Cannabis Access Laws: Effects on Sleep, Car Accidents, and Use Rates

By

Zachary S. Sturman

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Approved:
Paige Skiba, Ph.D.
Robert Mikos, J.D.
Michelle Marcus, Ph.D.
Mariana Carrera, Ph.D.

To my family.

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Chapter 1: The Effects of Cannabis Access Laws on Sleep

Abstract

This study is the first to examine the effects of cannabis access laws on sleep. Using a difference-in-difference design, I find that medical marijuana laws have no impact on sleep, while recreational marijuana laws cause people to lose an average of 38 minutes of weekly sleep. If these effects are confined to marijuana users, then these individuals lose just under 6 hours of sleep each week. This result is significant at the 1% level. Sleep loss from recreational marijuana is due to people falling asleep later at night rather than waking up earlier in the morning. It seems unlikely that marijuana users are aware of the drug's deleterious sleep effects, which suggests that current marijuana use rates are higher than they would be under full information. A back-of-the-envelope calculation suggests that these sleep reductions translate to around $200 billion in annual losses from automobile accidents, heart attacks, and worker productivity effects.

I. <u>Introduction</u>

People around the world spend more than a quarter of their time on sleep. In 1942, individuals slept an average of 8 hours per night, but that number has since fallen to an average of 6.8 hours per night (Horan, 2021). Health officials recommend at least 7 hours of sleep per night, yet only 40% of Americans get that much sleep. A meta-analysis concluded that short sleepers—those getting less than 7 hours per night of sleep—have a 12% greater mortality risk as well as heightened likelihood of other physical ailments (Cappuccio et al., 2010). This mortality risk increase is the equivalent of that caused by drinking five to six alcoholic beverages per day (Castelnuovo et al., 2006). In addition, each year, drowsy driving is responsible for over 90,000 crashes, 50,000 injuries, and 6,000 deaths in the U.S. (Centers for Disease Control and Prevention, 2017). Sleep impacts individual earnings, too. A 1-hour increase in average weekly sleep causes an estimated 1.1% increase in earnings in the short run and a 5% increase in the long run (Gibson & Shrader, 2018).

Understanding the determinants of sleep is crucial in alleviating the health and economic consequences that stem from inadequate sleep. As marijuana has been medically and/or recreationally legalized in 36 states, people increasingly use the drug for their health conditions. There is evidence that people substitute from over-the-counter sleep aids to cannabis when the latter becomes legally available (Doremus et al., 2019). Around 80% of marijuana users claim sleep drives their decision to use (Skobic et al., 2021). Although sleep is a common reason people use marijuana, the effect marijuana has on sleep remains unclear.

I employ a difference-in-difference design to provide the first causally identified analysis of the effect of marijuana legalization on sleep. Across specifications, I consistently find that medical marijuana laws ("MMLs") produce no effect on sleep outcomes, while recreational marijuana laws[1] ("RMLs") cause people to lose at least 38 minutes of sleep per week and stay up later at night. If the RML-induced sleep changes are concentrated in marijuana users, these effects reflect a loss of 50 minutes of sleep each night.

Males and those over the age of 24 see the highest increases in marijuana use following the passage of RMLs (Rotermann 2019; Weinberger et al., 2022). This is consistent with my analyses; these two groups—males and those over the age of 24—see the most pronounced reductions in sleep duration. This RML-induced reduction in sleep duration is not driven by an increase in any single time use category, such as socializing, relaxing, or leisure. Similarly, there is no evidence that these laws increase people's likelihood of engaging in activities outside the home or engaging in activities in the presence of others, either of which would point to an increased socialization story. To the contrary, willingness to pay estimates for increases in nightly sleep exceed the average monthly amount spent on marijuana, which suggests that marijuana users do not rationally account for marijuana-induced sleep losses in their buying decisions.

The results from this paper are important for medical personnel contemplating the role of cannabis as a sleep therapy, policymakers contemplating adding sleep to the list of approved qualifying conditions for medical marijuana use, and researchers interested in administering

[1] The use of the phrase "recreational marijuana law" ("RML") has been gradually superseded by "adult use law" or another similar term to reflect the fact that legal cannabis use is not always for recreational purposes. However, for consistency with the prior literature's preference for the shorthand of "MML" and "RML", I likewise still use "recreational marijuana law" and "RML" in this paper while acknowledging the drawbacks of this phraseology.

large-scale, randomized control trials aimed at better understanding the impacts of cannabis on sleep outcomes.

II. Background

The rapid decline in average sleep as well as the documented relationship between sleep and various health measures—including hypertension, poor cognitive functioning, memory problems, mood disorders, cardiovascular disease, type 2 diabetes, and various cancers—prompted the U.S. Centers for Disease Control in 2014 to declare inadequate sleep a public health epidemic (Pinholster, 2014). Economists have drawn similar conclusions about the effects of poor sleep. Recent work has found that inadequate sleep causes decreases in earnings (Shrader & Gibson, 2018), lowered performance on standardized tests (Groen & Pabilonia, 2019), poorer indicators of mental well-being (Mullins & White, 2019), increases in fatal automobile accidents (Smith, 2016), and elevated risks of obesity, diabetes, cardiovascular disease, and breast cancer (Giuntella & Mazzona, 2019).

Amid this backdrop of the well-documented relationship between insufficient sleep and various societal costs, the American Academy of Sleep Medicine has endorsed several policy levers aimed at improving sleep measures: instituting national standards for later school start times, stronger regulation of work hours, and elimination of daylight savings time (Barnes & Drake, 2015). However, legislative action aimed at improving sleep outcomes has been effectively nonexistent.[2] The private sleep aid market has—perhaps partly in the stead of government action—ballooned to $65 billion annually in the U.S. and $432 billion globally (Roberts, 2022). This market includes over-the-counter sleep aids, sleep masks, sound machines, special mattresses or pillows, smartphone applications, sound machines, and cannabidiol ("CBD") products. The efficacy of the products consumers buy in this minimally regulated market is not well known. For example, sales of CBD-based products, which are marketed as a sleep therapy, have grown in the last several years. However, in a recent double-blind study, Linares et al. (2018) found no statistically significant difference between the effects of CBD and those of a placebo on any sleep outcome.

Consumers have turned not only to CBD but also to marijuana as a form of sleep therapy. The passage of medical and recreational marijuana laws over the last two decades has removed legal consequences while also generating greater access to the drug, spurring increases in overall cannabis use rates. Roughly three-fourths of states allow medical or recreational cannabis use. When recreational cannabis is legally available, consumers substitute from traditional over-the-counter sleep aid medicines to marijuana (Doremus et al., 2019). Four-fifths of marijuana users claim sleep is a reason they use the drug (Skobic et al., 2021).

Given the prevalence of sleep-related marijuana use and the importance of alleviating sleep problems, understanding whether marijuana improves sleep outcomes is important for

[2] In fact, the federal government has acted only once as it relates to these policy recommendations, but in the exact opposite direction of what sleep experts counsel. Instead of voting to eliminate daylight savings time, in 2022 the Senate voted to make it permanent year-round. *See* David Sherpardson, "U.S. Senate Approves Bill to Make Daylight Saving Time Permanent," *Reuters* (2022), https://www.reuters.com/world/us/us-senate-approves-bill-that-would-make-daylight-savings-time-permanent-2023-2022-03-15/.

policymakers, health care providers, and consumers. The existing literature on this question comes from scientific and medical journals. The results from these studies are inconclusive, but generally suggest that marijuana (a) helps people fall asleep sooner, (b) might worsen overall sleep quality, and (c) has unclear effects on sleep duration, with some studies suggesting increases and others suggesting decreases on this front (Babson et al., 2017).

From a scientific standpoint, there are theoretically plausible explanations for why cannabis might increase *or* decrease sleep duration. CBD and tetrahydrocannabinol ("THC") are the two primary active ingredients in cannabis. THC is the ingredient responsible for the psychoactive "high" feeling that users experience. As has been discussed above, recent work suggests that CBD is not as efficacious for sleep improvements as was originally purported. THC and CBD together might generate sleep improvements, but it could also be the case that the combination of these two primary ingredients does not lead to sleep improvements, especially when CBD alone has not demonstrated therapeutic benefits for sleep.

This paper also seeks to provide a methodological contribution to this topic. While previous studies stem from small, non-representative trials or from associational studies that compare marijuana users to non-users, this paper exploits the variation in marijuana access law timing to understand the impact these laws have on sleep outcomes. This strategy has been used by previous work in the economics literature, which has found that medical marijuana laws ("MMLs") lead to a decrease in body mass index and in body weight (Sabia et al., 2017), a decrease in college students' time spent on education-related activities (Chu & Gershenson, 2018), and an increase in sexual activity (Baggio et al., 2019). This line of work also suggests that recreational marijuana laws ("RMLs") cause a decrease in tobacco use (Sabia et al., 2022) and in opioid prescribing (McMichael et al., 2020).

The impact MMLs and RMLs have on sleep is scientifically ambiguous, which motivates the research design in this study. One ex ante expectation is that if these laws have any effect on sleep, the effects should be stronger for RMLs than they are for MMLs, for two primary reasons. First, prior work suggests that RMLs cause cannabis use to increase at about two to three times the rate that MMLs cause cannabis use to increase (Maclean et al., 2017; Sabia et al., 2021; Wen et al., 2015). Second, while MMLs vary by state, they all require that patients register with the state and purchase cannabis under a "qualifying condition," or some ailment for which health care providers can prescribe the drug. In no MML state is sleep or sleep problems a qualifying condition. Therefore, people in MML states could be using medical marijuana for sleep purposes, but they would have to do so under the pretext of another qualifying condition. On the other hand, people in RML states can self-medicate because no medical condition is required for cannabis purchases in these states.

III. Data

As of 2021, 36 states and the District of Columbia have either a medical marijuana law ("MML") or recreational marijuana law ("RML") in place. I rely on McMichael et al. (2020), procon.org, pdaps.org, news articles, and my own Westlaw research on legal provisions for pinpointing when these laws become effective. Table 1 below shows the states that have recreational or medical laws in place alongside the years of enactment.

Table 1: Adoption of MMLs and RMLs

State	MML Year	RML Year
Alabama	2021	-
Alaska	1998	2015
Arizona	2010	2020
Arkansas	2016	-
California	1996	2016
Colorado	2000	2012
Connecticut	2012	2021
Delaware	2011	-
Washington, D.C.	2011	2015
Florida	2017	-
Hawaii	2000	-
Illinois	2014	2020
Louisiana	2019	-
Maine	1999	2016
Maryland	2014	-
Massachusetts	2013	2016
Michigan	2008	2018
Minnesota	2014	-
Missouri	2018	-
Montana	2004	2021
Nevada	2000	2017
New Hampshire	2013	-
New Jersey	2010	2021
New Mexico	2007	2021
New York	2014	2021
North Dakota	2016	-
Ohio	2016	-
Oklahoma	2018	-
Oregon	1998	2015
Pennsylvania	2016	-
Rhode Island	2006	-
South Dakota	2021	-
Utah	2018	-
Vermont	2004	2018
Virginia	2020	2021
Washington	1998	2012
West Virginia	2019	-

I use the American Time Use Survey ("ATUS") for sleep data. The use of the ATUS for sleep data is standard in the economics literature. After completing the Current Population Survey ("CPS"), a fraction of those CPS respondents is asked to participate in the ATUS. Accordingly, respondents' demographic information from the CPS can be linked to the ATUS. I link these datasets and include demographic information in my analyses. Although the ATUS provides survey responses on sleep instead of more objective measures of sleep, it is a nationally representative sample across all 50 states and the District of Columbia from 2003 to 2021. Motivated by other papers in the literature that employ the ATUS—Niekamp (2019) and Krueger & Mueller (2020)—I likewise restrict my sample to those between the ages of 18 and 65. This provides a sample size of 175,493 respondents. Table 2 shows basic demographic information about ATUS respondents in comparison to the share of the U.S. population for given demographic categories.

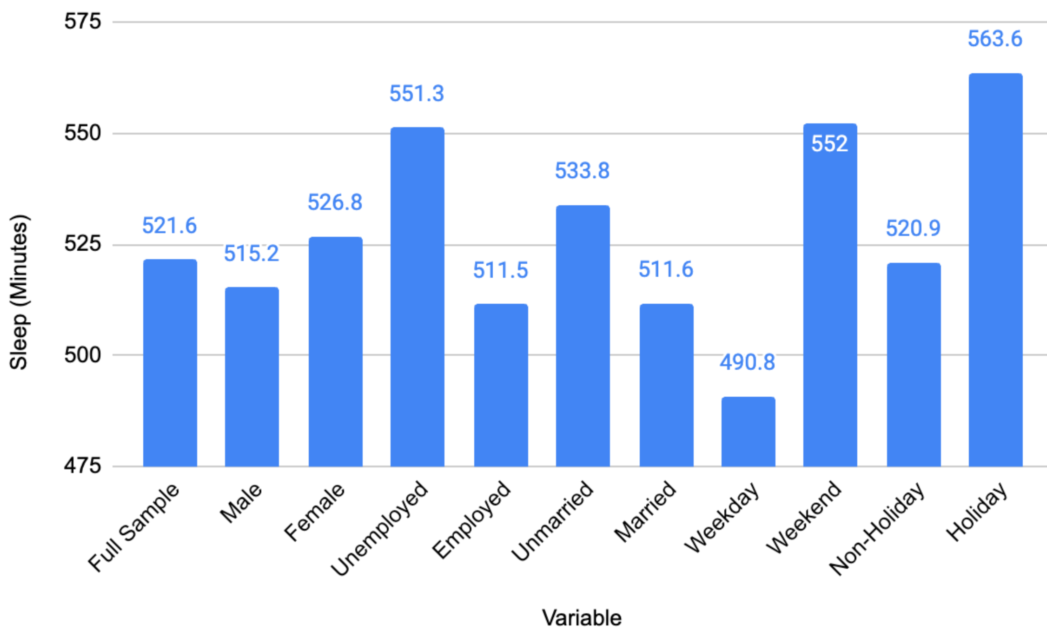
Table 2: ATUS Demographics, Summary Statistics

Covariate	ATUS Sample (share)	U.S. Population (share)
Male	0.45	0.49
Married	0.55	0.54
White	0.80	0.62
Employed	0.75	0.62
Veteran	0.07	0.07
Own Child in House	0.45	0.40

Sample size: 175,493

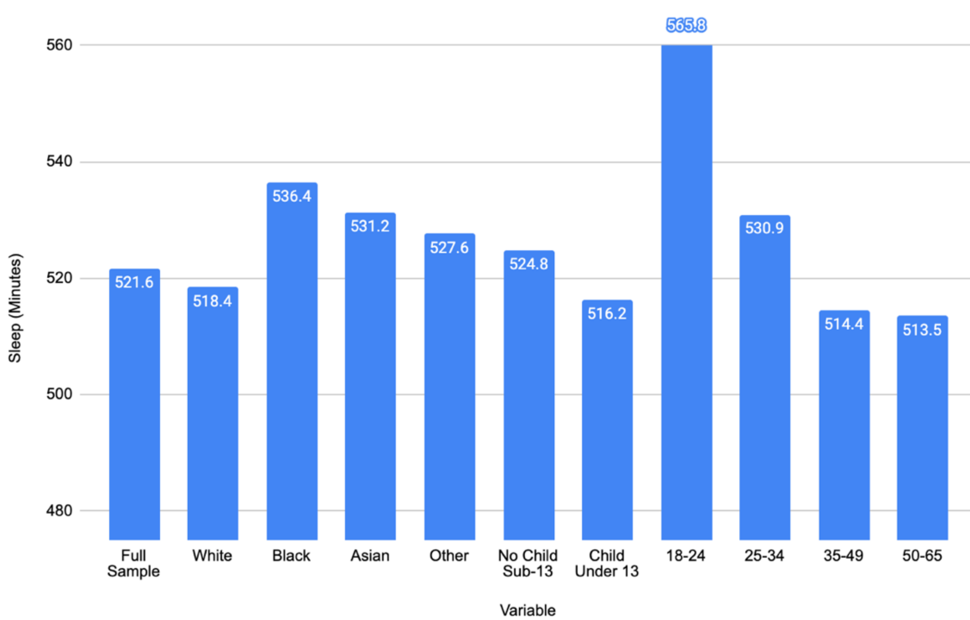
Table 2 shows that, though there is some overrepresentation for Whites and employed individuals, the ATUS sample is similar to the U.S. population. The ATUS oversamples people from more sparsely populated states, but survey weights are included to produce nationally representative estimates. The figures below provide basic descriptive statistics on sleep for the sample I use in my regressions.

Figure 1a: ATUS Mean Sleep by Subgroup



Figures 1a and 1b are separated for spacing purposes. These figures display the mean nightly sleep duration, in minutes, for each subgroup that is indicated on the x-axis.

Figure 1b: ATUS Mean Sleep by Subgroup, Continued



The differences in average sleep between ATUS subgroups, highlighted in Figures 1a and 1b, parallel the differences in average sleep between these subgroups more generally in the U.S. population. In the ATUS, shorter sleep is associated with being male, employed, middle-aged, and a parent. Sleep is also associated with weekdays and non-holidays in the ATUS. These ATUS group differences in average sleep comport with general U.S. population group sleep differences (Krishnan & Collop, 2006; Niekamp, 2019; Kunst, 2019; Webber, 2019), with the exception being that in the general population, married people report longer sleep than do unmarried people (Murez, 2022). Otherwise, the ATUS average sleep figures align with other studies on group differences in sleep in the general U.S. population.

IV. Methodology

Cannabis access laws cause an increase in marijuana use. Marijuana use rates are at about 8 to 9% of the population before a medical marijuana law ("MML") or recreational marijuana law ("RML") takes place and jump to about 10 to 11% after a law takes effect. Wen et al. (2015) shows that MMLs lead to a 14% increase in use. Maclean et al. (2017) and Sabia et al. (2021) show that RMLs cause an approximate 30% increase in cannabis use, and other work highlights that these RML-induced increases are sharpest for males and for those over the age of 24 (Rotermann, 2019; Weinberger et al., 2022; Hollingsworth et al., 2022). Based on this first stage of the effect that MMLs and RMLs have on cannabis use rates, I exploit the variation in the timing of MMLs and RMLs via a standard difference-in-difference design with state and year fixed effects. Compared to authors in the prior literature who use cannabis law enactment by year, I gain precision by coding whether an MML or RML is in place for a specific day in a specific year in my basic difference-in-difference specification. I first use the following two-way-fixed-effects difference-in-difference regression specification:

$$Y_{ist} = \beta_1 MML_{st} + \beta_2 RML_{st} + \pi X_{ist} + \gamma_s + \lambda_t + \varepsilon_{st}$$

The main dependent variable of interest, Y, is minutes of sleep for individual i in state s at time t. MML_{st} refers to whether state s had a medical marijuana law at time t, while RML_{st} indicates whether state s had a recreational marijuana law in place at time t. X is a vector of controls for whether someone has kids under the age of 13 in the household, age, sex, marital status, weekday indicator, holiday indicator, race, veteran status, indicator for whether a state's average annual sunset time is earlier than 6:30pm, and employment status. γ represents state fixed effects and λ represents year fixed effects. Errors are clustered at the state level.

The recently documented bias in traditional two-way-fixed-effects difference-in-difference regression designs motivates my use of a stacked difference-in-difference design. The comparison of later treated states to early (already) treated states can produce wrong-signed and thus biased estimates under the traditional two-way-fixed-effects framework (Goodman-Bacon, 2021). Accordingly, by re-arranging the data into stacks of the following categories—early treated states, later treated states, and never treated states—it is possible to remove the comparison of later treated to early (already) treated states. Accordingly, the stacked results here rely on three comparison groups: early treated states relative to later (and not yet treated) states, treated states relative to never treated states, and early treated states to both never and later (not yet treated) states.

There are six cohorts of treated states in the stacks. Using states that passed RMLs in 2021 would not allow for a post-period in the stacked regression specification, as my latest year of data is from 2021. For this reason, the 2020 cohort is the latest treatment cohort I use. I again include the following controls in this stacked design: whether someone has kids under the age of 13 in the household, age, sex, marital status, weekday indicator, holiday indicator, race, veteran status, indicator for whether a state's average annual sunset time is earlier than 6:30pm, and employment status.

Table 3: Stacked Regression Treatment Cohorts

Cohort	First Year of Treatment	States
1	2012	Colorado; Washington
2	2015	Alaska; Oregon; Washington, D.C.
3	2016	California; Maine; Massachusetts
4	2017	Nevada
5	2018	Vermont; Michigan
6	2020	Arizona; Illinois

For my stacked regression design, I use the following regression specification:

$$Y_{isy} = \beta^{stacked} RML_{sy} + \pi X_{isy} + \gamma_{sz} + \lambda_{yz} + \varepsilon_{zsy}$$

Y represents minutes of sleep for individual i in state s in year y, while RML takes on a value of 1 if a recreational marijuana law is in place in state s during or after year y and takes on a value of 0 otherwise. X is the same set of controls used in the traditional two-way-fixed-effects ("TWFE") model above. Z represents stacks in the stacked regression specification. I include state-by-stack fixed effects and year-by-stack fixed effects in this specification. State-by-stack fixed effects are analogous to state fixed effects in the TWFE specification, while year-by-stack fixed effects ensure that all comparisons occur within stacks. I do not find effects of MMLs on sleep outcomes, so I focus on the effects of RMLs on sleep outcomes in my stacked regression design. Appendix A1 shows that there is an average of about a decade between when an MML and a RML is enacted in each state, allaying concerns about MMLs affecting RML pre-trends. The demographic makeup of a state does not change after an RML takes effect, and demographic characteristics of RML versus non-RML state-years is also similar, as demonstrated in Appendix A2.

V. Results

A. Regression Results

My basic two-way-fixed-effects difference-in-difference regression results are shown below in Table 4.

Table 4: TWFE Difference-in-Difference Regression Results

	(1)	(2)	(3)
VARIABLES	No Controls	Full Set of Controls	Exclude California
MML	1.87	1.79	1.38
	(1.61)	(1.57)	(1.52)
RML	-4.44**	-5.37***	-5.69**
	(1.77)	(1.73)	(2.45)
Observations	175,493	175,493	157,990
Controls	No	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
CA Included	Yes	Yes	No

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

With the full set of controls included in my preferred TWFE specification in column 2, I find that marijuana medical marijuana laws ("MMLs") have no significant impact on sleep duration, while recreational marijuana laws ("RMLs") lead to an average reduction in sleep of about 5.4 minutes per night. This effect is significant at the 1% level. In column 3, I run the same regression with the full set of controls, but I exclude California from the analysis because the legal landscape for cannabis in California is somewhat distinct from that in other states. California's 1996 medical marijuana law was so broad as to constitute an arguably de facto recreational marijuana law, so column 3 assuages concerns that California might be confounding the results.

The results for the stacked regression design are shown below in Table 5. In column 1, I compare all six cohorts to never treated states. In column 2, I compare the first treated cohort with later treated cohorts. In column 3, I compare the first treated cohort with both later treated and never treated cohorts.

Table 5: Stacked Regression Results

VARIABLES	(1) Treated vs Never Treated	(2) Early Treated vs Later Treated	(3) Early Treated vs (Later Treated + Never Treated)
RML	-7.24**	-15.59**	-13.05*
	(2.78)	(6.89)	(6.58)
Observations	886,983	34,739	114,774
Controls	Yes	Yes	Yes
State-by-Stack FE	Yes	Yes	Yes
Year-by-Stack FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The stacked difference-in-difference regression results are consistent with the two-way-fixed-effects results and indicate that RMLs lead to a decrease in sleep duration of somewhere between 7 and 16 minutes per night. All columns in the stacked results are statistically significant and the point estimates are larger than they are in the two-way-fixed-effects section. This suggests that the basic TWFE results might be understating the negative impact RMLs have on sleep duration. Column 3 is significant at just the 10% level, barely shy of statistical significance at the 5% level. The point estimates are larger in columns 2 and 3 than in column 1, but the result from column 1 has higher statistical significance. Theoretically, column 2 could be the best comparison because later (not yet treated) RML states are more politically similar to early treated RML states than never treated RML states are. That is to say that states that eventually pass a recreational marijuana law might be more comparable than states that never pass such laws.

B. Event Studies

It might be the case that the effect of a new marijuana law on sleep occurs years after the passage of a law because dispensaries take time to open, and the public might experience an adjustment period.[3] Or it could be the case that the laws cause changes in sleep at first, but then people adapt over time and the sleep changes dissipate thereafter. To address these possibilities, I run event studies to capture whether these effects change over time. Figures 2a and 2b provide

[3] In addition, black market cannabis will be impacted by the introduction of legal cannabis sources. First-stage estimates relying on state registries fail to account for this interplay. Wen et al. (2015) instead rely on the National Survey on Drug Use and Health. This survey information on marijuana use predates cannabis law passage, helping mitigate black market concerns in helping to understand how cannabis use might be impacted by the enactment of legalization regimes.

the event studies for MMLs and RMLs, respectively, centered on years before and after treatment.

Figure 2a: Medical Marijuana Law Event Study

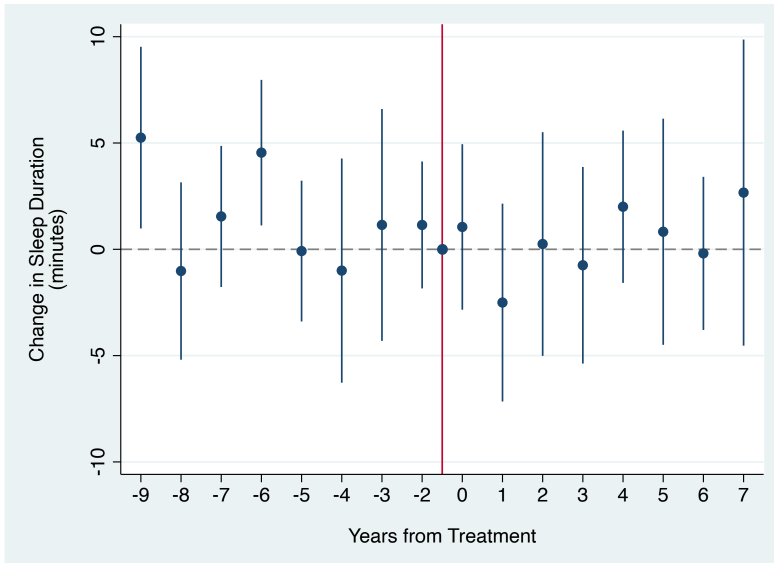
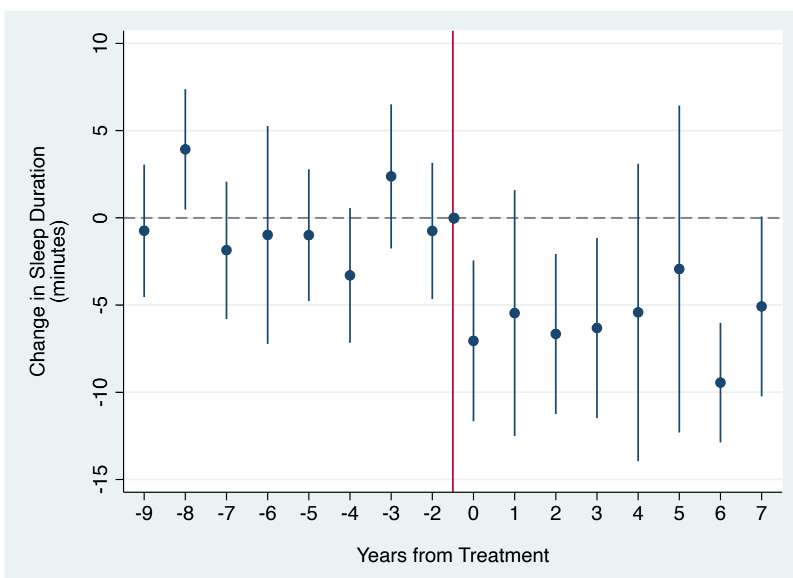


Figure 2b: Recreational Marijuana Law Event Study



Figures 2a and 2b comport with the main regression results indicating no change in sleep for MMLs and a reduction in sleep with RMLs. This decrease does not seem to grow or shrink over time but instead seems to stay rather stable. There is no evidence of pre-trends in these figures, which helps alleviate concerns about parallel trends assumptions for my difference-in-difference design.

C. Heterogeneous Effects

Existing first-stage literature generally suggests that cannabis use increases are most pronounced for males and for those over the age of 24. For this reason, in Table 6 I look to see whether the effects of cannabis access laws on sleep differ for these groups. The only control I omit is the subgroup of interest for each regression. For example, I exclude age as a control variable when running regressions for the effect MMLs and RMLs have on 18-to-24-year-olds' sleep duration. Additional heterogeneous results can be found in the appendix, but there is no reference point from prior literature for the first-stage cannabis use changes by race, marital status, or veteran status.

Table 6: Heterogeneous Effects, Sex & Age

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Full Sample	Male	Female	18-24	25+
MML	1.79	3.53	-0.06	10.60**	0.42
	(1.57)	(2.52)	(2.25)	(5.00)	(1.77)
RML	-5.37***	-6.21*	-4.36	2.71	-6.06***
	(1.73)	(3.24)	(2.71)	(8.03)	(2.08)
Observations	175,493	79,002	96,491	13,907	161,586
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6 shows that the effect of RMLs on sleep duration is most significant for males and for those at least 25 years old. That the effects are most pronounced among the two groups most likely to increase cannabis use after RML passage adds credibility to the results in this paper.

In all specifications other than ages 18-24, the MML coefficient is not statistically significant. It is unclear why MMLs appear to cause an increase in sleep duration for those between the ages of 18-24. Otherwise, the results from these separate regressions demonstrate the robustness of the negative effect of RMLs on sleep duration and the lack of an effect of MMLs on sleep duration.

D. Sleep Onset

Sleep duration is just one component of sleep. Another important piece is how long it takes for people to fall asleep, referred to as "sleep latency onset" or just "sleep onset." To make progress here, I re-arrange the ATUS data at the activity level instead of at the individual level, which permits inspection of activity start and stop times. I can test for whether the RML-induced sleep changes affect the the start and stop times for sleeping. To do so, I regress sleeping start time on these laws in column 1. If marijuana laws cause people to fall asleep earlier or later, then people might compensate for this change by adjusting when they wake up in the mornings. To assess whether this seems to be occurring, in column 2 I regress sleeping stop time on these laws.

Table 7: Falling Asleep & Waking Up Times

	(1)	(2)
VARIABLES	Falling Asleep	Waking Up
MML	-3.31**	0.25
	(1.34)	(1.34)
RML	7.14***	1.77
	(1.56)	(2.08)
Observations	177,495	170,193
R-squared	0.04	0.11
Controls	Yes	Yes
State FE	Yes	Yes
Year FE	Yes	Yes

Column 1 indicates when respondents start sleeping, while column 2 refers to when respondents stop sleeping. Therefore, a positive coefficient in column 1 corresponds to falling asleep later (sleeping less), while a positive coefficient in column 2 would correspond to waking up later (sleeping more). In column 1, I include start times between 7:30pm and 4:00am. In column 2, I include stop times between 4:00am and 10:00am.
*** p<0.01, ** p<0.05, * p<0.1

The results in Table 7 suggest that RMLs cause people fall asleep an average of 7 minutes later at night, while MMLs cause people to fall asleep an average of 3 minutes earlier at night. People do not seem to compensate for sleep changes by changing when they wake up. This is consistent with prior literature—especially in the daylight savings time context—suggesting that sleep changes occur more at night than in the morning because fixed work schedules, school schedules, and morning obligations are usually less flexible than are nighttime commitments (Niekamp, 2019). In addition, this result for RML sleep onset is consistent with the results in this paper on sleep duration. However, this result of RMLs causing people to fall asleep later at night stands in contrast to medical literature, which generally suggests that cannabis causes people to fall asleep more quickly.

VI. Mechanism

A. Substitution

This paper shows that RMLs lead to a reduction in sleep duration and that this reduction stems from people falling asleep later at night. Even though these findings are robust to alternative specifications and coding choices, the mechanism behind why RMLs cause poor sleep outcomes is not clear from the data so far. One way to understand more about the potential mechanism at play is to see if cannabis use might cause a change in time spent doing other activities. For instance, it could be that cannabis users are more likely to socialize, go out with friends, or engage in other activities that shift time away from sleeping. To make progress in testing for this possibility, I look at other categories of time use in the ATUS to identify if there are other activities outside of sleeping that see a corresponding change in time use alongside RML enactment. I explore this possibility by independently regressing the main time use categories in the ATUS on RMLs. In Tables 8 through 11, I do this with the traditional TWFE design as well as with all three stacked regression specifications.

Table 8: TWFE Mechanism Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Sleep	Naps	Relaxing & Leisure	Educ.	Eating & Drinking	Work	Social Events
RML	-5.37***	-0.64	-3.11	2.72	1.90**	1.18	-0.25
	(1.73)	(0.59)	(3.26)	(1.79)	(0.74)	(3.41)	(0.46)
Observations	175,493	175,493	175,493	175,493	175,493	175,493	175,493
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Stacked Mechanism Regression Results: Treated vs Never Treated

VARIABLES	(1) Sleep	(2) Naps	(3) Relaxing & Leisure	(4) Educ.	(5) Eating & Drinking	(6) Work	(7) Social Events
RML	-7.24**	-0.33	-3.62	3.44**	0.73	6.56	-0.70
	(2.78)	(0.79)	(3.07)	(1.35)	(0.82)	(4.18)	(0.68)
Observations	886,983	886,983	886,983	886,983	886,983	886,983	886,983
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Stack FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Stack FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Stacked Mechanism Regression Results: Early vs Later Treated

VARIABLES	(1) Sleep	(2) Naps	(3) Relaxing & Leisure	(4) Educ.	(5) Eating & Drinking	(6) Work	(7) Social Events
RML	-15.59**	-4.34*	6.86	6.81**	1.53	6.20	-3.20***
	(6.89)	(2.43)	(5.79)	(2.42)	(3.87)	(14.33)	(0.54)
Observations	34,739	34,739	34,739	34,739	34,739	34,739	34,739
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Stack FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Stack FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Stacked Mechanism Regression Results: Early vs (Later Treated + Never Treated)

VARIABLES	(1) Sleep	(2) Naps	(3) Relaxing & Leisure	(4) Educ.	(5) Eating & Drinking	(6) Work	(7) Social events
RML	-13.05*	-2.70	1.92	5.50***	1.73	11.97	-2.81***
	(6.58)	(2.29)	(5.68)	(1.66)	(3.52)	(13.61)	(0.42)
Observations	114,774	114,774	114,774	114,774	114,774	114,774	114,774
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Stack FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Stack FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The traditional TWFE results here imply that only the eating and drinking category shows an increase in reported time use following RMLs. This is consistent with Baggio & Chong's (2020) finding that RMLs lead to an increase in junk food sales; it is also consistent with the stereotype of marijuana consumption leading to the "munchies," or increased hunger. Accordingly, this would indicate that people might be consuming more marijuana, becoming hungry, and staying up later. However, the coefficient on eating and drinking is about one-third that of the sleeping coefficient, so this substitution story would not entirely explain the sleep reduction finding. Moreover, the statistical significance of eating and drinking disappears in all stacked regression specifications.

In the stacked results, the only category that is statistically significant in all specifications is the roughly 3.5-to-7-minute increase in education-related activities following the passage of RMLs. This result differs from that of Chu & Gershenson (2018), who see a reduction in education-related activities following the passage of MMLs. The result here might differ because I include more years of data, focus on the impact of RMLs instead of MMLs, and use new difference-in-difference estimators. Nonetheless, it does not seem likely that the increase in education-related activities is the reason why people sleep less after RMLs are passed. The point estimates for education-related activities are never more than one-half the point estimate for sleep duration reductions, so this finding does not reflect a pure substitution story. Moreover, education-related increases following RMLs are concentrated amongst those under the age of 25, while sleep decreases following RMLs are concentrated amongst those 25 or older. This is true for both the two-way fixed effects and the stacked results. Therefore, it is unlikely that those who are sleeping less are the same respondents who report increases in education-related activities.

Another result from the stacked regressions is that the coefficients for relaxing and leisure are never statistically significant. Social events is a subcategory of relaxing and leisure in the ATUS, and this coefficient is not significant in two specifications but is negative and statistically significant in two of the stacked regression specifications. That this coefficient is negative in these two stacked specifications means that people are not substituting from sleep to social events but instead means that people may be socializing less after the passage of RMLs. Therefore, one possible takeaway is that RMLs might cause cannabis users to stay up late and stay home but do not cause users to increase usage of the drug in social settings.

One potential concern is that observed sleep changes could be affecting daytime sleep instead of normal, nighttime sleep. To test this concern, I create a nap variable that records sleep only from the window of 11:30am to 7:30pm. Only in one specification is this nap coefficient significant, and only at the 10% level, which means that the sleep decreases are occurring at normal nighttime sleeping hours. I also test for whether the total minutes reported decreases with the passage of RMLs, but I consistently find no effect of RMLs on minutes reported.

But if people in the ATUS report (a) a reduction in sleep duration, (b) no overall change in the number of minutes reported, and (c) no corresponding increase in a particular category of time use, then there must be some way to account for the minutes taken away from the sleep category following the passage of RMLs. Appendix Table A4 elucidates that the substitution from sleep to other activities is not driven by one activity but instead by multiple activities, such that the effects are too small to detect with the main time use categories of the ATUS.

B. *Partying or Socializing with Others*

The ATUS asks respondents if they are with other people during reported activities and where activities take place. I analyze whether this information yields any evidence of increased socialization following the passage of cannabis access laws. Even if people do not increase time spent in the "eating & drinking" or "socializing & communicating with others" time use categories of the ATUS, there might be a change in where they engage in activities or with whom they engage in activities. To test for this possibility, in Table 12a, I regress the fraction of the total number of activities spent (1) alone, (2) with non-household members, and (3) performed at home on RMLs. I multiply this fraction by 100 for a more intuitive interpretation of the coefficients. I conduct the same analysis for the "eating & drinking" and "socializing & communicating with others" subcategories in Tables 12b and 12c, respectively. These are the subcategories most likely to capture changes in socialization-related behavior. Based on privacy reasons, the ATUS does not record information on where individuals sleep or with whom they sleep, so I cannot run these same regressions for sleep.

Table 12a: Effect of RMLs on Total Activities Performed Alone, with Non-Household Members, and at Home

VARIABLES	(1) Alone	(2) Non-Household Member	(3) Home
RML	0.27	-0.24	0.30
	(0.24)	(0.25)	(0.28)
Constant	23.01***	31.11***	37.48***
	(0.41)	(0.56)	(0.47)
Observations	175,493	175,493	175,493
Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

The omitted category in column 1 is with anyone at all (i.e., the activity is not performed completely alone). The omitted category for column 2 is alone or with anyone who is a household member, such as a spouse, child, or roommate. In column 3, the omitted category is at any location outside the respondent's house. *** p<0.01, ** p<0.05, * p<0.1

Table 12b: Effect of RMLs on Eating & Drinking Alone, with Non-Household Members, and at Home

VARIABLES	(1) Alone	(2) Non-Household Member	(3) Home
RML	-0.37*	0.22	0.05
	(0.22)	(0.17)	(0.19)
Constant	6.43***	7.22***	24.20***
	(0.32)	(0.33)	(0.49)
Observations	175,493	175,493	175,493
Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12c: Effect of RMLs on Socializing & Communicating with Others (Alone, with Non-Household Members, and at Home)

VARIABLES	(1) Alone	(2) Non-Household Member	(3) Home
RML	0.02	-0.26	-0.20
	(0.04)	(0.20)	(0.16)
Constant	0.10**	10.04***	4.86***
	(0.04)	(0.25)	(0.36)
Observations	175,493	175,493	175,493
Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 13a, 13b, and 13c do not provide evidence that RMLs cause people to increase the percentage of activities that take place with other individuals or that take place outside the home. Only column 1 of Table 13b is significant, and only at the 10% level. Therefore, these results do not support the idea that people turn to marijuana to party or socialize with others. Instead, it seems that RMLs do not cause respondents to increase the percentage of socialization-related activities that take place with other people or that take place outside the home.

C. Rational Use? Policy Implications

The mechanism behind the sleep reductions identified in this paper is not entirely clear, but the data do not point to a clear-cut substitution story. A few other explanations seem most likely. First, people could be staying up late at night to rationally enjoy the psychoactive high of marijuana while understanding the potential negative impacts on sleep. Second, people could rationally enjoy the high of marijuana without knowing its impacts on sleep. Third, people might self-medicate by taking marijuana for sleep therapy without recognizing that this approach could be counterproductive.

The fact that most marijuana users claim sleep is a primary reason they use runs counter to the first explanation. However, marijuana-induced sleep reductions could be offset by users' rational enjoyment of the psychoactive high that cannabis use induces, so this explanation is still possible. But if this were the case, marijuana users would need to value that "high" feeling more than they value the concordant effects on sleep. This is not supported by recent data suggesting that, compared to those with sleeping problems who are willing to pay an average of $66.69 per month for an hour increase in nightly sleep, users spend an average of $53.75 per month on cannabis products (Wood, 2022). Therefore, because the market price for marijuana is lower than the price placed on the sleep changes it causes, it is unlikely that cannabis consumers fully internalize the effects marijuana has on sleep. Instead, consumers are likely unaware that marijuana cause reductions in sleep duration and increases in sleep onset (the time it takes to transition from wakefulness to sleep).

Since users are probably unaware that marijuana use exacerbates sleep outcomes, it is likely that, all else equal, current marijuana use rates are higher than they would be under the presence of full information. This suggests caution for consumers who turn to marijuana as a sleep aid, medical practitioners who might recommend the drug for sleep improvements, and policymakers considering sleep problems as a qualifying condition for cannabis in MML states. The effects that marijuana has on sleep should be considered in the larger context of marijuana's impact in other domains, including but not limited to opioid use, automobile accidents, and recreational enjoyment.

Sleep duration and sleep latency onset are just two parts of sleep health. Another important aspect of sleep not explored in this paper is sleep quality, which is related to how much rapid-eye-movement sleep one achieves. Information on rapid-eye-movement sleep is not available in the data used in this paper. Moreover, it could be the case that marijuana impacts sleep hygiene in other ways as well. For instance, the drug could trigger forgetfulness in brushing one's teeth or taking medications before bedtime, or it could alter the regularity of when one attempts to sleep at night, but these aspects of sleep health are beyond the scope of this paper.

VII. Conclusion

This paper provides the first causally robust estimates of the effect of marijuana access laws on sleep. Medical marijuana laws ("MMLs") do not cause sleep changes, while recreational marijuana laws ("RMLs") cause people to stay up later and lose approximately 38 minutes of sleep each week. Only about 1 in 10 people in the U.S. consume marijuana; if the effects that RMLs have on sleep are restricted to marijuana users, then RMLs cause these individuals to lose approximately 50 minutes of sleep per night. These effects are concentrated most acutely in males and in those 25 and older, which are the two groups identified in previous literature that are most likely to increase cannabis use after the passage of RMLs. This adds credulity to the results identified in this paper.

It may be the case that MMLs have no impact on sleep duration because insomnia or sleep-related problems are not "qualifying conditions"—medical conditions for which doctors can legally prescribe marijuana—in any state with an MML in place, whereas RMLs cause changes in sleep duration because people are free to self-medicate with marijuana when RMLs are in place. Other research suggests that many marijuana users turn to the drug to alleviate sleeping problems, which lends support to this explanation. It is somewhat counter intuitive, then, that RMLs cause a decrease in sleep duration. The most likely explanation for this finding is that the combination of THC and CBD—the two primary active ingredients in marijuana—has no benefit for sleep, but people have nonetheless been using it for that purpose. But people use marijuana for reasons other than sleep, such as recreation. Still, the average amount people spend on marijuana is less than the estimated value they place on sleep, so this suggests that people do not fully account for marijuana-induced sleep costs when they consume the drug.

Sleep deteriorations caused by the passage of RMLs likely cause reductions in earnings for workers (Hafner et al., 2016), increases in fatal car crashes (Smith, 2016), and negative health consequences such as increased incidence of heart attacks (Toro et al., 2015), which together cost approximately $200 billion annually based on back-of-the-envelope calculations. Further research should continue to advance our understanding of the ways that marijuana impacts sleep. If marijuana becomes legal at the federal level in the years to come, then a large-scale, randomized control trial could shed light on this question. In the meantime, this paper is the first to address persistent endogeneity problems in the literature by providing causal estimates of the impact that marijuana access laws have on sleep.

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Appendix

Table A1: Time Between MMLs and RMLs (for states that have both)

State	Years Between MML & RML
Alaska*	16.3
Arizona	10.0
California*	20.0
Colorado*	12.0
Connecticut	9.1
Washington, D.C.	4.2
Illinois	6.0
Maine*	17.0
Massachusetts	4.0
Michigan	10.0
Montana	16.2
Nevada*	15.3
New Jersey	11.1
New Mexico	14.0
New York	7.1
Oregon*	16.7
Vermont	13.1
Virginia	1.0
Washington*	14.1
Mean	8.8
Mean*	11.4

Asterisk indicates that the state had a MML in place before 2003, the year the ATUS sample begins. Mean is the mean for all states that had MMLs and RMLs at some point in time, while Mean is the mean for just those states that had both MMLs and RMLs in the post-2002 analytic window of this paper.

The mean time between the passage of an RML and an MML in the sample is 8.8 years. Some states had an MML in place before 2003, the year the ATUS sample begins. Including those states brings the mean time between an RML and MML in a state to 11.4 years.

Table A2.1: Demographics (Share of Total): RML vs non-RML State-Years

Covariate	Non-RML	RML
Male	0.45	0.47
Married	0.55	0.53
White	0.80	0.81
Employed	0.75	0.75
Veteran	0.07	0.05
Own Child in House	0.46	0.42
Age 45+	0.45	0.47

Table A2.2: Demographics (Share of Total): RML States Pre- and Post-RML Enactment

Covariate	Pre-RML	Post-RML
Male	0.45	0.47
Married	0.55	0.53
White	0.80	0.81
Employed	0.74	0.75
Veteran	0.06	0.05
Own Child in House	0.47	0.42
Age 45+	0.45	0.47

Table A3.1: Heterogeneous Effects, Race

VARIABLES	(1) Full Sample	(2) White	(3) Black	(4) Asian	(5) Other
MML	1.79	1.95	4.71	-9.40	-0.73
	(1.57)	(1.78)	(4.67)	(6.05)	(11.90)
RML	-5.37***	-5.21**	-13.59	-2.45	-14.20
	(1.73)	(1.97)	(9.80)	(6.72)	(13.88)
Observations	175,493	140,347	23,871	7,097	4,178
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3.2: Heterogeneous Effects, Work

VARIABLES	(1) Full Sample	(2) Employed	(3) Not Employed	(4) Weekday	(5) Weekend
MML	1.79	1.12	3.84	3.59**	-2.24
	(1.57)	(2.02)	(3.82)	(1.73)	(2.14)
RML	-5.37***	-4.06*	-10.37**	-5.60**	-5.85**
	(1.73)	(2.19)	(4.46)	(2.29)	(2.22)
Observations	175,493	131,227	44,266	87,299	88,194
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3.3: Heterogeneous Effects, Veteran Status & Children in Household

VARIABLES	(1) Full Sample	(2) Veteran	(3) Non-Veteran	(4) Child Under 13	(5) No Child Under 13
MML	1.79	3.43	1.75	2.56	1.29
	(1.57)	(5.01)	(1.67)	(2.34)	(1.91)
RML	-5.37***	-20.35**	-4.70**	-2.29	-6.50***
	(1.73)	(9.69)	(1.86)	(3.95)	(2.27)
Observations	175,493	11,887	163,606	65,732	109,761
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: RMLs and Total Activities Reported

VARIABLES	(1) TWFE	(2) Stacked: Treated vs Never Treated	(3) Stacked: Early Treated vs Later Treated	(4) Stacked: Early Treated vs (Later Treated + Never Treated)
RML(TWFE)	0.29**			
	(0.11)			
RML (Stacked)		0.30*	0.27	0.30
		(0.17)	(0.40)	(0.37)
Observations	175,493	886,983	34,739	114,774
Controls	Yes	Yes	Yes	Yes
State FE	Yes	No	No	No
Year FE	Yes	No	No	No
State-by-Stack FE	No	Yes	Yes	Yes
Year-by-Stack	No	Yes	Yes	Yes

FE

In Table A4, I regress the total number of activities reported on RMLs, and I do so with all four regression specifications.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Robust standard errors in parentheses

Table A4 shows that there might be an increase in the total number of activities reported following the enactment of RMLs, but this result is not robust. The substitution from sleep to other activities is not driven by one activity but instead by multiple activities, such that the effects are too small to detect with the main time use categories of the ATUS.

Chapter 2: The Effects of Cannabis Access Laws on Car Crashes

Abstract

This study examines the effects of cannabis access laws on car crashes using a novel dataset I compile of all car accidents in 44 US states. Using a difference-in-difference design, I find that medical marijuana laws have no impact on crashes, while states recreational marijuana laws are associated with at least 10,000 fewer crashes per year. This reduction in crashes is concentrated among property-damage-only crashes that do not involve fatalities or injuries. After a state passes a recreational marijuana law, there is no change in registered vehicles, drivers, or total population. Though there is no evidence of changes in alcohol-related crashes after the passage of recreational marijuana laws, a substitution from alcohol to marijuana cannot be ruled out as a possible reason for the observed decline in property-damage-only crashes. Moreover, this paper highlights the importance of coding choices in the marijuana space, suggesting that the subjectivity therein is the most likely explanation for findings in this area.

I. Introduction

Driving a car is the most dangerous regular activity for most Americans, with roughly 40,000 people who die from car crashes and millions who are seriously injured in the United States each year (NHTSA, 2022). Globally, car crashes are even more commonplace, claiming more than a million lives annually, which is greater than total homicide and suicide deaths combined (Bolotnikova, 2021). Distracted driving, speeding, and drunk driving are the most common culprits for car crashes (I Drive Safely, 2022). Technological advances in automobile safety, as well as state- and federal policies such as speed limit reductions and stricter drunk driving laws have helped reduce the fatal crash rate in the U.S. However, there has been a recent plateau in the fatal crash rate. In addition, although the amount of total driving decreased during the COVID-19 pandemic, the number of fatal crashes increased (Bolotnikova, 2021) during the pandemic and has stayed elevated in 2021. Accordingly, lawmakers and interest groups are searching for ways to mitigate fatal crashes and overall crashes.

Given the fact that drunk driving is responsible for more than a quarter of all car fatalities as well as a large portion of non-fatal crashes (NHTSA, 2022), any policy changes that might affect drunk driving are especially relevant in understanding how to curb car accident risks. One such policy is marijuana legalization. 36 states have adopted medical or recreational marijuana laws. It is unclear whether marijuana and alcohol are economic substitutes (Anderson et al., 2013) or complements (Wen et al., 2015). If they are substitutes, then legalization-induced increases in marijuana use could lead to reductions in alcohol use and thus reductions in drunk driving. At the same time, driving while under the influence of marijuana is also dangerous, so a substitution from drunk driving to high driving might increase or decrease crash rates. On the other hand, if marijuana and alcohol are complements, then marijuana legalization policies would lead to more car crashes, not fewer.[4]

This paper explores the relationship between marijuana legalization laws and car accident outcomes based on the staggered timing of state-level marijuana legalization policies and builds on the existing literature in two primary ways. First, this paper incorporates more years of data than previous studies looking at the relationship between car accidents and marijuana laws. Second, this paper uses a unique dataset based on all car crashes (rather than fatal crashes) to better understand the impact these laws have on driving outcomes. Using a difference-in-difference regression design as well as a stacked regression design based on the differential rollout of marijuana legalization laws, I find that medical marijuana laws do not cause any changes in crash outcomes while recreational marijuana laws lead to roughly 8,400 fewer property-damage-only crashes per year in states that adopt these laws.

II. <u>Background</u>

A. Marijuana

Marijuana use remains federally illegal in the U.S., and it is still a "Schedule 1" drug according to the Drug Enforcement Agency, meaning it is in the category of drugs with the highest potential for abuse and has no accepted medicinal use (Drug Enforcement Administration, 2022). However, the last two decades have seen a wave of state-level marijuana

[4] This is under the assumption that driving while high on marijuana is more dangerous than driving sober. Public health research indicates this is true. (Blum, 2022).

legalization in form the medical marijuana laws ("MMLs") and, more recently, recreational marijuana laws ("RMLs"). MMLs require that a physician prescribes a patient marijuana to address a "qualifying condition" the state has enumerated, while RMLs require no such physician prescribing but still entail other regulations such as quantity limits and age restrictions.

California, Oregon, and Washington became the first states to implement MMLs in the late 1990s, and when the Obama Administration decided in 2009 that the Department of Justice would no longer enforce the federal Controlled Substances Act against citizens in states with marijuana legalization laws in place (Ogden, 2009), several states passed marijuana liberalization policies. As of February 2023, 36 states have either a MML or RML in place.

The staggered rollout of marijuana legalization laws has provided the foundation for several recent economics papers assessing the impacts these laws have on a variety of outcomes. Both medical and recreational laws have been shown to increase marijuana use rates by roughly 15 and 30 percent, respectively (Wen et al., 2015; Dave et al., 2022; Maclean et al., 2021). This is the first-stage evidence most papers in this space rely on when assessing the impacts these laws have on several outcomes.

B. Car Accidents

One important policy concern surrounding the passage of marijuana laws is the effects these policies have on car crashes, which claim more lives than any other normal activity and injure millions of Americans each year. The effect of increased marijuana use on car crash outcomes is theoretically ambiguous. Some evidence suggests marijuana and alcohol—which is a major contributor for car crashes—are substitutes while other research suggests they are complements. Moreover, even if there is some substitution, it is unclear whether driving under the influence of marijuana is more dangerous than driving under the influence of alcohol. Detecting the presence of marijuana in drivers is a newer and less scientifically rigorous[5] than is detecting the presence of alcohol in drivers (National Institute of Justice, 2021), so enforcement differences might also generate disparate effects on car crash outcomes.

Almost all papers in the economics literature studying car crashes use the federal government's dataset, which is administered by the National Highway Traffic Safety Administration, called the Fatality Analysis Reporting System ("FARS"). This means that these papers look at changes in fatal car crashes. Existing literature suggests that MMLs decrease fatal car crashes by about 10 percent (Anderson et al., 2013; Santaella-Tenorio et al., 2017; Cook et al., 2020). The link between RMLs and fatal crashes is less clear; while there is some evidence that RMLs cause no change in fatal crashes (Hansen et al., 2020), most papers suggest that RMLs increase fatal crashes (Sanatella-Tenorio et al., 2020; Aydelotte et al., 2019; Caputi, 2022).

The only economics paper not relying on FARS data indicates that MMLs have caused a reduction in insurance premiums of about $22 per year (Ellis et al., 2022). Ellis et al. (2022) provides an important contribution for understanding how MMLs impact all car crashes instead of just fatal crashes, as fatal crashes constitute roughly 1 percent of all crashes. I also provide a contribution in terms of understanding the impacts of marijuana laws on all car crashes instead of

[5] The U.S. Department of Justice's research apparatus released a summary of relevant scientific articles and concluded that "THC levels in biofluid [which is commonly used in testing if drivers are high on marijuana] were not reliable indicators of marijuana intoxication. Many of their study participants had significantly decreased cognitive and psychomotor functioning even when their blood, urine, and oral fluid contained low levels of THC." (National Institute of Justice, 2021).

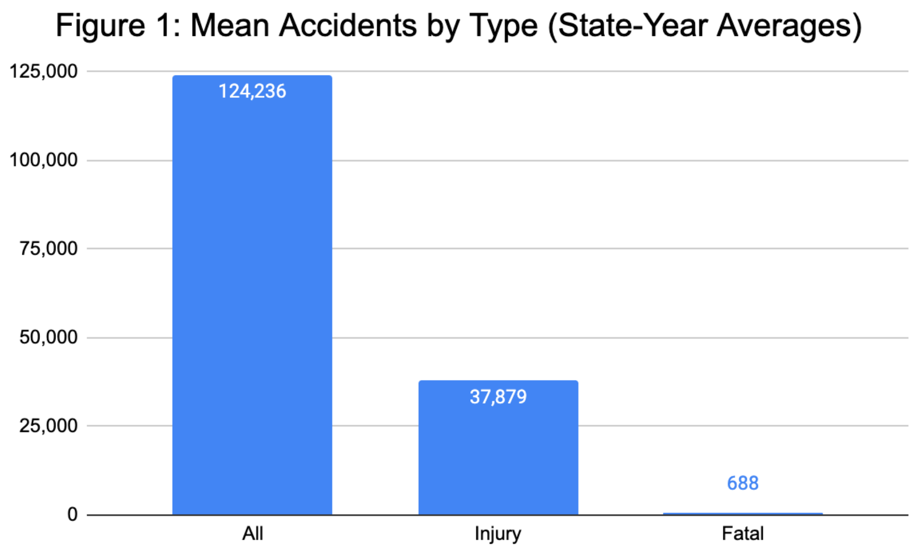
just fatal ones, but I do so with a new dataset, which I call the All-Accidents Dataset. This is a compilation of all car crash data from departments of transportation websites from 44 separate U.S. states. I look at both MMLs and RMLs, and I also include the most recent years of data available for each state.

III. <u>Data</u>

A. All-Accidents Dataset

I compile a novel dataset, coined the All-Accidents Dataset, to understand the impacts that MMLs and RMLs have on car crashes. I canvass every state government website to view car crash data and I individually contact departments of transportation when this data is not publicly available to collate 44 states' crash data. This is an important contribution not only for understanding the impacts of marijuana legalization policies on crash outcomes but also for future research on car crashes in the U.S. This is especially true given that the economics literature hitherto has relied on fatal crashes via the FARS notwithstanding the fact that—as Figure 1 below demonstrates—fatal crashes represent less than 1 percent of all crashes.

Figure 1: Mean Accidents by Type (State-Year Averages)



Relying on insurance premia is one way some researchers have tried to understand driver behavior and crash outcomes (Ellis et al., 2022), as insurers have incentives to generate accurate risk assessments for individuals. Nonetheless, using car crash data instead of insurance premia has several advantages. Namely, insurance premia reflect not only driver behavior but also extraneous information such as technological developments in car safety, crime statistics, and market power of firms in a state. In addition, insurance premia depend on fatal, injury, and property damage crashes, so it is impossible to disentangle the relationship between these separate types of crashes when using insurance premia along. Accordingly, the use of actual crash data overcomes these concerns.

Data from all car crashes could suffer from underreporting if individuals have incentives to keep crash experiences hidden from insurers or police. This is more concerning for property-damage-only crashes as opposed to fatal crashes or injury crashes because the latter more frequently inculcate ambulance drivers or other passersby and because injured or killed parties are more likely to seek legal recourse. That is to say, underreporting is a priori most problematic for those who present the least social cost (i.e., no injury nor death) to society. Moreover, given that this paper explores the relationship between marijuana laws and car crashes, the relevant dependent variable is the *relative* change in crashes. Therefore, it is unclear why underreporting of crash data would represent anything other than classical measurement error.

Each state administers its own collection and dissemination of non-fatal crash data. Unlike with fatal crash data, this non-fatal data is not required to be sent to the federal government. Accordingly, the data collection, documentation, organization, dissemination, and availability differ from state to state. The All-Accident Dataset captures the most common data in these state repositories: all crashes, injury crashes, property damage only crashes and, where available, fatal crashes, population, licensed drivers, and millions of vehicle miles traveled (VMT) per year. Figures 2a and 2b show that the states with the most VMT per year tend to be the states with the most crashes per year.

Figure 2a: VMT by State

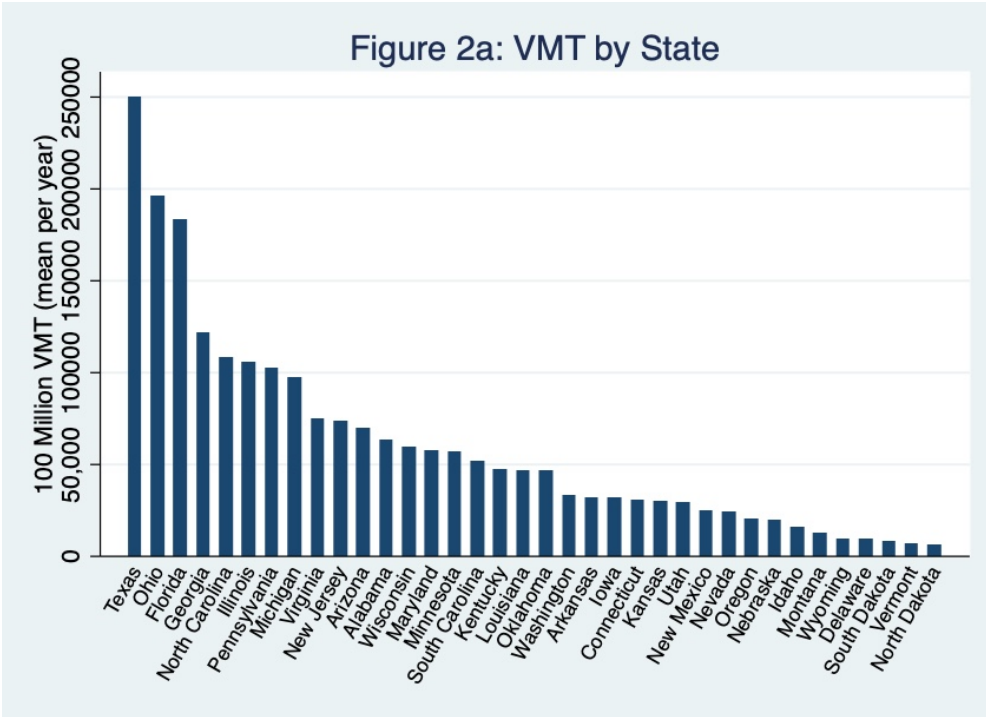


Figure 2b: Total Crashes by State

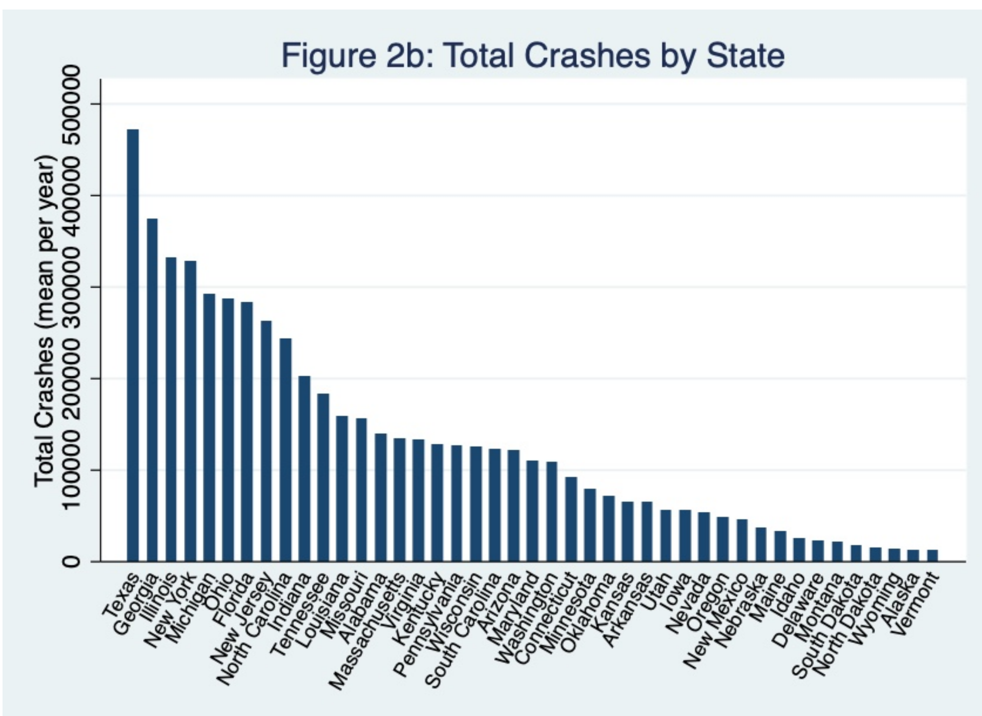


Figure 3a shows that crash rates—or the number of crashes per 100 million VMT—are not highest in the states with the largest populations or most VMT per year. Instead, there is no obvious pattern for which states see the highest overall crash rate. There is additional heterogeneity in the injury-, fatal-, and property damage only crash rates, as demonstrated by Figures 3b, 3c, and 3d. For example, while Oregon has the 11th highest total crash rate and 24th highest property damage only crash rate, it has the highest injury- and fatal crash rates in the All-Accidents Dataset. These figures highlight the importance of assessing crashes of different severities instead of relying exclusively on fatal crash information.

Figure 3a: Total Crash Rate by State

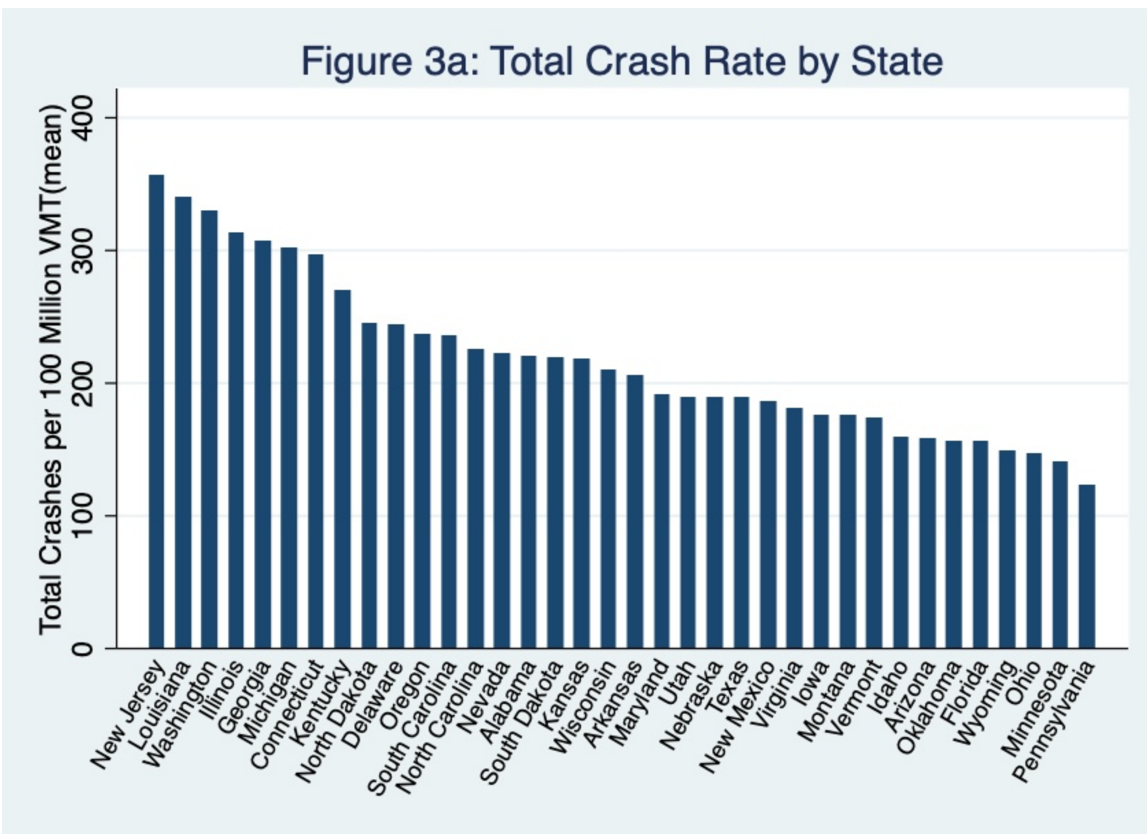


Figure 3b: Injury Crash Rate by State

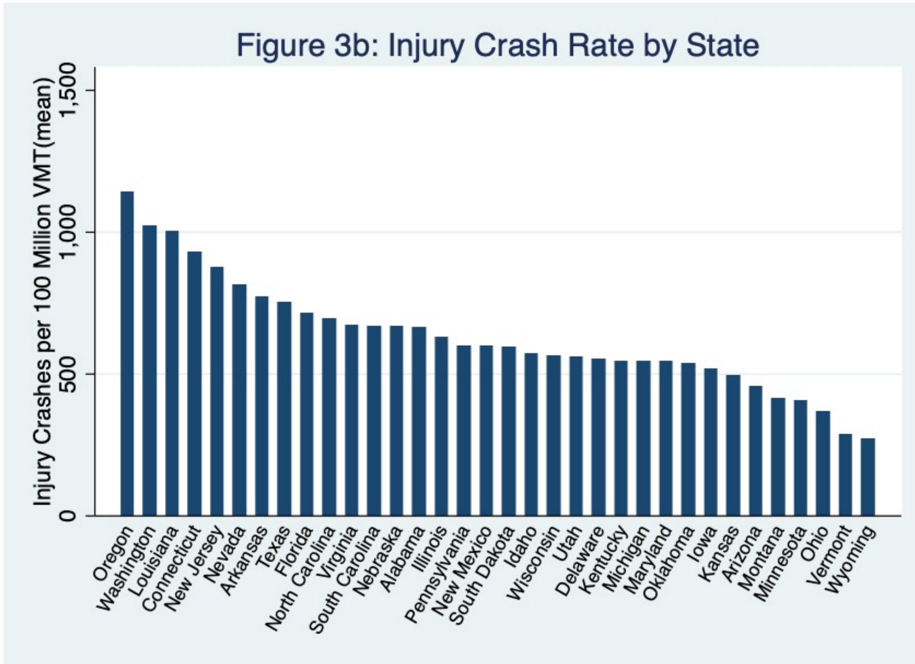


Figure 3c: Fatal Crash Rate by State

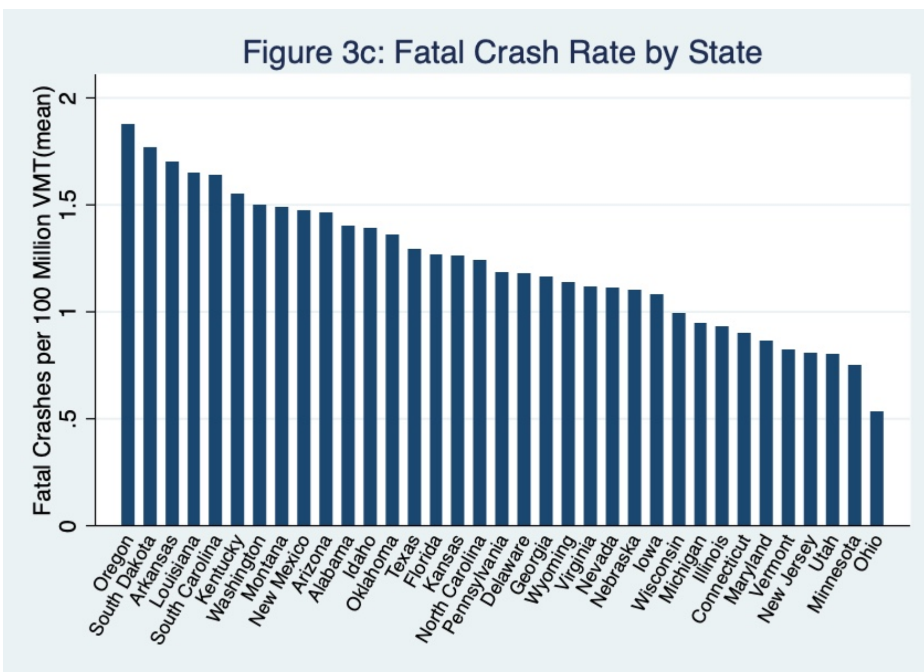
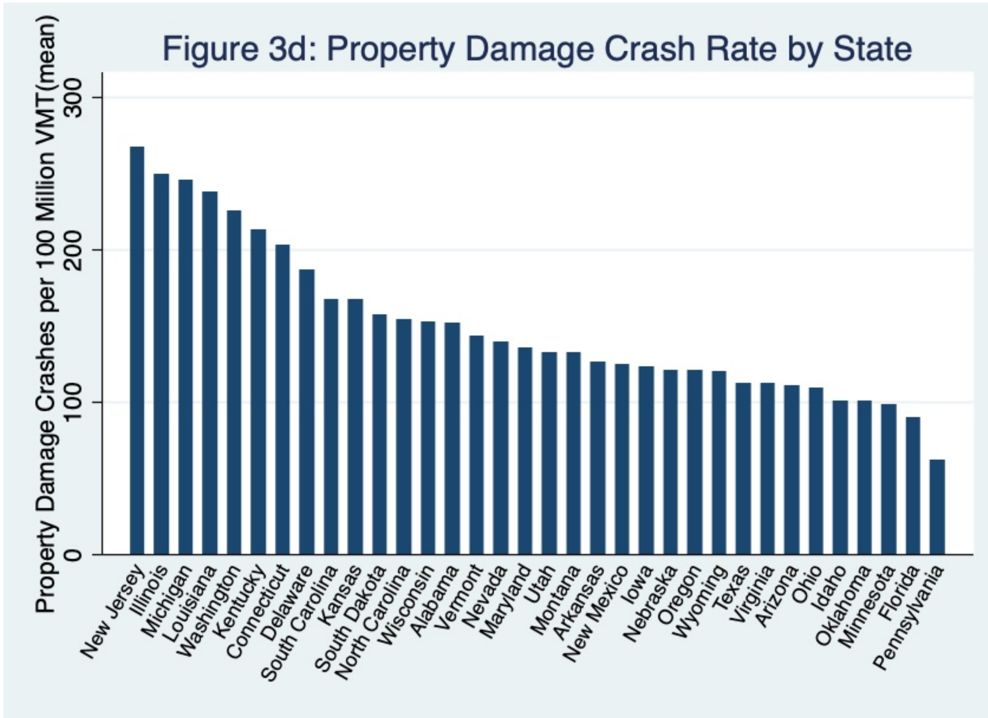


Figure 3d: Property Damage Crash Rate by State



B. Control Variables

Year and state fixed effects are included in all regression specifications, and the All-Accidents Dataset has crude crash data without control variables. State time-varying factors could influence accidents in ways that are unrelated to marijuana laws. I include the two most used state time-varying controls for accident studies: population and unemployment rate by state-year. A higher population is correlated with more accidents. A lower unemployment rate is also correlated with more accidents because employed people (a) drive to and from work more regularly and (b) have more spending power, so they are more likely to drive to spend their money. I merge population and unemployment rate data from the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics, 2022).

C. Marijuana Laws

As of 2022, 36 states and the District of Columbia have either a medical marijuana law ("MML") or recreational marijuana law ("RML") in place. I rely on McMichael et al. (2020), procon.org, pdaps.org, news articles, and my own Westlaw research on legal provisions for pinpointing when these laws become effective. Table 1 below shows the states that have recreational or medical laws in place alongside the years of enactment.

Table 1: Adoption of MMLs and RMLs

State	MML Year	RML Year
Alabama	2021	-
Alaska	1998	2015
Arizona	2010	2020
Arkansas	2016	-
California	1996	2016
Colorado	2000	2012
Connecticut	2012	2021
Delaware	2011	-
Washington, D.C.	2011	2015
Florida	2017	-
Hawaii	2000	-
Illinois	2014	2020
Louisiana	2019	-
Maine	1999	2016
Maryland	2014	-
Massachusetts	2013	2016
Michigan	2008	2018
Minnesota	2014	-
Missouri	2018	-
Montana	2004	2021
Nevada	2000	2017
New Hampshire	2013	-
New Jersey	2010	2021
New Mexico	2007	2021
New York	2014	2021
North Dakota	2016	-
Ohio	2016	-
Oklahoma	2018	-
Oregon	1998	2015
Pennsylvania	2016	-
Rhode Island	2006	-
South Dakota	2021	-
Utah	2018	-
Vermont	2004	2018
Virginia	2020	2021
Washington	1998	2012
West Virginia	2019	-

IV. Methodology

This paper relies on the plausibly exogenous increases in marijuana use that occur after the implementation of marijuana legalization laws. Other work shows that MMLs cause an approximate 14% increase in use (Wen et al., 2015) while RMLs cause a roughly 30% increase in use (Maclean et al., 2020; Dave et al., 2022), with this RML-based use increase highest for males and those 25 or older (Rotermann, 2019; Weinberger et al., 2022; Hollingsworth et al., 2022). I take advantage of the fact that MMLs and RMLs occur at different times in different states by using a traditional difference-in-difference design with state and year fixed effects represented by the following regression specification:

$$Y_{st} = \beta_1 MML_{st} + \beta_2 RML_{st} + \pi X_{st} + \gamma_s + \lambda_t + \varepsilon_{st}$$

The main dependent variable of interest, Y, is a crash statistic for state s in year t. I look at a variety of crash statistics, including total crashes, injury crashes, property damage crashes, fatal crashes, as well as crash rates (i.e., crashes per 100 million VMT) for each of these categories. MML_{st} refers to whether state s had a medical marijuana law in year t, while RML_{st} indicates whether state s had a recreational marijuana law in place in year t. X is a vector of state time-varying controls, including the state's unemployment rate in year t as well as the state's population in year t. γ represents state fixed effects and λ represents year fixed effects. Errors are clustered at the state level.

Goodman-Bacon (2021) showed that the comparison of later treated units to earlier, already treated units in a standard two-way-fixed-effects difference-in-difference regression design can introduce estimates of the wrong sign that are biased. Several new estimators and approaches avoid this "bad" comparison of later treated to earlier treated units, and I incorporate one such design called a stacked regression specification. I re-organize the data into stacks of three groups—never treated, early treated, and later treated states—and I am thus able to select which comparisons of states occur in my regression specification.

The stacked regression design requires post-period data and a balanced panel, so I do not include states that passed marijuana laws in 2021 so that I have post-period data. Table 2 below shows the stacked treatment cohorts for RMLs. I focus on RMLs because I find effects for RMLs but not for MMLs in my traditional two-way-fixed-effects design.

Table 2: Stacked Regression Treatment Cohorts

Cohort	First Year of Treatment	States
1	2012	Washington
2	2015	Alaska; Oregon; Washington, D.C.
3	2016	Maine; Massachusetts
4	2017	Nevada
5	2018	Vermont; Michigan
6	2020	Arizona; Illinois

For my stacked regression design, I use the following regression specification:

$$Y_{sy} = \beta^{stacked} RML_{sy} + \pi X_{sy} + \gamma_{sz} + \lambda_{yz} + \varepsilon_{zsy}$$

Y represents the crash variable for state s in year y, while RML takes on a value of 1 if a recreational marijuana law is in place in state s during or after year y and takes on a value of 0 otherwise. X is the same set of controls used in the traditional two-way-fixed-effects ("TWFE") model above. Z represents stacks in the stacked regression specification. I include state-by-stack fixed effects and year-by-stack fixed effects in this specification. State-by-stack fixed effects are analogous to state fixed effects in the TWFE specification, while year-by-stack fixed effects ensure that all comparisons occur within stacks.

V. **Results**

Using a traditional TWFE design and a stacked design, Tables 3a and 3b show the effects of MMLs and RMLs on total crashes as well as crashes of various severity types: fatal, injury, and property damage only crashes. Though these categories can have overlap in some datasets (e.g., people who are killed are also injured), these categories are mutually exclusive in this dataset. Accordingly, the sum of fatal, injury, and property damage only crashes equal the total crashes in the All-Accidents Dataset.

Table 3a: Raw Crash Counts TWFE

	(1)	(2)	(3)	(4)
VARIABLES	Total Crashes	Fatal Crashes	Injury Crashes	Property Damage Crashes
MML	-4,777.69	-10.73	-1,570.88	-3,079.12
	(4,409.94)	(27.08)	(1,245.56)	(3,825.93)
RML	-8,953.72***	-1.63	-554.49	-8,424.64***
	(3,292.96)	(21.61)	(1,051.65)	(3,006.72)
Constant	73,850.58***	840.42***	51,728.10***	42,144.95***
	(17,933.01)	(96.51)	(3,335.97)	(14,081.03)
Observations	791	766	756	756
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3b: Raw Crash Counts Stacked

VARIABLES	(1) Total Crashes	(2) Fatal Crashes	(3) Injury Crashes	(4) Property Damage Crashes
RML	-11,084.31**	5.31	-596.93	-10,371.19**
	(5,047.58)	(18.86)	(1,217.05)	(4,459.39)
Constant	45,794.13**	598.83***	47,883.16***	21,776.53
	(22,065.35)	(109.35)	(4,755.96)	(16,700.18)
Observations	3,790	3,657	3,620	3,620
Controls	Yes	Yes	Yes	Yes
State-by-Stack FE	Yes	Yes	Yes	Yes
Year-by-Stack FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results here indicate that MMLs have no impact on crash outcomes, while RMLs lead to a reduction in total crashes. Column 4 elucidates that the effects of RMLs on crashes are concentrated among property damage crashes, which are crashes that involve no injuries or deaths. On average, there are between 8,953 to 11,084 fewer crashes after a state passes an RML.

I next look to see whether the raw crash changes identified in Tables 3a and 3b correspond to similar results for crash rates. I follow the prior literature on crash rates by using crashes per 100 million vehicle miles traveled ("VMT") as the dependent variable in columns 1 through 4 of Tables 4a and 4b.

Table 4a: Crash Rates TWFE

VARIABLES	(1) Total Rate	(2) Injury Rate	(3) Fatal Rate	(4) Property Damage Rate
MML	5.29	-12.42	0.04	8.66
	(9.71)	(15.72)	(0.05)	(9.56)
RML	-12.97	55.35	0.09	-19.33**
	(13.58)	(66.96)	(0.12)	(8.92)
Constant	239.40***	1,005.54***	2.88***	141.48***
	(17.16)	(39.15)	(0.08)	(18.96)
Observations	643	608	618	608
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4b: Crash Rates Stacked

VARIABLES	(1) Total Rate	(2) Injury Rate	(3) Fatal Rate	(4) Property Damage Rate
RML	-8.48	70.83	0.08	-16.81*
	(14.31)	(69.17)	(0.07)	(8.78)
Constant	197.50***	740.75***	1.21***	131.64***
	(16.84)	(56.02)	(0.10)	(19.63)
Observations	3,053	2,883	2,920	2,883
Controls	Yes	Yes	Yes	Yes
State-by-Stack FE	Yes	Yes	Yes	Yes
Year-by-Stack FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results in these columns are largely consistent with Tables 3a to 3b and show that MMLs cause no change in accident rates while RMLs cause a decrease in the property damage crash rate for the stacked regression specification. The point estimate for the total crash rate is still negative, but loses statistical significance.

Tables 5a and 5b below look at whether the severity of crashes change after the implementation of MMLs and RMLs. Column 1 refers to the percent of accidents that are fatal, while column 2 indicates the number of injuries per crash.

Table 5a: Crash Severity TWFE

	(1)	(2)
VARIABLES	Share Fatal	Injuries per Crash
MML	-0.00	-0.02
	(0.02)	(0.01)
RML	0.07**	0.04*
	(0.03)	(0.02)
Constant	1.17***	0.56***
	(0.04)	(0.05)
Observations	765	720
State FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5b: Crash Severity Stacked

	(1)	(2)
VARIABLES	Share Fatal	Injuries per Crash
RML	0.06**	0.04**
	(0.02)	(0.02)
Constant	0.67***	0.63***
	(0.05)	(0.05)
Observations	3,651	3,470
Controls	Yes	Yes
State-by-Stack FE	Yes	Yes
Year-by-Stack FE	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Since RMLs cause property damage crashes to decrease but do not cause a decrease in the other two crash types—fatal and injury crashes—it is not surprising that the percent of fatal accidents and injuries per crash both increase following the passage of RMLs.

VI. <u>Mechanism</u>

A. Alcohol to Marijuana Substitution

Some states do not include alcohol crash information or, if they do, it is not recorded the same way across states. For example, some states have information on alcohol "fatalities", while others have information on alcohol "fatal crashes". These are related but different variables. Figures 6a and 6b show the impacts of MMLs and RMLs on alcohol-related crashes and alcohol-related crash rates. There are more observations in Table 6a than there are in Table 6b because crash rates require information on the annual number of VMT, while raw crash numbers do not.

Table 6a: Marijuana Laws and Alcohol Crashes

VARIABLES	(1) Total Alcohol Crashes	(2) Fatal Alcohol Crashes	(3) Injury Alcohol Crashes	(4) Property Damage Alcohol Crashes
MML	368.35	-13.26	187.06	456.41
	(684.55)	(11.24)	(332.16)	(701.58)
RML	223.35	12.56	474.26**	146.27
	(427.23)	(25.66)	(200.47)	(354.66)
Constant	6,108.77	214.64***	5,484.48***	161.58
	(4,063.67)	(39.01)	(1,161.64)	(3,154.71)
Obs.	451	448	340	326
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6b: Marijuana Laws and Alcohol Crash Rates

VARIABLES	(1) Total Alcohol Crash Rate	(2) Fatal Alcohol Crash Rate	(3) Injury Alcohol Crash Rate	(4) Property Damage Alcohol Crash Rate
MML	2.89	0.01	1.14	3.30
	(3.02)	(0.03)	(1.37)	(3.48)
RML	1.44	0.06**	1.11	1.36
	(1.69)	(0.03)	(0.84)	(1.62)
Constant	13.72	1.14***	5.30	-7.43
	(20.05)	(0.07)	(5.76)	(15.00)
Obs.	383	380	280	266
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The key takeaway from Tables 6a and 6b is that there is not a clear substitution story. In other words, it is not the case that there is a decrease in RML-induced alcohol crashes that would explain the previously identified decrease in overall crashes. Instead, these tables suggest that RMLs might cause an increase in alcohol injury crashes as well as an increase in the fatal alcohol crash rate. There is no evidence of drivers switching from alcohol to marijuana after RMLs; this instead leaves room for the possibility that alcohol and marijuana are complements for drivers in this sample. However, given the fact that alcohol crash data is spottier in the All-Accidents Dataset, the alcohol to marijuana substitution possibility cannot be ruled out.

B. Less Driving? Population Changes?

RMLs might cause a reduction in total crashes or in property damage only crashes through several channels, and Tables 6a and 6b do not support an alcohol to marijuana substitution story. It might instead be the case that RMLs cause people to drive less, which would mean that the annual number of vehicle miles traveled ("VMT") would decrease. Alternatively, it could be the case that the passage of an RML is correlated with population changes that—while not necessarily caused by the passage of the marijuana law—would incidentally affect crash outcomes. To test these possibilities, in Tables 7a and 7b I separately regress vehicle miles traveled, registered vehicles, licensed drivers, and total population in a state on MMLs and RMLs using both the TWFE and stacked regression specifications.

Table 7a: Vehicle Statistics TWFE

	(1)	(2)	(3)	(4)
VARIABLES	VMT	Registered Vehicles	Licensed Drivers	Total Population
MML	-746.70	145,011.01	49,774.38	-11,438.15
	(840.87)	(196,640.53)	(50,196.15)	(172,446.65)
RML	-2,402.35**	-20,315.47	-136,648.05*	-223,750.50
	(1,044.36)	(189,764.20)	(70,039.93)	(181,884.76)
Constant	21,053.57***	370,603.05	952,234.15***	3,196,651.13***
	(3,822.22)	(1,038,442.69)	(241,802.06)	(259,937.59)
Observations	644	343	343	797
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7b: Vehicle Statistics Stacked

VARIABLES	(1) VMT	(2) Registered Vehicles	(3) Licensed Drivers	(4) Total Population
RML	-1,824.93	-105,254.71	-170,161.97*	-123,759.90
	(1,122.17)	(159,939.58)	(95,411.93)	(139,979.08)
Constant	5,116.22	1,419,091.07**	1,209,040.74***	4,211,254.54***
	(7,601.49)	(502,150.45)	(323,249.69)	(202,469.72)
Observations	3,059	1,693	1,612	3,826
Controls	Yes	Yes	Yes	Yes
State-by-Stack FE	Yes	Yes	Yes	Yes
Year-by-Stack FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 7a and 7b show that there is no discernable change in VMT, registered vehicles, licensed drivers, or total population following the passage of marijuana liberalization policies. It is still possible that while a state's total population does not change following RML enactment, the composition of the population could change. For example, safer drivers could be more likely to move to states with recently enacted RMLs, while dangerous drivers could be more likely to leave such states. The data here do not have a way to test this possibility, but it seems unlikely given the lack of changes in the total population.

C. *Ride Sharing*

First, RMLs could cause drivers to rely on public transportation and ride-sharing options more heavily. The lack of a decrease in VMT means that people are traveling the same amount before and after RMLs. So, this could mean that marijuana users do not wish to drive when using the drug and instead are more likely to use a safer transportation alternative. Drivers could be less likely to drive and more likely to rely on ride-sharing or public transportation if they (a) have more sense-of-mind when using marijuana compared to using alcohol so as to choose not to drive, (b) use marijuana at times when they are more able to plan for other transportation options,[6] or (c) are fearful of consequences from high driving driving. This would explain the decrease in total crashes as well as the decrease in property damage crashes when RMLs are passed. There need not be an alcohol-to-marijuana substitution for this to occur, as people who use marijuana and use alternative transportation could be in safer cars than non-marijuana-using drivers. In fact, there is such evidence suggesting that ride-share drivers from companies like Uber and Lyft are safer than those who do not drive for ride-share companies (Lien, 2016).

D. Venue Shift

If the above-mentioned mechanisms—alcohol to marijuana substitution, changes in driving or in a state's population, likelihood of relying on ride-sharing or public transportation—do not explain the reduction in total crashes and in property damage crashes identified in this paper, then a venue shift might instead be the answer. It is possible that the passage of marijuana laws causes people to engage in activities in areas that are safer for driving. This could be true if, for example, people are more likely to gather at someone's residence instead of in a public

[6] Drunk driving might happen more often than high driving because people usually drive their cars to work, and sometimes part take in the culture of post-work "happy hour." There is not an analogous "happy hour" of people consuming marijuana at public establishments directly after work. Therefore, an increase in marijuana consumption might lead to a decrease in happy hour attendance—where people already have cars at work—that leads to an increase in ride-sharing or public transportation, which causes a decrease in total accidents.

establishment where more cars are nearby. This possibility cannot be tested with the data here but cannot be ruled out.

E. *Data, Laws, and Coding*

Another possible explanation is that differences in judgment calls surrounding coding might explain the results identified in this paper. As has been noted in the background section of this paper, the economics literature on the impacts of RMLs on fatal crashes has produced somewhat mixed results, with most papers suggesting that RMLs cause an increase in fatal crashes. There is no definitive reason why the prior literature looking at the impacts of RMLs on fatal crashes is not consistent. Worse yet, while most papers in the economics literature indicate that RMLs cause an increase in fatal crashes, almost all papers therein suggest that MMLs cause a *decrease* in fatal crashes. The literature has yet to legitimately acknowledge, let alone explain, the discrepancy in these findings.

Ex ante, it should not be expected that MMLs cause fatal crashes to decrease while RMLs cause fatal crashes to increase. These papers rely on the same underlying principle: changes to the legality of marijuana provide plausibly exogenous changes in marijuana use rates, as evidenced by the fact that both MMLs and RMLs cause an increase in marijuana use rates. There is therefore no clear reason why the literature has produced such mixed results. This is the case not just for the effects of marijuana laws on car crashes but also for the effects of marijuana laws on opioid-related outcomes. These are the most two most studied topics in the marijuana literature, yet in both areas there exist studies with inconsistent results.

Instead of an alcohol substitution or Uber story explaining the findings identified in this paper, it could be case that the economics literature on marijuana is at a crossroads. There exist many areas for methodological choices in this sub-field when analyzing the impacts of marijuana laws on outcomes: law passage date versus law enactment date versus first dispensary opening date, city versus state level analysis, and whether to include both MMLs and RMLs in the same regression specifications.[7] Divergent coding choices on these dimensions all result in publications in top health economics journals. Accordingly, it could be the case that a researcher's subjective choice of how to code these marijuana laws has more of an impact on dependent variable outcomes than does any other mechanism-related explanations. This seems like the most pressing issue in this sub-field and the most likely explanation.

VII. Discussion & Conclusion

This is the first paper to use a dataset with all crashes in 44 U.S. states in the economics literature and it is the first to do so in the marijuana space. With this unique dataset, I find no crash outcome changes for MMLs and find that RMLs are associated with approximate 10,000 fewer crashes per year. This decrease in total crashes is concentrated in property-damage-only crashes, which see a roughly 8,425 decrease per year. This result is consistent with recent work finding that RMLs cause no change in fatal crashes (Hansen et al., 2020). This result is also consistent with previous studies in terms of magnitude. There is an average of 83,438.75 property damage crashes and 124,236.4 total crashes per state-year in the All-Accidents Dataset,

[7] A related question is whether the 50-state difference-in-difference design (or even sub-state level analysis) can be conducted for marijuana laws due to the heterogeneity of laws and difference in use rate increases. The first-stage literature elucidates that MMLs and RMLs both cause increases in marijuana use rates, but it is not clear (a) how these increases differ by state and (b) how these increases in use rates change over time after the laws are enacted. It could be the case that some states should be re-weighted to reflect relatively higher use rate increases.

so the figures identified here represent a 10.1 percent reduction in property damage crashes, which is in line with previous studies that rely on fatal crash data.

The mechanism underlying the RML-related decreases in crashes identified in this paper is not well understood. There are several possibilities, including a substitution from alcohol to marijuana or an increase in the likelihood of ride sharing services. The lack of a clear mechanism in this paper, as well inconsistent findings in the marijuana-car-crash literature more generally, underscores the centrality of coding choices in the marijuana space. This subjectivity surfaces as the most likely reason for findings in the crash literature that do not comport with one another.

Looking at all crashes instead of just fatal ones is a major contribution given the fact that over 99 percent of crash activity is non-fatal. In the marijuana space, the use of non-fatal crash data is crucial because most marijuana-induced crashes are non-fatal. In other words, the vast majority of crashes are non-fatal, and that is true whether those crashes are rooted in distracted driving, speeding, alcoholic intoxication, or driving while high on marijuana. Therefore, if we are to understand the impacts that marijuana laws have on driving behavior, the first place to look should be non-fatal crash data.

The more general relationship between fatal and non-fatal driving behavior is a question left for future research, but this paper highlights the importance of better understanding that interplay. Fatal crashes have the highest social cost per crash, but they are probably also the most difficult to impact through public policy due to their rarity. Accordingly, a shift towards studying non-fatal crashes is warranted in the economics literature, and this paper is key in marking that shift.

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Chapter 3: Medical Marijuana Laws: Legitimate Medical Care or Cannabis Gatekeeping?

Abstract

This paper examines the relationship between medical marijuana programs and recreational marijuana programs to better understand if this relationship is causal and why consumers switch from one to the other. I first document the substitution from medical to recreational cannabis that occurs when the latter becomes available. I add causal evidence for this relationship by comparing Arizona's medical cannabis trends before- and after- recreational sales initiation to New Mexico's medical cannabis trends during the same period, and I find that Arizona saw a dip in medical cannabis while New Mexico did not. I then try to tease out why consumers switch to recreational marijuana. It could be that marijuana is simply easier to obtain, so consumers who view cannabis in a medical sense still turn to the recreational market. I find evidence to the contrary. Novice cannabis users are more likely to prefer edibles than are experienced users, and the share of edibles as a fraction of total cannabis increases in the medical sector after recreational sales begin in Arizona. In New Mexico, almost all qualifying conditions decline on the medical registries, but the few that do not are both hard to fake and more likely to be the result of physician-initiated prescribing behavior. Overall, this indicates that a large fraction of consumers likely uses medical cannabis programs to obtain drugs rather than to explore expert medical counsel from healthcare providers. This study is important for states contemplating the implementation of medical or recreational cannabis regimes and for states considering similar programs for other drugs, such as psychedelic therapies.

I. Introduction

Every state with a recreational marijuana law—more commonly known as an "adult use" law—has previously first had a medical marijuana law in place as well. When a state with a medical marijuana law passes a recreational law and begins recreational sales, medical sales and medical patient numbers typically drop (Abbott, 2023). There seems to therefore be significant substitution between recreational and medical cannabis. However, it could be the case that some other change contemporaneous with the recreational law (instead of the recreational law itself) leads to the drop in the stock of medical cannabis users. To better test this possibility, a comparator state that did not pass a recreational law at the same time can be used as a control group to see how that comparator state's medical registry changes during the same period. This paper presents such a test by comparing medical cannabis figures for Arizona before and after its January 2021 recreational sales began to New Mexico's medical cannabis figures during the same period. The results here support the notion that recreational sales, as opposed to some other change, appear to cause the drop in medical patients and medical sales in a state. Importantly, it is the case that medical sales and medical patients do not vanish when recreational laws arise, so this means there are benefits and costs to both regimes.

Given the substitution from medical to recreational sales after the latter becomes available, the next natural question is what drives this substitution? On the one hand, this could reflect a situation wherein it is simply easier to obtain marijuana on the recreational market. There is less paperwork, no requirements for obtaining a medical card nor a doctor's prescription, and less red tape in the recreational space.[8] This says little about marijuana and more about consumers' disfavor for government bureaucracies. On the other hand, a switch from medical to recreational marijuana could signal that medical patients are not "patients" in the typical sense of the word. Instead of turning to doctors for medical expertise[9], advice, counsel, and medication, they turn to doctors as drug gatekeepers. In this scenario, the patients seek doctors with the direct goal of obtaining cannabis—to self-medicate or for personal pleasure—instead of the doctors steering patients to cannabis for legitimate, science-backed, therapeutic relief. This paper provides evidence that the latter gatekeeper function seems to occur in medical marijuana regimes. In New Mexico, there are a few qualifying conditions that do not see a pronounced drop in medical patient numbers, and these qualifying conditions also appear to be those wherein physician expertise is likely. This could mean that for most qualifying conditions, switching from medical to recreational marijuana might be the result of a reduction in gatekeeper power. In Arizona, there is an increase in the medical registry's fraction of cannabis-infused edibles purchased when recreational sales begin, which is also consistent with a potential gatekeeper story.

[8] As will be discussed, there are benefits to purchasing from either regime. For instance, there are stronger legal protections for those who buy medical cannabis than for those who buy recreational cannabis.
[9] Seeking medical counsel is not dispositive in disentangling this dynamic because people who take over-the-counter products such as acetaminophen need not always consult a healthcare provider before doing so. However, the medical justifications for cannabis are not as well established, so taking cannabis without physician counsel is different in this case when compared to taking well-established over-the-counter drugs.

II. **Background**

A consumer's decision to switch from medical to recreational marijuana depends primarily on two factors: purchasing motivation and acquisitional ease. In terms of purchasing motivation, a consumer will, *ceteris paribus*, be more likely to stay on the medical program if his doctor is the one who initiated the cannabis prescription. On the other hand, a patient who initiates the cannabis discussion with the doctor is less likely to stay on the medical program. Whether a patient views the medical cannabis program as an opportunity to receive expert physicians' counsel on a new class of therapies or as a de facto source of recreational drugs with unavoidable physician transaction costs is largely orthogonal to the intricacies of how a state establishes its medical marijuana program.

In terms of acquisitional ease, a consumer will use whichever system provides the most favorable cost-benefit analysis. Consumers place different values on the costs and benefits of these different marijuana programs, so there exists heterogeneity in the types of patients who might opt for one system over the other. Table 1 below outlines the key differences between medical and recreational cannabis regimes in Arizona and New Mexico.

Table 1: Benefits and Costs of Medical versus Recreational Marijuana Programs

	Medical Marijuana	Recreational Marijuana
Excise Tax	✗	✓
Requires Qualifying Medical Condition	✓	✗
Waiting Period for Permit (Card) to Obtain Cannabis	✓	✗
Must be 21 or Older	✗	✓
State-Level Protections from Employers	✓	✗
Legal Reciprocity with Other States' Medical Regimes	✓	✗
Must See Physician before Purchasing Marijuana	✓	✗
Card Updating Required for Change of Address	✓	✗

An excise tax on recreational but not medical marijuana means that recreational marijuana is more expensive than medical marijuana in Arizona and New Mexico. However, other hidden costs drive up the overall price of medical marijuana. Namely, under medical regimes, users must pay for a doctor consultation to be prescribed the drug, which averages around $75 to $100 per year (Green Health Docs, 2023). For consumers under 21 and for those who place a high value on establishing heightened job security, medical marijuana programs are more attractive relative to recreational marijuana programs. Accordingly, Table 1 shows that a user's individualized preference set will determine her likelihood of preferring medical or recreational marijuana.

Medical marijuana laws differ by state, so the costs and benefits of staying part of the medical marijuana program also vary by state. Table 2 below outlines some of the key differences between the marijuana regimes in Arizona and New Mexico.

Table 2: Differences between Marijuana Regimes in Arizona and New Mexico

	Arizona	New Mexico
Medical Sales Tax	5.6%	None
Recreational Excise Tax	16%	12%
Physician Appointment Charge (Yearly Estimate)	$75-100	$99
Medical Card Initial Fee (Initial Card Fee for SNAP Eligible Residents)	$150 ($75)	Free
Medical Card Renewal Fee (Renewal Card Fee for SNAP Eligible Residents)	$150 ($75)	Free
Time to Receive Medical Card after Application	5 Days	5 Days
Allows Telehealth (Video) Physician Appointments	✓	✓
Medical Card Validity (Years)	2 Years	1 Year
Number of Qualifying Conditions	13	28

Table 2 shows that the fees, requirements, and details of marijuana programs are different in Arizona and New Mexico. For example, if a person suffers from a medical affliction that is a qualifying condition in New Mexico but not in Arizona, then New Mexico's medical marijuana program might attract more patients per capita and might also have a relatively higher share of patients who initiate marijuana use at the discretion of a physician. At the same time, some challenges identified in Table 1 apply to consumers in both Arizona and New Mexico; if consumers face too high of costs on the medical market relative to the recreational market in either state, then this could cause a system-wide shift in consumers moving to the recreational regime that is independent of gatekeeper views or other intricacies of the states' respective marijuana programs. Parsing out which explanation is more likely requires a deeper analysis of the data in each state.

III. Data

A. Why Arizona and New Mexico?

This paper relies on data from Arizona and New Mexico to understand the impacts that recreational marijuana sales have on choices to consume medical marijuana. These states are appropriate choices for this paper because they (i) are geographic neighbors with one another and therefore good comparators, (ii) enacted recreational marijuana laws at different times, (iii) include detailed monthly data on medical cannabis patients, (iv) publicize monthly recreational and medical sales data after recreational sales begin, and (v) began recreational sales relatively quickly after the enactment of their respective recreational marijuana laws. Table 3 below details each state's MML enactment date, RML enactment date, RML sales start date, and time window of data used in this paper.

Table 3: Data Overview, Arizona and New Mexico Marijuana Laws

	MML Date	RML Date	RML Sales Begin	Analytic Data Window
Arizona	2010	Nov. 30, 2020	Jan. 22, 2021	Jan. 2016 – Feb. 2023
New Mexico	2007	April 12, 2021	April 1, 2022	Jan. 2017 – Jan. 2023

B. Sales Data

I include monthly medical and recreational sales data from the Arizona Department of Revenue from January 2021 through December 2022 (Arizona Department of Revenue, 2023). Arizona enacted its recreational law on November 30, 2020, and began sales January 22, 2021, making the state the fastest to bring recreational cannabis to market after the passage of such a law. Arizona began taxing both medical and recreational marijuana in January of 2021. Figure 1a below shows the trends in Arizona's medical and recreational sales for all available months in the dataset.

Figure 1a: Arizona Medical and Recreational Sales

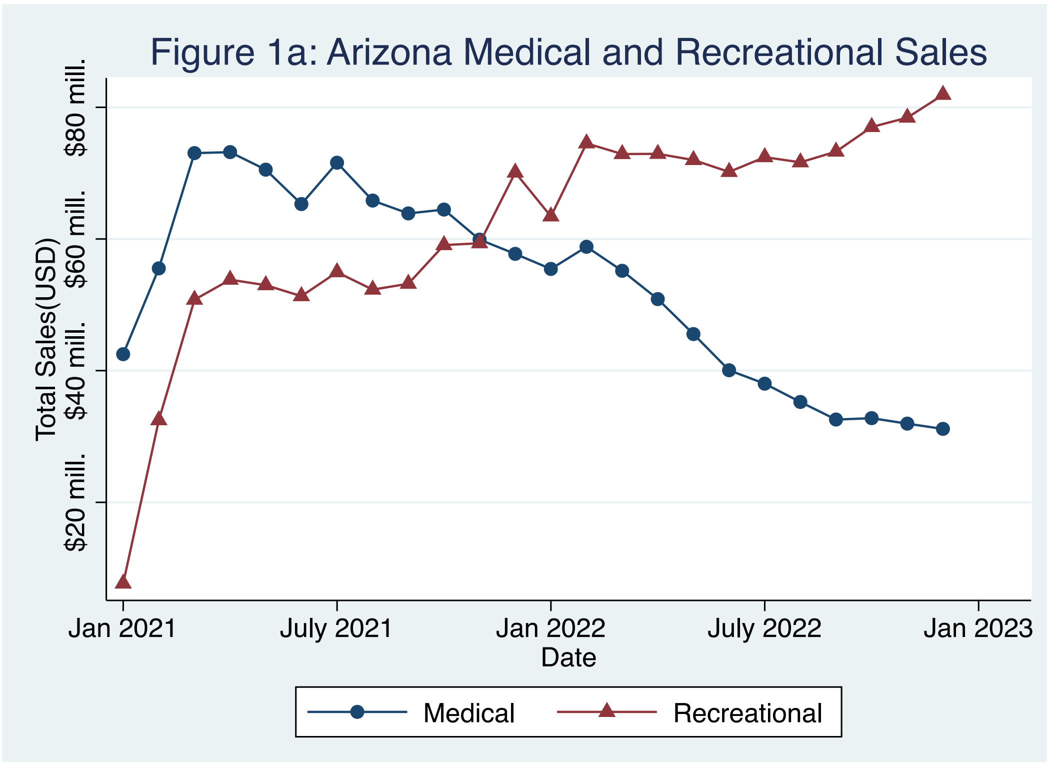


Figure 1a shows that in Arizona, as recreational sales increase, medical cannabis sales decrease. Summing the two lines at any point gives the total amount of taxable marijuana sold in that month of that particular year, which totals more than $100 million in January of 2023.

I rely on the New Mexico Regulation and Licensing Department for monthly medical and recreational cannabis sales data (NMRLD, 2023). New Mexico's recreational sales began in April 2022, just over a year after the passage of its recreational marijuana law. In Figure 1b below, I plot the taxable marijuana sales in New Mexico from April 2022 through February 2023.

Figure 1b: New Mexico Medical and Recreational Sales

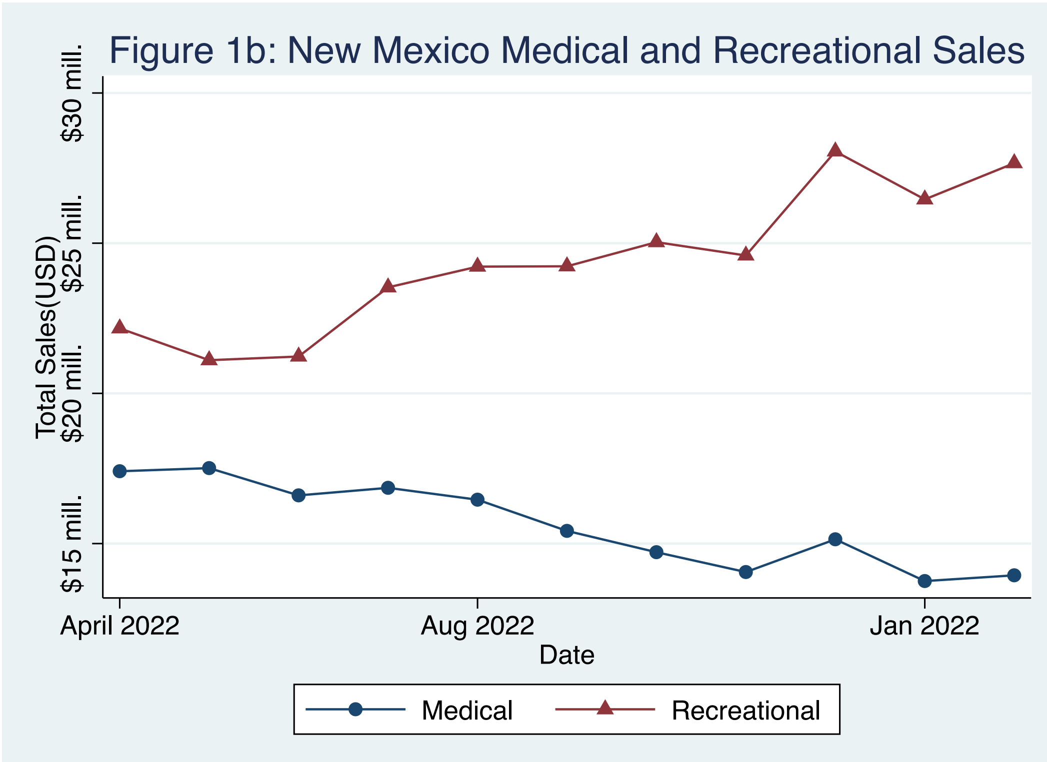


Figure 1b shows that New Mexico and Arizona have similar patterns of medical sales decreasing when recreational sales begin. New Mexico has fewer total sales than does Arizona, which is logical given that Arizona's population is more than three times that of New Mexico's (World Population Review, 2023).

C. Patient Data

For medical cannabis patient statistics, I rely on the New Mexico Department of Health's monthly Medical Cannabis Patient Statistics Reports (NMHD, 2023) and the Arizona Department of Health's Medical Marijuana Monthly Reports (ADHS, 2023). Both sources include the total number of patients on the medical cannabis registries each month as well as the number of patients in each qualifying condition category each month. In Arizona, these reports also include monthly medical cannabis transaction data, which includes the total pounds sold, marijuana (“flower”) pounds sold, and edible pounds sold.

In Arizona, there are 13 qualifying conditions and in New Mexico there are 28. Arizona’s recreational sales began in January of 2021, which is before New Mexico permitted recreational sales. Accordingly, Arizona’s medical registry numbers decline earlier than do New Mexico’s. Table 4 below provides summary statistics of the qualifying conditions in each state in order of frequency on the medical registries in Arizona and New Mexico. This Table represents data from December 2020, just before the medical registries evidenced dips in the patient data.

Table 4: Qualifying Conditions by Order of Frequency, December 2020

Ranking (order of frequency)	Arizona (n)	New Mexico (n)
1	Chronic Pain (276,449)	PTSD (56,038)
2	Cancer (6,283)	Chronic Pain (32,746)
3	PTSD (3,569)	Cancer (5,110)
4	Seizures (1,314)	Painful Peripheral Neuropathy (2,139)
5	Glaucoma (1,164)	Inflammatory Autoimmune-Mediated Arthritis (1,833)
6	Nausea (1,144)	Epilepsy (1,148)
7	Muscle Spasms (1,120)	Obstructive Sleep Apnea (802)
8	HIV/AIDS (1,001)	HIV / AIDS (696)
9	Crohn’s Disease (703)	Multiple Sclerosis (685)
10	Hepatitis C (667)	Opioid Use Disorder (533)
11	Cachexia (604)	Glaucoma (523)
12	Alzheimer’s (131)	Intractable Nausea / Vomiting (486)
13	Sclerosis (38)	Parkinson’s Disease (360)
14	-	Crohn’s Disease (275)
15	-	Anorexia / Cachexia (264)
16	-	Hospice Care (257)
17	-	Ulcerative Colitis (228)
18	-	Damage to the Nervous Tissue of the Spinal Cord (205)
19	-	Autism Spectrum Disorder (111)
20	-	Hepatitis C (90)
21	-	Spasmodic Torticollis (67)
22	-	Alzheimer’s (52)
23	-	Amyotrophic Lateral Sclerosis (25)
24	-	Spinal Muscular Atrophy (13)
25	-	Inclusion Body Myositis (10)
26	-	Huntington’s Disease (9)
27	-	Friedreich’s Ataxia (5)
28	-	Lewy Body Disease (1)

*New Mexico had 104,655 patients on its medical cannabis registry in December 2020, while Arizona had 295,295. Summing the qualifying conditions will result in numbers greater than total patient numbers because patients can exhibit multiple qualifying conditions.

Table 4 shows that there is greater variety in the types of qualifying conditions patients have in New Mexico compared to Arizona, where chronic pain is dominant. In fact, the patient discrepancies between Arizona and New Mexico for the same qualifying condition hints at a possible gatekeeping story. For example, there are 56,038 patients with PTSD in New Mexico while there are only 3,569 PTSD patients in Arizona. In addition, New Mexico's population is less than one-third that of Arizona's. This means that, if the medical registries are reflective of the underlying incidence of PTSD in these states, then PTSD is more than 47 times as common in New Mexico than it is in Arizona. This seems implausible. Instead, it is likely that PTSD is a catch-all for other ailments in New Mexico or that chronic pain in Arizona includes patients who should realistically be classified under the PTSD banner.

IV. <u>Methodology</u>

A. Additional Causal Evidence: New Mexico as a Comparator

Intuitively, the introduction of recreational cannabis sales alongside a concurrent reduction in medical cannabis sales raises the possibility that the former causes the latter. Nonetheless, it could be the case that something besides recreational sales caused the medical cannabis decline. Using a comparator state that did not have recreational sales during this period but did have medical sales would provide additional evidence in trying to disentangle this relationship. This paper does so by comparing (a) Arizona's medical statistics before and after its introduction of recreational sales to (a) New Mexico's medical statistics before and after Arizona's introduction of recreational sales during the same period.

If both Arizona and New Mexico's medical programs both see the same post-recreational declines in medical figures, then this would suggest that something other than Arizona's recreational law is responsible for the medical marijuana declines. However, if New Mexico's trends stay constant alongside Arizona's dips, then this indicates that Arizona's recreational sales caused the decline in the state's medical sales. This will be explored graphically. Importantly, this section drops observations after April 2022, when New Mexico's recreational sales began.

B. Medical Trends Pre- and Post-RML Sales Commencement

Given the additional support for a relationship between the introduction of recreational cannabis and a decline in medical cannabis, a closer inspection of the medical cannabis data might help reveal whether consumers use the medical cannabis regime for a gatekeeper function. A patient's switch from medical cannabis to recreational cannabis could reflect either the doctor-as-medical-expert or the doctor-as-drug-gatekeeper story, so this switching information in isolation does not indicate one possibility over the other. Furthermore, there can exist consumers who are incentivized by either regime. For example, a person who views her doctor as a cannabis gatekeeper might refuse to switch from medical to recreational purchasing because she values the legal protections afforded to her by the medical cannabis system. At the same time, a person who views her doctor as a legitimate healthcare provider might nonetheless switch from medical to recreational cannabis purchasing because she finds it much more convenient to forego the hassle of renewing her medical cannabis card.

Although a medical-to-recreational switch alone does not reveal if a patient views the medical program in a gatekeeper or medical provider function, we might expect there to be differing rates of switching based on how the patient views this dynamic. All else equal, if the doctor raises the idea of cannabis as a therapy to the patient, then a patient would be less likely to switch from medical to recreation cannabis compared to the scenario wherein the patient is the one who used the doctor as a gatekeeper for cannabis. This is the case because the patient would be more likely to rely on the medical provider's expertise in deciding whether to continue using cannabis if the patient-initiated cannabis use at the physician's suggestion.

We should expect to see more medical-seeking patients (as opposed to gatekeeper-seeking patients) in qualifying conditions that are both harder to fake and for which marijuana is not widely viewed as a therapy. Chronic pain is an example of a qualifying condition that is both easy to fake and widely viewed as a candidate for marijuana therapy, so this is the sort of qualifying condition that should see high rates of switching if there are differences across qualifying conditions. If switching patterns are uniform across qualifying conditions, then this would indicate that (a) gatekeeper-oriented patients are evenly distributed across all qualifying conditions, (b) medical marijuana programs do not attract gatekeeper-oriented patients, or (c) both gatekeeper-oriented and medical-expertise-seeking patients switch from medical to recreation regimes at similar rates notwithstanding their aforementioned incentives that differ by qualifying condition.

A final exercise for trying to better grasp whether medical cannabis programs serve a drug-gatekeeper or medical-therapy purpose is the rates at which switching patients substitute away from smoking-oriented cannabis and consumable cannabis. Evidence suggests that experienced cannabis users are more likely than novice cannabis users to prefer smoking as the method of cannabis intake, while novice users are more likely than experienced users to prefer edibles as an intake method (Donnan et al., 2022). By definition, novice cannabis users are more likely than experienced users to be directed by a physician towards marijuana; experienced users, on the other hand, are more likely to solicit physicians who can authorize their marijuana use. Therefore, if there is no gatekeeper function occurring, then the substitution from medical to recreational marijuana is unlikely to differ by intake method. If there is a gatekeeper story occurring, then we should expect to see the percent of edibles sold in the medical registry to increase after the initiation of recreational sales.

V. Results

A. Adding New Evidence: New Mexico as a Comparator for Arizona

Arizona's medical cannabis registry had been growing before recreational cannabis sales began. After recreational sales picked up, medical patient numbers and sales declined each month. Figure 2a shows this trend.

Figure 2a: Arizona Recreational Sales and Medical Patients

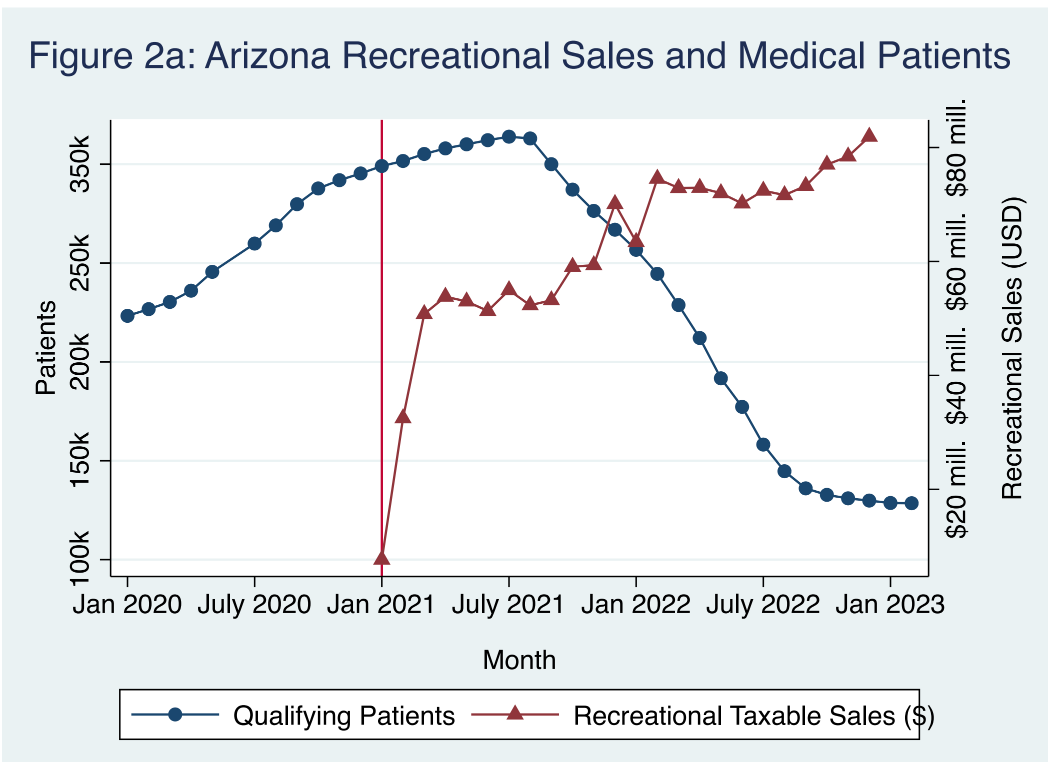
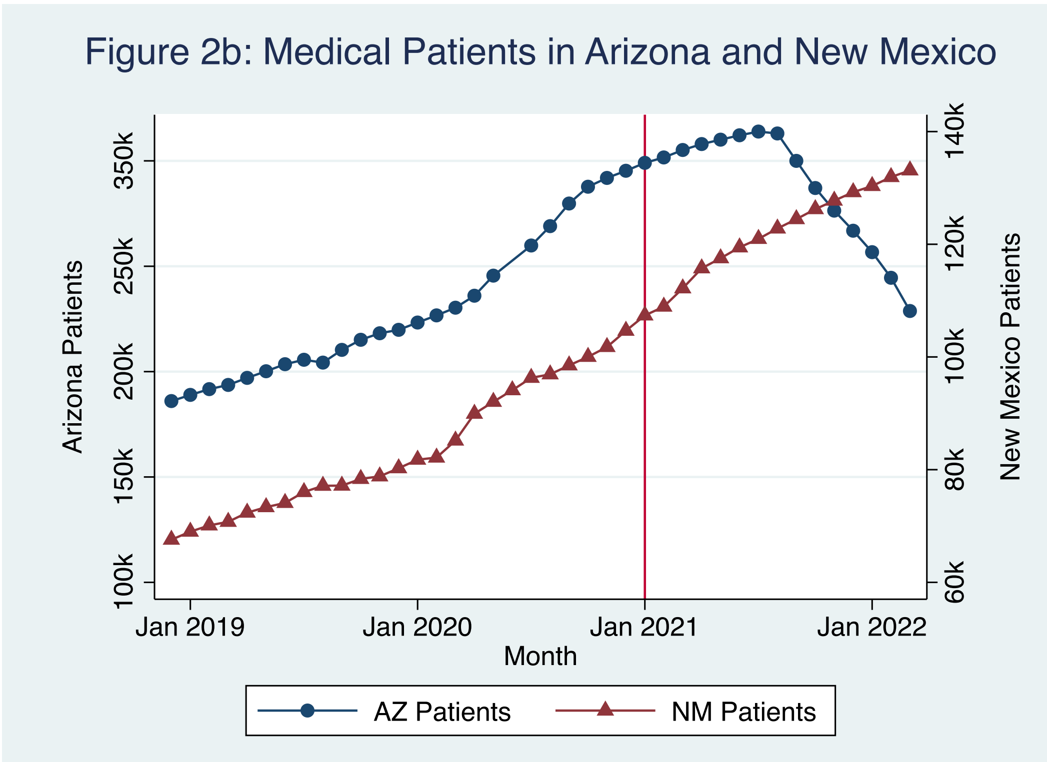


Figure 2a establishes the association between the rollout of recreational sales and the decline in the number of medical cannabis patients. Next, to better understand whether some other simultaneous change is responsible for the drop, I include New Mexico as a comparator group.

Figure 2b: Medical Patients in Arizona and New Mexico



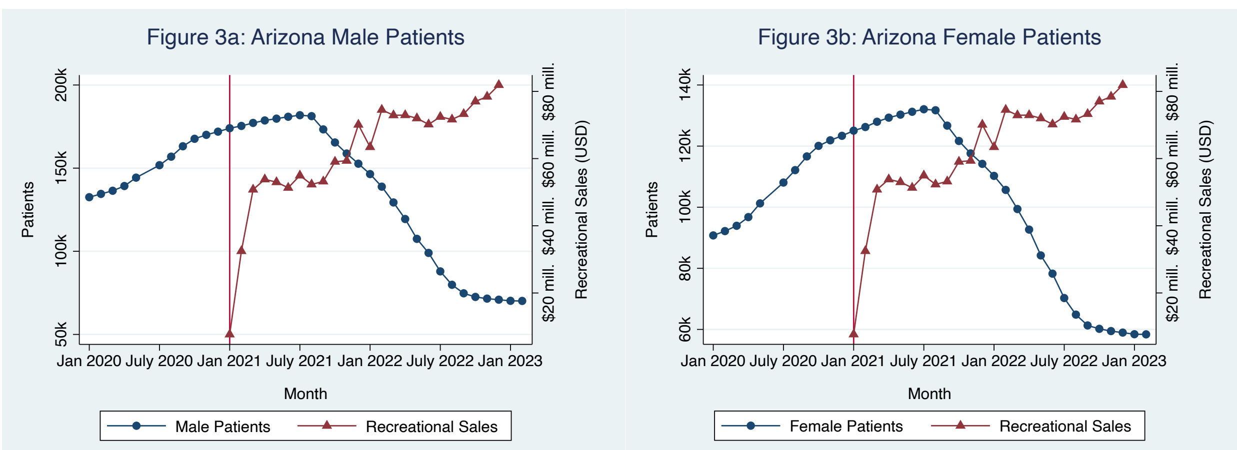
Graphically, Figure 2b suggests that the recreational sales commencement in January 2021 is the event responsible for Arizona's drop in medical patients. Otherwise, if some other nationwide or regional event were responsible for a drop in medical patient reductions, then we would expect to also see a drop in New Mexico medical cannabis patients at the same time. We instead see that New Mexico's medical cannabis registry grows at the same rate before and after the introduction of recreational cannabis in Arizona.

B. Arizona: Medical Trends Pre- and Post-RML Sales Commencement

Given the evidence in this paper that the ramp-up of recreational sales in Arizona seems to have caused the reduction in medical cannabis statistics, this section further explores what might be responsible for that reduction. To do so, I look at trends in medical cannabis reductions to determine whether any particular patient categories display atypical trends during this period. I separately perform the same analysis for Arizona and New Mexico, and I include a vertical line that represents the start of recreational sales in each state. I also include the number of recreational sales, in tens of millions of dollars, over the same period.

Figures 3a and 3b below show Arizona's patient trends over time by sex.

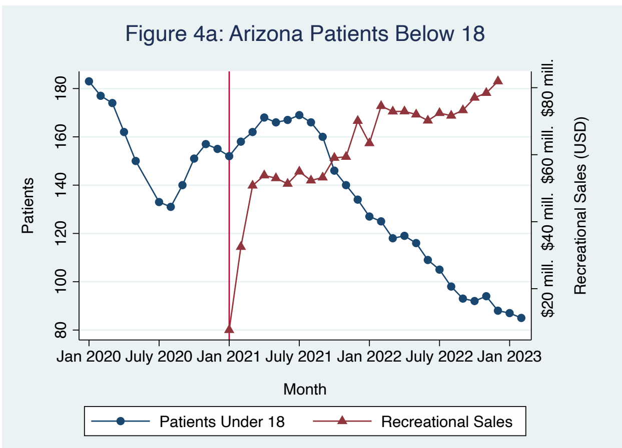
Figures 3a & 3b: Arizona Patients by Sex

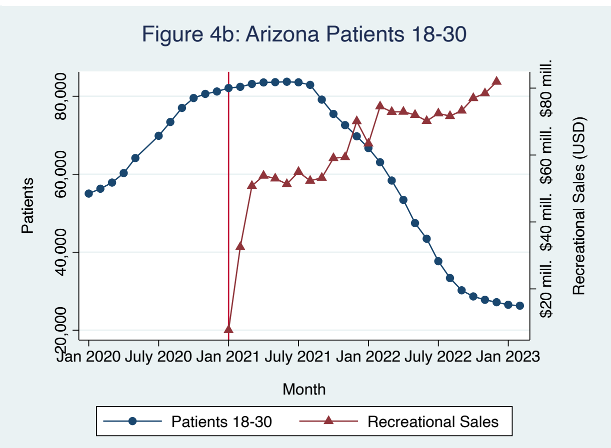


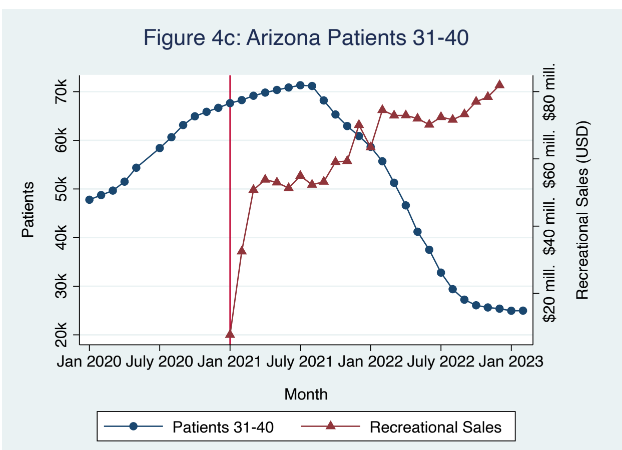
Figures 3a and 3b show that there is a virtually identical trend for both males and females in the Arizona data before and after recreational sales take place in the state. There are more males than females on the medical registry because males are more likely to consume marijuana, but the overall trends appear the same.

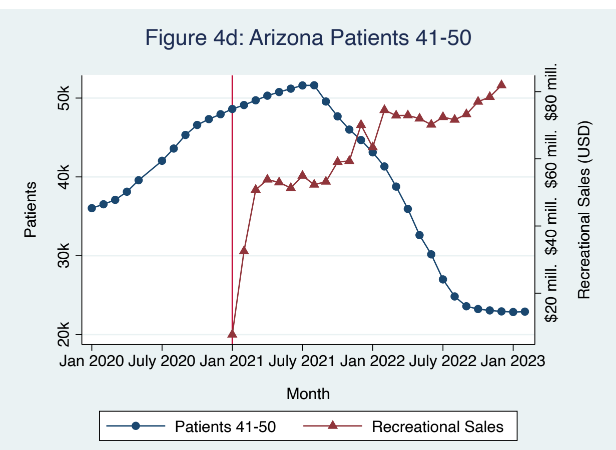
Next, in figures 4a through 4h, I compare trends in Arizona's medical cannabis registrants based on different age classifications. These classifications come from the monthly reporting categories.

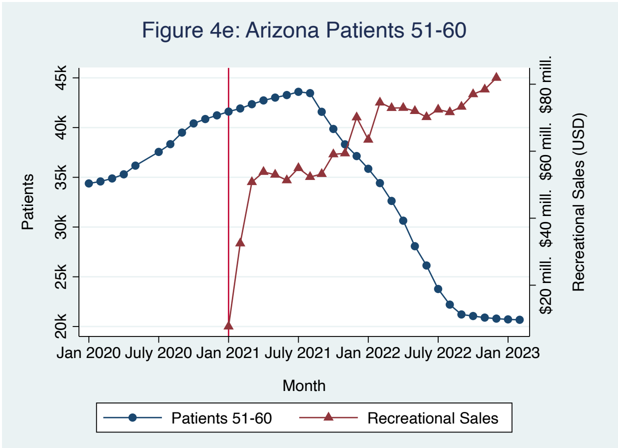
Figures 4a-h: Arizona Patients by Age

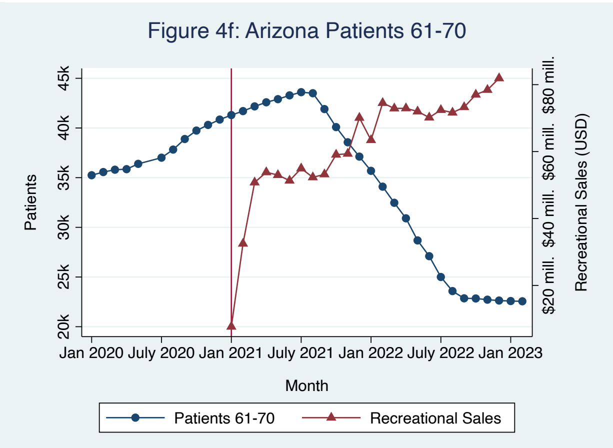


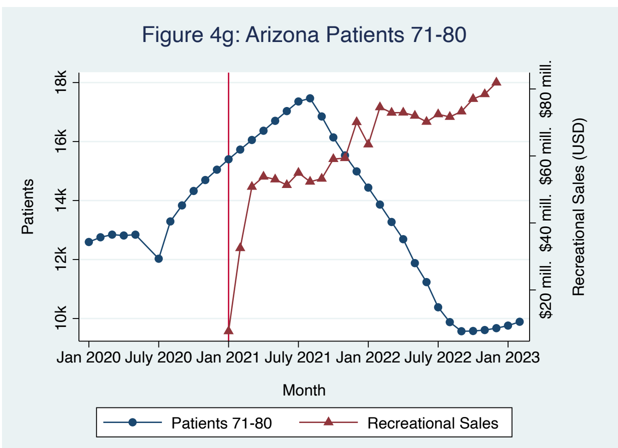


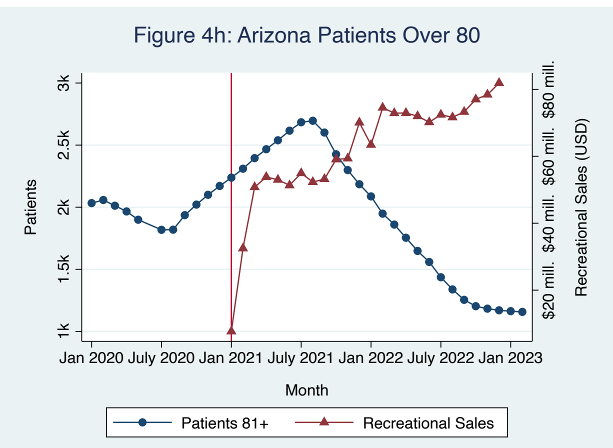












Figures 4b through 4h look similar, indicating that all these age categories see a similar drop in medical patients after the introduction of recreational sales. Figure 4a is not dissimilar from the other figures, but it does show an initial downward-sloping trend in the pre-period before again increasing. There could be something idiosyncratic about those in this under-18-years-old category—such as parental approval changing during the COVID-19 pandemic or physicians being unwilling to prescribe cannabis to minors during this time—that explains this momentary pre-period decline. But this could also result from the fact that there is more noise in this subgroup, especially given that there are never more than 200 patients in this age category.

The post-period data shows the same pattern as does every other age category. If there were a more gradual decline in any age group, it should be in this youngest group or in the oldest age group because these groups are probably those wherein physician-initiated cannabis prescriptions are most likely to occur. The evidence from these figures does not support that story and instead shows similar trends in all age categories.

Medical patients incorporate cost-benefit factors into the decision of whether to switch to recreational purchasing. All else equal, if the cost of medical cannabis is lower, then this should cause a more gradual decline in patients who experience a lower cost. Patients in Arizona who are eligible for benefits from the Supplemental Nutrition Assistance Program ("SNAP") pay less for medical cannabis cards than do non-SNAP patients. SNAP patients pay $75 every two years to maintain medical cannabis status, while non-SNAP patients pay $150 every two years. To see whether SNAP-eligible patients are less likely to depart from the medical registry, Figure 5 below depicts the number of SNAP-eligible patients over time.

Figure 5: Arizona SNAP-Eligible Patients

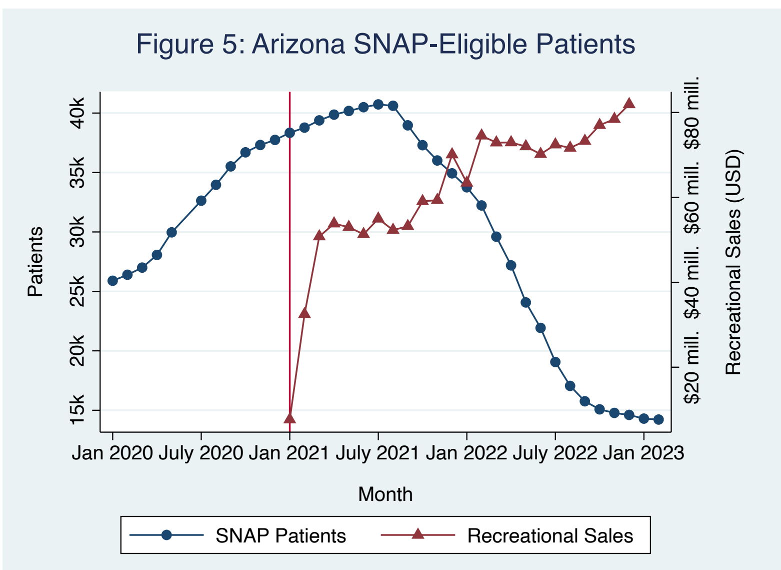
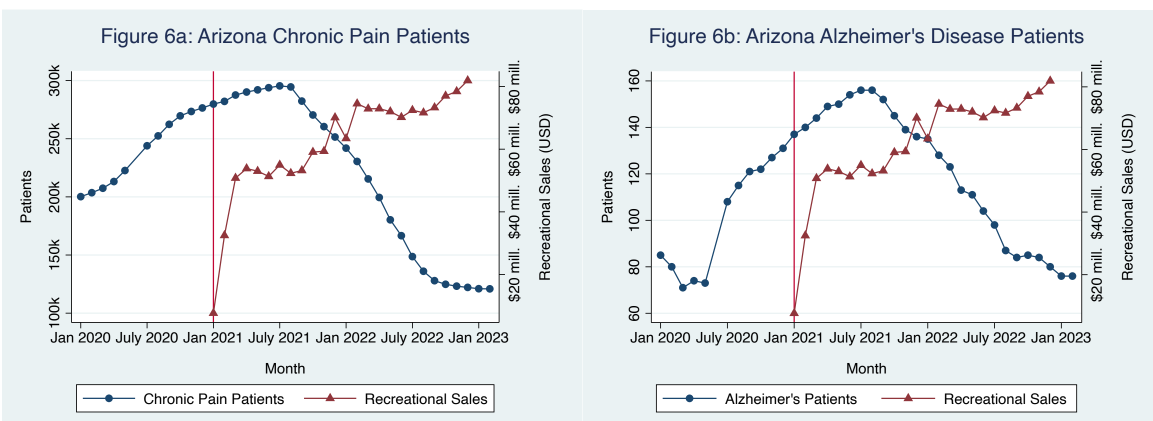


Figure 5 does not reveal a gatekeeping story because SNAP-eligible patients—who should theoretically be more price-sensitive and thus more likely to stay on the medical registry—see a trend that looks identical to all other medical patients. However, this does not foreclose the gatekeeping story. While SNAP-eligible patients see lower costs for medical cannabis card renewals, they also have lower wealth than non-SNAP patients. Therefore, the $75 differential every two years between these two patient groups could be offset by an even larger wealth endowment differential between the two groups.

Moreover, it could be the case that the medical cannabis requirements in Arizona are sufficiently onerous such that consumers across all patient categories are pushed into the recreational market. Figures 6a and 6b below look at whether dropout trends differ for chronic pain patients versus Alzheimer's Disease patients.

Figure 6a & 6b: Arizona Patients by Qualifying Condition



Chronic pain and Alzheimer's disease are dissimilar qualifying conditions. There are up to 300,000 chronic pain patients in Arizona's cannabis program, while there are never more than 180 Alzheimer's patients in that period. Also, Alzheimer's Disease is presumably more difficult to fake than is something like chronic pain, so chronic pain patients would ex-ante be expected to have a higher likelihood of viewing doctors as drug gatekeepers than would Alzheimer's disease patients. Nonetheless, Figures 6a and 6b show that these two qualifying conditions demonstrate the same trends. There is therefore no evidence[10] from the Arizona data that trends differ by qualifying condition in ways that might reveal a gatekeeping story.

One other source of possible indicia of a gatekeeping story is the composition of cannabis products over time. As has been noted, experienced marijuana users—who are more likely to view doctors in the gatekeeping function—are significantly more likely than novice marijuana users to prefer smoking as their preferred marijuana intake method (Donnan et al., 2022). Novice users, on the other hand, are more likely than experienced users to prefer edibles as an intake method. Therefore, if there is a greater fraction of edible users staying in the medical program, this would support a gatekeeping story. To explore this, Figures 7a through 7d display the trends in medical cannabis product type—total marijuana, marijuana flower, marijuana edibles, and other marijuana products—over time.

[10] There is almost certainly a data input error that causes a sharp kink in other qualifying conditions' graphs in Arizona after January 2021. This kink is consistent across all other qualifying condition categories but is not included here, and it is believed that further focus would distract from the key trends in the Arizona data.

Figures 7a-7d: Arizona by Cannabis Product Type

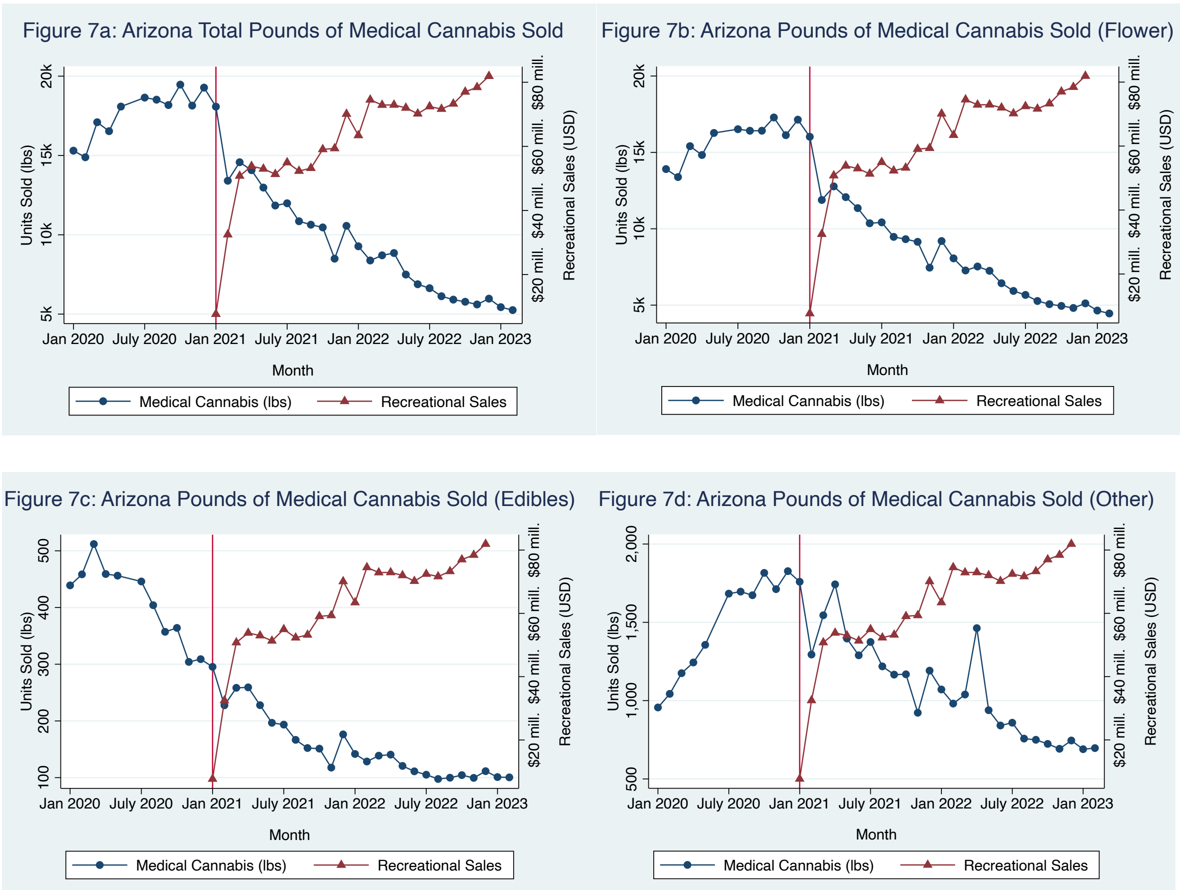


Figure 7a shows, not surprisingly, that total medical marijuana (in pounds) decreases after the onset of recreational sales. Figures 7b and 7d show that medical cannabis “flower” and medical cannabis “other products” see a similar pattern. Figure 7c, on the other hand, suggests something different. It reveals that (a) there had already been a downward trend in medical edibles before the start of recreational sales and (b) that this downward trend becomes less steep after the introduction of recreational cannabis. Figure 7e below plots the trend of the percent of medical edibles as a fraction of total medical marijuana over time.

Figure 7e: Arizona Edibles as Percent of Total Cannabis

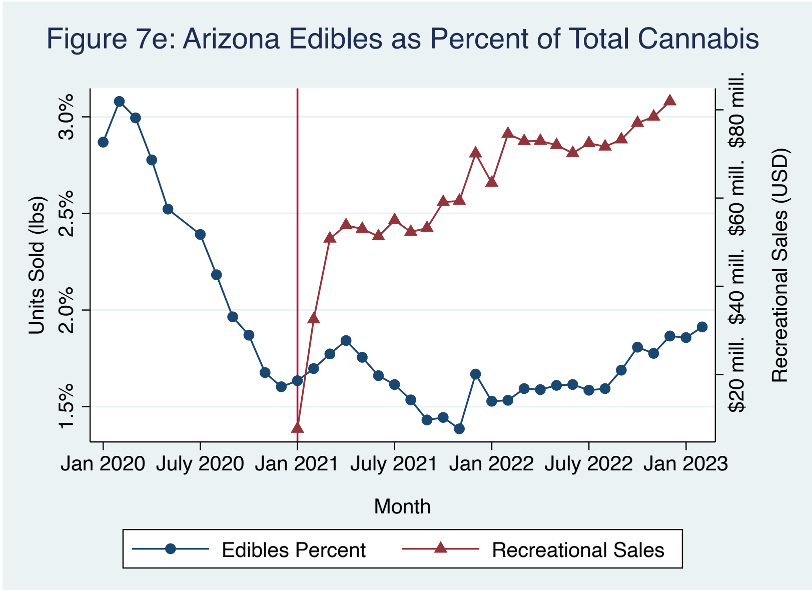


Figure 7e is the strongest evidence of a gatekeeping story in the Arizona data. The percent of medical edibles (relative to total medical marijuana sales) has a slight uptick when recreational sales begin and this percent stays relatively steady thereafter. In other words, Figure 7e shows that, after the introduction of recreational marijuana, edible-preferring consumers are more likely to stay on the medical registry than are flower-preferring consumers. Flower-preferring consumers are more likely to be experienced users and are therefore more likely to view doctors as gatekeepers of desirable drugs. This supports the idea that a large portion of medical-to-recreational switching consumers could do so under the rationale that the doctors' gatekeeping function has been eliminated.

C. New Mexico: Medical Trends Pre- and Post-RML Sales Commencement

The same analysis can be performed for New Mexico. New Mexico introduced recreational sales in April of 2022, publicizes monthly recreational sales data, has a smaller patient registry than does Arizona, and has more than double the number of qualifying conditions when compared to New Mexico. New Mexico's monthly data is not as detailed as Arizona's, but it does include information on total patients each month as well as patients in each qualifying condition category each month. Figure 8 shows the number of medical patients each month in New Mexico as well as the number of recreational sales in the state, with the vertical red line marking April 2022 when recreation sales commenced.

Figure 8: New Mexico Medical Patients and Recreational Sales

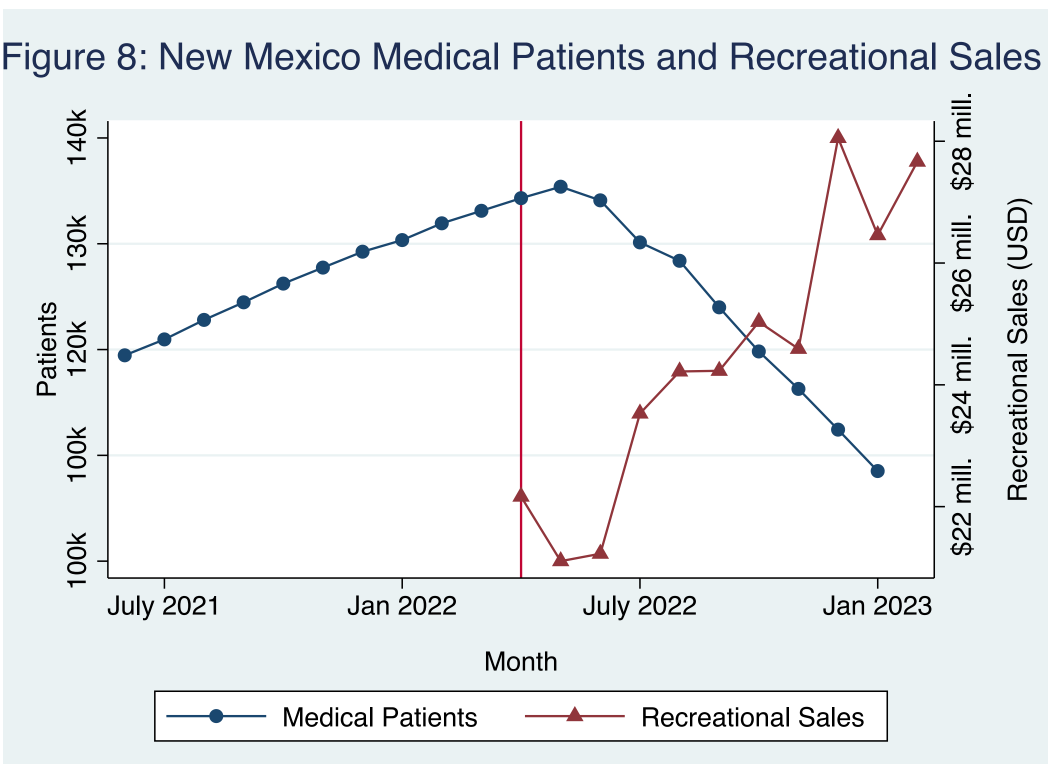


Figure 8 shows that New Mexico has the same two trends that Arizona has after the introduction of recreational marijuana. First, medical marijuana patients decline. Second, this decline is not immediate but rather takes time to materialize based on how quickly recreational sales ramp up.

To see if there is any indication of why medical cannabis users might switch to recreational purchases, Figures 9a through 9h plot New Mexico patients by qualifying condition over time.

Figure 9a-9h: New Mexico Patients by Qualifying Condition

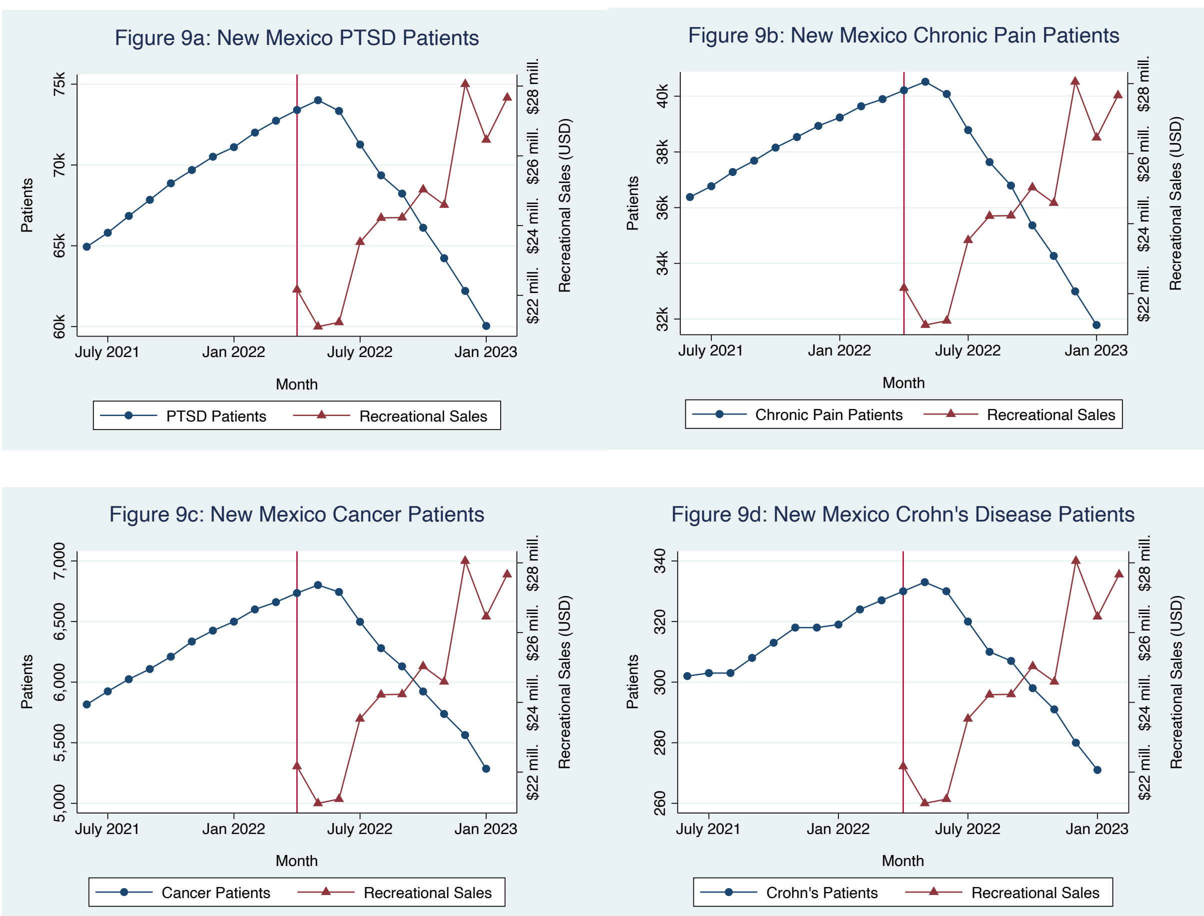


Figure 9e: New Mexico Obstructive Sleep Apnea Patients

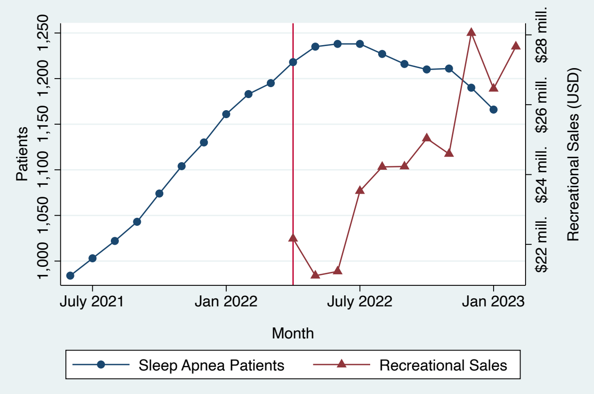


Figure 9f: New Mexico Opioid Use Disorder Patients

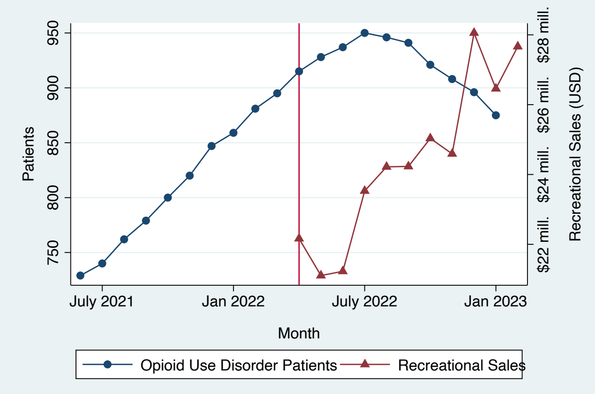


Figure 9g: New Mexico Autism Spectrum Disorder Patients

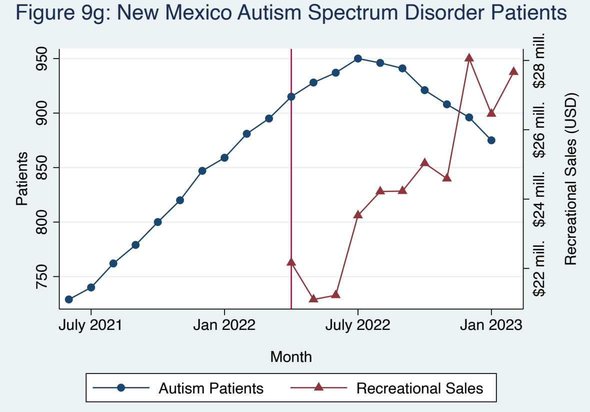
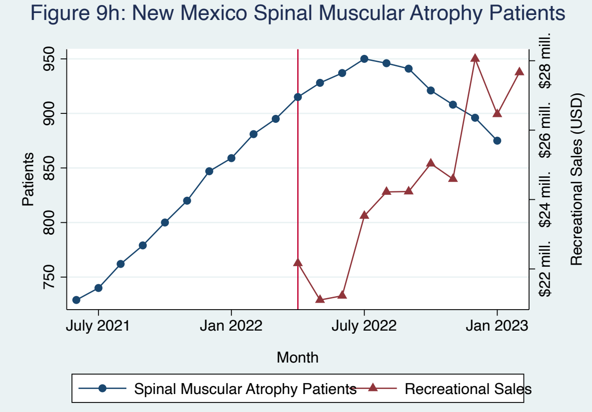


Figure 9h: New Mexico Spinal Muscular Atrophy Patients



There are 28 qualifying conditions in New Mexico, but only 8 are shown here for brevity. The remaining 20 qualifying condition graphs look largely like Figures 9a through 9d. All these graphs have strong similarities with Figure 8's overall downward trend in medical patients after recreational cannabis introduction. However, Figures 9e through 9h reveal that patients with these qualifying conditions are less likely to opt out of medical cannabis in New Mexico.

These conditions—autism, opioid use disorder, obstructive sleep apnea, and spinal muscular atrophy—differ from one another in terms of physical diagnoses and frequency, but some common elements seem to surface. First, these conditions are all difficult to falsify. Unlike conditions like PTSD or chronic pain, spinal muscular atrophy is more clearly defined and less based in cognitive evaluations. Therefore, it is unlikely that gatekeeping-oriented consumers would use these as pretextual qualifying conditions for the purpose of obtaining marijuana. Second, these are not conditions for which marijuana is widely viewed as a medical therapy. That is to say that a doctor might be more likely to initiate cannabis-as-a-therapy conversations for autisms patients than she is for patients with other qualifying conditions like PTSD who are already aware of cannabis use's therapeutic potential. Therefore, these Figures are consistent with the idea that, although a large fraction of medical patients might view the medical regime as a gatekeeping enterprise, there could be patients concentrated in particular condition categories—like autism, opioid use disorder, obstructive sleep apnea, and spinal muscular atrophy—wherein doctors truly are medical *providers* in the sense that they recommend and prescribe cannabis for ailing consumers (rather than vice versa).

VI. Discussion & Conclusion

When states move from medical cannabis programs to implement new recreational cannabis regimes, there is usually a decline in the number of patients and sales in the medical cannabis program. This paper documents that trend in Arizona and adds further support for a causal explanation by comparing Arizona's drop in medical cannabis statistics with New Mexico's medical cannabis statistics at the same time. While New Mexico's figures continued to trend in the same direction, Arizona's saw a sharp reversal and decline after the initiation of recreational sales.

Another important takeaway from this analysis is the fact that the drop in medical cannabis does not occur instantaneously with the passage of a recreational law. Instead, this substitution seems to occur in line with how quickly recreationally sales grow. This means that one purported reason—strengthened legal protections—for patients staying on medical registries after recreational marijuana introduction is not supported by the data. If this were the case, then switching from medical to recreational cannabis would likely occur directly after recreational law passage rather than directly after recreational law sales; the date of sales rather than law passage is the reality evidenced by the data in this paper.

States always adopt a medical marijuana law before instituting a recreational marijuana law, and this study shows provides additional support for the idea that the latter causes a drop in the former's patient numbers. State legislatures are often wary of implementing large-scale changes, so they opt for a middle ground—a medical law—so that doctors and healthcare providers can assure a safe, science-backed introduction of cannabis in a state. For this to be true, though, it should be the case that patients genuinely use medical marijuana programs for medical ailments. Looking at the substitution between medical and recreational cannabis can help tease out whether this is occurring. The results in this paper suggest that the medical regimes in Arizona and New Mexico probably afford remaining registrants with legitimate outlets for medicinal relief, but there is also evidence that patients in the medical program might view the system as a conduit for obtaining drugs.

After the introduction of recreational sales in Arizona, the fraction of edibles as a percent of total marijuana rises in the medical registry. Put differently, people who prefer smoking marijuana (as opposed to ingesting edibles) are the most likely to depart from the medical marijuana program and into the recreational regime. Experienced users are more likely to choose smoking as their preferred cannabis intake method. Therefore, experienced cannabis users are especially likely to leave the medical program and to move to recreational purchases. This provides evidence for the idea that the observed drop in medical cannabis numbers after recreational onset might be explained by substituting consumers always viewing the medical program something other than a place to solicit expert medical counsel.

24 of the 28 qualifying conditions in New Mexico's medical cannabis registry saw similar rates of decline after recreational marijuana surfaced. But in the 4 conditions that did not see a sharp decline in medical cannabis—autism, opioid use disorder, obstructive sleep apnea, and spinal muscular atrophy—there seems to be commonalities that point to a possible gatekeeper substitution story. All these conditions are hard to fake, meaning that consumers who do not have these conditions are less likely to nonetheless pretend to have these conditions so as to obtain marijuana. Moreover, marijuana is not widely understood to be a medical therapy for these conditions, so it is probably more likely that a doctor is the one suggesting cannabis as a therapy to the patient (rather than the patient suggesting cannabis to the doctor). Accordingly, this provides evidence that some fraction of the medical registry in New Mexico is a de facto recreational regime with physician gatekeeping but that patients with these specific, qualifying conditions might experience it as a legitimate medical program.

Finally, the discrepancy in cannabis registry rates for different qualifying conditions points to a possible gatekeeper story. There are roughly 16 times as many PTSD medical cannabis patients in New Mexico than there are in Arizona, yet Arizona's population is more than three times that of New Mexico's. This means that PTSD would have to be 48 times more common in New Mexico than in Arizona for this discrepancy to reflect true underlying disease affliction rates. Instead, it seems likely that consumers turn to different qualifying conditions—chronic pain in Arizona and PTSD in New Mexico, for example—in each state to achieve their goals in obtaining cannabis.

This paper helps explain the underlying motivations consumers might have when switching from medical to recreational cannabis. This is important for lawmakers, medical professionals, and policy groups who contemplate the role of cannabis as a medical therapy. This is also important for states that have adopted or consider adopting additional drugs as medical therapies. For example, in December of 2022, Colorado became the second state to legalize medical use of psilocybin (hallucinogenic mushrooms). Sales are slated to begin in Colorado in 2024 (Mohammadi, 2022). This paper highlights that, before the rollout of Colorado's medical program or others like it, special attention should be paid to the interaction between medical and recreational markets as well as legal regimes in a state. It is impossible to establish a strict demarcation between health care provision of drugs and the unintentional attraction of recreational users, but the results from this paper elucidate that studying the relationship between medical and recreational marijuana can help to draw that important line more carefully.

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