws to reduce opioid use.

In addition to varying across payers, RCLs and MCLs also vary in their effect on different types of providers and physician specialties. 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. We further test whether cannabis access laws facilitate the substitution of cannabis for pain medications below.

Robustness and extensions

Robustness of the primary results

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 6 reports results that vary the definition of MCLs. Panel A 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). Panel B 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 Panels A and B, while not identical to, are consistent with the results from our primary models.[20]

Next, prior work has shown that must-access PDMPs can impact prescription opioid use (Buchmueller and Carey, 2018; Patrick et al., 2016). To control for the roles must-access PDMPs play, the models reported in Panel C of Table 6 include an indicator variable for whether a state maintained one of these PDMPs. Relatedly, the models in Panel C include an indicator variable for whether a state had enacted legislation to regulate pain clinics. The models in Panel C 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.

To test the results of the specialty-specific, payer-specific, and specialty-payer-specific models, we re-estimated the models in Table 6 for all of these limited samples. In general, altering the specifications in the ways reported in Table 6 does not meaningfully change any of the limited-sample results. Of note is that including an indica-

[19] Government assistance may vary from state to state, but often patients qualify for this assistance when they do not qualify for Medicaid. This suggests that these patients may have greater resources with which to access recreational cannabis than Medicaid patients.

[20] Prior work has also separated MCLs that allow for home cultivation of cannabis (Ozluk, 2017). While we have no reason to doubt the effect of cultivation-specific MCLs, we are not able to test these laws with our data. Only one state enacted a law allowing cultivation during our study period that would permit us to observe opioid prescriptions before and after the change. Because the effect of cultivation-specific MCLs would not be well-identified, we do not report any cultivation-specific MCL results.

Table 6
Regression results from alternative specifications.

Panel A: Regression results with pain-specific MCLs.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.087**	−0.069**	−0.040**	−0.005**	−0.010**
	(0.004)	(0.003)	(0.002)	(1.696e - 4)	(0.001)
MCL – Pain-Specific	−0.089**	−0.098**	−0.055**	−0.001**	−0.016**
	(0.004)	(0.004)	(0.002)	(1.796e - 4)	(0.001)
Observations	10,884,224	10,884,224	10,884,224	10,884,224	10,884,224
R-squared	0.806	0.823	0.848	0.799	0.634

Panel B: Regression results with dispensary-specific MCLs.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.082**	−0.065**	−0.037**	−0.004**	−0.009**
	(0.004)	(0.003)	(0.002)	(1.705e - 4)	(0.001)
MCL – Dispensary	−0.045**	−0.061**	−0.028**	0.001**	−0.010**
	(0.003)	(0.003)	(0.002)	(1.379e - 4)	(4.788e - 4)
Observations	10,884,224	10,884,224	10,884,224	10,884,224	10,884,224
R-squared	0.806	0.822	0.848	0.799	0.634

Panel C: Regression results with additional controls.

	(1) ln(MME total)	(2) ln(total days' supply)	(3) ln(number of opioid patients)	(4) ln(pct of patients receiving opioids)	(5) I(provider prescribed any opioids)
Recreational (RCL)	−0.095**	−0.082**	−0.045**	−0.005**	−0.012**
	(0.004)	(0.003)	(0.002)	(1.703e - 4)	(0.001)
Medical (MCL)	−0.020**	−0.043**	−0.016**	0.001**	−0.009**
	(0.003)	(0.003)	(0.002)	(1.399e - 4)	(0.001)
PDMP (must access)	−0.127**	−0.125**	−0.078**	−0.002**	−0.016**
	(0.004)	(0.003)	(0.002)	(1.533e - 4)	(0.001)
Pain Clinic Legislation	0.026**	0.009	0.008	−0.002**	0.002
	(0.007)	(0.006)	(0.004)	(2.971e - 4)	(0.001)
Medicaid Expansion	0.016**	0.017**	0.007**	0.001**	0.003**
	(0.004)	(0.003)	(0.002)	(1.572e - 4)	(0.001)
Observations	10,884,224	10,884,224	10,884,224	10,884,224	10,884,224
R-squared	0.806	0.823	0.848	0.799	0.634

Notes: The dependent variable in each model is reported at the top of each column. All specifications include a series of individual provider fixed effects and year fixed effects. The specifications in Panel C include, in addition to the variables of interest, an indicator variable for whether a state had must-access prescription drug monitoring program, an indicator for whether a state had enacted pain clinic legislation, and an indicator for whether a state had expanded Medicaid under the Affordable Care Act. 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 7
Regression results for the effect of cannabis access laws on NSAID prescribing.

	(1) ln(total days' supply)	(2) ln(number of NSAID patients)	(3) ln(pct of patients receiving NSAIDs)	(4) I(provider prescribed any NSAIDs)
Recreational (RCL)	−0.028**	−0.013**	0.001	−0.004**
	(0.003)	(0.002)	(0.001)	(0.001)
Medical (MCL)	−0.016**	−0.010**	−0.001**	−0.001*
	(0.003)	(0.001)	(9.18e - 5)	(0.001)
Observations	10,884,224	10,884,224	10,884,224	10,884,224
R-squared	0.806	0.849	0.717	0.611

Notes: The dependent variable in each model is reported at the top of each column. All specifications include 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.

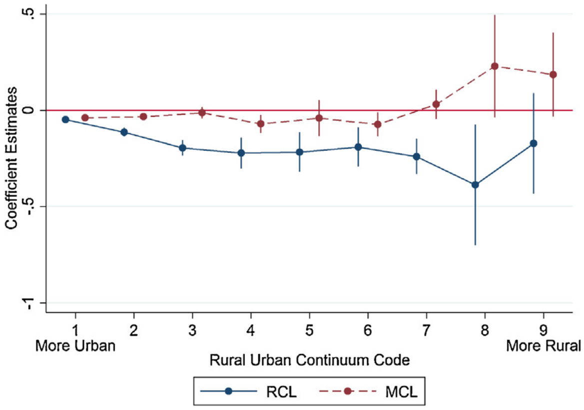

Fig. 3. Effect of Cannabis Access Laws on Morphine Milligram Equivalents in Different Rural and Metropolitan Areas. Notes: Each point represents the coefficient on the RCL or MCL indicator variable estimated in a specification limited to counties with the rural urban continuum code listed below. In total, the points represent coefficients from nine separate regression models. Each model includes, in addition to the RCL and MCL indicator variables, a series of individual provider fixed effects and year fixed effects. Standard errors are clustered at the provider and state levels, and the bars represent 99 percent confidence intervals based on these standard errors.

tor variable for Medicaid expansion does not change the positive effect of MCLs among the Medicaid population.

In addition to the robustness checks reported here, Appendix A 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.

Results by rural status

As suggested by the results of Bradford and Bradford (2018), the effect of cannabis access laws may vary by whether a provider practices in a rural or urban area. To examine this possibility, we re-estimate our primary specification—focusing on MMEs for the sake of brevity—across each of the Department of Agriculture's (USDA) nine rural-urban continuum codes. The USDA assigns each county in the United States one of these codes periodically, and we use the classification adopted by the USDA in 2013.[21] More urban areas are assigned lower codes, and codes increase for more rural counties. A full description of the USDA's rural-urban continuum codes is provided in the appendix.

Fig. 3 reports the results from a series of regression models focusing on MMEs. We estimate a separate model for each rural-urban continuum code (nine total), and each model includes both the RCL and MCL indicator variables. Each point in Fig. 3 represents the coefficient on one of these variables. RCLs reduce MMEs in all but the most rural counties. MCLs reduce the amount of MMEs prescribed in more urban counties, but they have a statistically insignificant, positive effect on MMEs in more rural counties.

Though Bradford and Bradford (2018) only separate counties into two general rural and urban categories, the pattern of effects present in Fig. 3 parallels their results. They find statistically significant, negative effects of MCLs on prescriptions for various conditions among the Medicare population in urban counties, but MCLs have no statistically significant effects in rural counties. Our results similarly suggest that MCLs have relatively stronger effects in urban counties than rural counties.

Results for other pain medications

One of the primary—though, not the only—mechanisms by which RCLs and MCLs may reduce opioid prescriptions is by allowing those suffering from pain, particularly chronic pain, to substitute cannabis for opioids in the treatment of their pain. If RCLs and MCLs facilitate prescription substitution in this way, they should similarly facilitate the substitution of cannabis for other pain medications, and prior work has found evidence suggestive of this type of substitution (Bradford and Bradford, 2017, 2016). To test whether RCLs and MCLs reduce prescriptions for pain beyond opioids, we examine a set of prescriptions for non-steroidal anti-inflammatory (NSAID) drugs.[22] Though they lack the potency (and side effects) of opioids, NSAIDs are commonly used to treat pain. If RCLs and MCLs allow patients to substitute cannabis for other pain treatments, NSAID prescriptions should decline.

Table 7 reports results from a series of regression models that examine the amount of NSAIDs prescribed between 2011 and 2018. NSAIDs lack MMEs, but other than omitting this outcome measure, the NSAID models in Table 7 are identical to the opioid models in Table 3. RCLs and, to a lesser extent, MCLs reduce the total days' supply of NSAIDs, the number of different patients to whom providers prescribe NSAIDs, and the likelihood that a provider prescribes any NSAIDs. MCLs, but not RCLs, reduce the percentage of a provider's patients receiving NSAIDs.

With the exception of the percentage of patients receiving NSAIDs/opioids, RCLs and MCLs have stronger effects on opioid use in Table 3 than they do on NSAID use in Table 7. This smaller effect is consistent with opioids treating more severe pain and cannabis being a better substitute in this context. Sufferers of pain for which NSAIDs may be appropriate may be less likely to incur the (legal and medical) risks of using cannabis than sufferers whose pain is sufficient to warrant opioids. Overall, the results in Table 7, combined with earlier results, suggest that increasing patients' ability to substitute cannabis in the treatment of pain is an important mechanism by which RCLs and MCLs reduce opioid prescriptions. These results also imply that individuals are more willing to substitute cannabis for opioids than they are other pain medications.

[21] The 2013 classification falls in the middle of our data period and is the most recent classification. To be clear, we do not have access to individual county information, and we do not observe any geographic location for providers below the state level. The data supplier included rural-urban continuum codes.

[22] A full list of all NSAIDs we consider (organized by NDCs) is provided in the appendix. This list was obtained from ncqa.org.

Limitations

While our analysis of prescription opioids relies on a dataset uniquely well-suited to the task and on an identification strategy that controls for many factors that may influence a provider's decision to prescribe opioids, it is not without limitations. First, none of our analysis is conducted at the patient level for reasons of confidentiality.[23] Accordingly, we cannot examine some outcomes that imply problematic opioid prescribing patterns, such as receiving opioids from multiple providers or receiving a prescription for more than 90 MMEs per day. Future work, however, should investigate these, and other, patient-level outcomes. An analysis of the individual data may also provide some insight into the mixed results for Medicaid and cash paying patients. Second, because we do not observe diagnosis or procedure information for individual patients, we cannot evaluate whether RCLs and MCLs reduce inappropriate opioid prescriptions based on the patient's illness or injury. Third, while we observe many state law changes, our data begin in 2011, which means we are unable to take advantage of state law changes prior to 2011 in our analysis. Collectively, these limitations prevent us from analyzing certain outcomes of interest—which future work should explore—but they do not undermine the overall conclusions drawn from our analysis.

Conclusion

The results of this study suggest that passing cannabis access laws reduces the use of prescription opioids across several different measures of opioid prescriptions. 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 cannabis access 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.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jhealeco.2019.102273.

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