The Impact of Legalizing Medical Marijuana on Exit from Unemployment*

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Abstract

An increasing number of studies have attempted to examine the impact of medical marijuana laws (MMLs). Specifically, marijuana use could influence individuals' work capacity and willingness to work. In this paper, I focus on unemployed individuals and examine the causal impact of legalizing medical marijuana on exit from unemployment. By using the linked monthly Current Population Survey (CPS) data between 2002 and 2012 and a discrete-time hazard model, I find that MMLs decreased exit from unemployment. In a competing risks model where both exits to employment and not-in-labor-force are examined, I show that a reduction in exit from unemployment was derived from a decreased exit to employment (2.09 pp, 17.6%), rather than from changes in labor force participation. Based on interaction-weighted (IW) estimates, I confirm that the results were robust to heterogeneity across states and time given a staggered treatment adoption. This study provides an important perspective that MMLs could have a negative impact on labor market outcomes.

JEL Codes: H75, I12, I18, J20, J64

Keywords: marijuana use, medical marijuana laws, unemployment duration, exit from unemployment, discrete-time hazard model

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1. Introduction

Despite the addictive features of marijuana, medicinal usage of marijuana has been approved by many state legislatures. With the Compassionate Use Act of 1996, California was the first to permit medical marijuana use among qualified patients and many states followed. For adult recreational use, Colorado and Washington first implemented recreational marijuana laws in late 2012, although no retail recreational sales were available until 2014 (Insurance Institute for Highway Safety, 2021). As of August 2021, there were 36 states with medical marijuana laws (MML henceforth) and 19 states with recreational marijuana laws (RML henceforth) in the United States (Insurance Institute for Highway Safety, 2021).

As the increasing number of states legalize, many researchers have evaluated the impact of marijuana legalization through a variety of outcomes. In particular, given the fact that medical marijuana use can help individuals manage chronic conditions and relieve pain, increased access to medical marijuana through the passage of MMLs could influence individuals' work capacity as well as willingness to work. Nevertheless, only a few studies have examined the impact of MMLs on labor market outcomes and no clear-cut consensus has yet been achieved (see section 2.3 for more details).

The current study attempts to evaluate the labor market impact of MMLs. By focusing on unemployed individuals, I examined if MMLs had any impact on the probability that they transition out of unemployment status. The unemployed population may be more likely to have any medical conditions than the general population (Schmitz, 2011) and medical marijuana can be effective. Hypothetically, improved work capacity and perceived health by medical marijuana can have a positive labor market impact among the unemployed with chronic conditions. On the other hand, if medical marijuana users consumed marijuana more recreationally, negative impacts on labor outcomes may be observed if they experienced work-impeding side-effects from substance use disorder.

To test these hypotheses, I used the linked monthly Current Population Survey (CPS) data between 2002 and 2012 within a discrete-time hazard framework. Considering the short panel structure of CPS, I could trace transitions of each unemployed individual's labor force status and control for weekly unemployment duration. In addition, given the dynamic impact of MMLs and to test for pre-trends in exit hazards between MML and non-MML states, I examined event study models.

The empirical results showed that post-MMLs, unemployed individuals were less likely to exit from unemployment. Importantly, based on a competing risks model where two different destinations of the exit are considered, I found that the decreased exit from unemployment was largely due to a reduction in exit to employment, rather than changes in labor force attachment among the unemployed. Hence, unemployed individuals became less likely to find a new job through the passage of MMLs, although they still stayed in the labor force. In the case of event study results, no significant differences in exit rates were observed among MML and non-MML states during pre-MML periods. Overall, the results were largely consistent with the static two-way fixed effects results and were robust to heterogeneity across states and time, which addresses recent difference-in-differences critiques on heterogeneous treatment effects with a staggered treatment adoption (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021)[1]. To the best of my knowledge, no previous studies have examined the unemployed and estimated whether MMLs could have a negative impact on exit from

[1] To do this, I used the interaction-weighted (IW) estimator based on Sun and Abraham (2021).

unemployment. This would add to the limited MML literature that investigated labor market outcomes.

Importantly, this study expands on the literature on extended unemployment insurance (UI) and unemployment spells. Particularly, I followed the theoretical and empirical settings of Farber et al. (2015) and Farber and Valletta (2015) that examined the impact of extended UI benefits on exit from unemployment with the discrete-time hazard model. Overall, the literature indicated that extended UI benefits tended to lengthen unemployment durations and/or discourage exit from unemployment (Bratberg and Vaage, 2000; Card and Levine, 2000; Jurajda and Tannery, 2003; Farber et al., 2015; Farber and Valletta, 2015). This study would be an intersection of the MML and extended UI benefit literature that would provide new insight on exit from the unemployment model, which I also find an important contribution.

The remainder of the manuscript proceeds as follows. First, the following section provides a brief background of MML and evaluates a variety of relevant previous studies (section 2). Next, the theoretical framework of estimating exit hazards is demonstrated (section 3). After explaining the analysis data and setting (section 4), the empirical framework (section 5) and empirical results (section 6, section 7, and section 8) are provided. Finally, section 9 discusses the results and section 10 concludes.

2. Background

2.1. Marijuana regulations in the United States

Although an increasing number of states implements or considers marijuana legalization, marijuana use is federally illegal since the Marihuana [sic] Act of 1937, and marijuana has been classified as a Schedule I drug since 1970 by the Controlled Substance Act, meaning no medical use is accepted. In the 1970s, several states started to decriminalize the possession of marijuana (Pacula et al., 2003). Usually, decriminalization of marijuana implies no arrest, prison time, or criminal record for the first-time (and subsequent) possession of a reasonably small amount of marijuana for personal use (NORML, 2021). Many states do not impose penalties on those aged 21 and over. However, some penalties might be given to minors, such as fines, community service, and/or drug education (Marijuana Policy Project, 2021).

Table 1 shows the effective dates of MMLs and RMLs for states that have legalized marijuana. As of August 2021, more than half of U.S. states including the District of Columbia have implemented MMLs. In comparison with MMLs, RMLs have been introduced relatively recently. This was one reason why the current study focused on evaluating MMLs. While RML states allow any adult aged 21 and over to purchase marijuana products in local dispensaries, medical marijuana is restricted to qualified patients and each state has different eligibility conditions. Eligible patients may obtain marijuana from private/collective cultivation and/or state-authorized dispensaries (Sabia and Nguyen, 2018).

2.2. Medical marijuana use and labor market outcomes

Marijuana refers to products processed from the cannabis plant. The cannabis plant contains compounds known as cannabinoids and there are two major cannabinoids: tetrahydrocannabinol (THC) and cannabidiol (CBD). Smoking, vaping, or even eating cannabis products could affect one's brain and body in many ways. For medicinal use, it is reported that marijuana use can be effective for chronic pain, neuropathic pain, spasticity, nausea, sleep disorders, anxiety, and inflammatory bowel disorders (Hill, 2015; Whiting et al., 2015; Goldenberg et al., 2017). Also, marijuana can be an alternative to other prescribed drugs such as opioids (Ozluk, 2017). Studies have found that marijuana use improved chronic conditions on par with other prescribed drugs with fewer side effects (Reiman et al., 2017; Vigil et al., 2017).

Nevertheless, there are studies that demonstrate the negative health impacts of marijuana use. Williams and Skeels (2006) directly examined cannabis consumption in the past week and year and found that cannabis use reduced self-assessed health status. van Ours and Williams (2012) showed that cannabis use reduced the physical and mental wellbeing of men and women. Overall, moderate cannabis use might not involve seriously harmful health effects, while heavy cannabis users, who are already susceptible to mental health issues, could experience reduced mental well-being (van Ours and Williams, 2015). Marijuana use alone would be less likely to involve a fatal overdose unlike opioids or alcohol consumption (CDC, 2021).

Many studies examined the direct relationship between marijuana use and labor market outcomes, without the context of marijuana legalization laws. Studies found that marijuana use may negatively affect labor market outcomes such as wage and employment (Register and Williams, 1992; DeSimone, 2002; van Ours, 2007; Ayllon and Ferreira-Batista, 2018). Although Williams and van Ours (2020) showed that early cannabis users[2] among young males accepted job offers more quickly, the wage rate was lower, compared with non-cannabis users. Another array of studies, however, found null impacts of marijuana on labor outcomes (Kagel et al., 1980; Kaestner, 1994; van Ours, 2006). Overall, results are mixed and may depend on sample and setting.

[2] Early cannabis users were defined as individuals who used cannabis before entering the labor market and job search.

In the next section, I review the literature on marijuana legalization laws. Essentially, the results may differ with the studies mentioned above as MML and RML studies will mostly provide intent-to-treat (ITT) estimates.

2.3. Literature on marijuana legalization laws

Given the growing number of states that legalize marijuana use, extant literature has examined a variety of outcomes that MMLs and RMLs have impacts on. This includes, but is not limited to, spillovers to prescribed drugs, cocaine, alcohol, and/or tobacco (Wen et al., 2015; Choi et al., 2016; Ozluk, 2017; Leung, 2019), traffic fatalities (Anderson et al., 2013; Hansen et al., 2018; Cook et al., 2020), birth outcomes (Baggio et al., 2019; Meinhofer et al., 2021), neighborhood crime (Brinkmand and Mok-Lamme, 2019), and academic outcomes and mental health (Leung, 2019). Especially, studies confirmed the first stage impact of MMLs on marijuana consumption (Pacula et al., 2015; Wen et al., 2015; Sabia and Nguyen, 2018), with some evidence that there may be a spillover to recreational marijuana use (Wen et al., 2015).

Of the many relevant outcomes, labor market outcomes in response to MMLs would be of main interest in this study. Ullman (2017) was the first to estimate the impact of MMLs on a labor market-related outcome. Post-MMLs, the study found a reduction in sickness absence among full-time employees. On the other hand, Sabia and Nguyen (2018) examined typical labor market outcomes such as employment, hours of work, and wages. Using monthly CPS data, they showed that MMLs were not associated with the outcomes among working-age adults. Similarly, Guo et al. (2021) also examined the impact of MMLs on employment and wages but at the county-quarter level. By comparing bordering counties in states with difference in MML status, they found no MML impacts on employment and inconclusive effects on wages. In an alternative specification, they showed a suggestive decrease in wages in rural areas, possibly due to reduced mental health. At the state-by-year level, Anderson et al. (2018) showed a decreased expected number of workplace fatalities among workers aged 25 to 44, following MMLs. Importantly, Nicholas and Maclean (2019) focused on older workers (aged 51 and over) with chronic conditions, who would more likely be qualified for medical marijuana. Through the passage of MMLs, results demonstrated that older workers in the sample experienced lower pain, better self-assessed health, and increased hours of work.

Closer to the current study, Jergins (2019) examined the transition of labor force status, using a variety of transition variables. By observing the change in labor force status across American Time Use Survey (ATUS) and CPS, the paper found that MMLs increased labor force attachment among females (aged 30 to 39) but reduced among males (aged 20 to 29). However, Jergins (2019) did not examine the transition from unemployment and was restricted to observing one-time transitions of each individual. Finally, two MML studies examined the impact on Social Security Disability Insurance (SSDI) and/or workers' compensation (WC) claims. Based on the Annual Social and Economic Supplement (ASEC) of the CPS data between 1990 and 2013, among workers aged 23 to 62, Maclean et al. (2018) reported an increase in SSDI claiming (and WC claiming but imprecise) while Ghimire and Maclean (2020) demonstrated a decline in WC claiming[3]. Although focused on RMLs, two other studies

[3] Regarding work capacity, these may indicate opposing results. While the increased SSDI claiming might imply decreased work capacity, the decline in WC claiming could represent improved work capacity among individuals, post-MMLs. Maclean et al. (2018) hypothesized that work-impeding side effects of marijuana use by medical and/or recreational purposes could have derived the negative impacts of MMLs.

demonstrated similar results on SSDI and WC claiming (Abouk et al., 2021; Maclean et al., 2021)[4].

Combined with studies in the previous section without marijuana legalization context, it appears that there seems to be no clear-cut consensus about the impact of marijuana use on labor market outcomes. Particularly, whether MMLs would improve or worsen work capacity and willingness to work, and then how that would affect labor market outcomes of individuals are unclear, mainly because only a handful of studies have examined it to date. The current study provides one perspective that MMLs could negatively affect the likelihood of exit from unemployment, which would contribute to the limited literature of MMLs on labor outcomes. In addition, I examine the impact of MMLs on exit from unemployment using the discrete-time hazard framework, controlling for individuals' weekly unemployment duration within a single spell of unemployment. To my best knowledge, this is the first to do so. The present study also attempts to address the recent difference-in-differences critiques that event study results robust to treatment effects heterogeneity across states and time are provided (Sun and Abraham, 2021).

3. Theoretical framework

To estimate the probability of exit from unemployment among the unemployed, I consider the discrete-time hazard model by controlling for individuals' unemployment duration in discrete time (i.e., weekly or monthly durations). In the discrete-time hazard model, one needs to construct a panel dataset so that one could observe if a spell (: unemployment) ends for each

[4] To be precise, Maclean et al. 2021 examined both SSDI and supplemental security income (SSI) for disability assistance claims. Although disability claiming was increased through the passage of RMLs, no change was observed in new beneficiaries.

individual at a given spell duration (: unemployment duration). Spells that never end until the last observed period are right-censored.

Following Farber and Valletta (2015)'s framework, let D be a discrete random variable that represents an unemployment duration for each unemployment spell. If a spell ends at a certain duration D^*, one can consider the hazard function $h(D^*)$ of exit from unemployment, considering that the unemployment duration has lasted until D^*. For each individual, $h(\cdot)$ is defined as a probability function that represents the hazard of spell ending, that depends on individual and state-level controls, including unemployment duration.

Oftentimes, individuals need to stay unemployed long enough until they are first observed as "unemployed" in a survey. Let D_0 denote this duration of unemployment. Then, one can construct the conditional probability that an unemployment spell ends at duration D^* as follows:

$$(1) P(D = D^* | D \geq D_0) = \frac{h(D^*) \prod_{t=1}^{D^*-1}(1-h(t))}{\prod_{t=1}^{D_0-1}(1-h(t))} = h(D^*) \prod_{t=D_0}^{D^*-1}(1-h(t)).$$

Note that the probability is conditional on the minimum duration of D_0 to be first observed in the survey and assumes independence across survey months for every unemployed individual.

In the case of spells that never end until the last observed survey (: right-censored), one can consider the conditional probability that an unemployment spell has a duration of at least D^* as:

$$(2) P(D \geq D^*|D \geq D_0) = \frac{\prod_{t=1}^{D^*}(1-h(t))}{\prod_{t=1}^{D_0-1}(1-h(t))} = \prod_{t=D_0}^{D^*}(1-h(t)).$$

By combining equations (1) and (2), one can construct the likelihood function for each individual, that addresses both cases that a spell ends within the analysis period and a spell is censored.

Now, consider the latent variable model for individual i at time t:

$$(3)\ Y_{it}^* = X_{it}\beta + u_{it}, \quad Y_{it} = 1[Y_{it}^* > 0]$$

where Y_{it}^* is the latent variable, Y_{it} is the observed dependent variable, X_{it} is a vector of controls, and β is a vector of parameters. u_{it} is the disturbance term with a standard normal distribution. Then, the hazard of exit from unemployment of individual i at time t is given as:

$$(4)\ h(t) = P(Y_{it} = 1|X_{it}) = P(Y_{it}^* > 0|X_{it}) = P(-u_{it} < X_{it}\beta|X_{it}) = \Phi(X_{it}\beta)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. Note that equation (4) represents the probit model and X_{it} contains an individual unemployment duration to control for a baseline hazard.

Importantly, the hazard function $h(t)$ above estimates the probability of exit from unemployment, which examines a single risk of exiting unemployment status (single risk model). However, one may also be interested in examining whether individuals who exit from unemployment find *a new job* or *leave the labor force*. Hence, a competing risks model which addresses two different destinations of the exit is also considered by estimating exit to employment and exit to not-in-labor-force (NILF), separately.

4. Data

4.1. Linked CPS and sample restriction

To estimate the probability of exit from unemployment, I use basic monthly CPS data from Jan. 2002 through Dec. 2012[5]. The basic monthly CPS dataset is updated every month and administered by the U.S. Census Bureau and Bureau of Labor Statistics (BLS). The CPS was designed to provide recent information on the labor market involvement of the U.S. population. Specifically, it provides a variety of information on labor market outcomes such as labor force status (employed, unemployed, or NILF), weekly wages, hours of work, and unemployment duration including individual demographics. As the earliest possible date of a CPS interview is the 6th of each month, I code for changes in state-level MML status and potential UI weeks as of the 5th of each month, which could possibly have an impact on individuals' decision to exit from unemployment.

The CPS is essentially short panel data. Within a 4-8-4 survey design, each individual (household) would be surveyed and in the sample for the first 4 consecutive months, out of the sample for the following 8 months, and return to the sample for the last 4 months. Given this rotation structure, I construct a linked CPS dataset that traces individuals' labor market transitions. Following Farber et al. (2015), I link each individual in the sample to forward 2 survey months, and restrict the analysis sample among the linked observations (forward 2

[5] The rationale to restrict the data period to 2002 through 2012 was to conform to extended UI benefit data available from the U.S. Department of Labor (DoL), which is an important dimension of the analysis. Also, by restricting to until 2012, one can rule out any confounding impact of RMLs.

months) and those who were unemployed at least 3 months due to job loss[6]. By doing this, one can rule out the possibility of multiple spells of unemployment (i.e., restricted to single spells) and correct for spurious transitions within the "*matched*" data[7]. Figure 1 presents the structure of the linking procedure. The final sample would be among the unemployed at least 3 months (aged 18 to 69) and contains 54,270 observations total between Jan. 2002 and Dec. 2012.

4.2. Variables

The variables used in the empirical analysis were defined as follows. The dependent variable, $exit\ from\ U$ was a dummy variable that was equal to 1 if an unemployed individual transitioned out of unemployment status in the next monthly survey. In a similar manner, $exit\ to\ E$ and $exit\ to\ NILF$ were formulated to estimate the change in labor force status out of unemployment and transition into employment or economic inactivity. Unemployment duration was defined as the number of weeks being unemployed for each individual. To better control for a baseline hazard in the discrete-time hazard model, various functional forms of unemployment duration were formulated such as monthly unemployment duration, logarithmic unemployment duration, and polynomials of unemployment duration (quadratic and cubic). Gender, marital status, the interaction between gender and marital status, age category (10s, 20s, …, 60s), race/ethnicity groups, education level, and industry category (of individuals' jobs before unemployment) were employed as individual controls.

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[6] This is again to follow Farber et al. (2015)'s setting. Restricting the sample as among the unemployed at least 3 months due to job loss as the unemployment reason was to allow enough time that extended UI benefits can be an important factor for exit from unemployment and for eligibility to receive unemployment insurance.

[7] Farber et al. (2015) and Farber and Valletta (2015) referred to linking observations of an individual across survey months as "matching." They noted that there could be a concern of spurious transitions in monthly labor force status due to mismeasurement. To address this issue, I re-coded for those who were unemployed in month 1, exited from unemployment in month 2, and returned to unemployment in month 3, as being "unemployed" in month 2.

For the independent variables, MML was a dummy variable of primary interest in this study, which was equal to 1 when a state has legalized medical marijuana in a given survey month. MML effective dates were obtained from the Insurance Institute for Highway Safety (2021) and ProCon.org (2021). Figure 2 demonstrates trends in medical marijuana legalization across states between 2002 through 2012, which show that more states have implemented medical marijuana laws as time goes by.

$UI\ available$ was the independent variable from Farber et al. (2015) that was equal to 1 if an individual had potential UI benefit weeks that are longer than the current unemployment duration in a given month. To determine the maximum UI benefit duration for each state in a given month, regular UI weeks and weeks available by a variety of extended benefits programs, including extended benefit (EB), temporary extended unemployment compensation (TEUC), and emergency unemployment compensation (EUC08) were obtained from the DoL.

For the state-level controls, seasonally adjusted unemployment rate and growth rate of employment[8] were obtained from the BLS to control for local labor market conditions. As each state could have a different stance on drug use and regulations that can influence labor market outcomes, drug testing laws in three categories (pro-, anti-, and no/neutral-) were controlled following Bernardo and Nieman (2013) and Wozniak (2015). For example, pro-drug testing states may provide incentives on workers' compensation and legal protection with employers who implement drug testing. On the other hand, anti-drug testing states restrict or prohibit any drug testing procedures. Finally, cigarette taxes by state were used in analysis and obtained from the Centers for Disease Control and Prevention (CDC, 2020).

[8] To be precise, Farber et al. (2015) defined this growth rate as a 3-month annualized growth rate of log non-farm payroll employment.

4.3. Summary statistics

Table 2 displays the summary statistics for the whole sample (: column (1)), the sample of MML states (pre-MML periods, column (2)), and the sample of non-MML states (during all periods, column (3)). Across samples, one can observe that about 21-23% of the unemployed exit from unemployment on average. Among those who make it to the exit, about 12-13% of them exit to employment, while the remaining 9-10% exit to NILF. During 2002 through 2012, about 30% of states in the sample have implemented MMLs. About 70% of the unemployed in the whole sample had UI availability. Based on the whole sample, the average potential UI weeks by state were about 63 weeks. It is noticeable that only 8% of the MML states were classified as pro-drug testing compared with about 34% of the non-MML states. On average, each unemployed individual experienced about 44 weeks of unemployment duration, based on the whole sample[9]. The average age of the whole sample was about 42 years. In total, there were 54,270 observations in the analysis period during 2002 through 2012. Column (4) of Table 2 provides statistical differences of mean values between columns (2) and (3). Although they are mostly different, that may be natural given the fact that column (2) is based on pre-MML periods.

5. Empirical framework

5.1. Empirical model

To examine the impact of MMLs on the probability of exit from unemployment, equation (5) was estimated by the probit model within the discrete-time hazard framework, that was developed in section 3.

[9] Obviously, this number is based on the sample restriction of at least 3 months of unemployment.

$$(5)\ Y_{ist} = \alpha MML_{st} + \beta * UI\ Available_{ist} + X_{ist}\gamma + Z_{st}\lambda + \delta_s + \theta_t + \eta_{st} + u_{ist}$$

where i is the individual unit, s is state, and t represents month-year, which ranges from Jan. 2002 to Dec. 2012. Y_{ist} is a dummy variable that is equal to 1 if an unemployed individual i in state s exits from unemployment, exits to employment, or exits to NILF at month-year t. MML_{st} is a dummy variable equal to 1 if a state s has implemented medical marijuana laws at month-year t. $UI\ Available_{ist}$ is a dummy variable that was equal to 1 if an individual i in state s had longer potential UI weeks available than own unemployment duration at month-year t. X_{ist} is the vector of individual controls and includes a baseline hazard (i.e., unemployment duration)[10]. Z_{st} is the vector of state-level controls. δ_s and θ_t represent state and month-year fixed effects and η_{st} controls for the state-specific linear trends. u_{ist} is the disturbance term with a standard normal distribution and is clustered at the state level[11]. α and β are the coefficients that represent the impacts of marijuana legalization and UI availability, respectively. γ and λ are vectors of coefficients. Equation (5) is in the form of a standard difference-in-differences two-way fixed effects model.

5.2. Identification

In equation (5) above, α is of my main interest that identifies the impact of MMLs on exit from unemployment. Essentially, it is an intent-to-treat (ITT) estimate in terms of the impact of

[10] For the preferred specification, I use a set of monthly unemployment duration categories following Farber et al. (2015). That is, a set of dummies for months 4, 5, 6, 7-9, 10-12, and 13 and above is included in the specification (month 3 is the reference category). I also provide results of using different baseline hazard functions in a section of robustness checks.

[11] For the preferred specification, results were robust to the state-month level clustering.

MMLs on the exit hazard. In principle, my identification strategy is to exploit state-level variations in medical marijuana legalization laws, by controlling for state and time fixed effects as well as state specific linear trends. For the remainder of state-level confounders, seasonally adjusted unemployment rate and growth rate of employment can account for local labor market dynamics that could have influenced individuals' exit from unemployment. Importantly, I also control for state drug-testing laws and UI availability and job industry category for each unemployed individual, following Wozniak (2015) and Farber et al. (2015). One testable identification assumption for the difference-in-differences framework would be parallel trends between the treated (those in MML states) and untreated groups (those in non-MML states) over time in the absence of medical marijuana laws. To test this, the event study model will be considered in section 5.3. In addition, in order to address the recent critiques on the difference-in-differences two-way fixed effects model with staggered treatment adoption (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021), I also provide event study results, with an interaction-weighted (IW) estimator (Sun and Abraham, 2021) in a section of robustness checks, that are robust to heterogeneity in treatment effects across states and time.

5.3. Event study model

In practice, equation (5) in section 5.1. examines the static impact of MMLs on exit from unemployment. Now, one examines if there are any dynamic treatment effects of MMLs across time. To do so, consider the event study model as follows:

$$(6)\ Y_{ist} = \alpha + \sum_{k=L}^{-2} \beta_k\, Treat_{sk} + \sum_{k=0}^{H} \beta_k\, Treat_{sk} + X_{ist}\gamma + Z_{st}\lambda + \delta_s + \theta_t + \eta_{st} + u_{ist}$$

where k represents the quarter-year dimension and this was to reduce noise from the monthly-level analysis. Note that $k = -1$ is omitted for the reference quarter and equation (6) is estimated by the linear probability model (LPM)[12]. $Treat_{sk}$ is an event time dummy variable that is equal to 1 if the current period relative to the first treated period for a state s is quarter-year k. L and H are the lowest and highest quarter-year values around the event time. β_k is the coefficient that represents the impact of MMLs in the relative quarter-year k event time. All other components of equation (6) remain the same as earlier. In event study figures, I provide results on a [-8, 7] quarter interval (2 years before and after).

6. Results

6.1. The static impact of MMLs on exit from unemployment

Table 3 shows the static impact of MMLs on exit from unemployment using the probit model within the discrete-time hazard model framework. Reported estimates are average marginal effects.

Model 1 in Table 3 represents the single risk model and displays that, post-MMLs, the probability of exit from unemployment appeared to decrease by 1.43 pp (6.6% decrease relative to the mean exit rate), although at the 10% level of significance. Looking at the UI availability, the likelihood of exit from unemployment was reduced by 3.14 pp (14.5% relative decrease). Model 2 and Model 3 in Table 3 demonstrate the results of the competing risks model. Through the passage of MMLs, unemployed individuals were less likely to transition into employment by

[12] This is to conform to the Sun & Abraham (2021) results, which are robust to heterogeneity in treatment effects across state and time. The results are provided in a section of robustness checks.

2.09 pp (17.6% relative decrease) while the UI availability did not affect the exit to employment much (0.81 pp decrease). Importantly, MMLs did not affect labor force participation among the unemployed, based on Model 3 in Table 3. Unemployed individuals were more likely to stay in the labor force, given the UI availability.

6.2. The dynamic impact of MMLs on exit from unemployment, event study model

Using the event study design, Figure 3 provides the result of the dynamic impact of MMLs on exit from unemployment. Panel A in Figure 3 confirms that there is no evidence of pre-trends, compared to the reference quarter (t = -1), during the pre-MML quarters. Looking at the post-treatment periods, a statistically significant reduction in exit from unemployment was observed in the second quarter after treatment, which is in line with the static result of MMLs presented in section 6.1. In the case of Panel B of Figure 3, although one statistically significant increase in exit to NILF was found during pre-periods (t = -6), MML and non-MML states demonstrated common trends in exit hazards overall. The results on post-MMLs were also largely consistent with the static results shown above.

7. Sub-population analysis

In this section, I provide an extensive set of sub-population analyses. First, I examine the impact of MMLs on exit from NILF, not from unemployment, to investigate if MMLs have affected individuals' exit from economic inactivity. Next, I attempt to check if restricting the sample to those aged 18 to 60 would result in different outcomes. Compared to the original analysis sample (aged 18 to 69), they may be more active in job seeking and more likely to exit from unemployment. Finally, focused on exit to employment, I examine a variety of sub-samples by age, gender, marital status, veteran status, drug-testing laws, race/ethnicity, and education level.

7.1. Sub-population: MMLs on exit from NILF

Table 4 presents the impact of MMLs on exit from NILF, to employment, and to unemployment. Based on Model 1 to 3, one finds no evidence of changes in exit hazards post-MMLs and this is robust to different components of NILF (i.e., retired, disabled, or other). Note that, however, the results may not directly compare to the main results which examined exit hazards from unemployment. This is due to the inability to observe the duration of being NILF in data. On average, about 6.6% of individuals transitioned into the labor force.

7.2. Sub-population: aged among 18 to 60

Table 5 shows the result of the MML impacts when restricted to those aged 18 to 60. Overall, the results are consistent with the main results in both effect size and statistical significance, as shown in section 6.1. One observed change was that exit to employment was no longer affected by the UI availability dimension at any traditional significance level.

7.3. Sub-population: age, gender, marital status, veteran status

Table 6 shows the impact of MMLs on exit to employment by a variety of demographic variables. First, in Model 1 of Table 6, I separated the sample between young and older adults (10-30s vs 40-60s). Given the statistical significance, it appeared that the main results of the whole population may be derived from older adults. In model 2, female and male samples demonstrated similar results, in response to MMLs. In model 3, unmarried people were more responsive to MMLs. Importantly, veteran people showed a large decrease in exit to employment, post-MMLs, compared to non-veteran individuals, although at the 5% level of significance. Across specifications, the UI availability was largely insignificant in exit to employment, which is similar to the main result shown in section 6.1.

7.4. Sub-population: drug-testing laws

Table 7 provides results of the MML impact on exit to employment by state-level legal stance on drug-testing. Noticeably, there was no statistically significant impact of MMLs on the exit hazard among pro-drug testing states. On the other hand, anti-drug testing and no/neutral-drug testing states showed similar results and that coincides with the main result on exit to employment. The UI availability variable again showed similar results as before.

7.5. Sub-population: race/ethnicity

Table 8 presents the results of the MML impact by race/ethnicity heterogeneity. Overall, the UI availability did not change the exit rate to employment. Although MMLs influenced White, Black, and Hispanic people as similarly as before (with somewhat different effect sizes), Asian people were largely unresponsive to MMLs. Although at the 10% level of significance, the Other race sample of Model 5 showed an increase in exit to employment by about 9 pp.

7.6. Sub-population: education level

Finally, Table 9 provides the results by different educational levels. Looking at Model 4 of Table 9, unemployed individuals with a college degree were less likely to exit to employment with a large effect size (5.05 pp change). Overall, other samples appeared to be unresponsive to

MMLs. Among those with a college degree or beyond, the UI availability increased the likelihood of exit to employment by 4.02 pp.

8. Robustness checks

8.1. Event study model: fixed effects only

One might be concerned about the appropriate specification for running event study regression. In this section, I provide event study results with only state and month-year fixed effects in Figure 4. Note that state-level clustered errors were still utilized for statistical significance. Similar to Figure 3, the results are largely consistent with each other. In addition, no pre-trends were observed in any exit outcomes.

8.2. Event study model: interaction-weighted (IW) estimator

Considering a rising concern on the two-way fixed effects model with staggered treatment adoption, I attempt to provide event study results that are robust to heterogeneous treatment effects across states and time. By dropping "already-treated (or always-treated)" observations from the analysis sample, the event study model with an interaction-weighted (IW) estimator was employed (Sun and Abraham, 2021). Figure 5 provides the results of three different outcomes. Although with several statistically significant increases on pre-treatment periods, the results were broadly in line with the ones in Figure 3.

8.3. Alternative model specifications

As alternative model specifications, the linear probability model and logit model were examined in comparison to the probit model that was utilized in the main specification. The LPM specification particularly considers concerns about the incidental parameters problem of non-linear models with fixed effects. Across Model 1 and Model 2 of Table 10, one can observe that the results were mostly robust to alternative specifications, but with some differences in effect size and significance level across outcomes.

8.4. Alternative baseline hazard functions

Table 11 provides the results of using various baseline hazard functional forms, instead of the monthly unemployment duration categories that were used in the main specification. Looking at the impacts of MMLs on exit to employment, the results were robust to different baseline hazard functions across Model 1 to 7 of Table 11. The UI availability also showed similar results as previously, except for Model 1. The statistically significant increase due to available UI benefits in Model 1 may indicate a possible correlation between the UI availability and the uncontrolled individual unemployment duration[13], thus confirming the importance of including an appropriate baseline hazard function in the discrete-time hazard framework.

9. Discussion

Given the rising number of states that legalize medical marijuana, the current study examined if medical marijuana laws had an impact on exit from unemployment using the discrete-time hazard framework. Using the linked CPS data between 2002 and 2012, the empirical results provided some evidence that unemployed individuals were less likely to exit from unemployment through the passage of MMLs. Based on the competing risks model, it was

[13] Intuitively, there would likely be a negative correlation between the UI availability and individuals' unemployment duration, considering how the UI availability was defined. Individuals with a shorter unemployment duration would more likely be having a potential UI duration that is longer than their own unemployment duration.

shown that the reduction in exit from unemployment was derived from a decreased exit to employment (by 2.09 pp, 17.6% relative decrease to the mean), rather than through changes in labor force participation among the unemployed. Thus, unemployed individuals appeared to become less likely to find a new job while they still stayed in the labor force.

Across various event study results, one could confirm that there were overall no significant differences between MML and non-MML states in exit rates during pre-MML periods. The results on post-MML periods were largely in line with the static results.

In sub-population analyses, I found no impact of MMLs on individuals not-in-labor-force, unlike among the unemployed, and that the sample restriction to age 18 to 60 did not change the main results. Focused on exit to employment, sub-population results indicated that the main results were mainly derived by older adults, the unmarried, veterans, White, Black, Hispanic, and individuals with a college degree. It is noteworthy that individuals in pro-drug testing states did not show any statistically significant changes in response to MMLs, while ones in other states demonstrated the same results as previously. This may show a possibly limited impact of MMLs among pro-drug testing states. In robustness checks, I showed that event study results were robust to the change in specification and heterogeneity in treatment effects across states and time. The results were also robust with the LPM and logit models. Finally, I also tested a variety of baseline hazard functions and found that the results were all similar, except for the case when no baseline hazard was included in the regression.

In terms of the impact of MMLs on labor market outcomes, Jergins (2019) may be the only study that can be somewhat compared to this study. Although the paper did not examine transitions from unemployment, the paper showed that, post-MMLs, women aged 30 to 39 were more likely to exit from NILF while men aged 20 to 29 and 30 to 39 were more likely to exit to

NILF, between 2003 and 2015. In the current study, however, results from the NILF sample showed no changes due to MMLs and these may be natural given different analysis periods, sample restrictions, and settings. Compared with the other labor outcome studies in terms of MMLs, this study showed negative MML impacts, while most claimed positive impacts of MMLs (Ullman, 2017; Anderson et al., 2018; Nicholas and Maclean, 2019; Ghimire and Maclean, 2020). Again, this largely depends on the sample and setting. As Sabia and Nguyen (2018), Maclean et al. (2018), and Guo et al. (2021) found null and/or negative MML impacts on labor market outcomes, the impact of MMLs on labor outcomes is yet to be conclusive.

In the case of the UI availability dimension, I found a reduction in exit from unemployment by 3.14 pp, and this was derived by a decreased exit to NILF (by 2.21 pp), which are consistent with the findings in Farber et al. (2015) and Farber and Valletta (2015) in both effect size and statistical significance. Although spanned on different analysis periods, they found estimates of *UI available* around 2-3 pp (Farber et al., 2015) and 2-5 pp changes (Farber and Valletta, 2015). Given the fact that Farber and Valletta (2015) defined the UI availability in a slightly different way, the differences in effect size are quite reasonable.

10. Conclusion

The present study contributes to the existing literature in several aspects. First, the paper examines the impact of MMLs on the probability of exit from unemployment using the discrete-time hazard model by controlling for unemployment duration given a single unemployment spell. To the author's best knowledge, this paper would be the first to do so. Considering the limited literature of MMLs on labor market outcomes, the current study would provide one important perspective that MMLs could have a negative impact on individuals' labor outcomes, particularly among the unemployed. Importantly, this paper also attempted to address the recent critiques on the two-way fixed effects model, given staggered treatment adoption. By using the interaction-weighted (IW) estimates, the present study provided event study results that are robust to heterogeneity across states and time. Finally, this study presented an additional insight into the literature of extended UI benefit duration. As noted previously, the current study built on Farber et al. (2015) and Farber and Valletta (2015) and found that medical marijuana legalization could be a major factor to predict the probability of exit from unemployment, in addition to the availability of UI, which was previously unexplored in the extant literature. The current study will contribute to the existing literature in that it is an intersection of MML and extended UI benefit literature.

There could be many channels behind the findings of this study. First, unlike the beliefs in medical marijuana use that could enhance work capacity and help manage chronic conditions, using medical marijuana might not help someone find a job. As previous studies noted (Williams and Skeels, 2006; van Ours and Williams, 2012), marijuana use may be associated with adverse health outcomes. If marijuana use involves work-impeding side effects, that could worsen individuals' labor market outcomes. On the other hand, although medical marijuana use might not generate adverse health impacts, patients of medical marijuana users might require more time until they find a new job due to medical treatment associated with marijuana use. Importantly, there may be cases that patients use medical marijuana for recreational purposes. As Wen et al. (2015) showed, there may be a spillover to recreational marijuana use from medical marijuana access. If that is the case, there could be negative labor market impacts, post-MMLs, due to drug addiction or indulgence. Relatedly, first-time marijuana users given medical marijuana access could be subject to the gateway effect that they might transition to harder drugs such as heroin and cocaine, thus worsening labor outcomes. Examining economic substitutability and/or complementarity, studies found that marijuana use may be related to the usage of other prescribed drugs, cocaine, alcohol, and/or tobacco (Wen et al., 2015; Choi et al., 2016; Ozluk, 2017; Leung, 2019).

A caveat of this paper is that other than delineating the sample by a set of sub-populations, I did not disentangle the channel through which MMLs could have discouraged the unemployed individuals from the exit from unemployment. Another caveat is that the study provides the intent-to-treat (ITT) estimates of MMLs on exit hazards and was not able to observe if the unemployed individuals consumed medical marijuana, which could have affected labor outcomes. Finally, more state-level controls that are typically included in the MML literature may need to be considered, such as beer tax, minimum wage, prescription drug monitoring program, naloxone and good Samaritan laws, and pain clinic management law (Sabia and Nguyen, 2018; Ghimire and Maclean, 2020; Abouk et al., 2021). Considering the various potential channels discussed earlier, future research is warranted to possibly unravel the unknown mechanisms.

As more and more states participate in the wave of legalizing medical marijuana, policymakers may need to evaluate all the possible intended and unintended consequences of allowing medical marijuana use. In light of my findings, unemployed individuals could experience difficulties in finding a new job while still being attached to the labor force, and this needs to be taken into account among states that attempt to introduce the medical marijuana law.

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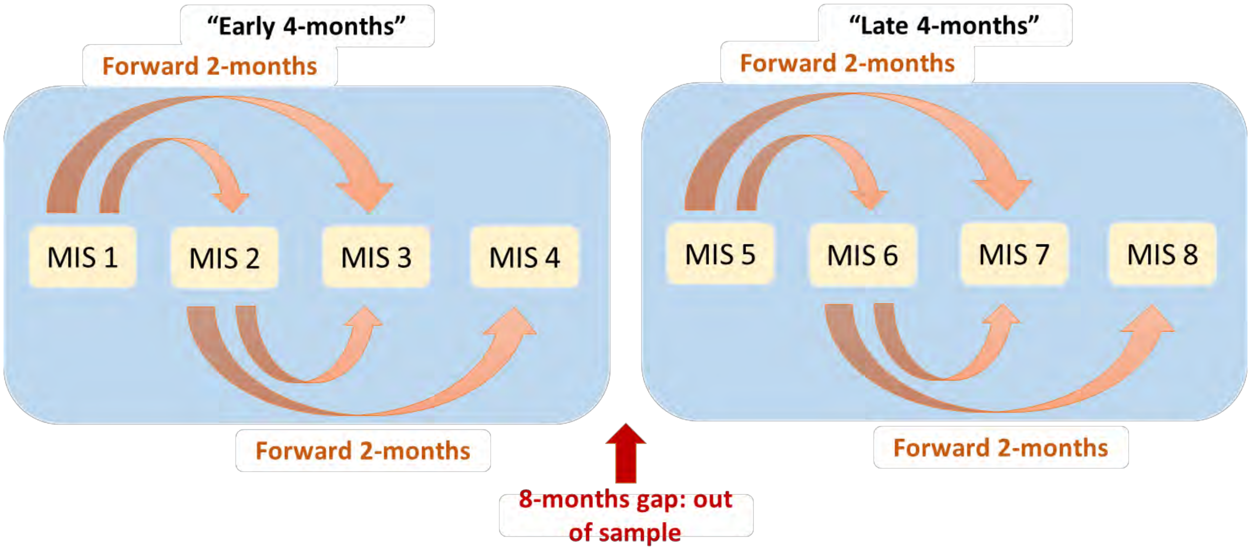
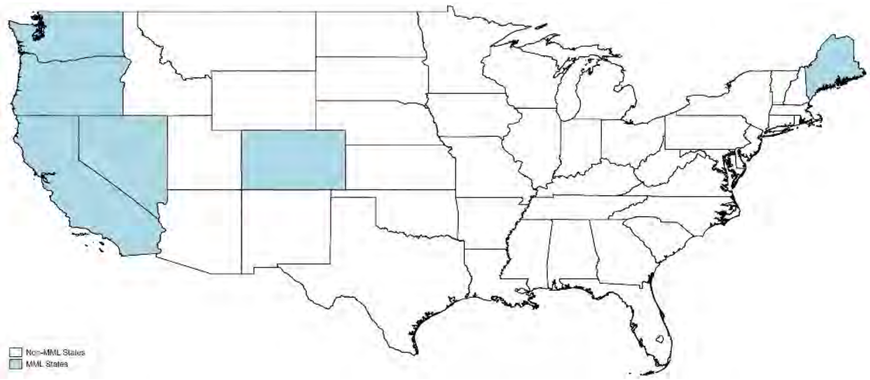
Figure 1. A schematic of the CPS linking procedure for a representative household



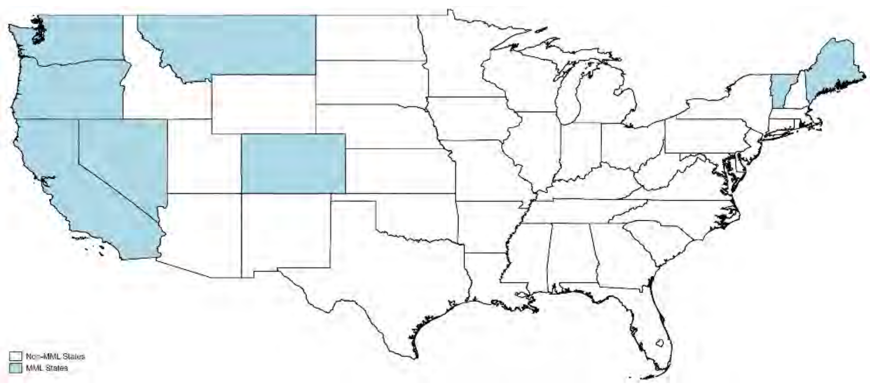
Note: For a representative household surveyed in the sample, the first two months of early and late monthly surveys remain after linking and sample restriction. In each of the first two months, transitions in labor force status are recorded. For example, if an individual was unemployed in month 1 and transitioned out of unemployment status in month 2, then that person is seen as exiting from unemployment following month 1. MIS: month-in-survey.

Figure 2. Trends in medical marijuana legalization during 2002 through 2012

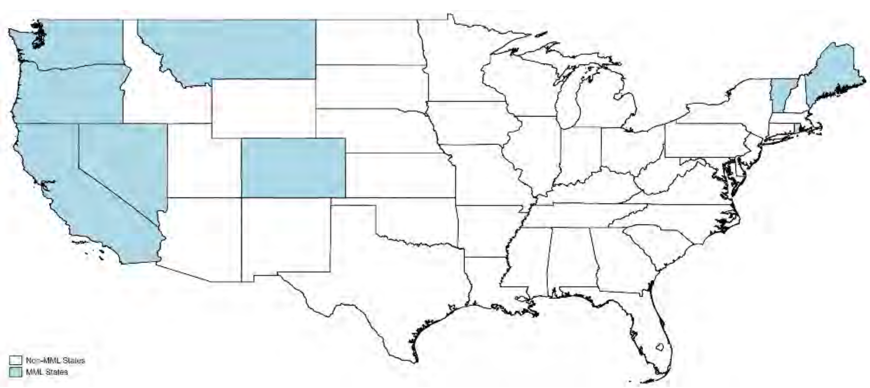
2002



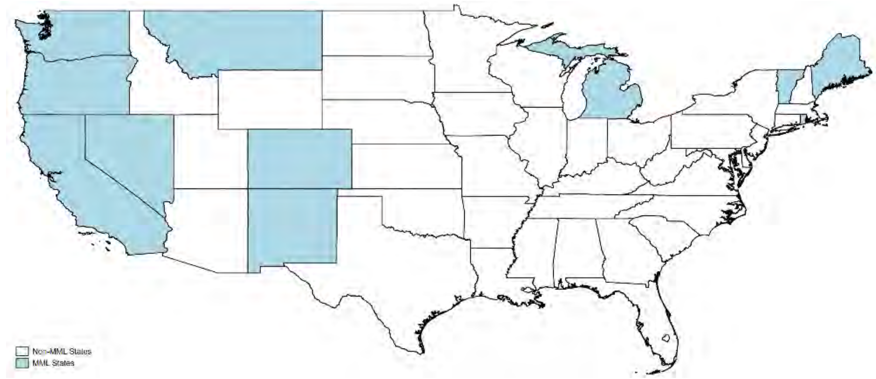
2004



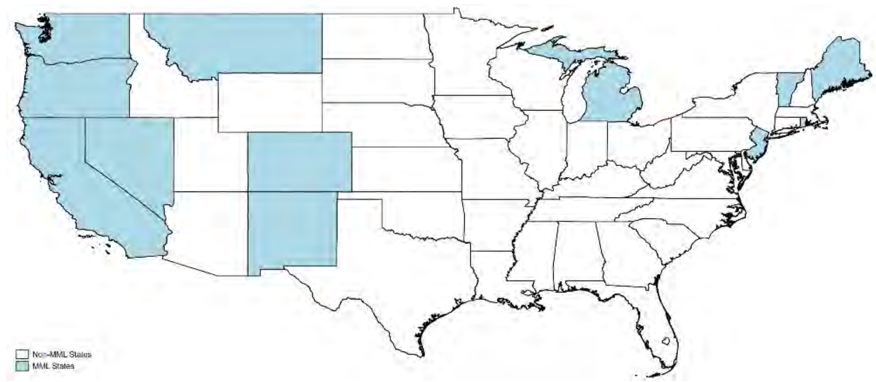
2006



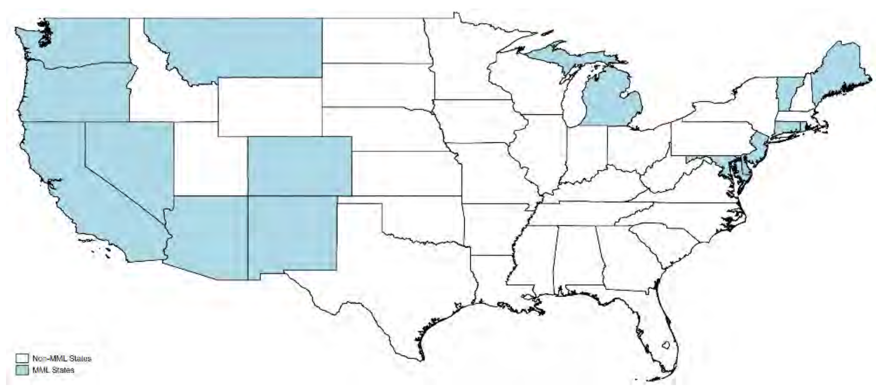
2008



2010



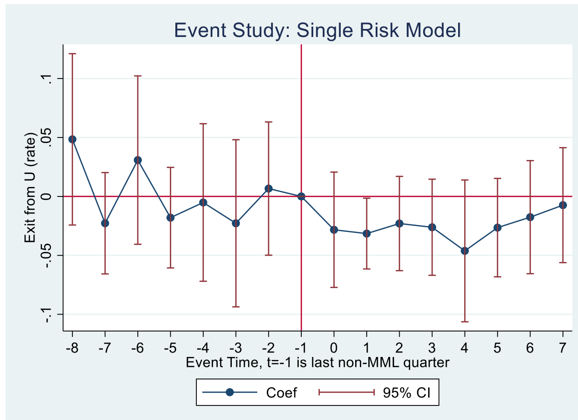
2012



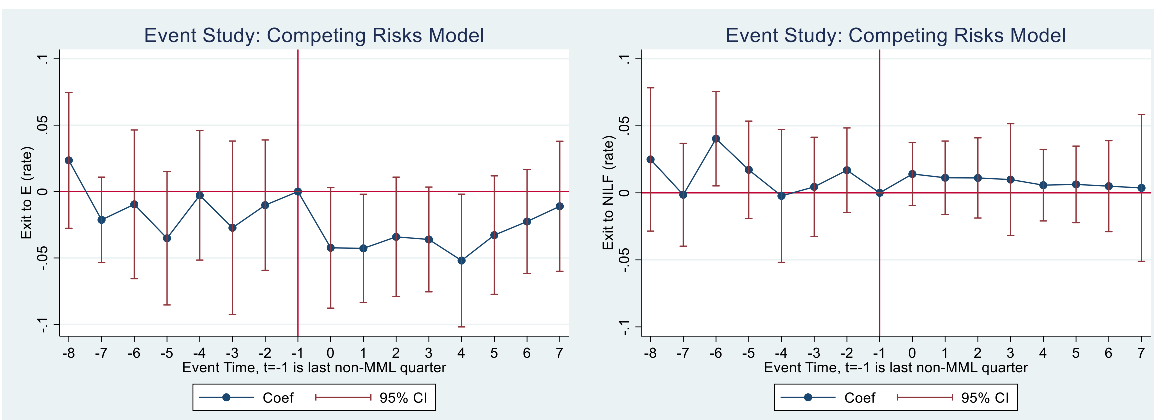
Note: Alaska and Hawaii were already MML states before 2002 and not depicted in the maps. Light blue colored states are MML states. MML status is as of December of each year.

Figure 3. The dynamic impact of MMLs on exit from unemployment

Panel A: Single risk model



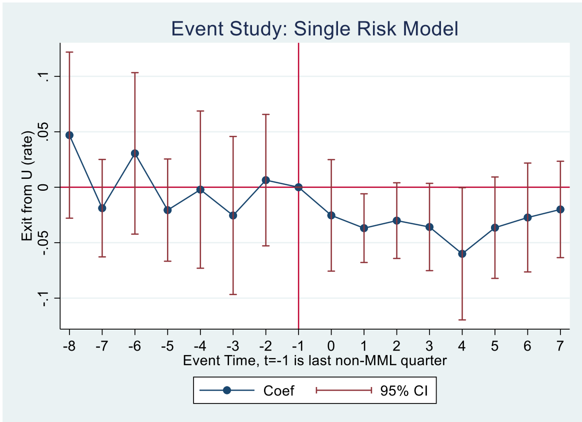
Panel B: Competing risks model



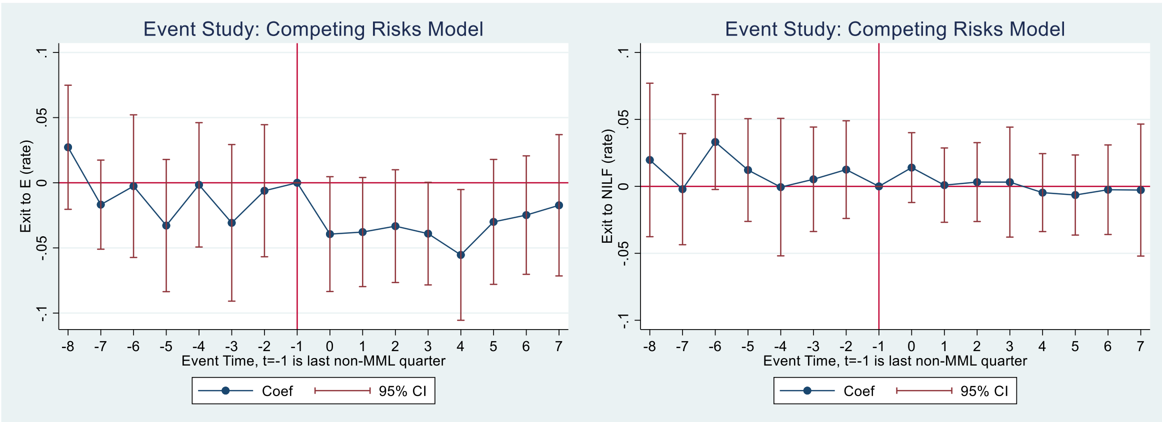
Note: Data used are linked CPS between 2002 and 2012. t= -1 is omitted for the reference quarter. The MML variable is now at the quarter level, for the event study specification. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Confidence intervals were clustered at the state level. U: unemployment. E: employment. NILF: not-in-labor-force. Coef: coefficient. CI: confidence interval.

Figure 4. The dynamic impact of MMLs on exit from unemployment: fixed effects only

Panel A: Single risk model



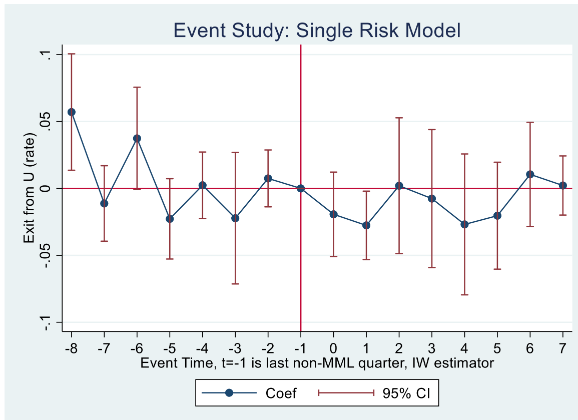
Panel B: Competing risks model



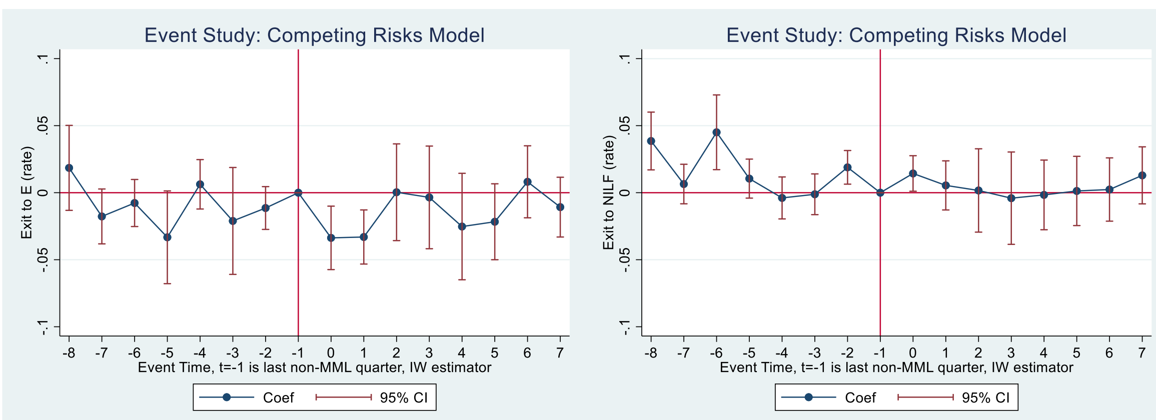
Note: Data used are linked CPS between 2002 and 2012. t= -1 is omitted for the reference quarter. The MML variable is now at the quarter level, for the event study specification. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state and month-year fixed effects but without any controls. Confidence intervals were clustered at the state level. U: unemployment. E: employment. NILF: not-in-labor-force. Coef: coefficient. CI: confidence interval.

Figure 5. The dynamic impact of MMLs on exit from unemployment: interaction-weighted (IW) estimator

Panel A: Single risk model



Panel B: Competing risks model



Note: Data used are linked CPS between 2002 and 2012. t= -1 is omitted for the reference quarter. The MML variable is now at the quarter level, for the event study specification. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Confidence intervals were clustered at the state level. To account for possible heterogeneous treatment effects across states and time, Sun and Abraham (2021)'s interaction-weighted (IW) estimator was employed to generate the figures (Stata command: *eventstudyinteract*). To conform to Sun and Abraham (2021)'s setting, "always-treated" MML states (treated pre-2002) were excluded from the analysis. U: unemployment. E: employment. NILF: not-in-labor-force. Coef: coefficient. CI: confidence interval.

Table 1. Effective dates of marijuana laws in the United States

State	MMLs	RMLs
Alabama	5/17/2021	
Alaska	6/1/1999	2/24/2015
Arizona	4/14/2011	11/30/2020
Arkansas	11/9/2016	
California	11/6/1996	11/9/2016
Colorado	6/1/2001	12/10/2012
Connecticut	10/1/2012	7/1/2021
Delaware	7/1/2011	
District of Columbia	7/27/2010	2/26/2015
Florida	3/25/2016	
Hawaii	6/14/2000	
Illinois	1/1/2014	1/1/2020
Maine	12/22/1999	1/30/2017
Maryland	6/1/2011	
Massachusetts	1/1/2013	12/15/2016
Michigan	12/4/2008	12/6/2018
Minnesota	5/30/2014	
Missouri	12/6/2018	
Montana	11/2/2004	1/1/2021
Nevada	10/1/2001	1/1/2017
New Hampshire	7/23/2013	
New Jersey	10/1/2010	1/1/2021
New Mexico	7/1/2007	6/29/2021
New York	7/5/2014	3/31/2021
North Dakota	4/17/2017	
Ohio	9/8/2016	
Oklahoma	7/26/2018	
Oregon	12/3/1998	12/4/2014
Pennsylvania	5/17/2016	
Rhode Island	7/1/2006	
South Dakota	7/1/2021	
Utah	5/8/2018	
Vermont	7/1/2004	7/1/2018
Virginia	7/1/2021	7/1/2021
Washington	12/3/1998	12/6/2012
West Virginia	7/1/2019	

Note: Effective dates are as of 8/14/2021. Data are from https://www.iihs.org/ and https://www.procon.org/. MMLs: medical marijuana laws. RMLs: recreational marijuana laws.

Table 2. Summary statistics

Sample:	(1) All states	(2) MML states (pre-MML)	(3) Non-MML states	(4) Difference: (3)-(2)
Dependent variables:				
Exit from U	0.216	0.231	0.220	-0.011*
Exit to E	0.120	0.134	0.121	-0.012***
Exit to NILF	0.096	0.097	0.099	0.002
Independent variables:				
MML	0.299	0.000	0.000	-
UI available	0.698	0.648	0.693	0.045***
State-level variables:				
Maximum UI weeks available	63.388	53.192	61.360	8.167***
SA unemployment rate	7.855	7.083	7.369	0.286***
SA growth rate of employment	0.001	-0.003	0.001	0.005***
Pro-drug testing	0.227	0.080	0.347	0.268***
Anti-drug testing	0.108	0.270	0.049	-0.221***
No/neutral-drug testing	0.665	0.650	0.604	-0.047***
Cigarette tax ($)	0.911	0.858	0.752	-0.107***
Individual-level variables:				
Unemployment duration (in weeks)	44.414	41.328	43.754	2.426***
Male	0.612	0.595	0.613	0.018***
Female	0.388	0.405	0.387	-0.018***
Married	0.487	0.473	0.490	0.017**
Unmarried	0.513	0.527	0.510	-0.017**
Age (in years)	42.222	42.358	42.093	-0.265
White	0.643	0.614	0.667	0.053***
Black	0.167	0.228	0.197	-0.031***
Hispanic	0.120	0.109	0.090	-0.018***
Asian	0.037	0.023	0.021	-0.002
Other race	0.032	0.026	0.024	-0.002
Less than high school	0.155	0.160	0.151	-0.008
High school	0.395	0.389	0.411	0.022***
Some college	0.270	0.236	0.267	0.031***
College	0.134	0.151	0.127	-0.023***
College or over	0.047	0.064	0.043	-0.021***
Veteran	0.088	0.081	0.091	0.010***
No veteran	0.912	0.919	0.909	-0.010***
Number of observations	54,270	5,975	32,047	-

Note: Data used are linked CPS between 2002 and 2012. Samples are among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. Note that column (2) represents characteristics of MML states during pre-MML years. On the other hand, column (3) shows characteristics of non-MML states during all years. Other race was defined as American Indian and multi-racial people. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. SA: seasonally adjusted. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. The static impact of MMLs on exit from unemployment

Variables	Model 1: Exit from U	Model 2: Exit to E	Model 3: Exit to NILF
MML	-0.0143*	-0.0209***	0.00410
	(0.00817)	(0.00514)	(0.00695)
UI available	-0.0314***	-0.00811*	-0.0221***
	(0.00511)	(0.00474)	(0.00359)
Mean of dep var	0.216	0.120	0.096
State	51	51	51
Observations	54,270	54,270	54,270
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. The impact of MMLs on exit from NILF

Variables	Model 1: Exit from NILF	Model 2: Exit to E	Model 3: Exit to U
MML	0.000759	3.08e-05	0.00103
	(0.00174)	(0.00152)	(0.00111)
Mean of dep var	0.066	0.044	0.021
State	51	51	51
Observations	1,014,459	1,014,459	1,014,459
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were not in the labor force. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The impact of MMLs on exit from unemployment: age restriction from 18 to 60

Variables	Model 1: Exit from U	Model 2: Exit to E	Model 3: Exit to NILF
MML	-0.0165*	-0.0219***	0.00273
	(0.00989)	(0.00588)	(0.00809)
UI available	-0.0283***	-0.00665	-0.0205***
	(0.00543)	(0.00500)	(0.00346)
Mean of dep var	0.216	0.122	0.094
State	51	51	51
Observations	50,588	50,588	50,588
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 60 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6. The impact of MMLs on exit to employment: age, gender, marital status, veteran status

Variables	Model 1: age		Model 2: gender		Model 3: marital status		Model 4: veteran status	
	10-30s	40-60s	Female	Male	Married	Unmarried	Veteran	No veteran
MML	-0.0205*	-0.0203**	-0.0202***	-0.0214***	-0.0156*	-0.0253***	-0.0477**	-0.0184***
	(0.0119)	(0.00832)	(0.00688)	(0.00648)	(0.00868)	(0.00894)	(0.0191)	(0.00501)
UI Available	-0.0132*	-0.00500	-0.0140*	-0.00445	-0.00781	-0.00722	-0.0113	-0.00819*
	(0.00714)	(0.00550)	(0.00751)	(0.00490)	(0.00710)	(0.00591)	(0.0144)	(0.00485)
Mean of dep var	0.134	0.110	0.110	0.126	0.126	0.113	0.122	0.120
State	51	51	51	51	51	51	51	51
Observations	22,632	31,638	21,065	33,205	26,446	27,824	4,616	49,508
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly were dropped. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. The impact of MMLs on exit to employment: drug-testing laws

Variables	Model 1: Pro-drug testing	Model 2: Anti-drug testing	Model 3: No/neutral-drug testing
MML	-0.0111	-0.0237***	-0.0222***
	(0.0113)	(0.00895)	(0.00661)
UI available	0.00412	-0.0320*	-0.00845*
	(0.0118)	(0.0168)	(0.00501)
Mean of dep var	0.120	0.133	0.118
State	51	51	51
Observations	12,312	5,783	36,114
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly were dropped. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. The impact of MMLs on exit to employment: race/ethnicity

Variables	Model 1: White	Model 2: Black	Model 3: Hispanic	Model 4: Asian	Model 5: Other race
MML	-0.0165**	-0.0356**	-0.0437**	-0.0101	0.0897*
	(0.00796)	(0.0180)	(0.0179)	(0.0658)	(0.0516)
UI available	-0.00932	-0.0110	-0.0186	0.0551**	0.0320
	(0.00643)	(0.00896)	(0.0120)	(0.0249)	(0.0335)
Mean of dep var	0.123	0.094	0.140	0.129	0.167
State	51	51	51	51	51
Observations	34,918	9,016	6,449	1,611	1,397
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly were dropped. Other race was defined as American Indian and multi-racial people. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. The impact of MMLs on exit to employment: education level

Variables	Model 1: Less than high school	Model 2: High school	Model 3: Some college	Model 4: College	Model 5: College or over
MML	-0.0413*	-0.0214	0.00313	-0.0505***	-0.0211
	(0.0218)	(0.0164)	(0.0151)	(0.0145)	(0.0383)
UI available	-0.00176	-0.0108	-0.0127	-0.00690	0.0402**
	(0.00976)	(0.00867)	(0.00873)	(0.0128)	(0.0205)
Mean of dep var	0.122	0.119	0.116	0.126	0.137
State	51	51	51	51	51
Observations	8,396	21,410	14,634	7,299	2,287
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly were dropped. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. The impact of MMLs on exit from unemployment: alternative specifications

Variables	Model 1: linear probability model			Model 2: logit model		
	Exit from U	Exit to E	Exit to NILF	Exit from U	Exit to E	Exit to NILF
MML	-0.0130	-0.0177***	0.00471	-0.0149*	-0.0208***	0.00435
	(0.00787)	(0.00417)	(0.00677)	(0.00829)	(0.00529)	(0.00697)
UI available	-0.0299***	-0.00495	-0.0250***	-0.0315***	-0.00961**	-0.0215***
	(0.00504)	(0.00455)	(0.00380)	(0.00512)	(0.00479)	(0.00355)
Mean of dep var	0.216	0.120	0.096	0.216	0.120	0.096
State	51	51	51	51	51	51
Observations	54,270	54,270	54,270	54,270	54,270	54,270
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories were included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. The impact of MMLs on exit to employment: alternative baseline hazard functions

Variables	Model 1: No baseline hazard	Model 2: Linear	Model 3: Weekly dummies	Model 4: Monthly dummies	Model 5: Logarithmic	Model 6: Polynomial: quadratic	Model 7: Polynomial: cubic
MML	-0.0218***	-0.0212***	-0.0211***	-0.0208***	-0.0208***	-0.0209***	-0.0209***
	(0.00478)	(0.00510)	(0.00509)	(0.00535)	(0.00516)	(0.00516)	(0.00520)
UI available	0.0340***	-0.0163***	-0.0171***	-0.0166***	-0.0150***	-0.0176***	-0.0187***
	(0.00334)	(0.00485)	(0.00516)	(0.00509)	(0.00493)	(0.00495)	(0.00502)
Mean of dep var	0.120	0.120	0.120	0.120	0.120	0.120	0.120
State	51	51	51	51	51	51	51
Observations	54,270	54,270	54,136	54,219	54,270	54,270	54,270
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models included state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly were dropped. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.