Pain Management and Work Capacity: Evidence from Marijuana Legalization

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November 2021

Abstract:

We study how the work capacity of the older working population responds to pain management therapy access, using the adoption of state recreational marijuana laws (RMLs) as a large policy shock to access to a non-pharmaceutical pain management option. We examine workers' compensation benefit receipt as a measure of work capacity, finding that receipt declines in response to RML adoption. We estimate concurrent reductions in pain medication use and declines in work-limiting disabilities. We consider a range of alternative mechanisms, but 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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Acknowledgments: We thank seminar participants at Indiana University, the Workers' Compensation Research Institute, and William Paterson University for helpful feedback. We also thank Abigail Friedman, Alex Hollingsworth, and session participants at the American Society for Health Economists Annual Meeting for helpful comments and suggestions. Powell gratefully acknowledges funding from NIDA (P50DA046351). All errors are our own.

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 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 it 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. 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 and their families. The WC program is designed specifically to transfer some of these costs from workers and families to

[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, Cronin, and Skira (2020) study the employment effect of the availability of antidepressants while Shapiro (2020) considers how workplace absenteeism responds to advertising for antidepressants.

governments and firms. In 2018, WC cash and medical payments to workers totaled $62.9 billion (Weiss, Murphy, and Boden 2020), equivalent to the size of annual Earned Income Tax Credit expenditures. The economic literature on WC typically focuses on the impacts of the incentives inherent in the system on injury duration (e.g., Meyer, Viscusi, and Durbin (1995); Neuhauser and Raphael (2004); and Cabral and Dillender (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 costs and benefit receipt.[3]

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,[4] though some of these MMLs were quite restrictive. By October 2021, 37 states and the District of Columbia had adopted MMLs (ProCon.org 2021a), but numerous states that have legalized medical marijuana[5] do not consider chronic pain, the most commonly reported reason for using medical marijuana (Park and Wu 2017; Kosiba, Maisto, and Ditre 2019), as a qualifying health condition.[6,7] 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

[3] 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, Reville, and Seabury (2007); and Dillender (2015)). Further, Ohsfeldt and Morrisey (1997) study the effect of beer taxes on WC and workplace injuries.
[4] Marijuana is not likely to improve health *per se*, but use of this product may allow better symptom management.
[5] For example, Alabama, Georgia, Indiana, Kentucky, Mississippi, Missouri, New Jersey, North Carolina, Oklahoma, South Carolina, Tennessee, Utah, Virginia, and Wyoming 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).
[6] 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).
[7] 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.

recreational marijuana use for adults 21 and older. As of October 2021, marijuana use is legal for recreational purposes in 18 states and the District of Columbia (ProCon.org 2021b).

Critics argue that legalization of marijuana will lead to greater addiction to harder drugs, crime,[8] healthcare costs, and other social ills within the population while harming health and labor market outcomes.[9] However, marijuana legalization is popular among Americans: in 2019, 67% supported legalization for recreational use, and 91% supported legalization for recreational or medical use (Daniller 2019). Despite popular 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, Milligan, and Wise 2017; Cutler, Meara, and Richards-Shubik 2013; Lopez-Garcia, Maestas, and Mullen 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). While WC expenditures are high, they have recently been on a decline. Figure 1A depicts trends in WC real expenditures in the U.S. over the period 2010 to 2018. Notably, the most recent decline in WC costs began in 2012, the first year in which a state adopted an RML.

[8] Recent work suggets little evidence that marijuana being a gateway to harder drugs and crime (Sabia et al. 2021).
[9] 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).

There is limited – though growing – evidence on the economic consequences of RMLs. These policies improve access to marijuana even beyond MMLs (Hollingsworth, Wing, and Bradford 2019; Cerdá et al. 2020), leading to reduced demand for other types of pain management therapies (Wen and Hockenberry 2018; McMichael, Van Horn, and Viscusi 2020; Chan, Burkhardt, and Flyr 2020; Carrieri, Madio, and Principe 2020; Wen et al. 2021). This evidence indicates that RMLs improve access to an additional channel for managing pain and other health conditions, suggesting potential benefits on populations at risk of workplace injuries.[10]

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.[11] This population is 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, Martin, and Gu 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, Martin, and Gu 2020). Chronic pain prevalence is substantially higher among adults 45 to 64 years (Dahlhamer et al. 2018).[12] At the same time, rates of marijuana *misuse* are lower among older (vs. younger) adults (see Table 1 in Choi, DiNitto, and Marti (2017)), suggesting that concerns regarding negative health and labor market implications associated with legalization may be muted for this population.

[10] 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).
[11] For example, Bütikofer and Skira (2018) study ages 40-60; Garthwaite (2012) studies ages 55-75.
[12] Chronic pain is defined as pain on most days or every day in the past six months (Deyo et al. 2015).

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). 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'), which corresponds to a 21.1% reduction, after states legalize marijuana for recreational use. Similarly, we find that average annual individual income received from WC declines by $20.16 (or 18.8%) post-RML. Results are similar using a two-stage difference-in-differences approach that is robust to concerns about staggered adoption in the presence of treatment effect heterogeneity (Gardner 2021). The results are not driven by pre-existing trends, and falsification exercises suggest that observing estimates of this magnitude is statistically rare. While our estimated effect sizes are large, they are consistent with prior research on the effects of pain medication availability on work absences.

We find evidence that marijuana use, but not misuse, increases after RML adoption, which is in line with additional medical use among older adults. We also show that prescriptions for medications used to treat chronic pain decrease post-RML, suggesting increased use of marijuana for treatment of pain. 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 more background about WC and marijuana legalization. Section 3 discusses the data and empirical methods. We present results in Section 4, including sensitivity analyses. 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, Cui, and Dworsky 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.[13]

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, Murphy, and Boden 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.[14]

2.2. Related literature on marijuana legalization laws

While there is a large literature on the effects of state MMLs,[15] 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 adults increases by 28% following RML adoption. Hollingsworth, Wing, and Bradford (2019), and Maclean, Ghimire, and Nicholas (2020) 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-

[13] These state actions could contribute to the decline in WC expenditures documented in Figure 1A.
[14] Some programs reimburse medical marijuana, but none reimburse recreational marijuana.
[15] Several studies examine the impact of individuals' marijuana use on labor market outcomes. See, Zwerling, Ryan, and Orav (1990); Register and Williams (1992); Macdonald et al. (2010); and Williams and van Ours (2020).

trivial increase in measures of marijuana use following RML adoption. However, the literature has not yet reached full consensus. Hansen, Miller, and Weber (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, Madio, and Principe 2020; McMichael, Van Horn, and Viscusi 2020; Wen et al. 2021). For example, 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, 2017). Similarly, Chan, Burkhardt, and Flyr (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 (though dissipating in the long-run), implying that both opioid use and misuse decline as legal marijuana access expands. However, using NSDUH data, Ali et al. (2021) do not find evidence of changes in self-reported prescription pain reliever misuse rates.

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. For example, 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. Thus, 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 were enrolled in state medical marijuana programs.[16] Essentially all adults can legally access marijuana in states with RMLs. These features, and likely others, of the policies and their target populations potentially lead to different groups of new users and, in turn, heterogeneous implications for labor market outcomes.

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 individuals. 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. Anderson, Rees, and Tekin (2018) show that workplace fatalities fall following MML passage among workers 25 to 44 years (coefficient estimates are imprecise for other age groups). Finally, in related work, 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

[16] 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).

receiving WC benefits declines by 13% post-MML, further motivating the choice of sample in this paper.

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, Doremus, and Stith (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, Ghimire, and Nicholas (2020), 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.[17] 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.

All states that have adopted an RML to date, except Maine, allow employers to enforce a zero-tolerance workplace and fire workers for off-work marijuana use.[18] 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.

[17] The authors note some declines in employment among women with young children post-RML, however.
[18] 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, Benson, and Joy 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, Maisto, and Ditre 2019; Reinarman et al. 2011). In a recent meta-analysis, 64% of patients reported using marijuana to treat chronic pain (Kosiba, Maisto, and Ditre (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 both 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); reduced human capital accumulation (Chatterji 2006); worsened cognition, concentration, and mental functioning (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. On the other hand (as noted in Section 2.2), Anderson, Rees, and Tekin (2018) show a decline in fatal workplace injuries 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, Doremus, and Stith 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).[19,20] The ASEC is fielded each year between February and April, and collects detailed information on income, insurance, poverty, and other socio-economic variables on approximately 150,000 respondents.[21] WC income in the ASEC reflects income received over the previous calendar year, thus our analysis captures WC income received over the period 2010 to 2018. When discussing these data, 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, Macpherson, and DuMond 1997; Bronchetti and McInerney 2012; Bronchetti and McInerney 2019), and we view the ASEC as the most suitable dataset for our research.

[19] We exclude the survey collected in 2020 (which captures claiming in 2019) due to the COVID-19 pandemic.
[20] The American Community Survey (ACS) does not collect information specifically on WC benefit receipt.
[21] 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.

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 adults up to age 65 years. We have 517,351 respondents in our analysis sample.[22]

3.2. RML Coding

Data on RMLs are obtained from Chan, Burkhardt, and Flyr (2020) and ProCon.org (2021b).[23] We match the RML variable to our data based on state, month, and year. Figure 2 graphically depicts states that have adopted an RML by October 2021. By the end of our study period (2018), nine states and DC had an RML in place, although 16 states and DC had adopted such a law by October 2021.

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 2021b), prescription drug monitoring programs or PDMPs (Ali et al. 2017), naloxone & Good Samaritan laws (Prescription Drug Abuse Policy System 2020),[24] 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 earned income tax credit (EITC) as a share of the federal EITC, governor political party,[25] and population (University of Kentucky Center for Poverty Research 2020).

[22] We exclude respondents with remaining missing information on WC and demographics (outlined in Section 3.5).
[23] We confirm our effective dates using RAND policy data, PDAPS, NORML.org, and our own reading of original state statutes where inconsistencies across sources appear. Full details on request.
[24] We code these two variables as one indicator that takes on a value of one if a state has both policies in place following Ghimire and Maclean (2020). Coefficient estimates are nearly identical if we include two variables.
[25] We follow Maclean and Saloner (2018) and treat the mayor of DC as the de facto govenor of that locality.

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 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,[26] 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 overall. In addition, 6.3% of the sample resides in a state with an active 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:

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

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 RML in state *s* in year *t*. $P_{s,t}$ is a vector of state-level time-varying

[26] Many WC claims are 'medical only' and do not involve any lost work time (Weiss, Murphy, and Boden 2020).

factors (see Section 3.3). $X_{i,s,t}$ is a vector of respondent-level characteristics.[27] We provide evidence about the importance of these control variables in Section 4.3.

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 in robustness analyses unweighted results are similar. We test the sensitivity of our results to other functional forms. We cluster standard errors by state (Bertrand, Duflo, and Mullainathan 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.[28] In the first stage of 2SDiD, the relationships between the time-varying covariates[29] and fixed effects with the outcome variable are estimated using only untreated observations. The estimated parameters are

[27] 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).

[28] The Gardner (2021) method permits use of individual-level data while 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.

[29] 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.

then used to residualize the outcomes for treated and untreated observations.[30] Because these parameters are estimated using only untreated observations, they are not impacted by 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 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.[31] 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. This effect implies a 17.8% reduction relative to the counterfactual benefit receipt rate (0.9 ppts). 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

[30] This residualization approach is also discussed in Borusyak, Jaravel, and Spiess (2021). Powell (2021) introduces a similar approach and discusses the benefits in applications without staggered adoption.
[31] 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.

unaffected by these controls. Appendix Table 1 provides a full set of coefficient estimates from this specification. 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, equivalent to 21.1% reduction. This effect size is large, which is in line with the substantial effects on marijuana use found in the literature (discussed further in Section 5.1). However, based on our estimated standard error, we also cannot statistically rule out a 5.8% decrease in the probability of receiving any income from WC in the past year.

In Panel B of Table 3, we estimate the 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).[32] 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 or 18.8% compared to the counterfactual mean. Examination of the lower tail of the estimated 95% confidence interval shows that we cannot rule out effect sizes as small as 1.6%.

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 (24.4%)

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

and the level of WC income declines by $23.34 (21.8%). Both coefficient estimates are statistically different from zero at the 1% level.

Due to concerns about inference with only 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 as well in Section 4.3.4.

4.2. Alternative measures of work capacity

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 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.

4.3. Internal validity

4.3.1. Parallel trends

To test for possible threats to identification, we first 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 year of RML adoption; thus, we may observe a partial effect in the year prior to adoption. We group all other post-adoption years into one or more years post-policy.[33]

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,

[33]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 October 2021 are coded as zero for all lead and lag variables.

followed by a sharp decrease in the partially-treated year and another decline beginning in the first fully-treated year. Figures 3A and 3B suggests 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 our TWFE and 2SDiD results, we report results using TWFE regressions for the remainder of the paper.

4.3.2. 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 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, Elder, and Taber 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.

4.3.3. 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. Results are reported in Appendix Table 4 and do not reveal any evidence that RMLs induce migration among our age group. 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.

4.3.4. 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.

4.3.5. Additional sensitivity tests

Finally, we report the results of a series of sensitivity tests in Appendix Table 5A.

We find that our coefficient estimates are robust to including state-specific linear time trends (Panel A) and Census region-by-year fixed effects (Panel B), 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 lag the RML indicator by one year in Panel C. 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. Next, in Panel F, we aggregate the data to the state-year level (see Panel H below as well). The coefficient estimates are similar but less precise. In Panel G, 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 H, 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. The results are similar.

Finally in Panel I, 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. Our main coefficient estimates do not appear to be driven by our choice of functional form.

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 2021b) 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 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, Wing, and Bradford 2019; Maclean, Ghimire, and Nicholas 2020). We test this relationship in our context using the public use NSDUH (SAMHSA, 2021a). A limitation of the public use NSDUH is that we cannot isolate older adults. Instead, we examine marijuana use among 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) (SAMHSA, 2021b). The TEDS is a national database of admissions to standalone SUD treatment, and TEDS-tracked facilities predominantly include facilities that receive public funding or are tracked for a state-specific reason. While not capturing the universe of SUD treatment, TEDS includes roughly two-thirds of specialty 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, Pacula, and Taylor 2020; Maclean, Horn, and Cantor 2020). We select admissions where the patient is 40 to 64 years of age;[34] 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, Madio, and Principe 2020; Wen and Hockenberry 2018; McMichael, Van Horn, and Viscusi 2020; Wen et al. 2021). Additionally, the literature finds that RMLs reduce opioid-related mortality and ED episodes (Chan, Burkhardt, and Flyr 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

[34] We cannot more accurately match our main sample based on age categories in the TEDS.

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).[35] We use the list of opioids prescribed to Medicare Part D beneficiaries in Ellyson, Grooms, and Ortega (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.[36] Neither data source allows us to isolate our key population of interest, but we examine these measures as proxies for 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.

[35] We obtain the 2010-2012 Medicare Part D data from ProPublica (ProPublica, 2017) and the 2013-2018 data from CMS (2021).
[36] We draw IQVIA data from the Centers for Disease Control and Prevention (2020) and weight by this population.

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: 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, Doremus, and Stith (2020).[37] Data are converted to a rate per 100,000 residents, and we weight by this population. We present CBP results in Appendix Table 9. We observe no change in either type of establishments post-RML, 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

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.[38] The BLS Survey of Occupational Injuries and Illnesses (SOII) collects workplace injury data from approximately 200,000 employers (U.S. Bureau of Labor Statistics, 2021).[39] 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,[40] offering

[37] 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).
[38] There are concerns about the quality of the data prior to 2011 so we begin our analysis with the 2011 data.
[39] Some groups are excluded: federal employees, the self-employed, and small farms (<10 workers).
[40] Workers are often ineligible for cash WC benefits unless they miss at least three days of work.

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% reduction. The estimate for non-traumatic estimates implies a 16.4% decrease relative to baseline,[41] similar to our WC estimates.

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[42] of their industry in their state in 2011 (the year prior to the first RML adoption).[43] 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

[41] The point estimates for traumatic and non-traumatic estimates, in levels, are relatively similar. However, most injuries are traumatic so the implied proportional effects are very different.
[42] The injury rate is defined as injuries per 100,000 workers in the industry. Non-workers are assigned a workplace injury rate of zero.
[43] The SOII provides injury rates by NAICS. We map the NAICS codes to the 1990 Census industry codes provided in the IPUMS CPS.

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 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.[44] The magnitudes are larger for physically demanding jobs, though the differences are small (see Appendix Table 12).

We also estimate separate regressions for men and women (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

[44] 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.

decline in WC benefit receipt by 0.19 ppts, equivalent to a 21.1% decrease, and annual income received from WC declines by $20.16 (or 18.8%) 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 into safer industries.

The magnitudes of our coefficient estimates are reasonably similar to those found in the literature relating access to pain management therapies and measures of work capacity, though direct comparisons are difficult due to the varying contexts. Garthwaite (2012) estimates 10% labor supply reductions resulting from the removal of Cox-2 inhibitors.[45] Similarly, Bütikofer and Skira (2018) find that work sickness absences are very responsive to the introduction (7-12% decreases) and removal (12-16% increases) of these drugs from the market. Disability benefit receipt is also meaningfully impacted following removal of these medications from the market.

[45] 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.

The effect size of marijuana legalization on WC claiming and income appears to be more substantial than that of MMLs on the same outcomes. We find a 21.1% decline in WC claiming post-RML. In comparison, Ghimire and Maclean document a 13% decline in WC claiming for older adults after states adopted medical marijuana laws. The relative magnitudes of the results are consistent with RMLs affecting a substantially larger share of the population than MMLs. These differential effects seem plausible as recreational marijuana is more readily accessible than medical marijuana for which the patient requires a formal prescription from a healthcare professional. The ability to purchase the medication 'over-the-counter' (OTC) may reduce hassle costs and/or stigma, which have been found to affect access in the context of other health products. For example, the conversion of nicotine replacement therapies (used for smoking cessation) to OTC status lead to an increase in their use (Keeler et al. 2002). In fact, we observe large increases in marijuana use due to RMLs and evidence of corresponding reductions in alternative medications treating chronic pain.

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 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, Zivin, and Goldstein (2008); Garthwaite (2012); Bütikofer and Skira (2018), and Bütikofer, Cronin, and Skira (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.

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)	(0.0007)	(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)	(8.04)	(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

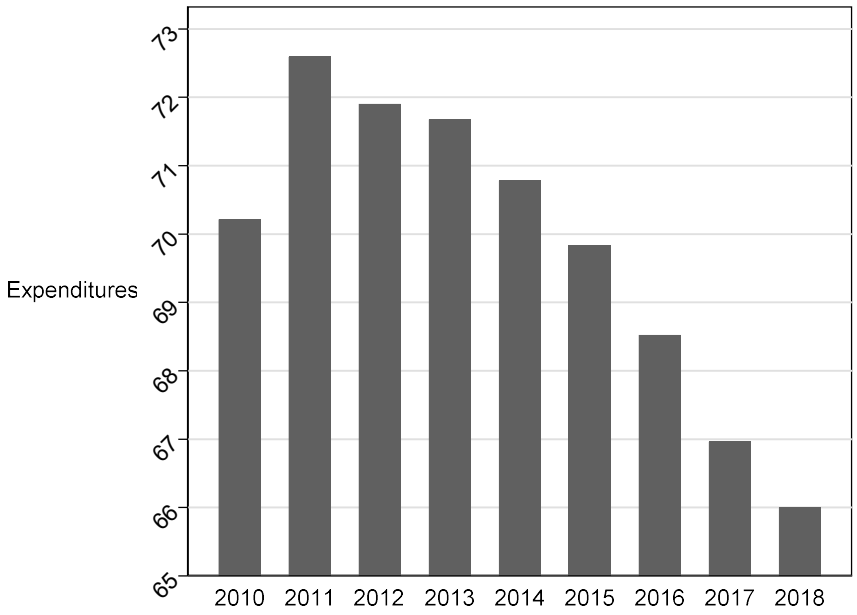
Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is the respondent. Individual controls include age in years, female, African American, other race, Hispanic ethnicity, high school 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)

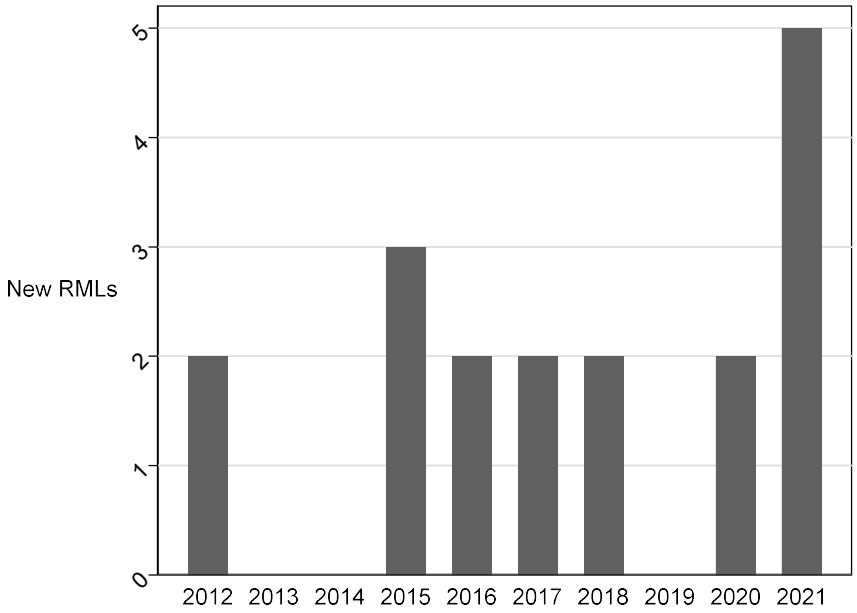
Notes: The sample includes respondents 40 to 62 years in the ASEC or monthly CPS. The unit of observation is a respondent. All models include state controls, individual controls, state fixed effects, and year fixed effects. State controls include MML, prescription drug monitoring program, naloxone & 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.

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



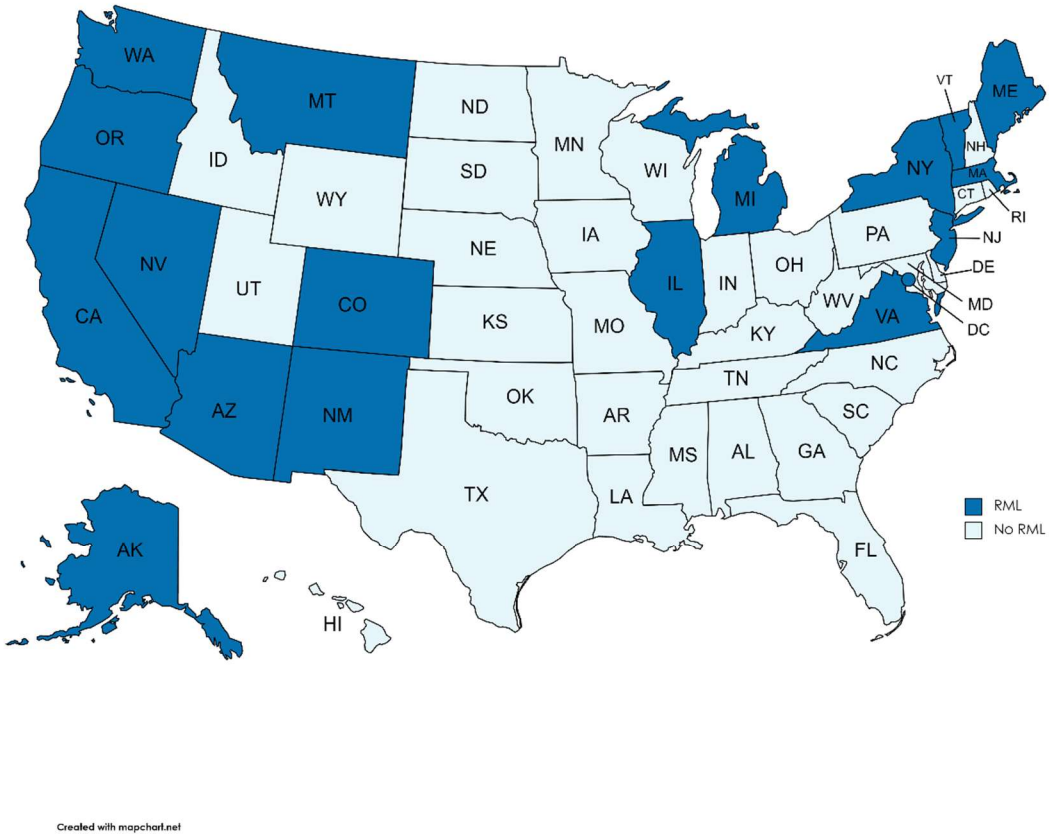
Notes: The figure is based on Table 5 in Weiss et al (2020). We inflate nominal values to 2020 dollars using the Consumer Price Index. See text for details.

Figure 1B. RML adoptions and announcements as of October 2021



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.

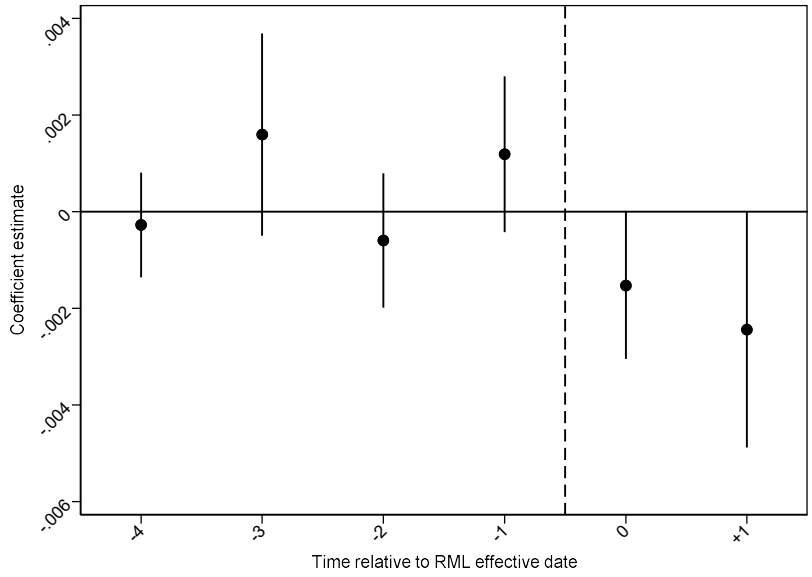
Figure 2. States with an RML implemented or announced by October 2021



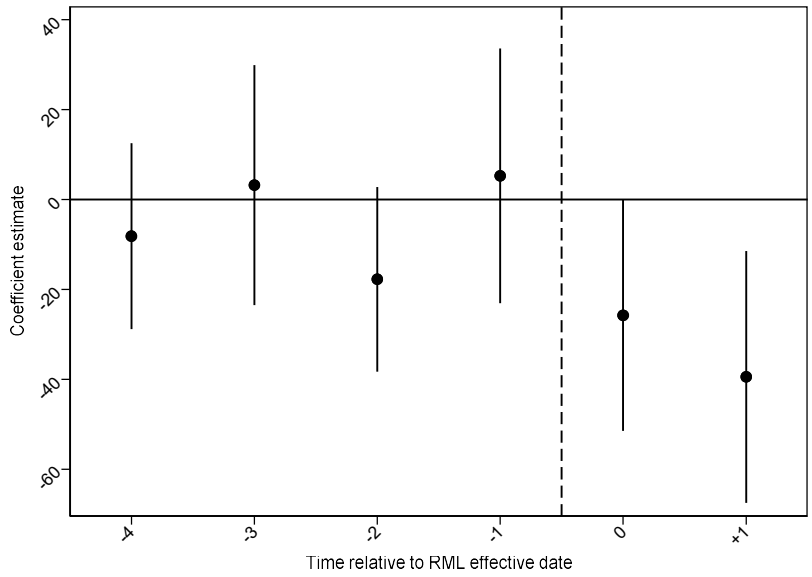
Notes: The figure is based on data reported in Chan et al (2019) and ProCon.org (2021). Note that law changes are coded as of January 1st of each year. RML effective dates (adopted or announced by October 2021) are as follows: Alaska: February 2015; Arizona: November 2020; California: November 2016; 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



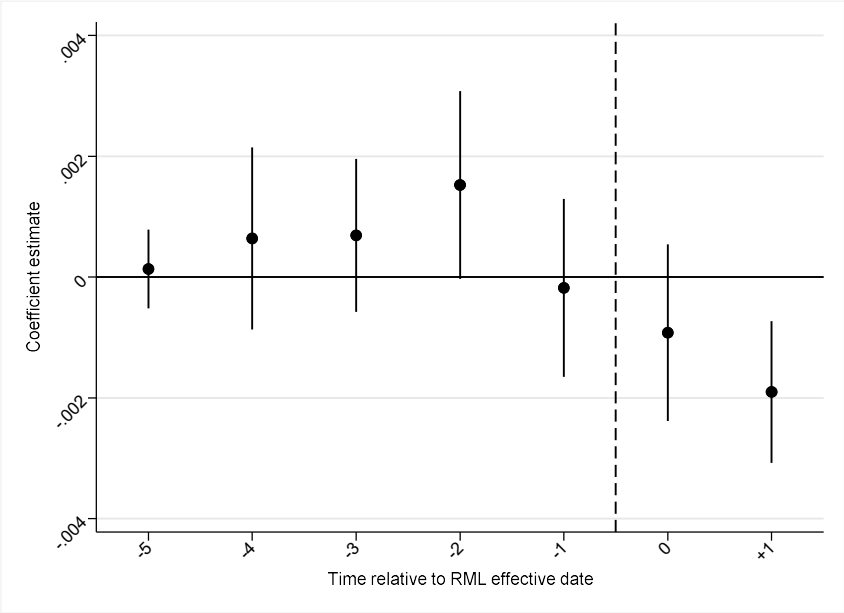
Panel B: WC income



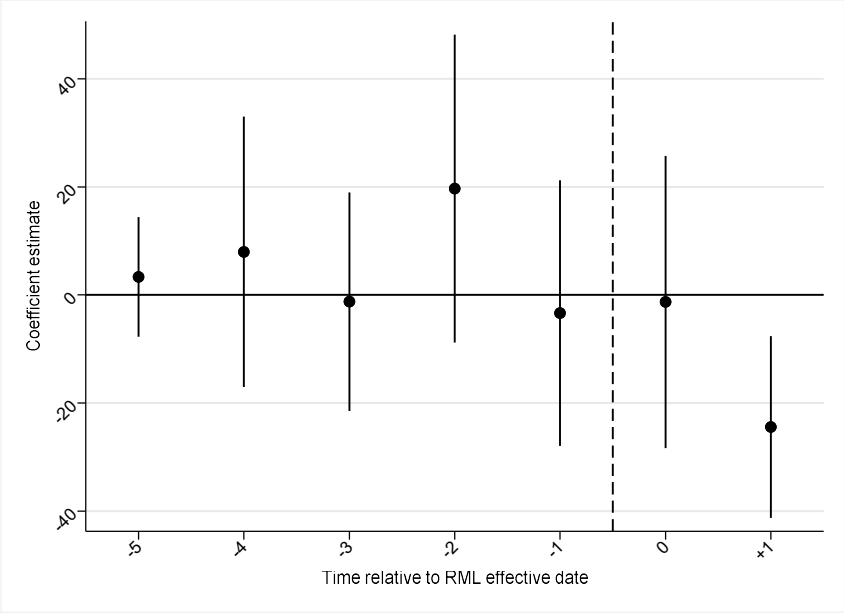
Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. Circles represent coefficient estimates and 95% confidence intervals are depicted by vertical 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



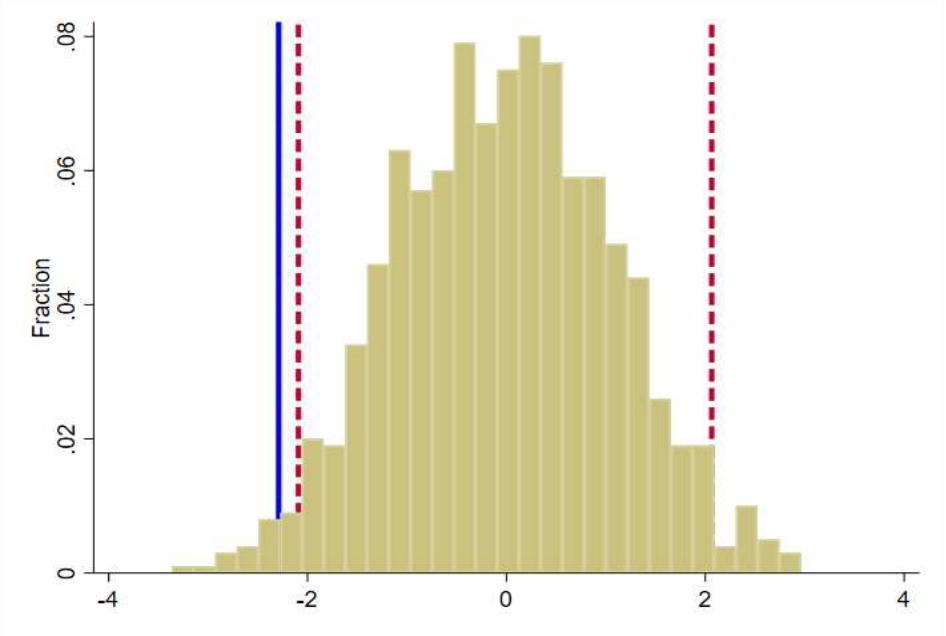
Panel B: WC income



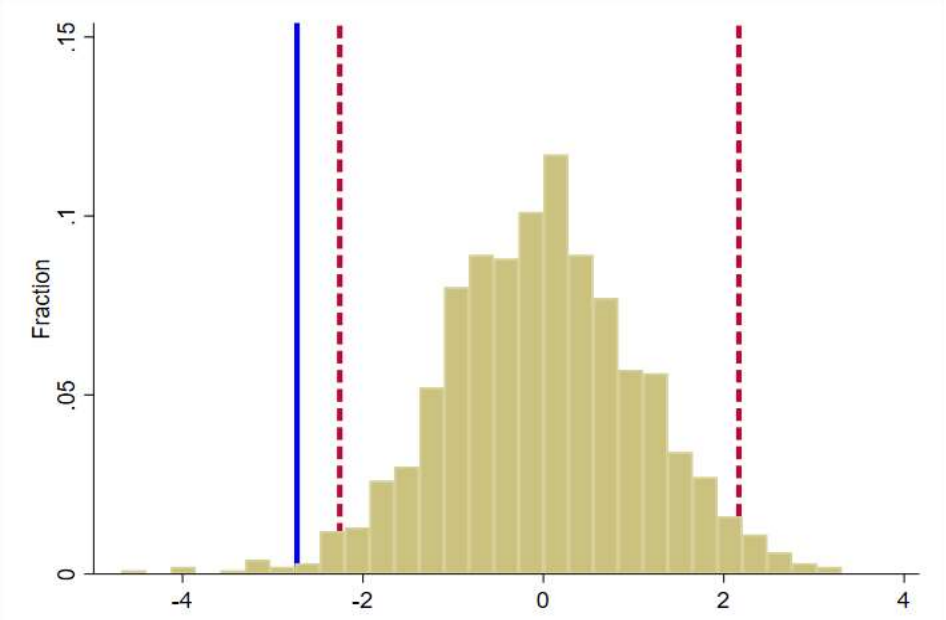
Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. Circles represent coefficient estimates and 95% confidence intervals are depicted by vertical 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.

References:

Abouk, R., and S. Adams. 2019. Legal cannabis access and the obesity of younger children. In *University of Wisconsin-Milwakee Mimeo*.

Ali, M.M., W.N. Dowd, T. Classen, R. Mutter, and S.P. Novak. 2017. "Prescription drug monitoring programs, nonmedical use of prescription drugs, and heroin use: Evidence from the national survey of drug use and health." *Addictive Behaviors* 69:65-77.

Ali, M.M., C.B. McClellan, R. Mutter, and D.I. Rees. 2021. Recreational marijuana laws and the use of opioids: Evidence from nsduh microdata. National Bureau of Economic Research.

Altonji, J.G., T.E. Elder, and C.R. Taber. 2005. "Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools." *Journal of Political Economy* 113 (1):151-184.

Anderson, D.M., D.I. Rees, and E. Tekin. 2018. "Medical marijuana laws and workplace fatalities in the united states." *International Journal of Drug Policy* 60:33-39.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. "How much should we trust differences-in-differences estimates?" *The Quarterly Journal of Economics* 119 (1):249-275.

Borgelt LM, Franson KL, Nussbaum AM, Wang GS. 2013. "The Pharmacologic and Clinical Effects of Medical Cannabis." *Pharmacotherapy: The Journal of Human Pharmacology and Drug Therapy.* 33(2):195-209.

Borusyak, K., X. Jaravel, and J. Spiess. 2021. Revisiting event study designs: Robust and efficient estimation. In *arXiv preprint*

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

———. 2017. "Medical marijuana laws may be associated with a decline in the number of prescriptions for medicaid enrollees." *Health Affairs* 36 (5):945-951.

Bronchetti, E.T. 2012. "Workers' compensation and consumption smoothing." *Journal of Public Economics* 96 (5-6):495-508.

Bronchetti, E.T., and M. McInerney. 2012. "Revisiting incentive effects in workers' compensation: Do higher benefits really induce more claims?" *ILR Review* 65 (2):286-315.

———. 2017. Does increased access to health insurance impact claims for workers' compensation? Evidence from massachusetts health care reform.

Bronchetti, E.T., and M.P. McInerney. 2019. "Health care reform and workers' compensation: Evidence from massachusetts." *ILR Review*.

Bureau of Labor Statistics. 2016. Nonfatal occupation injuries and illnesses requiring days away from work, 2015. Washington, DC: Bureau of Labor Statistics.

Bütikofer, A., C.J. Cronin, and M.M. Skira. 2020. "Employment effects of healthcare policy: Evidence from the 2007 fda black box warning on antidepressants." *Journal of Health Economics* 73:102348.

Bütikofer, A., and M.M. Skira. 2018. "Missing work is a pain: The effect of cox-2 inhibitors on sickness absence and disability pension receipt." *Journal of Human Resources* 53 (1):71-122.

Cabral, M., C. Cui, and M. Dworsky. 2019. What is the rationale for an insurance coverage mandate? Evidence from workers' compensation insurance. In *National Bureau of*

Economic Research Working Paper Series. Cambridge, MA: National Bureau of Economic Research.
Cabral, M., and M. Dillender. 2020. The impact of benefit generosity on workers' compensation claims: Evidence and implications. In *National Bureau of Economic Research Working Paper Series*. Cambridge, MA: National Bureau of Economic Research.
Callaway, B., and P.H.C. Sant'Anna. 2020. "Difference-in-differences with multiple time periods." *Journal of Econometrics*.
Carrieri, V., L. Madio, and F. Principe. 2020. "Do-it-yourself medicine? The impact of light cannabis liberalization on prescription drugs." *Journal of Health Economics* 74:102371.
Centers for Disease Control and Prevention. 2020. U.S. Opioid dispensing rate maps. Atlanta, GA: Centers for Disease Control and Prevention.
Centers for Medicare & Medicaid Services (CMS). 2021. "Medicare Part D Opioid Prescriving Rates by Geography." https://data.cms.gov/summary-statistics-on-use-and-payments/medicare-medicaid-opioid-prescribing-rates/medicare-part-d-opioid-prescribing-rates-by-geography.
Cerdá, M., C. Mauro, A. Hamilton, N.S. Levy, J. Santaella-Tenorio, D. Hasin, M.M. Wall, K.M. Keyes, and S.S. Martins. 2020. "Association between recreational marijuana legalization in the united states and changes in marijuana use and cannabis use disorder from 2008 to 2016." *JAMA Psychiatry* 77 (2):165-171.
Chakraborty, A., J. Doremus, and S. Stith. 2020. The effects of recreational cannabis access on the labor market: Evidence from colorado.
Chan, N.W., J. Burkhardt, and M. Flyr. 2020. "The effects of recreational marijuana legalization and dispensing on opioid mortality." *Economic Inquiry* 58 (2):589-606.
Charles, K.K., M.S. Johnson, M. Stephens Jr, and D.Q. Lee. 2019. Demand conditions and worker safety: Evidence from price shocks in mining. National Bureau of Economic Research.
Chatterji, P. 2006. "Illicit drug use and educational attainment." *Health Economics* 15 (5):489-511.
Choi, N.G., D.M. DiNitto, and C.N. Marti. 2017. "Nonmedical versus medical marijuana use among three age groups of adults: Associations with mental and physical health status." *The American Journal on Addictions* 26 (7):697-706.
Coe, N.B., and G. Zamarro. 2011. "Retirement effects on health in europe." *Journal of Health Economics* 30 (1):77-86.
Coile, C., K. Milligan, and D.A. Wise. 2017. "Health capacity to work at older ages: Evidence from the united states." In *Social security programs and retirement around the world: The capacity to work at older ages*, 359-394. University of Chicago Press.
Cutler, D.M., E. Meara, and S. Richards-Shubik. 2013. Health and work capacity of older adults: Estimates and implications for social security policy. Social Science Research Network.
Dahlhamer, J., J. Lucas, C. Zelaya, R. Nahin, S. Mackey, L. DeBar, R. Kerns, M. Von Korff, L. Porter, and C. Helmick. 2018. "Prevalence of chronic pain and high-impact chronic pain among adults—united states, 2016." *Morbidity and Mortality Weekly Report* 67 (36):1001.
Daniller, A. 2019. Two-thirds of americans support marijuana legalization. In *Fact tank: News in the numbers*: Pew Research Center.
Dave, D., and S. Mukerjee. 2011. "Mental health parity legislation, cost-sharing and substance-abuse treatment admissions." *Health Economics* 20 (2):161-183.

de Chaisemartin, C., and X. d'Haultfœuille. 2020a. Difference-in-differences estimators of intertemporal treatment effects. In *Social Science Research Network Working Paper Series*: Social Science Research Network.
———. 2020b. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110 (9):2964-96.
Deyo, R.A., S.F. Dworkin, D. Amtmann, G. Andersson, D. Borenstein, E. Carragee, J. Carrino, R. Chou, K. Cook, and A. DeLitto. 2015. "Report of the nih task force on research standards for chronic low back pain." *Physical Therapy* 95 (2):e1-e18.
Dillender, M. 2015. "The effect of health insurance on workers' compensation filing: Evidence from the affordable care act's age-based threshold for dependent coverage." *Journal of Health Economics* 43:204-228.
Dong, X. 2020. *The economic impact of government regulations on marijuana and immigration*. Ph.D., Syracuse University, Syracuse, NY.
Dragone, D., G. Prarolo, P. Vanin, and G. Zanella. 2019. "Crime and the legalization of recreational marijuana." *Journal of Economic Behavior & Organization* 159:488-501.
Drake, C., J. Wen, J. Hinde, and H. Wen. 2021. "Recreational cannabis laws and opioid-related emergency department visit rates." *Health Economics* 30 (10):2595-2605.
Dwyer, D.S., and O.S. Mitchell. 1999. "Health problems as determinants of retirement: Are self-rated measures endogenous?" *Journal of Health Economics* 18 (2):173-193.
Ellyson, A., J. Grooms, and A. Ortega. 2020. "Flipping the script: Evaluating the policy effects and restrictiveness of pdmps on opioid prescribing behavior." *Health Economics* Accepted.
Flood, S., M. King, S. Ruggles, and J.R. Warren. 2020. Integrated public use microdata series, current population survey. Minneapolis, MN: University of Minnesota.
Gardner, J. 2021. Two-stage differences in differences. https://jrgcmu.github.io/2sdd_current.pdf
Garthwaite, C.L. 2012. "The economic benefits of pharmaceutical innovations: The case of cox-2 inhibitors." *American Economic Journal: Applied Economics* 4 (3):116-37.
Ghimire, K.M., and J.C. Maclean. 2020. "Medical marijuana and workers' compensation claiming." *Health Economics* 29 (4):419-434.
Goodman-Bacon, A. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*.
Gruber, J., and A.B. Krueger. 1991. "The incidence of mandated employer-provided insurance: Lessons from workers' compensation insurance." *Tax Policy and the Economy* 5:111-143.
Hales, C.M., C.B. Martin, and Q. Gu. 2020. Prevalence of prescription pain medication use among adults: United states, 2015–2018. In *NCHS data brief* Hyattsville, MD: National Center for Health Statistics.
Hansen, B., K. Miller, and C. Weber. 2020. "Early evidence on recreational marijuana legalization and traffic fatalities." *Economic Inquiry* 58 (2):547-568.
Hansen, L.P. 1982. "Large sample properties of generalized method of moments estimators." *Econometrica*:1029-1054.
Hanson, K.L., J.L. Winward, A.D. Schweinsburg, K.L. Medina, S.A. Brown, and S.F. Tapert. 2010. "Longitudinal study of cognition among adolescent marijuana users over three weeks of abstinence." *Addictive Behaviors* 35 (11):970-976.
Hill, K.P. 2015. "Medical marijuana for treatment of chronic pain and other medical and psychiatric problems: A clinical review." *JAMA* 313 (24):2474-2483.

Hill, S.C., K.T. Solomon, J.C. Maclean, and M.F. Pesko. 2019. "Effects of improvements in the cps on the estimated prevalence of medical financial burdens." *Health Services Research* 54 (4):920-929.
Hirsch, B.T., D.A. Macpherson, and J.M. DuMond. 1997. "Workers compensation recipiency in union and nonunion workplaces." *ILR Review* 50 (2):213-236.
Hirth, R.A., M.E. Chernew, M.N. Turenne, M.V. Pauly, S.M. Orzol, and P.J. Held. 2003. "Chronic illness, treatment choice and workforce participation." *International Journal of Health Care Finance and Economics* 3 (3):167-181.
Hollingsworth, A., C. Wing, and A. Bradford. 2019. Comparative effects of recreational and medical marijuana laws on drug use among adult and adolescents. In *Social Science Research Network Woking Paper Series*: Social Science Research Network
Irons, J.G., K.A. Babson, C.L. Bergeria, and M.O. Bonn-Miller. 2014. "Physical activity and cannabis cessation." *The American Journal on Addictions* 23 (5):485-492.
Jinks, L., T.J. Kniesner, J. Leeth, and A.T. Lo Sasso. 2020. "Opting out of workers' compensation: Non-subscription in texas and its effects." *Journal of Risk and Uncertainty* 60 (1):53-76.
Kaestner, R., and M. Grossman. 1998. "The effect of drug use on workplace accidents." *Labour Economics* 5 (3):267-294.
Keeler, T.E., T.w. Hu, A. Keith, R. Manning, M.D. Marciniak, M. Ong, and H.Y. Sung. 2002. "The benefits of switching smoking cessation drugs to over-the-counter status." *Health Economics* 11 (5):389-402.
Kline, P., and A. Santos. 2012. "A score based approach to wild bootstrap inference." *Journal of Econometric Methods* 1 (1):23-41.
Kosiba, J.D., S.A. Maisto, and J.W. Ditre. 2019. "Patient-reported use of medical cannabis for pain, anxiety, and depression symptoms: Systematic review and meta-analysis." *Social Science & Medicine* 233:181-192.
Krueger, A.B. 1990. "Incentive effects of workers' compensation insurance." *Journal of Public Economics* 41 (1):73-99.
Lakdawalla, D.N., R.T. Reville, and S.A. Seabury. 2007. "How does health insurance affect workers' compensation filing?" *Economic Inquiry* 45 (2):286-303.
Leigh, J.P. 2011. "Economic burden of occupational injury and illness in the united states." *The Milbank Quarterly* 89 (4):728-772.
Lopez-Garcia, I., N. Maestas, and K.J. Mullen. 2019. Latent work capacity and retirement expectations. In *Stanford University mimeo*.
Lynch, M.E., and F. Campbell. 2011. "Cannabinoids for treatment of chronic non-cancer pain; a systematic review of randomized trials." *British Journal of Clinical Pharmacology* 72 (5):735-744.
Macdonald, S., W. Hall, P. Roman, T. Stockwell, M. Coghlan, and S. Nesvaag. 2010. "Testing for cannabis in the work-place: A review of the evidence." *Addiction* 105 (3):408-416.
MacKinnon, J.G., and M.D. Webb. 2020. "Randomization inference for difference-in-differences with few treated clusters." *Journal of Econometrics*.
Maclean, J.C., K.M. Ghimire, and L. Nicholas. 2020. "Marijuana legalization and disability claiming." *Health Economics* Forthcoming.
Maclean, J.C., B.P. Horn, and J.H. Cantor. 2020. "Business cycles and admissions to substance abuse treatment." *Contemporary Economic Policy* 38 (1):139-154.

Maclean, J.C., and B. Saloner. 2018. "Substance use treatment provider behavior and healthcare reform: Evidence from massachusetts." *Health Economics* 27 (1):76-101.
McMichael, B.J., R.L. Van Horn, and W.K. Viscusi. 2020. "The impact of cannabis access laws on opioid prescribing." *Journal of Health Economics* 69:102273.
Meyer, B.D., W.K. Viscusi, and D.L. Durbin. 1995. "Workers' compensation and injury duration: Evidence from a natural experiment." *The American Economic Review*:322-340.
Moffitt, R. 1992. "Incentive effects of the us welfare system: A review." *Journal of Economic Literature* 30 (1):1-61.
National Academies of Sciences, E., and Medicine. 2017. *The health effects of cannabis and cannabinoids: The current state of evidence and recommendations for research*: National Academies Press.
National Institute on Drug Abuse. 2020. How does marijuana use affect school, work, and social life? Bethesda, MD: National Institute on Drug Abuse.
Neuhauser, F., and S. Raphael. 2004. "The effect of an increase in worker's compensation benefits on the duration and frequency of benefit receipt." *Review of Economics and Statistics* 86 (1):288-302.
Nicholas, L.H., and J.C. Maclean. 2019. "The effect of medical marijuana laws on the health and labor supply of older adults: Evidence from the health and retirement study." *Journal of Policy Analysis and Management* 38 (2):455-480.
Ohsfeldt, R.L., and M.A. Morrisey. 1997. "Beer taxes, workers' compensation, and industrial injury." *Review of Economics and Statistics* 79 (1):155-160.
Pacula, R.L., D. Powell, P. Heaton, and E.L. Sevigny. 2015. "Assessing the effects of medical marijuana laws on marijuana use: The devil is in the details." *Journal of Policy Analysis and Management* 34 (1):7-31.
Park, J.-Y., and L.-T. Wu. 2017. "Prevalence, reasons, perceived effects, and correlates of medical marijuana use: A review." *Drug and Alcohol Dependence* 177:1-13.
Powell, D. 2021. The labor supply consequences of the opioid crisis. In *RAND Working Paper Series*.
Powell, D., R.L. Pacula, and E. Taylor. 2020. "How increasing medical access to opioids contributes to the opioid epidemic: Evidence from Medicare Part D." *Journal of Health Economics* 71:102286.
Powell, D., and S. Seabury. 2018. "Medical care spending and labor market outcomes: Evidence from workers' compensation reforms." *American Economic Review* 108 (10):2995-3027.
Prescription Drug Abuse Policy System. 2020. Prescription drug abuse policy system.
ProCon.org. 2021a. Legal medical marijuana states and dc. ProCon.org.
———. 2021b. Legal recreational marijuana states and dc. ProCon.org.
ProPublica. 2017. Prescriber Checkup. https://www.propublica.org/datastore/dataset/prescriber-checkup (last accessed October 10, 2021).
Register, C.A., and D.R. Williams. 1992. "Labor market effects of marijuana and cocaine use among young men." *ILR Review* 45 (3):435-448.
Reinarman, C., H. Nunberg, F. Lanthier, and T. Heddleston. 2011. "Who are medical marijuana patients? Population characteristics from nine california assessment clinics." *Journal of Psychoactive Drugs* 43 (2):128-135.

Roodman, D., M.Ø. Nielsen, J.G. MacKinnon, and M.D. Webb. 2019. "Fast and wild: Bootstrap inference in stata using boottest." *The Stata Journal* 19 (1):4-60.
Sabia, J.J., D.M. Dave, F. Alotaibi, and D.I. Rees. 2021. Is recreational marijuana a gateway to harder drug use and crime? National Bureau of Economic Research.
Sabia, J.J., and T.T. Nguyen. 2018. "The effect of medical marijuana laws on labor market outcomes." *The Journal of Law and Economics* 61 (3):361-396.
Schmidheiny, K., and S. Siegloch. 2020. On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization. In *ZEW-Centre for European Economic Research Discussion Paper*.
Shapiro B. 2020. Promoting wellness or waste? Evidence from antidepressant advertising. Becker Friedman Institute for Research in Economics Working Paper.
Substance Abuse and Mental Health Services Administration (SAMHSA). 2021a. National Survey on Drug Use and Health (NSDUH). https://pdas.samhsa.gov/saes/state.
Substance Abuse and Mental Health Services Administration (SAMHSA). 2021b. Treatment Episode Data Set (TEDS). https://wwwdasis.samhsa.gov/dasis2/teds.htm.
Summers, L.H. 1989. "Some simple economics of mandated benefits." *The American Economic Review* 79 (2):177-183.
Thirumurthy, H., J.G. Zivin, and M. Goldstein. 2008. "The economic impact of aids treatment labor supply in western kenya." *Journal of Human Resources* 43 (3):511-552.
United States Census Bureau. 2021. County Business Patterns. https://www.census.gov/programs-surveys/cbp/data/datasets.html.
U.S. Bureau of Labor Statistics. 2021. Survey of Occupational Injuries and Illnesses (SOII). https://www.bls.gov/iif/oshstate.htm.
U.S. Department of Labor. 2016. Does the workers' compensation system fulfill its obligations to injured workers? Washington, DC: U.S. Department of Labor.
Ullman, D.F. 2017. "The effect of medical marijuana on sickness absence." *Health Economics* 26 (10):1322-1327.
University of Kentucky Center for Poverty Research. 2020. State level data of economic, political, and transfer program information for 1980-2018. Lexington, KY: University of Kentucky.
Van Ours, J.C., and J. Williams. 2012. "The effects of cannabis use on physical and mental health." *Journal of Health Economics* 31 (4):564-577.
Van Ours, J.C., J. Williams, D. Fergusson, and L.J. Horwood. 2013. "Cannabis use and suicidal ideation." *Journal of Health Economics* 32 (3):524-537.
Volkow, N.D., R.D. Baler, W.M. Compton, and S.R. Weiss. 2014. "Adverse health effects of marijuana use." *New England Journal of Medicine* 370 (23):2219-2227.
Watson, S.J., J.A. Benson, and J.E. Joy. 2000. "Marijuana and medicine: Assessing the science base: A summary of the 1999 institute of medicine report." *Archives of General Psychiatry* 57 (6):547-552.
Weiss, E., G. Murphy, and L.I. Boden. 2020. Workers' compensation benefits, costs, and coverage – 2018 data. Washington, DC: National Academy of Social Insurance.
Wen, H., and J.M. Hockenberry. 2018. "Association of medical and adult-use marijuana laws with opioid prescribing for medicaid enrollees." *JAMA Internal Medicine* 178 (5):673-679.

Wen, J., H. Wen, J. Butler, and J.C. Talbert. 2021. "The impact of medical and recreational marijuana laws on opioid prescribing in employer-sponsored health insurance." *Health Economics*.

Whiting, P.F., R.F. Wolff, S. Deshpande, M. Di Nisio, S. Duffy, A.V. Hernandez, J.C. Keurentjes, S. Lang, K. Misso, and S. Ryder. 2015. "Cannabinoids for medical use: A systematic review and meta-analysis." *JAMA* 313 (24):2456-2473.

Williams, J., and J.C. van Ours. 2020. "Hazardous or not? Cannabis use and early labor market experiences of young men." *Health Economics* 29 (10):1148-1160.

Winward, J.L., K.L. Hanson, S.F. Tapert, and S.A. Brown. 2014. "Heavy alcohol use, marijuana use, and concomitant use by adolescents are associated with unique and shared cognitive decrements." *Journal of the International Neuropsychological Society: JINS* 20 (8):784.

Zwerling, C., J. Ryan, and E.J. Orav. 1990. "The efficacy of preemployment drug screening for marijuana and cocaine in predicting employment outcome." *JAMA* 264 (20):2639-2643.

ONLINE APPENDIX

Appendix Table 1. Effect of recreational marijuana law passage on Workers' Compensation benefit receipt: All 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**
	(0.0007)	(8.04)
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: Include region-by-year fixed effects		
RML	-0.0010	-14.55
	(0.0014)	(8.72)
Observations	517,351	517,351
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: Aggregate data to the state-year level††		
RML	-0.0013	-15.67
	(0.0010)	(13.36)
Observations	459	459
Panel G: Control for state-level WC policy variables		
RML	-0.0019**	-31.88***
	(0.009)	(9.77)
Observations	517,351	517,351
Panel H: Use de Chaisemartin and D'Haultfoeuille (2020a, 2020b)††		
RML	-0.0016*	-16.73**
	(0.0009)	(9.02)
Observations	459	459
Panel I: 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 law		
RML	-0.0020	-21.36
	(0.0014)	(13.59)
RML dispensary law	0.0007	3.69
	(0.0018)	(27.21)
RML+RML dispensary law	-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.

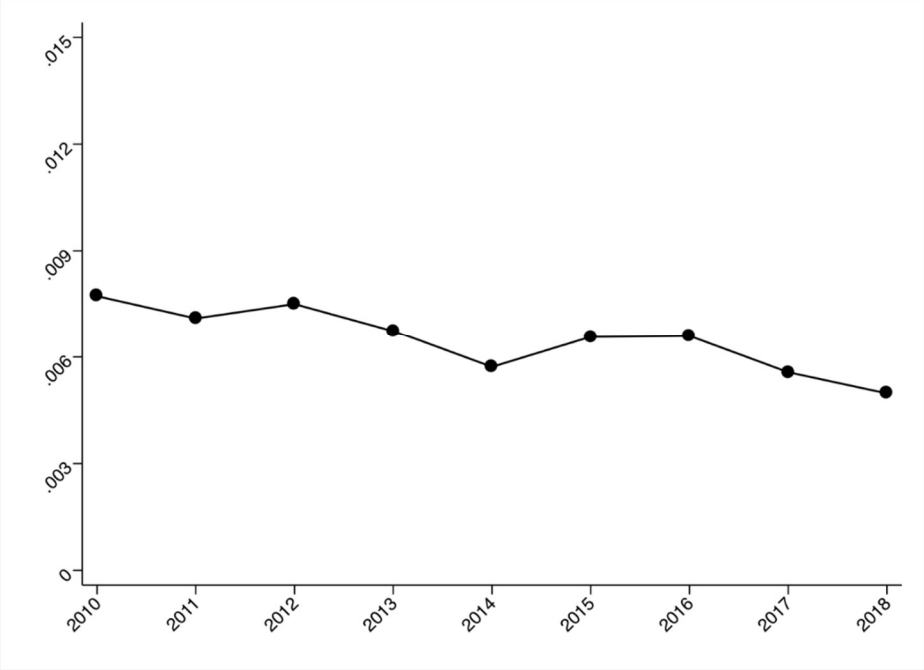
Appendix Table 13. Effect of recreational marijuana law passage on Workers' Compensation benefit receipt, heterogeneity by sex

Outcome:	Any WC income	WC income
	Panel A: Men	
RML (lagged one year)	-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: Women	
RML (lagged one year)	-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

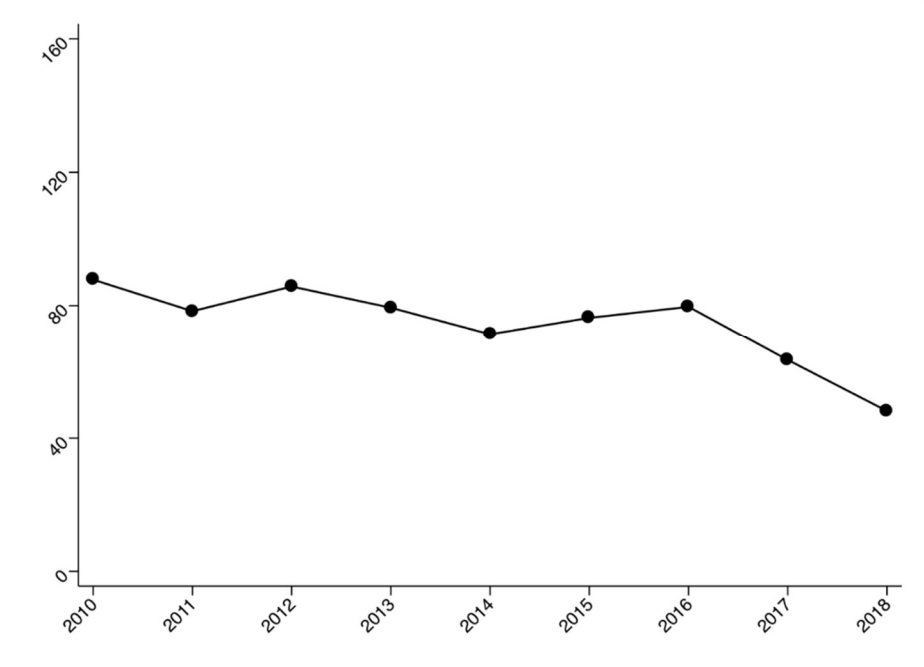
Notes: Dataset is ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. The unit of observation is a respondent in state in a year. All regression models control for state characteristics (MML, prescription drug monitoring program, 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.

Appendix Figure 1. Trends in Workers' Compensation benefit receipt in each year of the study period

Panel A: Any WC income



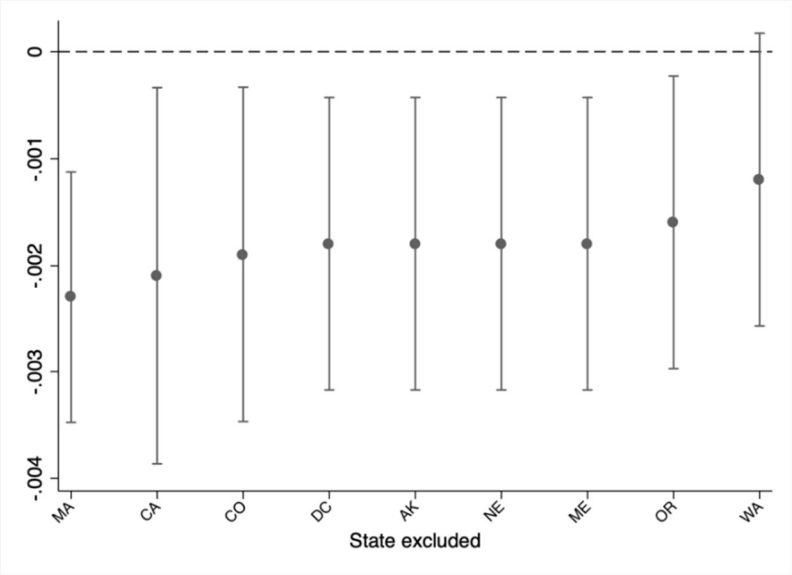
Panel B: WC income



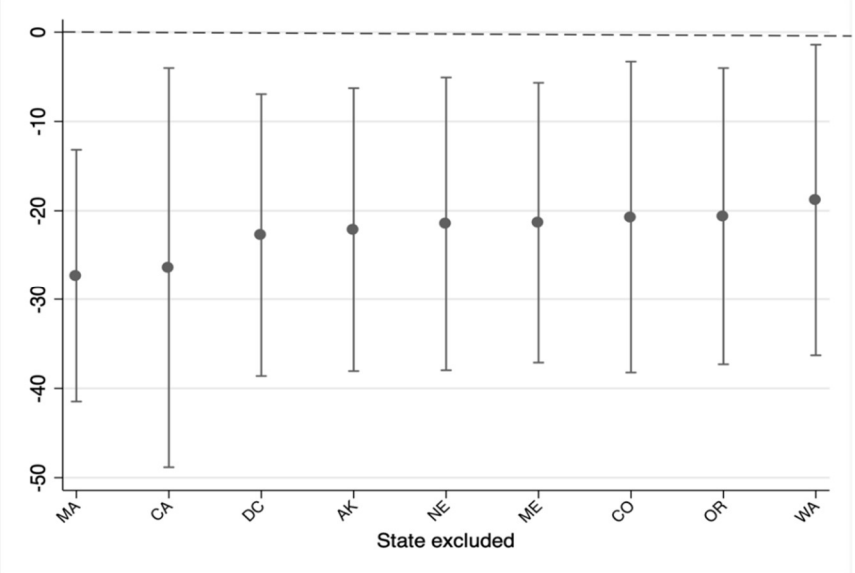
Notes: The data source is the ASEC 2011 to 2019, which captures WC benefit receipt over the period 2010 to 2018. The sample includes respondents 40 to 62 years. Data are aggregated to annual level and weighted by ASEC survey weights.

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.