Pain Management and Work Capacity: Evidence from Marijuana Legalization

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Abstract:

We study whether the work capacity of the older working population responds to improved pain management therapy access. We use the adoption of state recreational marijuana laws (RMLs) as a large policy shock to access to a non-pharmaceutical pain management option. We focus on workers' compensation benefit receipt as a measure of work capacity, finding that receipt declines in response to RML adoption. We estimate concurrent reductions in prescription pain medication use and declines in work-limiting disabilities. After considering a range of alternative mechanisms, the evidence suggests that the primary driver of the reductions in workers' compensation benefits is improvements in work capacity.

Keywords: marijuana policy, regulation, workers' compensation, work capacity

JEL codes: I12, I18, J24, J32

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1. Introduction

The continued legalization of marijuana in the United States has been controversial, including its potential to harm the productivity of the workforce.[1] We study the effects of recent state laws that legalize the recreational use of marijuana on work capacity – the ability to productively engage in paid employment – among older working-age adults. A small literature considers the work capacity impacts of the availability of prescription pain management therapies with a similar focus on this population (Garthwaite, 2012, Bütikofer and Skira, 2018).[2] In this paper, we use recreational marijuana law (RML) adoption as a large shock to the availability of an alternative form of chronic pain management; in particular, one that does not require a prescription or a consultation with a healthcare professional but may pose other concerns such as stigma, safety concerns, and issues related to drug testing at work.

We examine workers' compensation (WC) benefit receipt as a useful signal of diminished work capacity given that WC permits us to target an especially relevant population that would potentially benefit from additional access to pain management therapies. Moreover, workplace injuries are of important policy concerns in themselves given the substantial costs of workplace injuries to the national economy (Leigh, 2011) and the financial burdens associated with WC. Marijuana can potentially be used to treat many symptoms associated with common injuries that lead to a WC claim. Using a national sample of U.S. workers 2011-2018, Baidwan et al. (2020) show that 82% of the five most common WC claims are for injuries that cause chronic pain and could be effectively managed with marijuana used medically.[3] Further, chronic

[1] See National Institute on Drug Abuse (2020) and https://www.usnews.com/news/best-states/articles/2018-08-01/the-legalization-of-recreational-marijuana-an-economic-opportunity-for-states (last accessed 10/15/2021).
[2] Related, Bütikofer et al. (2020) study the employment effect of the availability of antidepressants while Shapiro (2020) considers how workplace absenteeism responds to advertising for antidepressants.
[3] In particular, 30.1%, 20.8%, and 8.9% of such WC claims are due to strains, contusions, and sprains.

pain is by far the most commonly stated reason for medical use of marijuana among patients (Kosiba et al., 2019) and 50-80% of injured workers prescribed any medication are prescribed an opioid pain reliever (Thumula et al., 2017),[4] suggesting substantial scope for expanded access to this product to improve work capacity and reduce WC. Marijuana may be an attractive option to patients as marijuana is less addictive with a lower risk of overdose than alternative treatments (e.g., opioids), does not require a (costly) consultation with a healthcare professional (when the product is legalized recreationally), can treat various symptoms associated with pain[5] (e.g., pain, anxiety, depression, insomnia), and can (unlike over-the-counter pain relievers such as Aspirin) be used safely by patients with kidney or other problems (Roumie and Griffin, 2004, Whelton, 1995). We also study a host of complementary measures to help determine whether changes in WC benefit receipt reflect changes in work capacity for the affected population instead of other possible economic and behavioral responses to RML adoption.

Most of the costs of workplace injuries are borne by workers. The WC program is designed specifically to transfer some of these costs from workers to governments and firms. In 2018, WC cash and medical payments to workers totaled $62.9 billion (Weiss et al., 2020), equivalent to the size of annual Earned Income Tax Credit (EITC) expenditures. While WC expenditures are high, they have recently been on a decline: Figure 1A depicts trends in WC real expenditures in the U.S. 2010-2018, the sample period for our analysis. The economic literature on WC typically focuses on the impacts of the incentives inherent in the system on injury duration (e.g., Meyer et al. (1995); Neuhauser and Raphael (2004); and Cabral and Dillender

[4] Workers who require surgery and are away from work less than seven days are excluded from the sample.
[5] Pain can impact health broadly defined. For example, healthcare professionals often prescribe anti-depressants along with pain medication due to the negative impacts of pain on mental health (Sansone and Sansone, 2008).

(2020)) or the program's consumption smoothing benefits (Bronchetti, 2012). There is less evidence on the impact of policies not directly targeting WC to affect benefit receipt.[6]

Due to marijuana's medicinal properties (Borgelt et al., 2013, Lynch and Campbell, 2011, National Academies of Sciences and Medicine, 2017), states initially passed medical marijuana laws (MMLs), providing legal protection for individuals with specific health conditions to use this product to treat symptoms associated with those ailments,[7] though some of these MMLs were quite restrictive. By February 2022, 37 states and the District of Columbia had adopted MMLs (ProCon.org, 2022a), but numerous states that have legalized medical marijuana[8] do not consider chronic pain, the most commonly reported reason for using medical marijuana (Park and Wu, 2017, Kosiba et al., 2019), as a qualifying health condition.[9,10] Following the wave of MML adoption, states have recently passed laws that legalize marijuana for broader use. The initial RMLs were adopted in 2012 when Colorado and Washington legalized recreational marijuana use for adults 21 and older. As of February 2022, marijuana use is legal for recreational purposes in 18 states and the District of Columbia (ProCon.org, 2022b).

Critics argue that legalization of marijuana will lead to greater addiction to harder drugs, crime,[11] higher healthcare costs, and other social ills within the population while harming health and labor market outcomes.[12] However, marijuana legalization is popular among Americans: in

[6] One exception is a small literature on the impacts of access to health insurance on WC claiming behavior (e.g., Bronchetti and McInerney (2017); Lakdawalla et al. (2007); and Dillender (2015)). Further, Ohsfeldt and Morrisey (1997) study the effect of beer taxes on WC and workplace injuries.
[7] Marijuana is not likely to improve health *per se*, but use of this product may allow better symptom management.
[8] For example, 14 states do not specifically list chronic pain as a qualifying health condition. Please see https://www.compassionatecertificationcenters.com/news/list-of-qualifying-health-conditions-for-medical-marijuana-in-each-state/ (last accessed 10/15/2021).
[9] Please see, for example, https://filtermag.org/heres-how-infuriatingly-hard-it-still-is-to-get-medical-marijuana-in-new-york/ (accessed 10/15/2021).
[10] Additionally, healthcare providers working in Federally Qualified Health Centers must adhere to federal law and cannot recommend marijuana, even in states where medical use of this product is legalized.
[11] Recent work does not suggest that marijuana is a gateway to harder drugs and crime (Sabia et al., 2021).
[12] Please see, for example, https://marijuana.procon.org/ and https://www.haylor.com/wp-content/uploads/2014/05/Assurex-Marijuana-White-Paper.pdf (all websites accessed 10/15/2021).

2019, 67% supported legalization for recreational use, and 91% supported legalization for recreational or medical use (Daniller, 2019). Despite widespread support and legislative efforts by some lawmakers (e.g., the Marijuana Opportunity Reinvestment and Expungement [MORE] Act of 2019, which proposes decriminalization), marijuana use has been prohibited federally since the Marihuana Act of 1937, leading to a direct conflict between state and federal law.

There is significant policy interest in improving the work capacity of older adults in the U.S., especially given its implications for social insurance programs (Coile et al., 2017, Cutler et al., 2013, Lopez-Garcia et al., 2019). We study WC as an important metric of work capacity for this population and due to independent policy interest in the determinants of WC benefit receipt. Moreover, healthcare access more generally can have large impacts on the work capacity of the WC population (Powell and Seabury, 2018).

There is limited – though growing – evidence on the economic consequences of RMLs. These policies improve access to marijuana even beyond MMLs (Hollingsworth et al., 2019, Cerdá et al., 2020, Maclean et al., 2020a), leading to reduced demand for other types of pain management (Wen and Hockenberry, 2018, McMichael et al., 2020, Chan et al., 2020, Carrieri et al., 2020, Wen et al., 2021, Drake et al., 2021). This evidence indicates that RMLs improve access to an additional channel for managing pain and other health conditions, suggesting potential benefits for populations at risk of workplace injuries.[13]

We investigate the effect of state RMLs on WC receipt among adults ages 40 to 62 years of age ('older adults'). We study older adults given the focus on this population in the literature studying the labor supply effects of access to pain management therapies.[14] This population is

[13] For example, 30% of all fatal and nonfatal occupational injuries and illnesses are due to musculoskeletal disorders, such as back pain, hernias, sprains, strains, and tears, alone (Bureau of Labor Statistics, 2016).
[14] For example, Bütikofer and Skira (2018) study ages 40-60; Garthwaite (2012) studies ages 55-75.

more likely to experience conditions for which marijuana may be effective in symptom management and to use prescription medications for which marijuana may serve as a therapeutic substitute (Nicholas and Maclean, 2019, Hales et al., 2020). Over the period 2015 to 2018, only 5.4% of adults 20 to 39 years reported use of a prescription pain medication in the past 30 days compared to 12.7% of adults 40 to 59 years and 15.1% of adults 60 years and older (Hales et al., 2020). Chronic pain prevalence is substantially higher among adults 45 to 64 years than younger adults (Dahlhamer et al., 2018). At the same time, rates of marijuana *misuse* are lower among older (vs. younger) adults (see Table 1 in Choi et al. (2017)), suggesting that concerns regarding negative implications associated with legalization may be muted for older adults.

We evaluate the effect of RMLs on WC benefit receipt and WC income over the period 2010 to 2018 using the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). Most WC claims are 'medical only' and do not require time away from work (Baidwan et al., 2020). Thus, we focus on WC claiming that requires time away from work as our metric of work capacity. We also assess possible mechanisms explaining the changes in WC benefit receipt by studying marijuana use and misuse; use of therapeutic substitutes (medications used to treat chronic pain); and a broader set of work capacity measures including self-assessed health and the incidence of work-limiting disabilities. RML adoption could impact WC benefit receipt through several channels, and we consider a range of possible mechanisms such as changes in labor supply, labor demand shocks, and other possible factors.

Our results show a decline in WC benefit propensity of 0.19 percentage points ('ppts') after states legalize marijuana for recreational use. We find that the average annual individual income received from WC declines by $20.16 post-RML. Results are similar using a two-stage difference-in-differences approach that is robust to bias with a staggered adoption in the presence of treatment effect heterogeneity (Gardner, 2021). Results are not driven by pre-existing trends, and falsification exercises suggest that observing estimates of this magnitude is statistically rare.

We find evidence that marijuana use, but not misuse, increases after RML adoption, which is in line with additional medical use among older adults. Prescriptions for medications used to treat chronic pain decrease post-RML, suggesting increased use of marijuana for pain treatment. We observe complementary evidence that RMLs reduce self-reported work-limiting disability propensities. The observed reduction in WC benefits is not due to a concurrent decrease in labor supply mechanically reducing WC participation or due to industry composition shifts which lead to a higher share of the workforce working in safer industries. Instead, we observe an *increase* in labor supply post-RML, which is further consistent with RMLs improving work capacity among older adults. These results suggest that RMLs reduce work limitations related to chronic health conditions and, overall, improve work capacity among older adults.

In the next section, we provide background on WC and marijuana legalization. Section 3 discusses the data and methods. We present results in Section 4. We evaluate mechanisms in Section 5. Section 6 considers treatment heterogeneity. We conclude in Section 7.

2. Background

2.1. Workers' Compensation Insurance

WC was one of the earliest social insurance programs in the U.S. The program was designed as a compromise to shield employers from tort liability, and to provide income and medical assistance to injured workers. Except for Texas, where employer participation in WC is optional (Cabral et al., 2019, Jinks et al., 2020), almost all wage and salary workers are covered by WC. Employers typically purchase WC coverage or self-insure to meet these obligations, though the costs of WC benefits, like many other mandated benefits, could be passed on to employees through reduced compensation (Summers, 1989, Gruber and Krueger, 1991).

These programs represent a critical component of the social safety net as they offer financial protection to injured/ill workers. The Department of Labor, however, recently issued a report which 'sounds an alarm' regarding deteriorating benefits in state WC programs (U.S. Department of Labor, 2016). State attempts to reduce WC costs highlight increased policy demand for mechanisms to decrease injury rates and subsequent WC participation.

While there are differences across states, most WC programs in the U.S. require employers to provide employees who become injured or ill while working with cash and medical benefits as the employee recovers. Employees unable to recover are evaluated for permanent disability benefits. The wage-replacement rate for WC is typically two-thirds of an employee's pre-injury/illness gross wage with minimum and maximum benefits levels varying by state (Weiss et al., 2020). Benefits are offered to the employee regardless of fault, but covered employees are prohibited from suing the employer in relation to the injury or illness.[15]

2.2. Related literature on marijuana legalization laws

While there is a large literature on the effects of state MMLs,[16] fewer studies have evaluated RML impacts given their recent adoption. We focus on studies examining RML effects and draw upon studies evaluating the effects of MMLs on particularly relevant outcomes.

Several studies establish that adult marijuana use increases post-RML, typically estimating very large effect sizes relative to MMLs. Using data from the National Survey on Drug Use and Health (NSDUH), Cerdá et al. (2020) show that past-30 day marijuana use among

[15] Some programs reimburse medical marijuana, but none reimburse recreational marijuana.
[16] Several studies examine the impact of individuals' marijuana use on labor market outcomes. See, Zwerling et al. (1990); Register and Williams (1992); Macdonald et al. (2010); and Williams and van Ours (2020).

adults increases by 26-37% post-RML. Hollingsworth et al. (2019), and Maclean et al. (2020a) report similarly large effect sizes in their analyses of RML effects in the NSDUH. Dragone et al. (2019) study the legalization of recreational marijuana in Washington and Oregon (compared to border counties) also using NSDUH data and find that RML adoption increases marijuana use by 25%. On net, most studies show a non-trivial increase in measures of marijuana use following RML adoption. However, the literature has not yet reached full consensus. Hansen et al. (2020) show no change in marijuana-involved traffic fatalities following RML adoption in Oregon and Washington relative to comparison groups generated using synthetic control methods.

A growing literature considers whether RMLs reduce use of pain management therapies which are therapeutic substitutes for marijuana (Wen and Hockenberry, 2018, Carrieri et al., 2020, McMichael et al., 2020, Wen et al., 2021). Wen and Hockenberry (2018) document that, post-RML, prescriptions for chronic pain medications decline by 6% among Medicaid enrollees. Since all states adopting RMLs previously had MMLs, this finding suggests that RMLs impact access to marijuana for pain management purposes even beyond the extent to which MMLs do (Bradford and Bradford, 2016, Bradford and Bradford, 2017). Chan et al. (2020) show that RMLs reduce opioid mortality by 20% to 35% and Drake et al. (2021) find that opioid-related emergency department episodes decline by 8% in the short-run, implying that both opioid use and misuse decline as legal marijuana access expands. However, Ali et al. (2021) do not find evidence of changes in self-reported prescription pain reliever misuse rates in the NSDUH.

Marijuana access may influence labor market outcomes, and the direction of the relationship may vary across demographics and margins of labor market engagement. An important point of distinction is that the marginal user who is induced to consume marijuana following an MML versus an RML potentially differs. RMLs permit legal access to marijuana (regardless of intent) for adults 21 years and older, while MMLs allow only individuals who can demonstrate a legitimate medical need for the medication for a specified set of conditions. The number of individuals who gain access to marijuana following an RML adoption is likely much larger than the number gaining access post-MML, which can be quite restrictive in some states (Smart, 2015), and the populations potentially have different underlying health statuses (i.e., the population gaining access to medical marijuana through an MML is likely sicker than that for RMLs). Based on our calculations, in 2019, 2% of the population in MML states was enrolled in state medical marijuana programs.[17] Essentially all adults can legally access marijuana in states with RMLs. These features, and likely others, of the policies and their target populations likely lead to different groups of new users and, in turn, heterogeneous implications for work capacity.

A small literature studies changes in labor market and social insurance outcomes due to MML adoption. Using the CPS, Sabia and Nguyen (2018) conclude that the passage of an MML permitting open marijuana dispensaries may decrease wages among younger males but has limited effect on other non-elderly adults. Nicholas and Maclean (2019) focus on adults 50 and older in the Health and Retirement Study and document that passage of an MML leads to an increase in the probability of working full-time and the number of hours worked per week among those participating in paid employment. Ullman (2017) finds that increased marijuana consumption due to MML adoption reduces work absences as measured in the CPS. In work closely related to the current study, Ghimire and Maclean (2020) find that following the adoption of an MML, WC benefit receipt declines by 7%. The decline is driven primarily by older adults, for whom the probability of receiving WC benefits declines by 13% post-MML, further

[17] Calculations made using data from https://www.statista.com/statistics/743485/medical-marijuana-patient-population-united-states-by-state/ and https://www.mpp.org/issues/medical-marijuana/state-by-state-medical-marijuana-laws/medical-marijuana-patient-numbers/ (last accessed 10/15/2021).

motivating the choice of sample in this paper. Comparably, Anderson et al. (2018) show that workplace fatalities fall 20% post-MML among workers 25 to 44 years (coefficient estimates are negative and similarly sized, but imprecise, for other age groups, including older adults).

Of particular relevance to our work, four recent studies examine the impact of recreational marijuana access on labor market and social insurance outcomes. First, Chakraborty et al. (2020), using county-level data over the period 2011 to 2018 from Colorado, show that the opening of dispensaries (but not RMLs *per se*) reduces unemployment rates but has minimal effects on labor market participation or wages. Second, Maclean et al. (2020a), using data from the Social Security Administration, show that disability applications for disability – Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI) – increase post-RML, but successful applications (i.e., applications awarded benefits by SSA reviewers) are not appreciably changed following law passage. They also find that RML adoption does not lead to observable changes in wages or labor force participation rates among adults (though the unemployment rate declines by 6%). Third, Abouk and Adams (2019) show that employment propensity increases post-RML.[18] Fourth, Dong (2020), using administrative WC data from Oregon, shows that workplace injuries increase after a county legalizes the sale of recreational marijuana, with effects driven by younger workers.

Most states that have adopted an RML to date, allow employers to enforce a zero-tolerance workplace and fire workers for off-work marijuana use (ProCon.org, 2022b).[19] Thus, some workers who would otherwise use marijuana (medically or recreationally) following an RML adoption may be deterred from using this product for fear of job loss. We expect fear of job loss to mute the possible gains and harms of RMLs.

[18] The authors note some declines in employment among women with young children post-RML, however.
[19] See https://www.nolo.com/legal-encyclopedia/state-laws-on-off-duty-marijuana-use.html (accessed 10/15/2021).

Previous studies on WC and marijuana legalizing policies have only studied MMLs and did not dive into understanding the mechanisms behind this relationship. The existing research on the relationship between RMLs and labor supply outcomes more broadly has rarely tried to disentangle the importance of labor demand shocks due to the expansion of a new industry versus the work capacity effects on individuals gaining access to a new form of pain management. Our paper considers a wide range of possible mechanisms, studies several intermediate outcomes to understand the potential for RMLs to improve therapeutic access, and evaluates complementary health metrics among older adults.

2.3. Mechanisms for a relationship between RMLs and Workers' Compensation

We hypothesize that access to marijuana through RMLs increases its medical use and, in turn, allows better management of symptoms that impede work capacity (Watson et al., 2000, Lynch and Campbell, 2011, Hill, 2015, Whiting et al., 2015, National Academies of Sciences and Medicine, 2017). Chronic pain management is likely to be particularly important in our context as this is the health condition most commonly reported among medical marijuana users (Park and Wu, 2017, Kosiba et al., 2019, Reinarman et al., 2011). In a recent meta-analysis, pain was the most commonly stated reason for using marijuana, with 64% of patients reporting marijuana use to treat chronic pain (Kosiba et al. (2019)).

Improvements in symptom management may prevent an individual from receiving WC or may shorten the period of job separation. There are other possible mechanisms that could also lead to changes in WC benefit receipt following an RML adoption. We describe these channels and will empirically test them alongside tests about the role of changes in work capacity.

RML adoption could lead to changes in labor supply- and demand-side factors which could plausibly impact WC benefit receipt. In terms of labor supply, marijuana used recreationally could reduce labor supply through addiction (Volkow et al., 2014); impaired mental and physical health (Van Ours and Williams, 2012, Van Ours et al., 2013); lower human capital accumulation (Chatterji, 2006); worse cognition and concentration (Hanson et al., 2010, Volkow et al., 2014, Winward et al., 2014); and reduced motivation (Irons et al., 2014). Such pathways may prompt some workers, perhaps those marginally attached to the labor market or with preexisting conditions, to place a WC claim.

Moreover, additional marijuana use could increase workplace injury rates, especially traumatic injuries, by worsening concentration. Kaestner and Grossman (1998), for example, provide evidence that drug use increases workplace injuries among males. However (as noted in Section 2.2), Anderson et al. (2018) show a decline in workplace fatalities of up to 20% post-MML among some worker groups. Thus, the net effect on injury rates is an empirical question, and we will consider a range of possible mechanisms.

RMLs may also offer a boost to the economy (Chakraborty et al., 2020). Improved labor market opportunities could increase WC receipt as there are more employed individuals 'at risk' of a work-related injury. Labor demand shifts could also affect the composition of employed individuals, leading to ambiguous effects on the propensity to claim/duration of WC benefits. As the number of available jobs is rising with increased demand for recreational marijuana, employees may be less concerned about possibly sending a negative signal regarding their productivity to the employer (and thereby risking job loss) through placing a WC claim, thus benefit receipt could increase post-RML. Alternatively, economy-wide positive demand shocks may lead to employers prioritizing workplace safety and training (Charles et al., 2019), thus minimizing the risk of a work-related injury and WC receipt.

In sum, there are various mechanisms linking RML adoption to WC benefits. Some mechanisms suggest that WC benefits will decline post-RML (e.g., improved pain management) while others suggest that WC benefits could increase (e.g., increased labor demand and risk for injury). We test the net relationship, and specific mechanisms outlined here, empirically.

3. Data and Methods

3.1. Worker's Compensation data

Our primary dataset is the 2011 to 2019 ASEC, prepared by the Integrated Public Use Microdata (IPUMS) system (Flood et al., 2020).[20,21] The ASEC is fielded each year February to April, and collects detailed information on income, insurance, poverty, and other socio-economic variables on 150,000 respondents.[22] ASEC WC income reflects income received over the past calendar year, thus our analysis captures WC income received 2010 to 2018. We will refer to the *calendar year* (which we label 'year'), not the *survey year*.

ASEC information is self-reported; however, given that state WC systems are independent, locating harmonized national sources with detailed information about recipients, such as age, is difficult. The ASEC is commonly used by economists to study WC outcomes at a national level (Ghimire and Maclean, 2020, Krueger, 1990, Gruber and Krueger, 1991, Hirsch et al., 1997, Bronchetti and McInerney, 2012, Bronchetti and McInerney, 2019), and we view the ASEC as the most suitable dataset for our research.

We truncate the sample at age 62 as most Americans become eligible for Social Security benefits at this age which may impact decisions to claim WC. Results are similar if we include

[20] We exclude the survey collected in 2020 (which captures claiming in 2019) due to the COVID-19 pandemic.
[21] The American Community Survey (ACS) does not collect information specifically on WC benefit receipt.
[22] There was a change in the ordering of some income questions in 2014 in the ASEC (Hill et al., 2019). We do not suspect that this change impacts our analysis since we include year fixed effects in all regression models.

adults up to age 65 years. Respondents with missing WC outcomes and demographics (outlined in Section 3.5) are excluded. We have 517,351 respondents in our analysis sample.

3.2. RML Coding

RML data are obtained primarily from Chan et al. (2020) and ProCon.org (2022b).[23] We match RMLs to our data based on state, month, and year. We define a state as having an RML in place when the law initially becomes effective. Figure 2 graphically depicts states that have adopted an RML by February 2022. By the end of our study period (2018), nine states and DC had an RML in place, although 16 states and DC had adopted a law by February 2022.

3.3. State-level control variables

In some models, we include several state-level variables that are potentially correlated with RML adoption and WC benefit receipt. We control for MMLs (Sabia and Nguyen, 2018, ProCon.org, 2022b), prescription drug monitoring programs or PDMPs (Ali et al., 2017), naloxone & Good Samaritan laws (Prescription Drug Abuse Policy System, 2020, Ghimire and Maclean, 2020), and pain clinic management laws (Prescription Drug Abuse Policy System, 2020). In addition, we control for several state-level labor market policies and characteristics: the effective minimum wage (in 2018 dollars), the state EITC as a share of the federal EITC, governor political party (treating the DC mayor as the de facto governor (Maclean and Saloner, 2018)), and population (University of Kentucky Center for Poverty Research, 2020).

3.4. WC outcomes and summary statistics

We study two measures of WC benefit receipt based on survey responses in the ASEC. First, we use an indicator for any WC income. Second, we examine the level of WC income (in

[23] We confirm effective dates using RAND policy data, PDAPS, NORML.org, and state statutes. There are differences across sources, we reply on the state statutes when there is mis-match. Details available on request.

2018 dollars). These outcomes refer to receipt of cash benefits only and we will frequently refer to them as 'WC benefits,' though they exclude medical benefits, vocational rehabilitation vouchers, and other types of reimbursements provided by WC systems.

Table 1 reports summary statistics for the full sample of states and then stratified by RML adoption. Data are weighted by ASEC-CPS provided survey weights. For adopting states, the summary statistics refer to the average prior to adoption. Just under 1% of the full sample reports receiving WC benefits and average (unconditional) WC income in the sample is \$75. In addition, 6.3% of the sample resides in a state with an effective RML during our time period, reflecting that most RMLs were adopted closer to the end of the sample. State- and individual-level characteristics are broadly similar across the two groups of states. We discuss balance further in Section 4.3.2. Appendix Figure 1 reports national trends in any WC income and WC income (in 2018 dollars) over our study period. Both outcomes are trending downward modestly, which is in line with trends in costs based on administrative data (Figure 1A).

3.5. Methods

We estimate two-way fixed effects (TWFE) models to study the impact of RML passage on WC benefit receipt outcomes:

(1) $$WC_{i,s,t} = \beta_0 + \beta_1 RML_{s,t} + P_{s,t}\beta_2 + X_{i,s,t}\beta_3 + \theta_s + \tau_t + \varepsilon_{i,s,t},$$

where $WC_{i,s,t}$ is a WC outcome for respondent *i* in state *s* in calendar year *t*. $RML_{s,t}$ is an indicator variable for an effective RML in state *s* in year *t*. $P_{s,t}$ is a vector of state-level time-varying factors (see Section 3.3). $X_{i,s,t}$ is a vector of respondent-level characteristics.[24] We provide evidence about the importance of these control variables in Section 4.3.

[24] We include age in years, sex (male and female, male is omitted), race (White, Black, and other, White is omitted), ethnicity (Hispanic and non-Hispanic, non-Hispanic is omitted), and education (less than high school, high school, some college, and a college degree or higher, less than high school is omitted).

We include state (θ_s) and year fixed effects (τ_t), the former account for time-invariant state factors while the latter control for common nationwide shocks. We estimate Equation (1) using weighted least squares, applying ASEC survey weights provided by IPUMS in our analyses of WC benefit receipt outcomes, although as we show that unweighted results are similar. We also test the sensitivity of our results to other functional forms. We cluster standard errors by state (Bertrand et al., 2004) in our main analysis. We will also conduct inference using a score bootstrap and permutation tests, given that these approaches often have better properties for a small number of treated clusters.

Recent work documents that TWFE methods are vulnerable to bias from heterogeneity in treatment effects across states that adopt policies at different points in time (Goodman-Bacon, 2021, Callaway and Sant'Anna, 2020). To address this concern, we implement a two-stage difference-in-differences (2SDiD) method proposed by Gardner (2021) that is not vulnerable to this concern and present the results alongside our main TWFE results.[25] In the first stage of 2SDiD, the relationships between the time-varying covariates[26] and fixed effects with the outcome variable are estimated using only untreated observations. The estimated parameters are then used to residualize the outcomes for treated and untreated observations.[27] Because these parameters are estimated using only untreated observations, they are not vulnerable to concerns about treatment effect heterogeneity. In the second stage, the residualized outcomes are regressed on the treatment variable (using all observations). Gardner (2021) develops 2SDiD in

[25] The Gardner (2021) method permits use of individual-level data while many alternative approaches among the new difference-in-differences estimators require aggregating the data. We believe there may be benefits to controlling for individual-level characteristics in our analyses.
[26] Gardner (2021) only briefly addresses covariates, but the approach is straightforward to extend to account for time-varying control variables. The residualization step includes the control variables. If state-specific treatment effects are correlated with the covariates, TWFE can be biased even without staggered adoption (Powell, 2021). However, estimating the parameters associated with the covariates using only untreated data avoids these concerns.
[27] This residualization approach is also discussed in Borusyak et al. (2021). Powell (2021) introduces a similar approach and discusses the benefits in applications without staggered adoption.

a GMM framework and standard errors are estimated accounting for the two stage estimation process (Hansen, 1982) and state-level clustering.

Finally, we report 'counterfactual outcomes' in our tables to help benchmark the magnitudes of the coefficient estimates. These counterfactual outcomes are estimated using a baseline regression model that controls for the RML and state and time fixed effects.[28] We then subtract off the causal impact of RMLs to estimate the outcome value in the absence of RML adoption. We report the average of these 'untreated' outcomes for all treated observations.

4. Results

4.1. Effect of RMLs on WC benefits

Our main findings are reported in Table 2. We report results using TWFE and 2SDiD; our results are nearly identical across the two estimators. In the first column, we include state and year fixed effects only. We estimate that RML adoption reduces the probability of WC benefit receipt by 0.16 ppts, statistically significant from zero at the 1% level. In Column 2, we add individual-level controls and the estimated effect is not meaningfully changed. We add state-level controls in Column 3 and, again, the coefficient estimate is unaffected by these controls. Appendix Table 1 provides a full set of coefficient estimates from this specification.[29] Finally, in Column 4, we repeat the Column 3 analysis except we use unweighted regression. The coefficient estimate is very similar.

Our preferred estimate (Column 3) implies that RML adoption leads to a reduction in WC receipt among adults 40 to 62 years of age by 0.19 ppts. In Panel B of Table 3, we estimate the

[28] Alternatively, we could present the counterfactual outcomes implied by each model. RML estimates are relatively stable across models so, for the sake of consistency, we hold the calculation of the counterfactual outcomes constant.
[29] We note that MML adoption appears to no longer predict WC benefit receipt in the period in which RMLs are in place (Appendix Table 1). Ghimire and Maclean (2020), who document that MMLs reduce the WC outcomes we study, close their panel in 2012 and thus do not consider any of the 'RML era' in their study.

effect of RML adoption on annual WC income, a measure which combines both the extensive margin effect (WC benefit receipt) as well as any intensive margin effects (e.g., shorter injury durations and claiming periods).[30] This result is robust to including individual controls (Columns 2), state-level controls (Column 3), and removing survey weights (Column 4). In our preferred model – Column 3 – we estimate that RMLs decrease WC income by $20.16.

Results are robust to applying 2SDiD and, as we report in Section 4.3.5, are also robust to an alternative estimator developed to address bias from heterogeneity in staggered treatment rollout. For example, in our preferred specification, the 2SDiD approach suggests that, post-RML, the probability that a respondent reports any WC income declines by 0.22 ppts and the level of WC income declines by $23.34. Both coefficient estimates are statistically different from zero at the 1% level.

Due to concerns about inference with a few treated units (Brewer, Crossley, and Joyce 2017), we also include *t*-statistics generated by testing the null hypothesis of no effect using a score bootstrap approach (Kline and Santos, 2012, Roodman et al., 2019) for our preferred specification (Column 3) in Table 2. For both WC outcomes, we can reject the null hypothesis at the 5% level using this method. We present permutation tests in Section 4.3.4.

4.2. Discussion of magnitudes

We find that RML adoption leads to a reduction in WC receipt among adults 40 to 62 years by 21.1% and the level of WC income by 18.8% (comparing absolute effects – 0.19 ppts and $20.16 respecitvely – to counterfactual baselines). These effect sizes are non-trivial, which is in line with the very substantial RML effects on marijuana use found in the literature (for example, Cerdá et al. (2020) report effect sizes that range from 26% to 37% in the full sample,

[30] We cannot fully separate claim duration from higher benefits (due to higher pre-injury wages).

with larger effects among current marijuana consumers, discussed further in Section 5.1). However, our confidence intervals do not allow us to rule out effect sizes as small as a 5.8% decrease in the probability of any WC receipt and a 1.6% reduction in income from WC.

Benchmarking our estimates to the literature is challenging since there is little empirical evidence about the elasticity of workplace injuries or WC claiming behavior with respect to any policy shock. On the other hand, only about half of injured workers file WC claims (Lakdawalla et al., 2007), suggesting substantial scope for influencing claiming behavior. Even less is known about the size of the population on the margins of workplace injuries (e.g., classifying chronic back pain as a workplace injury).

However, the literature has found that rates of working and sickness absences respond considerably to changes in pain management access. Garthwaite (2012) estimates 10% labor supply (i.e., any work at all) reductions resulting from the removal of Cox-2 inhibitors.[31] Bütikofer and Skira (2018) find that work sickness absences are responsive to the introduction (7-12% decreases) and removal (12-16% increases) of these drugs from the market. The literature on marijuana access has found large effects on employment for the 51+ population (Nicholas and Maclean, 2019) and disability insurance (Maclean et al., 2020a). The most related research finds that MML adoption decreases WC receipt by 13% among older adults (Ghimire and Maclean, 2020). Similarly, Anderson et al. (2018) show a reduction in fatal workplace injuries following MML adoption by nearly 20%.[32]

Some of the estimated effects may occur due to reductions in opioid use, which is a therapeutic substitute for marijuana and used to treat chronic pain, which is the most common

[31] This reduction refers to the labor supply of a population disproportionately impacted by access to pain management therapies. Our estimates can also be viewed in a similar context since we focus on WC benefit receipt, a margin which would also be disproportionately impacted by pain management.
[32] Effects are only precise among those 25-44 years, but effects for workers 45-64 are negative and of similar size.

reason patients report using marijuana medically and very common among injured workers who require time away from work to recuover. We estimate a 9.7% reduction in opioid use (over the entire population) due to RML adoption (reported below in Section 5 of this paper, Table A7, last column). Using estimates found in Beheshti (2019), the estimated change in opioid pain reliever prescriptions by itself (and assuming that the relevant population experienced a 9.7% decline) implies a 0.19 ppt increase in employment as well as a large decline in SSDI receipt.[33] Unfortunately, there is little empirical evidence that quantifies the impact of opioid use on WC receipt specifically. However, Savych et al. (2019) use WC claims from 28 states and study the extent to which opioids impact temporary disability claim duration using an instrumental variables approach. The authors show that a 5.0 ppt decrease in longer-term opioid prescriptions, which the authors define as three or more opioid prescriptions, among workers with nonsurgical low back injuries (those likely to be treated with opioids) leads to a 12.6% decline (2.8 weeks per year) in temporary disability duration. Effect sizes are even larger when using a wider definition of injuries. Therefore, the substitution relationship between marijuana and opioids may serve as one of the mechanisms (or as a 'primary mechanism') of the effect.

In addition, RMLs may impact WC receipt through mechanisms other than reduced opioid use. Most WC claims are 'medical only' and we do not measure such claims (Baidwan et al., 2020). Thus, we may capture some workers who receive medical benefits but, due to RML adoption, do not require time away from work. Further, marijuana use post-RML may deter workers from placing a claim due to concerns about job loss.

4.3. Alternative measures of work capacity

[33] Beheshti (2019) estimates that a 10% reduction in hydrocodone prescriptions leads to an increase in the employment-to-population ratio of 0.2 ppts. Similar estimates of the relationship between opioid access and labor supply are found using other identification strategies (and alternative measures of opioid access/supply) in the literature (Krueger, 2017, Aliprantis et al., 2019, Powell, 2021).

WC benefits are an important metric of work capacity and a policy relevant outcome given the importance of the WC program from a social insurance and cost perspective. We next explore impacts on other available metrics related to work capacity in Table 3. In particular, we consider the following variables for older adults: (1) self-reported good, very good, or excellent health; (2) work-limiting disability; and (3) absence from work last week due to own health problems. Some of these measures are drawn from the basic monthly CPS files (Flood et al., 2020) while others are sourced from the ASEC, leading to different sample sizes.

We observe that, following an RML adoption, the probability of reporting good, very good, or excellent health increases by 1.93 ppts (2.3%). The probability of reporting a work-limiting disability declines by 0.74 ppts (6.8%). We do not estimate meaningful (or statistically significant) changes in the probability of being absent from work due to health problems, which is consistent with RML adoption allowing for overall longer-term improvements in symptom management rather than impacting short-term separations from work to address acute health problems. The findings in Table 3 are robust to applying the 2SDiD estimator.

Collectively, these results support the hypothesis that RMLs, by improving symptom management, promote work capacity. Further, these findings suggest that our main WC results are not an artifact of selecting a particular work capacity metric.

4.4. Internal validity

We next assess the internal validity of our design to common sources of bias in TWFE.

4.4.1. Parallel trends

First we estimate event studies to assess whether RML adopting and non-adopting states have different pre-existing trends. We include time-relative-to-adoption indicators from four years pre-policy through one year (or more) post-policy, normalizing any differences between adopting and non-adopting states five or more years (the omitted category) before adoption to zero. The zero category represents the first full RML adoption year; we may observe a partial effect in the year prior to adoption. We group all other post-adoption years into one+ years.[34]

Figure 3A, Panel A examines the propensity of WC receipt by year-relative-to-RML adoption. There is little evidence of any systematic pre-adoption differences, relative to the omitted category, between adopting and non-adopting states. At the time of adoption, there is a notable relative decline in WC benefit receipt. This reduced incidence persists into the next periods. We observe a similar pattern of coefficient estimates in Panel B for annual WC income.

We report comparable event studies using the 2SDiD method proposed by Gardner (2021) in Figure 3B. Again, we observe little evidence of systematic differences between adopting and non-adopting states pre-policy. There is a slight upward trend prior to adoption, followed by a sharp decrease in the partially treated year and another decline beginning in the first fully treated year. Figures 3A and 3B suggest that the reduction in WC benefits in adopting states is not an artifact of systematic trends existing prior to RML adoption. Given the similarity between TWFE and 2SDiD results, we report results using TWFE for the remainder of the paper.

4.4.2. Possible confounders

Next, we examine characteristics that predict RML passage to understand what is changing in adopting states relative to non-adopting states. To this end, we aggregate the data to the state-year level and regress the RML variable on state-level policies and demographics, and state and year fixed effects. Results are listed in Appendix Table 2. We find that states adopting

[34]Several states adopted an RML after 2018, we observe these states in their pre-treatment period and account for this change. For example, states that adopt a policy in 2019 are observed one-year pre-RML in 2018 and two years pre-RML in 2017, we code these states as one for the one-year policy lag in 2018 and one for the two-year policy lag in 2017 (Schmidheiny and Siegloch, 2020). States that did not adopt an RML or announce a date for a future RML by February 2022 are coded as zero for all lead and lag variables.

naloxone & Good Samaritan laws and higher minimum wages are more likely to adopt an RML, while states with increasing populations and shares of Blacks and Hispanics are less likely to do so. MML adoption and most of the laws in the model designed to curb access to opioids through supply-side efforts (e.g., PDMPs) do not predict RML adoption.

Additionally, we explore the sensitivity of our results to different sets of control variables. If our coefficient estimates change substantially as we include different sets of control variables, then we may be concerned that our findings are driven by unobservable heterogeneity rather than capturing a true RML effect (Altonji et al., 2005). We start from a regression specification that includes only the RML indicator, and state and year fixed effects (the same as Table 2, Column 1). To this parsimonious model, we sequentially include each state- and individual-level control variable and observe how the coefficient estimates change. Results are reported in Appendix Table 3. Our coefficient estimates are not appreciably changed as we add covariates. For any WC receipt, the coefficient estimates range from -0.0018 to -0.0019, compared to our baseline coefficient estimate of -0.0019. We conclude that the results are largely insensitive to the inclusion of any specific control.

4.4.3. Migration

Next, we explore the extent to which RML adoption leads to changes in migration patterns: are individuals more likely to move into or out of the state after RML adoption? Such behavior, if present, is a form of program-induced migration (Moffitt, 1992) or a violation of the stable units assumption required for TWFE methods. To explore this possibility, we use information on past-year migration available in the ASEC. We construct measures of any migration, in-migration, and out-migration among older adults. Results are reported in Appendix Table 4 and do not reveal any evidence that RMLs induce migration. Previous work, based on the full sample of adults, provides more evidence of migration effects (Maclean, Ghimire, and Nicholas 2020; Carlin et al. 2020), which may suggest that younger adults (or perhaps adults ages 63 and above, who are also not in our sample) migrate following adoption of an RML.

4.4.4. Randomization inference

In this section, we randomly re-shuffle our RML variable across states and re-estimate Equation (1). In the randomization process, we hold constant the number of states that adopt within each year. We follow MacKinnon and Webb (2020), and report *t*-statistics from this exercise. Results of the placebo analysis are reported in Figure 4. We mark the 2.5 and 97.5 percentiles of the placebo distribution as well as the *t*-statistic generated when RMLs are correctly assigned. We find that our main results are unlikely to occur by chance as the main *t*-statistics are below the 2.5^{th} percentile of the placebo distributions.

4.4.5. Additional sensitivity tests

Finally, we report the results of a series of sensitivity tests in Appendix Table 5A. While we note that we lose precision in some specifications that eliminate some of our limited variation, reassuringly, our coefficient estimates are very similar in all checks. We find that our coefficient estimates are robust to including state-specific linear time trends (Panel A), although results are less precise as we have less variation to use for identification of treatment effects as we add these area-level controls. Additionally, we exclude the Midwest region (which includes no state that adopted an RML during our study period) and lag the RML indicator by one year in Panels B and C respectively. The results are similar. We also control for respondent industry fixed effects (Panel D) and occupation fixed effects (Panel E). While there may be concerns that RMLs impact labor supply decisions on these margins, we find that the coefficient estimates are unaffected by the inclusion of these fixed effects. In Panel F, we add controls for state-level WC policy variables (i.e., maximum weekly benefits). Our results do not appear to be driven by concurrent shifts in WC benefit generosity. In Panel G, we apply the method proposed by de Chaisemartin and D'Haultfoeuille (2020a, 2020b) that accounts for heterogeneity in treatment effects, though it requires us to aggregate to the state-year level. This estimator addresses the same sources of bias as the Gardner (2021) method, with each making different assumptions.[35] Finally, in Panel G, we report results based on different regression model specifications. We use a probit model for any WC benefit receipt and a Poisson model for the WC income variable, reporting average marginal effects for each.

We also conduct a 'leave-one-out' analysis to assess differences across states in RML effects. While we use a single indicator for law passage, each law has unique characteristics (ProCon.org, 2022b) and therefore a potentially different effect on WC benefit receipt. We sequentially drop each treatment state from the sample and re-estimate Equation (1). This exercise allows us to explore whether our main findings (Table 2) are driven by the experience of a specific state. We graphically report the leave-one-out analysis results in Appendix Figure 2; WC benefit receipt is reported in Panel A and WC income is reported in Panel B. Our findings are similar across the leave-one-out samples.

5. Mechanisms

Our primary finding is that RML adoption reduces WC benefits. Any welfare calculus of RMLs and related policies depends on our understanding of *how* RMLs reduce WC benefit receipt. A reduction in WC benefits that is driven by reduced labor supply or other labor market distortions could imply that further legalization harms labor markets, while a reduction driven by

[35] We have also applied methods proposed by Callaway and Sant'Anna (2020) and results are similar.

better symptom management leads to the opposite conclusion. Here we attempt to discriminate between different causal chains with substantially discordant normative implications.

First, we assess evidence related to the causal relationship we hypothesize: following RML adoption, individuals increase use of marijuana in place of conventional medications used to treat chronic pain. Second, we consider alternative mechanisms such as broader changes in labor markets, in particular labor supply and demand, induced by RML adoption.

5.1. Marijuana use/misuse and prescription medication use

The literature provides evidence that RMLs increase adult marijuana use on the order of 20-38% (Cerdá et al., 2020, Dragone et al., 2019, Hollingsworth et al., 2019, Maclean et al., 2020a). We test this relationship in our context using the public use NSDUH (maintained by the Substance Abuse and Mental Health Services Administration [SAMHSA]). A limitation of the public use NSDUH is that we cannot isolate older adults. Instead, we examine all adults 26 years and older. The public use files include two-year averages so we match RMLs to the data on the second year of the average and weight by the state population 26 years and older. We document large increases in marijuana use post-RML (Appendix Table 6A): a 1.93 ppt (27.8% compared to the counterfactual) increase in any past month and a 2.59 ppt (23.9% compared to the counterfactual) increase in past year marijuana use.

Marijuana use may induce harms. To explore this possibility for our age group, we assess whether RMLs lead to increased problematic use of marijuana among older adults using data on marijuana-related admissions to SUD treatment in the Treatment Episode Dataset (TEDS) maintained by SAMHSA. The TEDS is a national database of admissions to standalone SUD treatment. While not capturing all SUD treatment, TEDS includes roughly two-thirds of standalone treatment received in the U.S. and these data are regularly used by economists to study SUD treatment outcomes (Dave and Mukerjee, 2011, Pacula et al., 2015, Powell et al., 2020, Maclean et al., 2020b). We select admissions where the patient is 40 to 64 years of age;[36] convert to a rate per 100,000 state residents 40-64 years; and weight by this population. We find no evidence that this measure of problematic marijuana use increases post-RML among older adults (Appendix Table 6B). We also observe no changes in non-marijuana admissions.

The increase in marijuana use coincides with meaningful reductions in use of opioids following RML adoption (Carrieri et al., 2020, Wen and Hockenberry, 2018, McMichael et al., 2020, Wen et al., 2021). Additionally, the literature finds that RMLs reduce opioid-related mortality and ED episodes (Chan et al., 2020, Drake et al., 2021) which is in line with using marijuana for pain management purposes in cases in which alternatives may be more dangerous. Thus, there is substantial scope for RMLs to impact pain management as well as other outcomes related to a large expansion of recreational marijuana use and sales. To further test for substitution from prescription medications used to treat chronic pain and marijuana in our time period and specification, we estimate the impact of RML adoption on Medicare Part D opioid prescription fills (proxied by the number of prescriptions and the daily supply per 100,000 Medicare beneficiaries in the state) from the Centers for Medicare and Medicaid Services (CMS).[37] We use the list of opioids prescribed to Medicare Part D beneficiaries in Ellyson et al. (2020), and we weight by the number of Medicare beneficiaries in the state. We also consider the total number of opioid prescriptions filled in retail pharmacies among the total population using data from IQVIA, which captures 90% of all such prescriptions.[38] Neither data source allows us to isolate our key population of interest, but we examine these measures as proxies for

[36] We cannot more accurately match our main sample based on age categories in the TEDS.
[37] 2010-2012 Medicare Part D data are from ProPublica and 2013-2018 data are from CMS.
[38] We draw IQVIA data from the Centers for Disease Control and Prevention (2020) and weight by this population.

the impact of RMLs on opioid use. Post-RML, our proxies of opioid prescriptions decline by 7.3% to 9.8% (comparing estimated coefficients to baseline counterfactuals) (Appendix Table 7), similar to effect sizes documented in the literature.

This section provides evidence, supporting findings in the literature, that marijuana use among adults increases substantially following RML adoption. This additional use is not accompanied with increases in marijuana-related dependence, though we also do not observe the full spectrum of marijuana-related harms so we cannot rule out possible harmful health consequences. Further, we show that patients substitute marijuana for prescription medications used to treat chronic pain, suggesting increased use of marijuana for pain management.

5.2. Changes in labor supply and job opportunities

To understand the broader context of changes in WC benefit receipt following RML adoption, we study labor supply more generally. The purpose of this exercise is to assess whether the changes in WC benefit receipt are a mechanical artifact of overall reduced labor supply; if RML adoption leads to an overall lowering of labor supply, then we would expect less WC, but such a relationship would be driven by a very different causal pathway than we have hypothesized (i.e., better pain management).

We evaluate measures of labor supply in Appendix Table 8. We consider the following outcomes among older adults: working in the past year, current labor force participation, working in the past week, usual hours worked per week in the past year (unconditional and conditional on any hours worked), any past year Social Security Disability Income (SSDI), and any past year Supplemental Security Income (SSI). Some of these outcomes are drawn from the ASEC while others are sourced from the monthly CPS, leading to different samples sizes.

We observe that, after RML adoption, the propensity to work in the past year and past week increases by 1.48 ppts and 2.30 ppts (1.9% and 3.0% relative to the counterfactual), respectively, while the unconditional and conditional (on any hours) number of hours usually worked per week increases by 1.20 and 0.40 hours or 4.2% and 1.0%. The probability of past year SSDI declines by 0.28 ppts while the probability of SSI is generally unchanged. SSDI and SSI can also be viewed as health metrics and complementary measures of work capacity. These results cast doubt on the possibility that RMLs reduce WC benefit receipt mechanically through decreased labor supply (i.e., reduced opportunities to incur injuries at work). Instead, we observe evidence of *increases* in labor supply, which – all else equal – would predict that WC income receipt should increase post-RML.

We also study whether RML adoption leads to changes in the number of establishments using the 2010 to 2018 County Business Patterns (CBP) data (United States Census Bureau, 2021). The CBP captures the universe of businesses establishments in the U.S. and is based on Internal Revenue Service tax filings. We consider two measures of establishments: total number of establishment and number of establishment in industries plausibly related to the recreational marijuana market as examined by Chakraborty et al. (2020).[39] Data are converted to a rate per 100,000 residents, and we weight by this population. We observe no change in either type of establishments post-RML (Appendix Table 9), suggesting that RMLs do not induce changes in the number of employers, which proxies imperfectly for job opportunities.

5.3. Changes in injury rates and industry composition

[39] We use the following NAICS codes: Natural Resources and Mining (11), Construction (23), Manufacturing (31-33), Trade (42, 44-45), Information (51), Financial Activities (52), Education (61), and Health Services (62).

We next provide evidence about whether we are observing differences in WC receipt (possibly through changes in claiming behavior) versus differences in injury rates. We use administrative data from the Bureau of Labor Statistics (BLS) on nonfatal workplace injuries among those 40 to 62 years of age in each state over the period 2011 to 2018.[40] The BLS Survey of Occupational Injuries and Illnesses (SOII) collects workplace injury data from approximately 200,000 employers Bureau of Labor Statistics (2021).[41] We use nonfatal cases involving days away from work as our measure of workplace injuries. This SOII variable shares some useful characteristics with WC benefit receipt since both require time away from work due to workplace injuries. The SOII measure does not necessarily imply WC benefit receipt,[42] offering an opportunity to distinguish between changes in injury rates and WC claiming behavior. The SOII data exclude some states and we are left with 337 observations from 41 states. We convert the injuries to rates per 100,000 residents 40-62 years and weight by this population. The SOII data also permit us to evaluate injuries based on injury type, and we separate traumatic injuries from non-traumatic injuries, reporting these alongside total injury rates. We expect traumatic injuries, which are much more common, to be less responsive to pain management therapy availability. Injuries such as sprains, strains, tears, hernias, and burns are classified as traumatic injuries, including complex region pain syndrome. Non-traumatic injuries include low back disorders, infectious diseases, and cancer. Results are reported in Appendix Table 10. We estimate a small reduction for traumatic injuries, equivalent to a 0.5% decline. The estimate for non-traumatic estimates implies a 16.4% decrease,[43] similar to our WC estimates.

[40] There are concerns about the quality of the data prior to 2011 so we begin our analysis with the 2011 data.
[41] Some groups are excluded: federal employees, the self-employed, and small farms (less than ten workers).
[42] Workers are often ineligible for cash WC benefits unless they miss at least three days of work.
[43] The coefficient estimates for traumatic and non-traumatic injuries, in levels, are relatively similar. However, most injuries are traumatic so the implied proportional effects are very different.

We also consider the possible role of changes to industry composition on affecting injury rates using the SOII data. One possibility is that RMLs alter the local economy in a way that shifts workers to safer jobs, explaining the reduction in injury rates and WC benefit receipt. We test this possibility by assigning each worker in the ASEC with the injury rate[44] of their industry in their state in 2011 (the year prior to the first RML adoption).[45] The motivation behind this test is to hold constant the industry injury rate such that the outcome (conditionally) only varies due to systematic movements in industry composition and extensive labor supply decisions. Holding the injury rate constant shuts down any endogenous within-industry changes to the injury rate due to RML adoption. We estimate a *positive* (statistically insignificant) effect on this predicted injury rate measure (Appendix Table 10, Column 4), suggesting that the decreases estimated for injury rates are not due to changes in labor force participation or industry composition.

5.4. Discussion of mechanisms

RML adoption may impact the local economy and labor supply in several ways. Studying WC receipt offers a useful window to understand how RMLs affect work capacity by concentrating on workplace injuries and recovery time from those injuries. However, changes in WC receipt may not necessarily solely reflect changes in work capacity if RMLs have broader impacts on the local economy. We considered several of these possibilities in this section.

We do not find evidence that RML adoption decreases WC receipt by reducing labor supply or labor demand. Moreover, adoption does not appear to shift workers into safer occupations. Instead, the evidence is consistent with improvements in work capacity. We observe complementary evidence that bolsters this interpretation. We find evidence that the

[44] The injury rate is injuries per 100,000 workers in the industry. Non-workers are assigned a rate of zero.
[45] The SOII provides injury rates by NAICS. We map NAICS codes to 1990 Census industry codes in the IPUMS.

additional access to marijuana increases marijuana use and decreases use of alternative pain management therapies, suggesting that RMLs increase marijuana use for pain management purposes. In addition, we estimate declines in work-limiting disabilities and SSDI receipt. In aggregate, the results suggest that RMLs improve work capacity among older adults.

6. Heterogeneity in RML effects

6.1. The importance of dispensaries

In our primary analysis, we use an indicator for any RML and do not distinguish between policies that protect dispensaries, legal establishments in which individuals can purchase marijuana, and those that do not. We next include a second indicator variable in Equation (1) that takes the value of one if a state RML provides the legal framework for dispensaries to operate (we do not alter our main RML indicator). We also separately consider whether there is a legal and *operational* recreational dispensary in the state. We report results based on the augmented specifications in Appendix Table 11; Panel A reports results for a law that allows dispensaries and Panel B reports results that use the first legal recreational marijuana dispensary in operation in a state. We do not observe any evidence that, conditional on RML, dispensaries (either measured as the legal framework allowing dispensaries or dispensaries in operation) lead to additional changes in WC claiming. We report tests of the combined effect (RML + dispensary) at the bottom, and they are similar to our prior coefficient estimates. Overall, we do not observe evidence suggesting that dispensaries are particularly important in this context.

6.2. Heterogeneity by respondent characteristics

We consider heterogeneity in RML effects across individuals based on the type of job they hold. We follow Ghimire and Maclean (2020) and separately consider those employed in 'physically demanding jobs' and other jobs.[46] The magnitudes are larger for physically demanding jobs, though the differences are small (see Appendix Table 12).

We also estimate separate regressions by sex (Appendix Table 13). WC benefit receipt is more common for men, and we estimate larger effect sizes for men than for women.

7. Discussion and Conclusion

Our study evaluates the effect of recent laws legalizing recreational marijuana on workers' compensation benefits among adults ages 40 to 62 in the U.S. The analysis reveals a decline in WC benefit receipt by 0.19 ppts and annual income received from WC declines by \$20.16 post-RML. We provide evidence that our results are not attributable to common threats to identification in TWFE models: bias from heterogeneous treatment effects across states that adopt policies at different points in time, differential pre-trends between adopting and non-adopting states, unobservable confounders, and program-induced migration. The findings are not sensitive to our proxy for work capacity; instead, we observe similar patterns of improved work capacity across different metrics, such as reductions in work-limiting disabilities and SSDI receipt. We conducted a detailed analysis of mechanisms to understand this relationship. First, we show that marijuana use – but not misuse – increases post-RML and reduces prescriptions for medications used to treat pain. Second, our mechanism analysis provides suggestive evidence that our results are not attributable to an overall reduction in labor supply or demand or systematic shifting of workers to safer industries.

Our findings suggest potentially important benefits to older workers and society at large. Broadly, we show non-trivial improvements in work capacity, which we proxy with WC benefit

[46] Occupation codes (based on IPUMS-provided variable occ90ly) 473-905 are coded as physically demanding, following Ghimire and Maclean (2020). We code all other occupations as not physically demanding. An example of a physically demanding (not physicially demanding) occupation is a miner (pharmacist). Not all individuals report occupational information and thus the sum of the stratified samples is smaller than the full sample size.

receipt and various other metrics in our mechanism analysis, among older adults. The ability to work likely has positive benefits to workers themselves due to improved earning capacity, and overall health and life satisfaction. Older workers are at elevated risk of leaving the labor market due to poor health (Dwyer and Mitchell, 1999). Keeping workers actively engaged in paid employment can have positive spillovers to Social Security and can reduce costs to state government and employers. Similarly, working can increase household income and improve health (Coe and Zamarro, 2011). Hirth et al. (2003) note how little evidence we have on the relationship between access to medical treatments and labor supply outcomes. Since that paper, a small literature has emerged on the availability of specific prescriptions drugs and labor outcomes (e.g., Thirumurthy et al. (2008); Garthwaite (2012); Bütikofer and Skira (2018), and Bütikofer et al. (2020); Shapiro (2020)). This paper provides additional evidence about the importance of pain management therapies on improving work capacity but finds that these gains are not limited to traditional pharmaceuticals.

There is a continuing debate in the U.S. on whether and how states should address marijuana legalization. To formulate a solution, identifying harms and benefits followed by the policy change is useful. Previous studies provide evidence on the positive and negative effects of marijuana legalization on several outcomes related to individuals' health and well-being; however, few have isolated the impacts on work capacity, a critical policy metric for our understanding of the value of pain management therapy access and the workforce productivity effects of marijuana access. The present study provides empirical evidence on the consequences of marijuana legalization on issues related to older adult work capacity.

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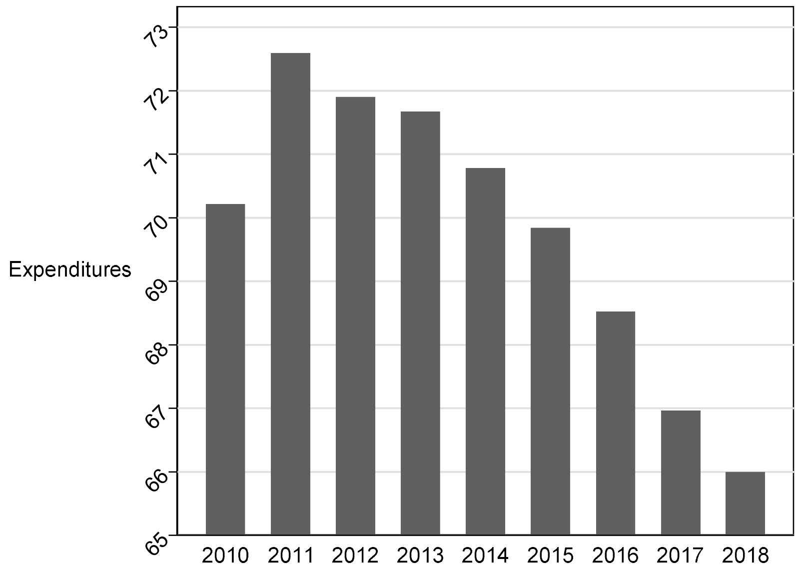
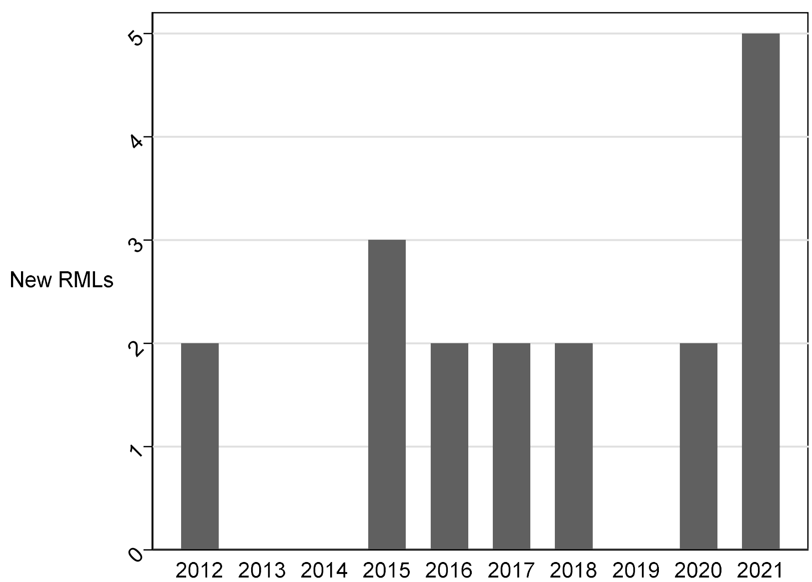
Figures

Figure 1A. Workers' compensation claiming costs in the U.S. (billions): 2010 to 2018



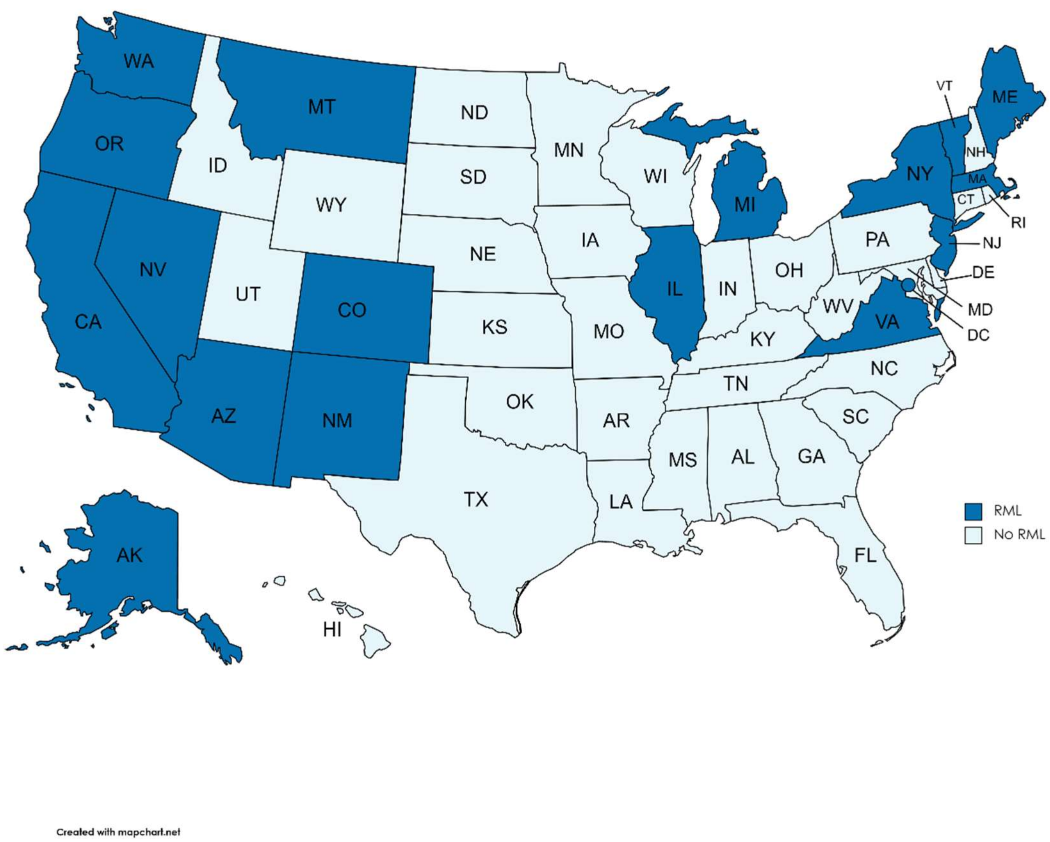
Notes: The figure is based on Table 5 in Weiss et al (2020). We inflate nominal values to 2020 dollars using the Consumer Price Index. See text for details.

Figure 1B. RML adoptions and announcements as of February 2022



Notes: The figure is based on data reported in Chan et al (2019) and ProCon.org (2021). Note that law changes are coded as of January 1st of each year. RML effective dates (adopted or announced by October 2021) are as follows: Alaska: February 2015; Arizona: November 2020; California: November 2016; Colorado: December 2012; District of Columbia: February 2015; Illinois: January 2020; Maine: January 2017; Massachusetts: December 2016; Michigan: December 2018; Montana: January 2021; Nevada: January 2017; New Jersey: January 2021; New Mexico: June 2021; New York: March 2021; Oregon: July 2015; Vermont: July 2018; Virginia: July 2021; and Washington: November 2012. See text for details.

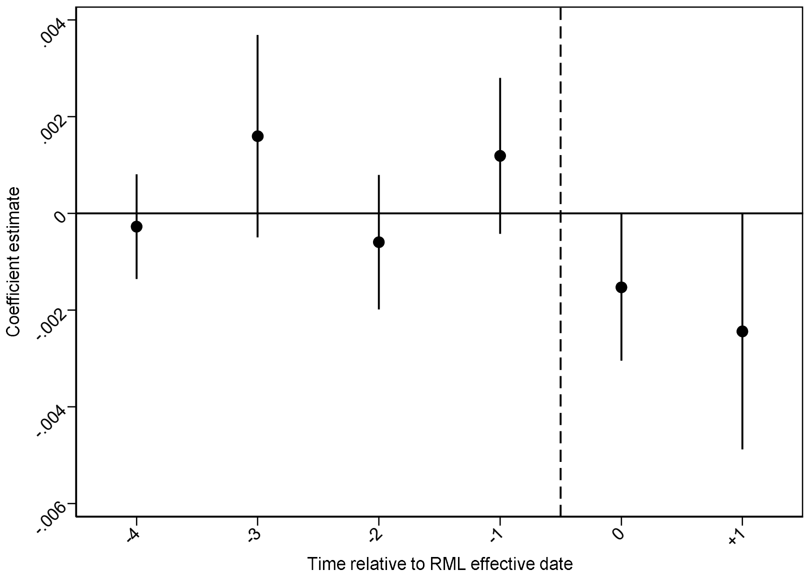
Figure 2. States with an RML implemented or announced by February 2022



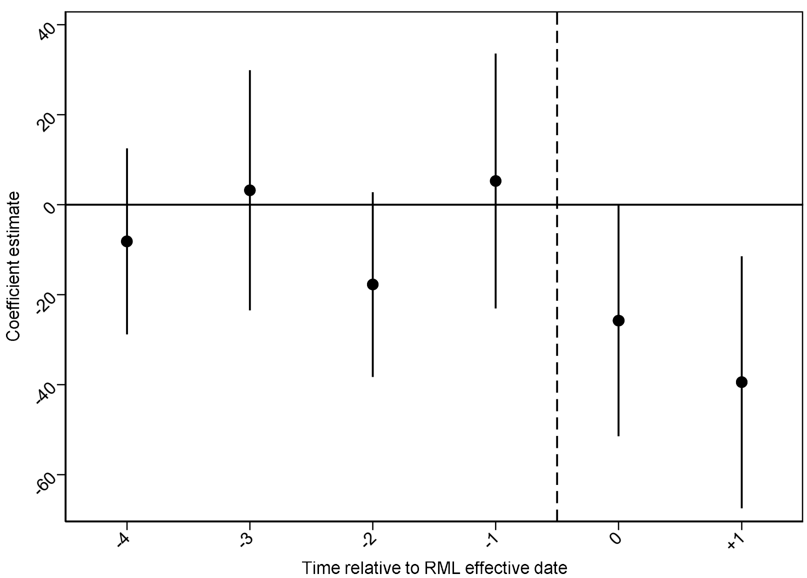
Notes: The figure is based on data reported in Chan et al (2019) and ProCon.org (2021). Note that law changes are coded as of January 1st of each year. RML effective dates (adopted or announced by October 2021) are as follows: Alaska: February 2015; Arizona: November 2020; California: November 2016; Colorado: December 2012; District of Columbia: February 2015; Illinois: January 2020; Maine: January 2017; Massachusetts: December 2016; Michigan: December 2018; Montana: January 2021; Nevada: January 2017; New Jersey: January 2021; New Mexico: June 2021; New York: March 2021; Oregon: July 2015; Vermont: July 2018; Virginia: July 2021; and Washington: November 2012. See text for details.

Figure 3A. The effect of recreational marijuana law passage on workers' compensation benefit receipt: Event study analysis

Panel A: Any WC income



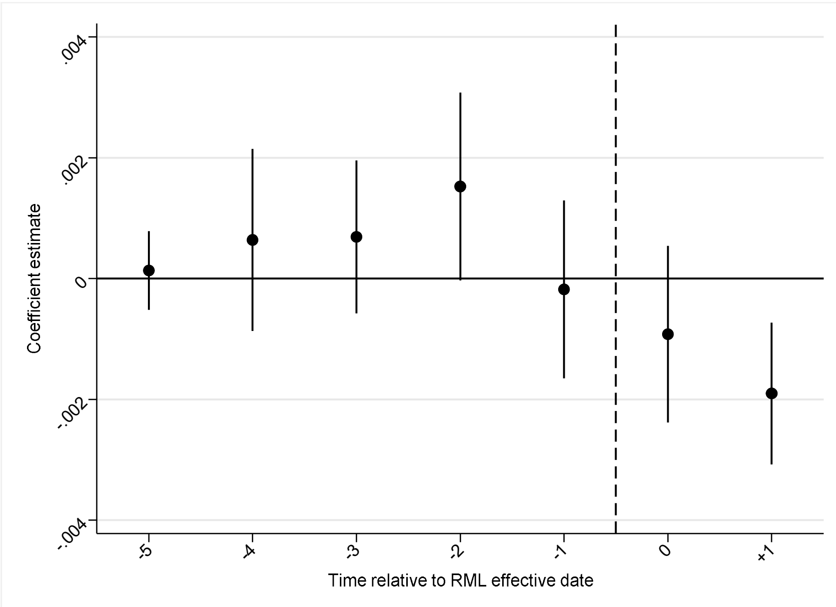
Panel B: WC income



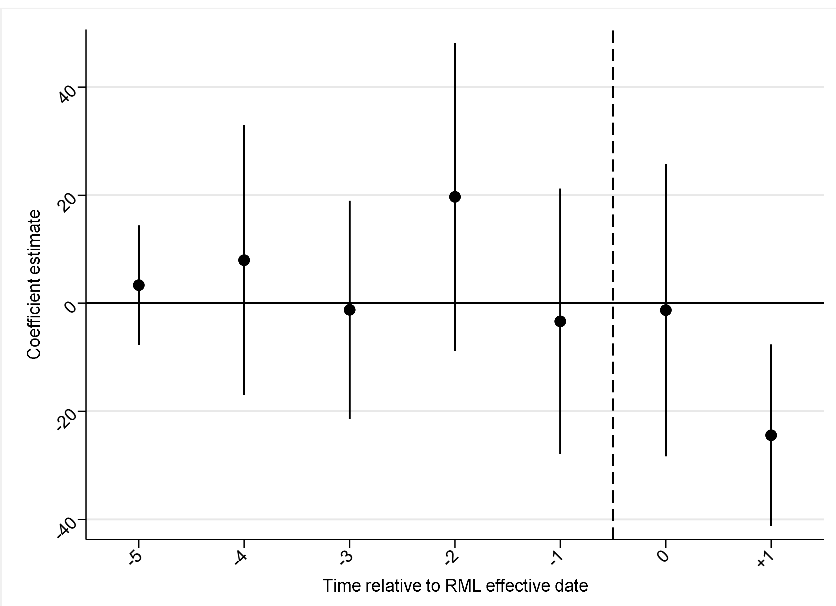
Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. Circles represent coefficient estimates and 95% confidence intervals are depicted by vertical lines. The omitted category is five or more years pre-RML passage; the "-1" period is partially treated. States that do not adopt an RML are coded as zero for all event-time indicators. The regression model controls for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Data are weighted by ASEC survey weights. Confidence intervals are clustered at the state level.

Figure 3B. The effect of recreational marijuana law passage on workers' compensation benefit receipt: Event study analysis using two-stage difference-in-differences

Panel A: Any WC income



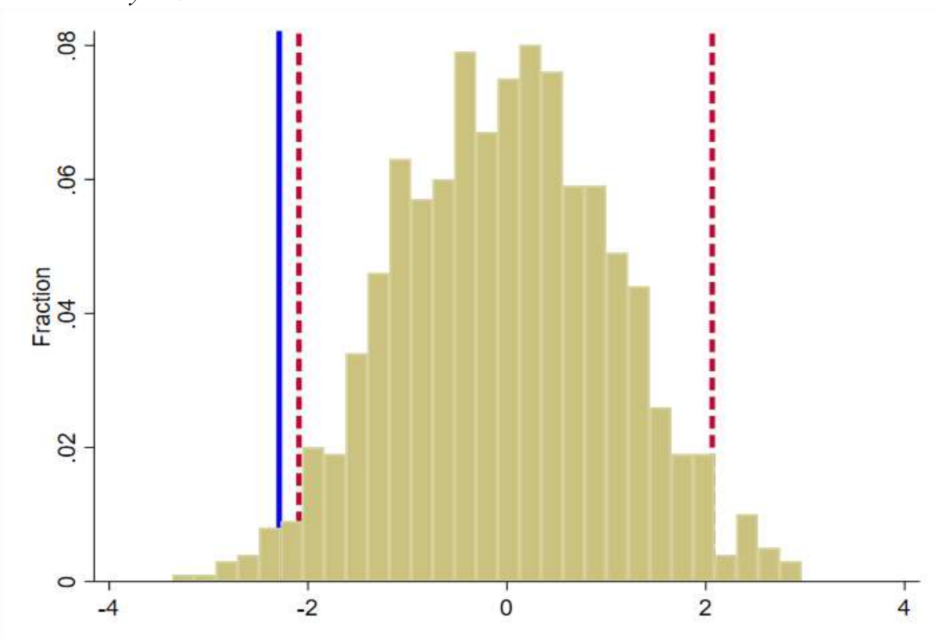
Panel B: WC income



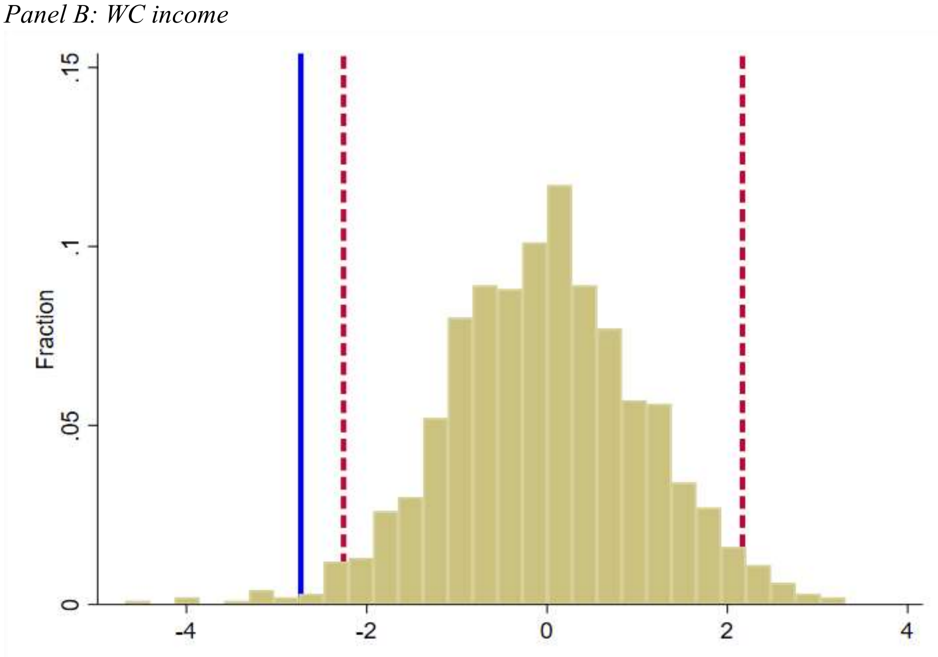
Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. Circles represent coefficient estimates and 95% confidence intervals are depicted by vertical lines. The "-1" period is partially treated. We estimate using 'Two-stage DID' models (Gardner 2021). This approach does not involve normalizing the event study estimates to zero in any specific period. States that do not adopt an RML are coded as zero for all event-time indicators. The regression model controls for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. These parameters are estimated in the first step and then the outcomes are residualized. Data are weighted by ASEC survey weights. Confidence intervals are clustered at the state level.

Figure 4. The effect of recreational marijuana law passage on workers' compensation benefit receipt: Falsification exercise

Panel A: Any WC income



Panel B: WC income



Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Data are weighted by ASEC survey weights. The x-axis reports the *t*-statistic value. We randomly assign states into treatment status, holding constant the number of states adopting in each year. The 'true' *t*-statistic is the solid blue line. The red dotted lines are the 2.5 and 97.5 percentiles of the placebo *t*-statistics. See text for more details.

Tables

Table 1. Summary statistics

Sample:	**All states (all years)**	**RML states (pre-RML years)**	**Non-RML states (all years)**
Outcome			
Any WC income (past year)	0.007	0.008	0.006
WC income (past year; $)	75.07	92.47	70.18
RML policy			
RML	0.063	0	0
State-level characteristics			
MML	0.396	0.863	0.191
Prescription drug monitoring program	0.937	0.976	0.920
Naloxone & Good Samaritan law	0.402	0.466	0.321
Pain clinic management law	0.247	0	0.346
Minimum wage ($)	8.439	8.895	8.102
State EITC ratio,	0.099	0.048	0.078
Governor Democrat	0.424	0.660	0.306
Population (millions)	1.411	2.122	1.141
Individual-level characteristics			
Age (years)	50.99	50.85	51.03
Male	0.487	0.492	0.485
Female	0.513	0.508	0.515
White	0.794	0.795	0.794
African American	0.123	0.085	0.142
Other race	0.083	0.120	0.064
Hispanic	0.143	0.184	0.123
Less than high school	0.104	0.115	0.098
High school	0.295	0.265	0.310
Some college	0.269	0.273	0.269
College degree or more	0.332	0.347	0.323
Observations	517,351	101,202	370,990

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. Data are weighted by ASEC survey weights. Dollar values expressed in 2018 terms.

Table 2. Effect of recreational marijuana law passage on workers' compensation benefit receipt

Specification:	(1)	(2)	(3)	(4)
		Panel A: Any WC income		
TWFE	-0.0016**	-0.0015**	-0.0019**	-0.0016**
	(0.0006)	(0.0006)	(0.0009)	(0.0008)
Two-stage DID	-0.0020***	-0.0021***	-0.0022***	-0.0015**
	(0.0006)	0.0006	(0.0005)	(0.0004)
RML state mean, pre-RML	0.008	0.008	0.008	0.008
Counterfactual mean	0.009	0.009	0.009	0.009
Bootstrapped *t*-statistic	--	--	-2.2540	--
Observations	517,351	517,351	517,351	517,351
		Panel B: WC income		
TWFE	-17.65**	-19.42***	-20.16**	-20.81**
	(6.84)	(6.73)	(8.02)	(9.67)
Two-stage DID	-19.86**	-20.27***	-23.34***	-17.86**
	(8.04)	(6.01)	(3.7118)	(7.52)
RML state mean, pre-RML	$92.47	$92.47	$92.47	$92.47
Counterfactual mean	$107.22	$107.22	$107.22	$107.22
Bootstrapped *t*-statistic	--	--	-2.1803	--
Observations	517,351	517,351	517,351	517,351
Data are weighted	Y	Y	Y	N
State fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Individual controls	N	Y	Y	Y
State controls	N	N	Y	Y

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is the respondent. Individual controls include age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education. State controls include MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population. All models include state fixed effects and year fixed effects. 'Two-stage DID' models use the Gardner (2021) residualization approach. All analyses are weighted by ASEC survey weights, unless otherwise noted. Standard errors are clustered at the state level and are reported in parentheses. 'Counterfactual mean' is the mean of the outcome for the treated observations in the absence of treatment (i.e., after subtracting off the treatment effect).
***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 3. Effect of recreational marijuana law passage on alternative measures of work capacity: Health outcomes

Outcome:	Good/very good/excellent health	Work limiting disability	Absent from work due to own health†
TWFE	0.0193***	-0.0074***	0.0006
	(0.0060)	(0.0026)	(0.0004)
Two-stage DID	0.0139**	-0.0078**	0.0004
	(0.00067)	(0.0032)	(0.0003)
RML state mean, pre-RML	0.886	0.111	0.0081
Counterfactual mean	0.849	0.109	0.0075
Observations	517,351	517,351	3,078,174
Dataset	ASEC	ASEC	Monthly CPS
(years)	(2011-2019)	(2011-2019)	(2010-2018)

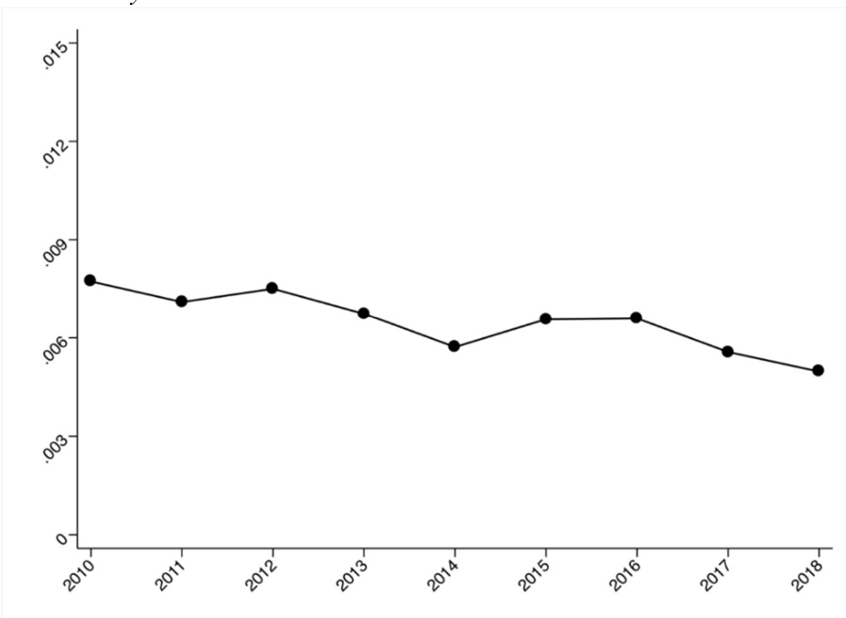
Notes: The sample includes respondents 40 to 62 years in the ASEC or monthly CPS. The unit of observation is a respondent. All models include state controls, individual controls, state fixed effects, and year fixed effects. State controls include MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population. Individual controls include age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education. 'Two-stage DID' models use the Gardner (2021) residualization approach. Data are weighted by ASEC survey weights in the ASEC data and monthly CPS survey person weights in the monthly CPS files. Standard errors are clustered at the state level and are reported in parentheses. 'Counterfactual mean' is the mean of the outcome for the treated observations in the absence of treatment (i.e., after subtracting off the treatment effect).
†Absent from work due to health is defined as reporting being absent from work in the past week due to own illness/injury/medical problems.
***,**,* = statistically different from zero at the 1%,5%,10% level.

ONLINE APPENDIX

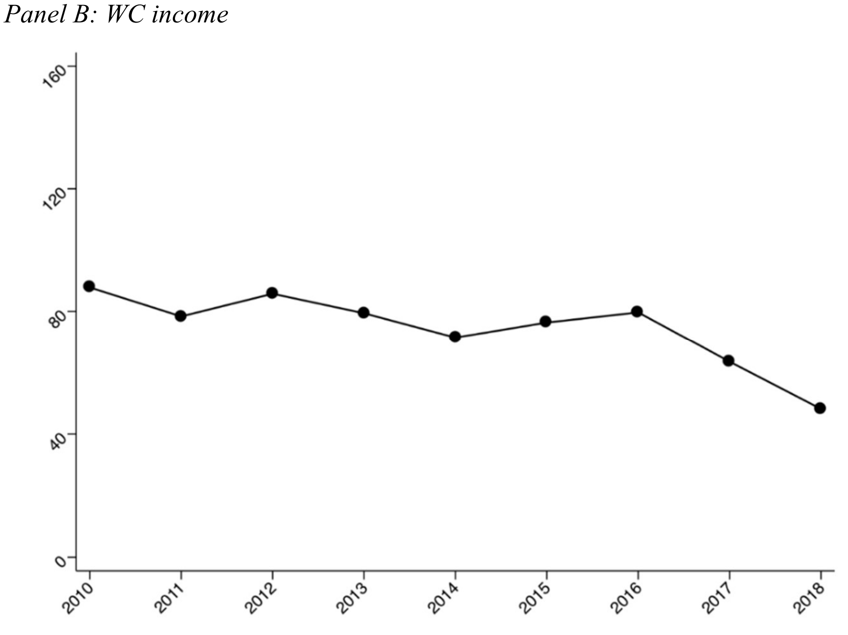
Appendix Figures

Appendix Figure 1. Trends in workers' compensation benefit receipt in each year of the study period

Panel A: Any WC income



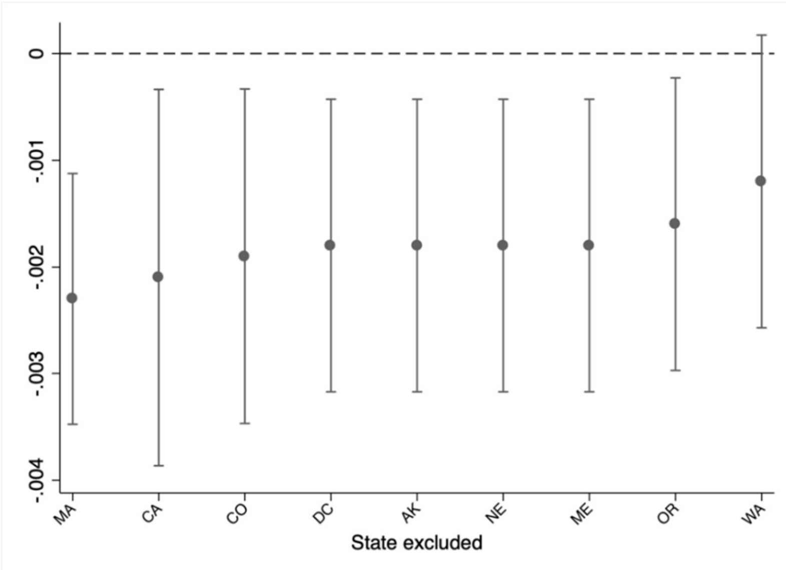
Panel B: WC income



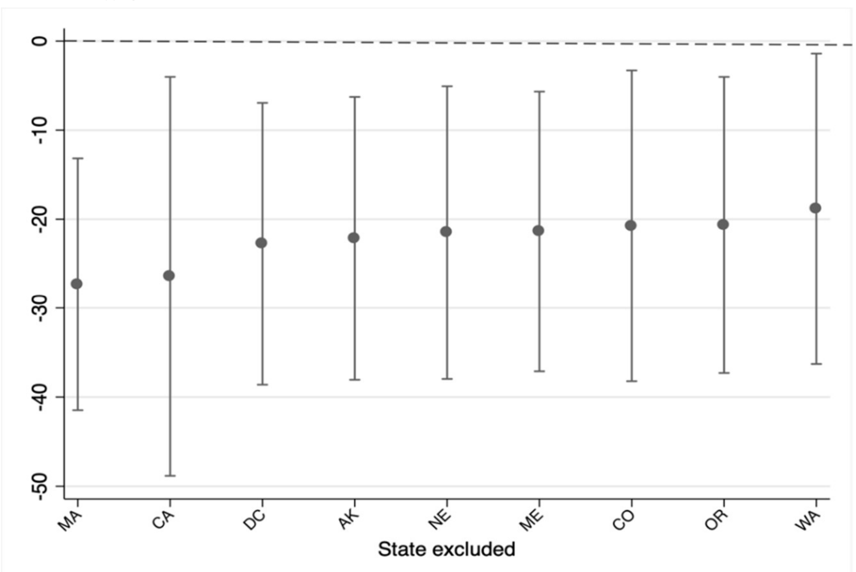
Notes: The data source is the ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. Data are aggregated to annual level and weighted by ASEC survey weights.

Appendix Figure 2. The effect of recreational marijuana law passage on workers' compensation benefit receipt: Leave-one-out analysis

Panel A: Any WC income



Panel B: WC income



Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. Circles capture the coefficient estimate and vertical bars capture 95% confidence intervals that account for within-state clustering for each leave-one-out sample. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Data are weighted by ASEC survey weights.

Appendix Tables

Appendix Table 1. Effect of recreational marijuana law passage on workers' compensation benefit receipt: All time-varying controls coefficient estimates

Outcome:	Any WC income	WC income
RML	-0.0019**	-20.16***
	(0.0009)	(8.02)
Other controls		
MML	-0.0010	-0.84
	(0.0007)	(9.70)
Prescription drug monitoring program	-0.0005	-13.60
	(0.0008)	(8.30)
Naloxone & Good Samaritan law	-0.0004	-12.44*
	(0.0005)	(7.01)
Pain management clinic law	0.0004	10.85
	(0.0008)	(11.43)
Minimum wage ($)	0.0002	5.63
	(0.0003)	(5.54)
State EITC ratio	-0.0004	-9.97
	(0.0008)	(10.60)
Governor Democrat	-0.0002	0.71
	(0.0005)	(6.86)
Population	-0.0000	-0.00
	(0.0000)	(0.00)
Age (in years)	0.0001***	2.06***
	(0.000)	(0.42)
Female	-0.0024***	-42.29***
	(0.0004)	(4.66)
African American	0.0005	-0.07
	(0.0005)	(5.86)
Other race	-0.0006	0.09
	(0.0005)	(8.14)
Hispanic ethnicity	0.0000	2.22
	(0.0000)	(9.73)
High school	0.0003	11.38
	(0.0007)	(9.23)
Some college	-0.0001	11.39
	(0.0006)	(12.71)
College degree or more	-0.0053***	-53.91***
	(0.0007)	(10.07)
RML state mean, pre-RML	0.008	$92.47
Counterfactual mean	0.009	107.22
Observations	517,351	517,351

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent. All regression models control for state fixed effects and year fixed effects. Omitted categories are male (sex), White (race), non-Hispanic (ethnicity), and less than high school (education). Data are weighted by ASEC survey weights. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 2. State-level correlates predicting adoption of a recreational marijuana law

Outcome:	**RML**
MML	-0.0362
	(0.0407)
Prescription drug monitoring program	-0.0010
	(0.0371)
Naloxone & Good Samaritan law	0.0890***
	(0.0326)
Pain management clinic	0.0813*
	(0.0459)
Minimum wage	0.1215***
	(0.0403)
State EITC ratio	0.5483*
	(0.3191)
Governor Democrat	-0.0166
	(0.0542)
Population	-0.0000*
	(0.0000)
Age	-0.0445
	(0.0587)
Female	0.0032
	(1.4295)
African American	-0.4717**
	(0.2193)
Other race	0.1263
	(0.3592)
Hispanic	-0.0012**
	(0.0007)
High school	-1.0327
	(0.6888)
Some college	-0.2509
	(0.6277)
College degree or more	-0.4071
	(0.5117)
Proportion	0.083
Observations	459

Notes: The unit of observation is a state in a year. The regression model is estimated with least squares and controls for state characteristics, state fixed effects, and year fixed effects. Omitted categories are male (sex), White (race), non-Hispanic (ethnicity), and less than high school (education). Note that we aggregate the demographics from the respondent-state-year to the state-year level, applying ASEC weights in the aggregation. Data are weighted by the state population. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 3. Effect of recreational marijuana law passage on workers' compensation benefit receipt: Add time-varying controls one at a time

Outcome:	Any WC income	WC income
Panel A: Baseline model		
RML	-0.0019***	-20.16**
	(0.0009)	(8.02)
Panel B: Progressively add control variables		
Added control: MML	-0.0018**	-17.88**
	(0.0008)	(7.05)
Added control: Prescription drug monitoring program	-0.0018**	-18.00**
	(0.0008)	(6.95)
Added control: Naloxone & Good Samaritan law	-0.0018**	-18.64**
	(0.0008)	(7.16)
Added control: Pain management clinic	-0.0018**	-17.31**
	(0.0008)	(7.27)
Added control: Minimum wage	-0.0019**	-22.52***
	(0.0008)	(8.21)
Added control: State EITC ratio	-0.0018**	-19.56**
	(0.0010)	(8.31)
Added control: Governor Democrat	-0.0018**	-19.54**
	(0.0009)	(8.18)
Added control: Population	-0.0018**	-19.60**
	(0.0009)	(8.19)
Added control: Age	-0.0018**	-19.48**
	(0.0009)	(8.15)
Added control: Female	-0.0018**	-19.53**
	(0.0009)	(8.19)
Added control: African American	-0.0018**	-19.52**
	(0.0009)	(8.18)
Added control: Other race	-0.0018**	-19.55**
	(0.0009)	(8.19)
Added control: Hispanic	-0.0018**	-19.63**
	(0.000)	(8.19)
Added control: High school	-0.0018**	-19.99**
	(0.0009)	(8.16)
Added control: Some college	-0.0018**	-20.06**
	(0.0007)	(8.03)
Added control: College degree or more	-0.0019**	-20.16**
	(0.0009)	(8.02)
RML state mean, pre-RML	0.008	$92.47
Counterfactual mean	0.009	107.22
Observations	517,351	517,351

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent. The baseline model controls for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Omitted categories are male (sex), white (race), non-Hispanic (ethnicity), and less than high school (education). Each row in Panel B progressively adds time-varying controls to the regression model. Data are weighted by ASEC survey weights. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 4. Effect of recreational marijuana law passage on migration into and out of states

Outcome:	Any migration	Migrate in	Migrate out
RML	0.0002	-0.0002	0.0004
	(0.0011)	(0.0006)	(0.0007)
Mean in RML states, pre-RML	0.011	0.008	0.003
Counterfactual mean	0.012	0.012	0.004
Observations	517,351	517,351	517,351

Notes: Dataset is ASEC 2011 to 2019, which captures migration over the period 2010-2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Data are weighted by ASEC survey weights. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 5. Effect of recreational marijuana law passage on workers' compensation benefit receipt, alternative specifications, and samples

Outcome:	Any WC income	WC income
Panel A: Include state-specific linear time trends		
RML	-0.0018	-17.07
	(0.0012)	(12.22)
Observations	517,351	517,351
Panel B: Exclude the Midwest region		
RML	-0.0018*	-17.12*
	(0.0009)	(8.80)
Observations	413,347	413,347
Panel C: Use lagged RML		
RML	-0.0018***	-21.98**
	(0.0007)	(8.04)
Observations	517,351	517,351
Panel D: Include industry fixed effects†		
RML	-0.0020**	-22.03***
	(0.0009)	(7.91)
Observations	517,351	517,351
Panel E: Include occupation fixed effects†		
RML	-0.0020**	-21.78***
	(0.0008)	(8.03)
Observations	517,351	517,351
Panel F: Control for state-level WC policy variables		
RML	-0.0019**	-31.88***
	(0.009)	(9.77)
Observations	517,351	517,351
Panel G: Use de Chaisemartin and D'Haultfoeuille (2020a, 2020b)††		
RML	-0.0016*	-16.73**
	(0.0009)	(9.02)
Observations	459	459
Panel H: Non-linear regression models		
RML	-0.0014**	-24.20***
	(0.0007)	(8.89)
Model	Probit	Poisson
Report average marginal effect?	Y	Y
Observations	517,351	517,351
Mean in RML states, pre-RML	0.008	$92.47
Counterfactual mean	0.009	$107.22

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects, unless otherwise noted. Data are weighted by ASEC survey weights. Standard errors are clustered at the state level and are reported in parentheses. Marginal effects reported in Panel I. See main text for explanations of other differences between panels.
***,**,* = statistically different from zero at the 1%,5%,10% level.
†Non-employed respondents receive a separate fixed effect for occupation and industry.
††Data are aggregated to the state-year level. The unit of observation is a state in a year.

Appendix Table 6A. Effect of recreational marijuana law passage on marijuana use among adults 26 years and older

Outcome:	Marijuana use in the past 30 days	Marijuana use in the past year
RML	0.0193***	0.0259***
	(0.0045)	(0.0056)
Mean in RML states, pre-RML	0.0654	0.1031
Counterfactual mean	0.0694	0.1082
Observations	459	459

Notes: Data set is the public use NSUDH 2009/2010 to 2017/2018. The sample includes respondents 26 years and older. The unit of observation is a state in a year. Data in the public use NSDUH data are reported in two-year averages. We use data averaged over the years 2009-2010, 2010-2011, 2011-2012, 2012-2013, 2013-2014, 2014-2015, 2016-2017, and 2017-2018. We match the RML data based on the second year of the two-year averages, that is: 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, and 2018. All regression models are estimated with least squares and control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population 26 years and older), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education – averaged to the state-year level), state fixed effects, and year fixed effects. Data are weighted by the state population ages 26 years and older. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 6B. Effect of recreational marijuana law passage on measures of marijuana misuse: Admissions to substance use disorder treatment

Outcome:	Marijuana primary	Any marijuana	No marijuana
RML	2.58	-0.24	-0.36
	(3.97)	(1.27)	(12.54)
Mean in RML states, pre-RML	33.54	9.09	130.95
Counterfactual mean	28.32	8.59	104.77
Observations	450	450	450

Notes: Dataset is the TEDS 2010 to 2018. The sample includes admissions to SUD treatment for which the patient is 40-64 years. We scale the outcomes by 40-64 population size. 'Marijuana primary' implies that the primary substance listed for the treatment admission is marijuana. 'Any marijuana' means that marijuana is listed as one of the substances for the treatment admission. The following states have missing years of TEDS data: Georgia (2016, 2017, and 2018); Oregon (2015, 2016, 2017, and 2018); and South Carolina (2014 and 2015). The unit of observation is a state in a year. All regression models are estimated with least squares and control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education – averaged to the state-year level), state fixed effects, and year fixed effects. Data are weighted by the state population ages 40-64. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 7. Effect of recreational marijuana law passage on prescription drug use: Prescriptions for medications used to treat chronic pain

Outcome:	Elderly adults: Scripts per 100,000	Elderly adults: Daily supply per 100,000	All residents: Scripts per 100
RML	-1,587***	-37,446***	-6.05***
	(361)	(7,659)	(1.80)
Mean in RML states, pre-RML	16,645	366,351	62.07
Counterfactual mean	21,659	492,454	61.76
Observations	459	459	459
Dataset	Medicare claims	Medicare claims	IQVIA
(years)	(2010-2018)	(2010-2018)	(2010-2018)

Notes: The Medicare claims sample includes prescription fills for pain medications among Medicare beneficiaries and the IQVIA sample includes all retail opioid prescriptions dispensed. We construct "per 100,000 beneficiaries" for the Medicare data. The IQVIA data are already scaled to represent "per 100 state residents." The unit of observation is a state in a year. All regression models are estimated with least squares and control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education – averaged to the state-year level), state fixed effects, and year fixed effects. Data are weighted by the number of state Medicare beneficiaries in the Medicare data and the state population in the IQVIA data. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 8. Effect of recreational marijuana law passage on labor supply measures

Outcome:	Worked last year	Labor force participation	Worked last week	Hours worked last week (uncond.)	Hours worked last week (cond.)	SSDI (any income)	SSI (any income)
RML	0.0148***	0.0007	0.0230***	1.2024***	0.4038***	-0.0028**	-0.0002
	(0.0026)	(0.0023)	(0.0025)	(0.0880)	(0.0390)	(0.001)	(0.0011)
Mean. RML states, pre-RML	0.768	0.768	0.697	28.36	39.59	0.014	0.028
Counterfactual mean	0.775	0.775	0.699	28.55	39.75	0.014	0.027
Observations	517,351	4,298,723	4,298,723	4,298,723	3,053,812	517,351	517,351
Dataset	ASEC	Monthly CPS	Monthly CPS	Monthly CPS	Monthly CPS	ASEC	ASEC

Notes: The sample includes respondents 40 to 62 years. The unit of observation is a respondent in the ASEC or monthly CPS. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, year fixed effects, and month-fixed effects (only for CPS monthly data). Data are weighted by ASEC survey weights in the ASEC data and monthly CPS survey person weights in the monthly CPS files. Standard errors are clustered at the state level and are reported in parentheses. We use the 2010-2018 monthly CPS files and the 2011-2019 ASEC files since the relevant (annual) outcomes in the latter then refer to 2010-2018.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 9. Effect of recreational marijuana laws on the number of establishments per 100,000

Outcome:	Total	Marijuana related†
RML	-7.20	22.42
	(111.38)	(66.97)
Mean in RML states, pre-RML	14,661	6,430
Counterfactual mean	14,082	6,161
Observations	459	459

Notes: Dataset is the CBP 2010 to 2018. The outcome is the number of establishments per 100,000 state residents. The unit of observation is a state in a year. All regression models control for state characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state policies (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population – averaged to the state-year), state fixed effects, and year fixed effects. Data are weighted by the state population. Standard errors are clustered at the state level and are reported in parentheses.

†Marijuana related establishments are defined as the following two-digit NAICS codes: Natural Resources and Mining (11), Construction (23), Manufacturing (31-33), Trade (42, 44-45), Information (51), Financial Activities (52), Education (61), and Health Services (62). See text for details.

***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 10. Effect of recreational marijuana law passage on injury outcomes

Outcome:	Non-fatal injury	Non-fatal traumatic injury	Non-fatal, non-traumatic injury	Predicted injury rate
RML	-5.22	-2.33	-2.90	5.60
	(15.00)	(15.05)	(1.74)	(10.02)
Mean in RML states, pre-RML	563.90	540.17	23.74	687.97
Counterfactual mean	485.24	467.54	17.70	844.41
Observations	337	337	337	344

Notes: Dataset is the BLS SOII 2011 to 2018. The sample includes injuries among those 40 to 62 years. The unit of observation is a state in a year. There are ten states with missing data in the BLS data, full details available on request. All regression models control for state characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education – averaged to the state-year level), state policies (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), state fixed effects, and year fixed effects. Data are weighted by the state population 40 to 62. Standard errors are clustered at the state level and are reported in parentheses. The predicted injury rate is constructed by assigning the 2011 injury rate to each person in the ASEC based on industry and state (0 if not working). Movements in this variable reflect changes in industry composition and labor force participation.

***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 11. Effect of recreational marijuana law passage on workers' compensation benefit receipt, allowing for dispensaries

Outcome:	Any WC income	WC income
Panel A: Control for dispensary provision		
RML	-0.0020	-21.36
	(0.0014)	(13.59)
RML dispensary provision	0.0007	3.69
	(0.0018)	(27.21)
RML+RML dispensary provision	-0.0013	-17.66
	(0.0008)	(18.03)
Panel B: Control for operating dispensary		
RML	-0.0018	-13.11
	(0.0016)	(17.15)
RML operating dispensary	0.0001	-11.65
	(0.0015)	(22.60)
RML+RML operating dispensary	-0.0018**	-24.76**
	(0.0007)	(10.53)
Prop./mean in RML states, pre-RML	0.008	$92.47
Counterfactual prop./mean	0.009	$107.22
Observations	517,351	517,351

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Data are weighted by ASEC survey weights. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 12. Effect of recreational marijuana law passage on workers' compensation benefit receipt, heterogeneity by job physicality

Outcome:	Any WC income	WC income
Panel A: Sample includes workers with a physically demanding job		
RML	-0.0026	-15.11
	(0.0021)	(21.28)
Mean in RML states, pre-RML	0.013	$89.60
Counterfactual mean	0.015	$102.45
Observations	98,670	98,670
Panel B: Sample includes workers with a non-physically non-demanding job		
RML	-0.0013	-4.28
	(0.0011)	(10.99)
Mean in RML states, pre-RML	0.005	$42.64
Counterfactual mean	0.006	$50.47
Observations	306,194	306,194

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The summation of the two sub-samples is less than the full sample due to missing information on job-type. See text for job-type definitions and details. The unit of observation is a respondent. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Data are weighted by ASEC survey weights. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.

Appendix Table 13. Effect of recreational marijuana law passage on workers' compensation benefit receipt, heterogeneity by sex

Outcome:	Any WC income	WC income
Panel A: Sample includes men		
RML	-0.0027**	-36.39*
	(0.0013)	(18.62)
Mean in RML states, pre-RML	0.0093	$120.68
Counterfactual mean	0.0106	$138.02
Observations	249,623	249,623
Panel B: Sample includes women		
RML	-0.0011	-4.97
	(0.0013)	(18.28)
Mean in RML states, pre-RML	0.0061	$57.18
Counterfactual /mean	0.0073	$77.78
Observations	267,728	267,728

Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. All regression models control for state characteristics (MML, prescription drug monitoring program, naloxone & Good Samaritan law, pain management clinic law, minimum wage [$], EITC ratio, Governor Democrat, and population), individual characteristics (age in years, female, African American, other race, Hispanic ethnicity, high school education, some college education, and college education), state fixed effects, and year fixed effects. Data are weighted by ASEC survey weights. Standard errors are clustered at the state level and are reported in parentheses.
***,**,* = statistically different from zero at the 1%,5%,10% level.