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MEDICAL MARIJUANA LAWS AND DISABILITY APPLICATIONS, RECEIPTS, AND TERMINATIONS

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Medical Marijuana Laws and Disability Applications, Receipts, and Terminations
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ABSTRACT

We study the effect of state medical marijuana laws (MMLs) on disability claiming. MMLs allow qualifying patients to legally use marijuana for medical purposes. We examine Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI) applications, new beneficiaries, and terminations. We use administrative data from the Social Security Administration coupled with a differences-in-differences design to study this question. We find that MML adoption increases application and new beneficiary rates, and reduces termination rates, although new beneficiary rate estimates are somewhat imprecise.

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1 Introduction

We offer the first evidence on the effect of laws related to a controversial medical intervention, medical marijuana, on two forms of disability claiming – Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI) – in the United States. SSDI is one of the largest social insurance programs in the U.S. and provides benefits to disabled workers. In 2017 this program cost the U.S. $138B (Social Security Administration, 2018a). SSI is a means-tested welfare program for low-income disabled or blind individuals with limited work experience. In 2017, the costs of SSI were $55B (Social Security Administration, 2018b). Collectively, these two programs provide disability benefits to approximately 16M U.S. residents. Although SSDI and SSI are costly, the programs are valued by individuals and their families as the programs offer earnings support and health insurance coverage when individuals become disabled and cannot work.[1]

Given high program costs, policymakers are grappling with strategies to support both SSDI and SSI without placing undue financial burden on taxpayers. As with many social insurance programs, both SSDI and SSI can potentially dis-incentivize labor market participation. Thus, assessing factors that influence the propensity to claim SSDI and SSI is imperative for understanding how public policies affect labor markets. On the other hand, testing the effectiveness of medical interventions that allow disabled individuals to return to paid employment is important for the overall health of the workforce and for reducing unnecessary government spending on social programs.

Beginning with California in 1996, U.S. states have implemented laws that legalize the use of marijuana for medical purposes ('MMLs') for patients with 'qualifying' health conditions. As of 2019, 34 states have implemented an MML. Supporters of these laws argue that access to medical marijuana will confer substantial health benefits to patients suffering from burdensome physical or mental symptoms which are not effectively treated by conventional medications and procedures. Opponents worry that MMLs provide an avenue to access marijuana for recreational, not medical, use and MMLs will foster marijuana addiction, misuse of other substances, and substance use-related social ills (e.g., crime, healthcare costs, traffic accidents, reduced productivity in the labor market) with, at best, marginal health benefits for the small number of legitimate medical users.

[1]Over our study period, 2001 to 2013, health insurance for non-elderly adults was tightly linked with employment in the U.S. For instance, in 2013, the last year of our study period, 74% of insured non-elderly adults were covered by employer-sponsored health insurance. Authors' calculation based on the 2013 American Community Survey (Ruggles et al., 2018).

Medical marijuana cannot cure underlying medical conditions, but may improve a disabled person's ability to manage symptoms and increase work capacity. Indeed, the available clinical literature suggests a role for medical marijuana in symptom management for many common health conditions. Randomized control trials show that medical marijuana can alleviate symptoms associated with anxiety, chronic pain, depression, psychosis, sleep disorders, and spasticity (Joy, Watson, & Benson, 1999; Lynch & Campbell, 2011; Hill, 2015; Whiting et al., 2015; National Academies of Sciences & Medicine, 2017). Patients themselves report using medical marijuana to manage symptoms related to health conditions (Nunberg, Kilmer, Pacula, & Burgdorf, 2011; Troutt & DiDonato, 2015; Reiman, Welty, & Solomon, 2017) and note that medial marijuana better mitigates symptoms than medications previously prescribed by their clinicians (Nunberg et al., 2011; Troutt & DiDonato, 2015; Vigil, Stith, Adams, & Reeve, 2017). Further, a recent study shows that MML passage reduces chronic pain and increases work capacity among older workers (Nicholas & Maclean, 2019).

There is substantial overlap in the health conditions that are relevant for disability claiming and medical marijuana. For instance, in 2017, the three most common impairments among SSDI disabled worker recipients were musculoskeletal system disorders (e.g., back injuries), neurological disorders (e.g., multiple sclerosis), and mental illnesses (e.g., anxiety) (Social Security Administration, 2018a). These are also common impairments among SSI recipients (Social Security Administration, 2018b). All of these conditions could qualify a patient for legal access to medical marijuana in most states that have adopted an MML (Bradford & Bradford, 2016; Sabia & Nguyen, 2018).

As we outline later in the manuscript, there is a complex set of pathways from MML passage to disability claiming, with improved symptom management being just one. These pathways leave the net effect of MMLs on disability claiming ambiguous. Given the theoretical ambiguity, we empirically address this question: we use administrative data from the Social Security Administration (SSA) to explore the extent to which passage of an MML affects disability applications, new beneficiaries, and terminations. Our findings suggest that passage of an MML leads to an overall increase in disability claiming. First, passage of an MML increases disability applications. Second, new beneficiaries increase post-MML, although our estimates are somewhat noisy. Third, we observe that medical terminations decline following passage of an MML. There is some evidence of heterogeneity in the precision of our estimates across SSDI and SSI, but effect sizes are relatively stable across programs.

Our study contributes to at least three strands of economic literature. First, the study adds to the literature on the health and social effects of MMLs by considering an unstudied, but economically important, outcome: disability claiming. Second, we add to the small literature highlighting the relationship between specific medical treatments, and work propensities generally and use of social insurance specifically. Previous economic research documents an increase in sick leave and disability claiming in response to aggressive monitoring of prescription opioids (Kilby, 2015) and the removal of Vioxx, a pain medication discontinued due to fatal side effects (Butikofer & Skira, 2016; Garthwaite, 2012). Third, our findings contribute to the literature on regulatory spillovers. MMLs have been shown to have spillover effects to public insurance programs (Bradford & Bradford, 2016, 2017; Bradford, Bradford, Abraham, & Adams, 2018; Bradford & Bradford, 2018; Wen & Hockenberry, 2018). More broadly, economists have assessed spillover effects from Workers Compensation program changes (McInerney & Simon, 2012), health insurance expansions (Burns & Dague, 2017), and raising the retirement age (Duggan, Singleton, & Song, 2007) to disability claiming.

The paper proceeds as follows. Section 2 provides background on the disability programs we study and a discussion of mechanisms through which we expect MMLs to influence disability claiming. Data, variables, and methods are discussed in Section 3. Our main findings are reported in Section 4. Sensitivity analysis and extensions are listed in Section 5. Section 6 concludes.

2 Disability programs and mechanisms

2.1 Disability programs

SSDI is a federal program that insures workers against the risk of a disability that prohibits work. This program, implemented in 1956, is funded by payroll taxes and is managed by the SSA. The objective of SSDI is to provide income supplements to workers who face substantial restriction in their capacity to work due to disability. While employed, workers pay a portion of their earnings into this insurance program. SSDI benefits are temporary or permanent, depending on the nature of the worker's specific disability, and are based on average historical earnings.

A worker is determined to be eligible for SSDI if she meets the following four conditions: (i) has a physical or mental condition that prevents any 'substantial gainful activity' ('SGA'),[2] (ii) the impairment is expected to last 12 months or to result in the worker's death, (iii) is under 65 years of age, and (iv) satisfies work history requirements (Social

[2]In 2019, the minimum monthly SGA earnings requirement for non-blind workers is $1,220 and $2,040 for blind workers.

Security Administration, 2018a). Impairments that are considered SSDI-eligible include conditions related to the musculoskeletal system, cardiovascular system, digestive system, immune system, or special senses and speech; respiratory disorders; genitourinary disorders; hematological disorders; skin disorders; endocrine disorders; congenital disorders; neurological disorders; mental disorders; and cancer. Applicants must undergo a medical screening process to determine if they are eligible for SSDI benefits. The period between the initial application and final decision can extend from six months to several years. In 2017, 8.7M disabled workers received SSDI benefits with an average monthly payout of $1,197 (Social Security Administration, 2018a).

SSI is a means-tested program for very low-income blind and/or disabled individuals. The program was implemented in 1974, federalizing state-run disability programs for the poor. SSI is funded through general taxes. SSI disability status is determined using the same standards as SSDI, but applicants must also demonstrate low income and asset levels (i.e., a maximum of $2,000 in assets for a single applicant), and do not face work history requirements. The average monthly SSI benefit in 2017 was $542 and the program covered 8.2M individuals (Social Security Administration, 2018b). There is a federally-established payment level with some states electing to increase the benefit using their own funds. SSI is considered assistance of last resort, thus all other benefits received by the individuals are considered. The typical duration from application to benefit receipt is 30 to 90 days.

'Concurrent claimants' receive both SSDI and SSI. A prospective beneficiary who applies for SSDI is also screened for SSI eligibility. If the SSDI determined benefit is sufficiently low, the individual may also be eligible for SSI benefits. Individuals may also apply for the programs separately. Concurrent claimants are a very low-income sub-set of SSDI claimants.

There are differences between the two programs. SSDI is available to disabled workers with sufficient work experience to qualify while SSI provides benefits to low-income and disabled individuals regardless of work history. SSDI recipients have access to Medicare (a federal insurance program for elderly adults and select groups of non-elderly adults) after two years of eligibility while SSI recipients are immediately eligible for coverage through their state's Medicaid program (a public insurance system for the poor).[3] In some cases, an SSDI beneficiary's dependents may also be eligible for benefits, this is not the case for SSI. While beneficiaries for both programs have their disability evaluated by the SSA every three to seven years, SSI recipients also have their income levels reviewed annually.

Table 1 reports demographics on non-claimants and claimants ages 18 to 64 years from the

[3] Some states have additional requirements for Medicaid; see Burns and Dague (2017) for more details.

2013 – the last year of our study period – Annual Social and Economic (ASEC) Supplement to the Current Population Survey (CPS); authors' calculation (King et al., 2018). Overall, disability claimants are disadvantaged across a range of measures: minority status, education, marriage outcomes, labor market participation, poverty status, earnings, and health status. For instance, while 12.7% of non-claimants have income below the federal poverty level (FPL), 61.5% of claimants fall below this threshold.

While there are official standards in place, there is a subjective component to the disability screening process as determining true disability status is complicated (Freedman et al., 2004; Keiser, 2010; Burkhauser, Fisher, Houtenville, & Tennant, 2014). This subjectivity adds uncertainty to the decision of whether or not to apply for disability benefits. Given the non-trivial transaction costs associated with placing a claim (e.g., medical and work history review for SSDI, a period of low earnings while largely out of the work force, stigma associated with applying for disability, and a medical review for the SSI claimant along with a family-level review of available income and assets), some prospective claimants may be induced into/out of claiming following small changes in disability benefit costs and benefits. We expect that marijuana obtained following an MML may influence claiming for such individuals on the margin of placing a claim.

2.2 Mechanisms

Access to marijuana through MMLs can potentially lead to changes in disability claiming in several ways. We take the canonical Grossman (1972) model as our starting point. Within this framework, health is a determinant of labor supply as health influences the amount of time a consumer can allocate to work (Currie & Madrian, 1999).

Equation 1 presents a simplified version of a Grossman labor supply equation:

$$D_t = F(H_t, W_t, Q_t) \tag{1}$$

Where D_t is a measure of disability claiming, H_t is individual health, W_t is the wage rate the worker can earn in the labor market, and Q_t is a vector of other factors that may affect labor supply. Disability claiming – which is a substitute for work for some individuals (Autor & Duggan, 2006) – is decreasing in H_t and W_t. We present this simple model to organize a discussion of the ways in which expanded access to medical marijuana, through

MMLs, may influence an individual's decision to claim disability.[4] [5] We note that MMLs may trigger changes in the propensity to claim and/or the duration of a claim.

MMLs, by increasing access to medical marijuana, could affect claiming by influencing symptoms (H_t) associated with health conditions that qualify workers for disability, for instance symptoms such as chronic pain. Several studies report evidence that MMLs promote a shift towards medical marijuana from formal prescription medications. Within Medicaid, Bradford and Bradford (2017) and Wen and Hockenberry (2018) show that following passage of an MML depression medications decline 13%, psychosis medications decline 12%, overall pain medications decline 11%, and opioid medications decline 6%. Comparable shifts away from traditional prescriptions are identified within Medicare (Bradford & Bradford, 2016; Bradford et al., 2018; Bradford & Bradford, 2018) and among the privately insured (Ozluk, 2017). Bachhuber, Saloner, Cunningham, and Barry (2014), and Powell, Pacula, and Jacobson (2018) find that passage of an MML reduces the opioid fatal overdose rate by as much as 24.8%, further suggesting that some individuals substitute marijuana for opioids post-MML. Many prescription medications impose side effects that may reduce work capacity. For example, side effects of opioids include addiction, confusion, feelings of weakness, and nausea, all of which could reduce capacity to work. Indeed, there is evidence that MML passage leads to improvements in many, but not all, health outcomes that are plausibly linked with work-capacity and, in turn, disability claiming (Anderson, Rees, & Sabia, 2014; Ullman, 2017; Abouk & Adams, 2018; Anderson, Rees, & Tekin, 2018). For instance, Sabia, Swigert, and Young (2017) find that following passage of an MML, days in poor physical and mental health decline while physical activity increases, and Nicholas and Maclean (2019) document that, among older workers, reported pain declines. If marijuana is equally, or perhaps more, effective than formal medications in symptom management and/or offers a less burdensome side effect profile, disability claiming should decline post-MML ($\partial D_t/\partial MML_t < 0$).

Individuals who use marijuana recreationally following passage of an MML may experience worse health (H_t) and, potentially, reduced wages (W_t) (Sabia & Nguyen, 2018).[6] Worsening health and lower wages should decrease labor supply and increase disability claiming.

[4] In the Grossman model, the time constraint is as follows: $L_t + V_t + W_t + S_t = 1$ where L_t is leisure time, V_t is time spent investing in health, W_t is working time and includes D_t, and S_t is sick time. We expect MMLs will change S_t overall. However, MMLs may also reduce V_t for some consumers, those who used marijuana medically when it was an illegal substance and now face reduced non-monetary costs of using this substance (e.g., time spent searching for a seller in the illegal drug market), and increase V_t for those who only begin to use marijuana medically following passage of an MML.

[5] We note that MMLs may influence disability claiming through Q_t. Such pathways are likely heterogeneous across workers and we leave this discussion for future work.

[6] During our study period, substance abuse is not a qualifying condition for disability.

If workers are intoxicated by marijuana, such use may increase the risk of a disability, leading to a claim. Several studies document that overall marijuana use and use that is likely to be recreational increases post-MML (Chu, 2014, 2015; Pacula, Powell, Heaton, & Sevigny, 2015; Wen, Hockenberry, & Cummings, 2015). For instance, Chu uses administrative data and shows that MML passage leads to a 10 to 20% increase in arrests for marijuana-related possession and substance abuse treatment admissions (Chu, 2014, 2015). These pathways suggest: $\partial D_t/\partial MML_t > 0$.

MMLs may also change the use of other substances (Anderson, Hansen, & Rees, 2013; Wen et al., 2015; Sabia et al., 2017; Chu, 2015). However, the findings are somewhat mixed. For example, Anderson et al. (2013) and Sabia et al. (2017) show that alcohol use declines post-MML while Wen et al. (2015) document an increase following law adoption. Chu (2015) shows that MMLs decrease heroin use but are unrelated to cocaine use. If substance use declines, all else equal, claiming should decline: $\partial D_t/\partial MML_t < 0$.

Features of the U.S. labor market and the disability claiming process itself suggest a link between MMLs and disability claiming. During our study period there was no legal protection for medical marijuana users against job termination due to drug use; if an employee who used marijuana medically tested positive for marijuana during a drug test, he could be fired. Losing a job could prompt an individual to apply to disability. The perception by a beneficiary that medical marijuana use will reduce labor market opportunities may prolong a claiming spell. If use of marijuana obtained through an MML alters an individual's peer group and the new peer group changes the costs and benefits of disability claiming (e.g, information about disability or stigma associated with receiving disability), then disability claiming may change. Peer effects have been identified in disability take-up (Furtado, Papps, & Theodoropoulos, 2019). Changes in providers (the majority of providers do not recommend marijuana) may lead to comparable changes in knowledge of or attitudes towards disability claiming. These pathways suggest $\partial D_t/\partial MML_t > 0$. If MML passage spurs an increase in new disability applications, this increase may reduce the amount of time SSA reviewers can allocate to reviews of ongoing claims, which may increase or decrease the number of terminated claims.

In summary, the potential effect of expanded access to marijuana through MMLs on disability claiming is unclear given the complex set of pathways that may act in conjunction, or in opposition, to one another. Further, the available related MML studies have not examined individuals who are likely to claim disability and are, by definition, in worse health. Thus, it is not clear how the extant findings generalize to disabled workers. Our objective in this study is to estimate the net effect of an MML passage on disability claiming.

3 Data, variables, and methods

3.1 Data and outcomes

We draw administrative data on the number of processed claims from the SSA State Agency Monthly Workload Data (SAMWD) over the period 2001 to 2013. The data are available from October 2000 onward and we start our study period with the first full year of data (2001). We truncate the data in 2013 as after this period states began to implement laws that legalized recreational use of marijuana and we wish to avoid confounding from these laws. Core provisions of the ACA came into effect in 2014, including state Medicaid expansions to previously ineligible adults and private insurance subsidies, which may have reduced the value of insurance offered through disability claiming. However, we report results using data through 2017 in a sensitivity check. The SAMWD are ideal for our study as they contain detailed month-by-month state-level information on claims for disability benefits processed by one of the state SSA agencies.

The number of disability claimants is a stock variable that is determined by flows into and out of disability. We focus on the following flow variables to understand the evolution of claims post-MML: new applications, new beneficiaries, and medical terminations of claims following a continuing disability review (CDR); the SSA reviews all ongoing claims every three to seven years to determine if the claimant remains medically eligible for benefits.[7]

We consider three types of claims: (i) SSDI and/or SSI ('total'), (ii) SSDI and SSI (SSDI and concurrent claims, which we refer to as 'SSDI'), and (iii) SSI only ('SSI'). A limitation of the SAMWD is that we cannot separate disabled child SSI terminations from adult SSI terminations; we can separate child and adult SSI applications and new beneficiaries. To ensure comparable outcomes, in the main analysis we include disabled child SSI in all SSI variables. However, as we show in a robustness check, our SSI application and new beneficiary results are not appreciably different when we exclude disabled child claims.

We convert total and SSDI claiming variables to the rate per 10,000 non-elderly adults using population data from the U.S. Census and age-share information from the Current

[7]CDRs can be medically-related or work-related. Medically-related CDRs occur more regularly for claimants with disabilities that, at the initial allowance, could improve (e.g., every three years) and less regularly for disabilities are unlikely to improve (e.g., every seven years). Work-related CDRs are performed if a claimant reports working and/or increases working. Working can imply that the claimant is no longer disabled. Information on work-related CDRs is not provided in the SAMWD.

Population Survey (CPS) (King et al., 2018); SSDI is available to non-elderly adults. For SSI claiming, we use the adult population (18 years and older) as there is no age limit to SSI eligibility. We use the term 'eligible adults' for these population variables. We aggregate the monthly-level data to the state-year level to smooth out seasonality in claiming,[8] leaving us with 663 observations.

3.2 State MMLs

We use data on state MML effective dates collected by Sabia and Nguyen (2018) to capture states' law environment. We report MMLs in Table 2 column 1. Using this information, we construct a variable coded one in state/year pairs with an MML in place and coded zero in state/year pairs when there is no MML. We code all laws as of January 1st of each year. For example, if a state implemented an MML in June of year t our variable is coded zero in all years prior to t and in year t, and one in years $t+1$ and onward.

3.3 Empirical model

We estimate the relationship between MMLs and disability benefit claiming with the following differences-in-differences-style (DD) regression model:

$$B_{s,t} = \beta_0 + \beta_1 MML_{s,t} + X_{s,t}\beta_2 + \lambda_s + \gamma_t + \mu_{s,t} \tag{2}$$

$B_{s,t}$ is a claiming rate variable in state s in year t. $MML_{s,t}$ is an indicator for a state MML. $X_{s,t}$ is a vector of state-level characteristics that plausibly predict disability claiming (demographics from the Current Population Survey, Medicaid Health Insurance Flexibility and Accountability [HIFA] Waivers, and marijuana decriminalization[9] (Pacula, Chriqui, & King, 2003; Atherly, Dowd, Coulam, & Guy, 2012; University of Kentucky Center for Poverty Research, 2018; Wen & Hockenberry, 2018)). λ_s is a vector of state fixed effects and γ_t is a vector of year fixed effects. We cluster standard errors around the state (Bertrand, Duflo, & Mullainathan, 2004). We weight regressions by the state eligible adult population.

DD regression models identify the effect of a treatment variable (MML passage in our

[8] SSA months have either four or five weeks as the SSA counts it work in weekly increments, leading to mismatch between an SSA work month and a calendar month. This difference also lead us to aggregate the data to the annual level. See the SAMWD website for more details: https://www.ssa.gov/disability/data/ssa-samowl.htm (accessed March 1st, 2019).

[9] We thank Rosalie Pacula for sharing an updated version of the marijuana decriminalization variable with us.

context) using within state variation. Thus, our effects are identified off the 12 states that adopted an MML over our study period (2001 to 2013); states that adopted MMLs outside this period do not offer variation that we can use for identification. Our comparison group therefore includes two groups of states: (i) states that adopted an MML prior to our study period ('treated controls') and (ii) states that did not adopt an MML by 2013. A concern with our comparison group is that treated controls may, due to the MML passed prior to our study period, be on a differential trend in disability claiming which may complicate interpretation of estimated generated in DD models.[10] In a robustness check, we exclude these states and show that our results are not appreciably different.

4 Results

4.1 Summary statistics

Table 3 reports summary statistics for the full sample, and for states that pass and do not pass an MML by the end of our study period. In the full sample, the number of total disability, SSDI, and SSI applications per 10,000 eligible adults are 145, 88, and 57. The corresponding rates for new beneficiaries are 50, 30, and 20. Terminated overall disability, SSDI, and SSI claim rates per 10,000 eligible adults are 5, 1.4, and 4. Application, new beneficiary, and terminated claims rates are lower in MML states than in non-MML states. For instance, the overall disability application rate per 10,000 eligible adults is 134 in MML states and 163 non-MML states. An MML is in place in 23% of the state-year pairs covered by our study period.

4.2 Regression analysis of disability claiming outcomes

Table 4 reports selected results generated in our DD regression models. We observe that post-MML, applications and new beneficiaries increase, while terminated claims decrease. While applications increase for all forms of disability we study, increases in new beneficiaries are driven by SSI claimants while declines in terminations are driven by SSDI claimants.

In particular, post-MML, overall disability, SSDI, and SSI applications increase by 7.3 per 10,000 eligible adults or 5.0% (relative effect sizes are compared to the sample mean), 3.8 per 10,000 eligible adults or 4.3%, and 3.5 per 10,000 eligible adults or 6.4%. SSI new beneficiary rates increase post-MML, but overall disability and SSDI new beneficiary rates

[10]If MMLs simply lead to a level shift in claiming this issue is not a concern.

are unchanged. In particular, following MML adoption, SSI new beneficiary rates increase by 1.2 per 10,000 eligible adults or 5.8%. Overall disability and SSDI terminated claims decline post-MML by 0.52 (10.3%) and 0.26 (18.5%) per 10,000 eligible adults in adopting states; the relative effect size for SSDI terminated claims is large as the baseline mean is low (1.4 per 10,000 eligible adults).

We observe some heterogeneity in MML effects across programs in terms of new beneficiary and termination rates; MMLs appear to change the former within the SSI population and the latter within the SSDI population. Our interpretation of these findings is that the heterogeneity is related to estimate precision and not implied effect size. For instance, the effect size for terminated SSI claims is similar, both in terms of absolute and relative terms, to the SSDI point estimate, however the former is not statistically different from zero. Examination of the effect sizes implied by the 95% confidence intervals surrounding our point estimates suggests similar relationships between MML passage and different types of disability claiming, thus we do not wish to overstate any heterogeneity in treatment effects.

A concern with our SSI findings is that medical marijuana may be too expensive for the very low-income SSI recipients; either in terms of the fixed cost of a medical marijuana card registration charged by many states or the variable cost of purchasing medical marijuana. While, to the best of our knowledge, there is no centralized and accurate national repository of medical marijuana prices, we have explored this question by reviewing state medical marijuana program websites and medical marijuana seller websites (full search details available on request). First, many states waive or reduce registration fees for low-income individuals, which would presumably include many prospective and current SSI recipients. Second, while there is variation in medical marijuana prices, some brands are relatively inexpensive (e.g., $5, which is less than the price of a package of tobacco cigarettes in some states) and many sellers offer reduced fees to low-income consumers. Third, cost may prevent low-income individuals from consuming a sufficient amount of medical marijuana which may reduce effectiveness, such 'under-dosing' may also apply to SSDI claimants.

4.3 Parallel trends

We apply DD-style models to estimate the effect of MMLs on disability claiming. A necessary assumption for the DD model to recover causal estimates is that treatment group (i.e., states that passed an MML) and comparison group (i.e., states that did not pass an MML) would have trended similarly in terms of outcomes had the treatment group not been treated; the 'parallel trends' assumption. While this assumption is untestable as counterfactual trends for the treatment group are not observed, we estimate an event-study to provide suggestive evidence. We first center the data around the event (MML passage) for adopting states. We impose endpoint restrictions and exclude state-year cells more than five years in advance of/following the event (Lovenheim, 2009); where the event is the MML effective year. We then construct indicators for one-year bins for each year pre- and post-event. We omit the indicator for five years prior to the event and code all states that do not adopt an MML by the end of our study period as zero. We control for all variables listed in Equation 2.

Figures 1, 2, and 3 report event study results for the applications, new recipients, and terminated claims. Each figure reports results for our three claiming groups: overall disability, SSDI, and SSI. Pre-event indicators do not suggest that adopting and non-adopting states followed differential trends in disability claiming. Examination of the lags suggests that effects persist throughout the post-period. We note that application effects may dissipate after roughly three to four years, but the confidence intervals are somewhat large, perhaps due to smaller cell-sizes in more distal years following MML passsage, which prevents us from ruling out continued increases in applications. Given that our event-studies provide suggestive evidence that our data satisfies the parallel trends assumption, we report DD results for the remainder of the manuscript.

4.4 Importance of specific MML provisions

In our main analysis we examine the effect of any MML. States, however, have elected to regulate medical marijuana in different ways; see Table 2 columns 2 through 5. We next investigate laws that allow for home cultivation of medical marijuana and operating dispensaries. We also examine whether an MML that mandates the state to establish and maintain a medical marijuana patient registry system influences our claiming outcomes. As outlined by policy scholars, MMLs that allow legal access to marijuana (cultivation and dispensaries) may have greater effects on marijuana use (Pacula et al., 2015; Sabia & Nguyen, 2018) and may have important effects on the supply of marijuana used for recreational purposes purchased in the illegal drug market (Anderson et al., 2013). Finally, requiring patients to register their marijuana use with the state may deter non-medical users (Wen et al., 2015). In addition to the differences in allowing access, we also check if MMLs allowing pain as a qualifying condition for eligibility have an impact different from others.

To this end, we estimate separate regressions that control for any MML and a particular provision; this specification allows us to capture the additional effect of MML provisions from any MML. However, we note that many states, particularly those that adopted MMLs after 2000, initially implemented laws that included these provisions, which limits the variation that we have to detect effects. We also report tests of the significance of the linear combination of the any MML and the specific provision. Results are reported in Tables 5 (applications), 6 (new beneficiaries), and 7 (terminated claims).

We find little evidence that the specific provisions that we study have differential effects on disability applications or new beneficiaries: coefficient estimates on the specific law provision variables are small and not statistically distinguishable from zero. However, we do observe that passage of MMLs that allow home cultivation increase SSDI terminations while MMLs that require a patient to register their use decrease this outcome.

5 Sensitivity analyses and extensions to other benefit claiming

5.1 Sensitivity analyses

We conduct a number of sensitivity analyses to ensure that our results are stable across a range of reasonable alternative samples and specifications. For brevity, we simply summarize these analyses and note when findings depart from our main results. We also conduct falsification testing, explore different definitions of our disability claiming variables, and further assess the validity of our DD design. Overall, our findings are robust to the sensitivity checks we conduct and support our design validity.

First, we include the years 2014 to 2017 – these years overlap with the time period in which states legalized recreational marijuana and the ACA insurance expansions went into effect, we exclude states that adopted MMLs prior to our study period and thus are 'treated controls' 2001-2013, and we include only those state/year pairs that we include in our event-study analysis (Tables 8, 9, and 10). Second, we explore the sensitivity of our results to different specifications and weighting schemes (Tables 11, 12, and 13). In particular, we exclude time-varying state-level control variables, include division-by-year fixed effects, include a separate linear time trend for states that adopt an MML, take the logarithm of claiming variables, use the untransformed count of claiming variables, and remove population weights. We note that we lose precision in some specifications.

Third, we conduct a falsification exercise to ensure that we are not erroneously attributing MML effects to some other variable that follows the same evolution across U.S. states as MMLs. To do so, we randomly re-assign MML effect dates across U.S. states and re-estimate our Equation 2 100 times, generating 'placebo estimates.' If we are indeed capturing a 'true' MML effect, and not some other unobserved factor, we would expect our main estimate to be an outlier relative to all placebo estimates (in the specifications in which we observe statistically significant MML effects). We report our placebo testing in Figures 4 (applications), 5 (new beneficiaries), and 6 (terminated claims). In all specifications in which we observe statistically significant MML effects in our main regressions (Table 4) our estimate is an outlier from the placebo estimates. We conclude from our falsification exercise that we are not capturing the effect of some other factor or policy in our main estimates. Fourth, we sequentially exclude each of the treated states (states that adopted an MML by March 2019, we include all adopting states – not just those states that adopted during our study period – for completeness) from our sample and re-estimate our DD-style regression. This check explores the extent to which our findings are driven by specific states. Results are reported graphically and provide no evidence that are results are driven by one particular state; see Figures 7 (applications), 8 (new beneficiaries), and 9 (terminated claims).

We also investigate whether passage of an MML induces individuals to move to, or away from, adopting states, i.e., program-induced migration (Moffitt, 1992). Such behaviors, if present, could lead to bias in our estimates of MML effects. We next study migration induced by MML using data from the 2001-2013 ACS which includes information on past year moves, which we aggregate to the state-year level. We explore migration effects among the full (i.e., no income exclusion) non-elderly and the non-elderly population within incomes at or below 250% FPL. Focusing on a lower income sample allows us to isolate a sample that is more likely to claim SSI. Results are reported in Table 14; we find no evidence that MMLs induce cross-state migration. A related question is the extent to which individuals who reside in states without an MML may purchase medical marijuana in other states that have such a law in place, which could lead to bias in our estimates of MML effects (Lovenheim, 2008). To explore this issue, we include an indicator for whether or not a border state has adopted an MML in Equation 2. Results are reported in Table 15 are very similar to our main findings.

In our main analyses, we include disabled children in our SSI variables. We next remove disabled children and re-estimate SSI applications and new beneficiaries claiming variables (we are unable to separate disabled children and adult SSI terminations). Results are reported in Table 16 and are similar to our main findings. We next separate 'concurrent' (SSDI and SSI) from SSDI claims and re-estimate Equation 2 to examine whether this population has a differential response to MMLs than the overall SSDI population (Table 17).

As we note in Section 2.1, the time period from initial SSDI application to award can take several years for some beneficiaries. Our primary specification, which uses the contemporaneous MML, may not adequately capture the time required for an application to complete this process. We are less concerned about time delays for SSI (which are typically determined with 30 to 90 days), and applications and terminations (which are most likely to respond to contemporaneous law changes). To explore the importance of time dynamics for new beneficiaries, we re-estimate Equation 2 sequentially using a one, two, three, and four year lag in the MML variable. While we are most interested in SSDI, we report new total, SSDI, and SSI beneficiary results for completeness. Results are reported in Table 18. We find no statistically significant evidence, using any of our lag structures, that MML passage leads to changes in the number of new SSDI beneficiaries. We note that the coefficient estimate in the SSI specification is no longer statistically distinguishable from zero in these alternative specifications. This finding is in line with our hypothesis that, due to the relatively short time period from initial application to claim determination, SSI outcomes should be more responsive to contemporaneous law changes.

Finally, we follow Pei, Pischke, and Schwandt (2018) and regress the MML indicator on our control variables to assess the extent to which our data satisfy the conditional independence assumption (Table 19). Reassuringly, our control variables do not individually or collectively predict MML passage.

5.2 Extensions to other forms of benefit claiming

We next examine if MMLs influence an additional form of benefit claiming: Unemployment Insurance (UI). UI benefits are paid to previously employed workers who enter an unemployment spell. MMLs plausibly affect claiming behaviors related to these benefits in similar ways as we hypothesize for SSDI and SSI benefits. However, given differences in the types of individuals who are likely to claim these benefits (for instance, SSDI and SSI claimants are particularly disadvantaged across several measures, see Table 1), effects need not be similar.

We draw data on state-level UI initial claims from the Department of Labor Unemployment Insurance Database. We aggregate the data to the state-level and convert to a rate per 10,000 non-elderly adults, and estimate Equation 2 to study the effects of MMLs on this outcome. Results are reported in Table 20. We find no statistically significant evidence that MML passage UI benefit claiming. However, we note that our standard error estimate is large and we cannot rule out an increase comparable to those we observe for SSDI. For example, examination of the upper tail of the 95% confidence interval surrounding our point estimate implies a 13% increase in UI initial claims.

6 Discussion

In this study we provide the first evidence on the effect of state MMLs on SSDI and SSI disability claiming. We use administrative data from the Social Security Association (SSA) on applications, new beneficiaries, and terminated claims over the period 2001 to 2013. We find that applications and new beneficiaries increase post-MML while terminated claims decrease. However, our new beneficiary estimates are somewhat noisy. Collectively, our findings suggest that most new disability applications that are attributable to MML passage are not legitimate claims. Put differently, upon review by an SSA medical examiner and financial review, these claims are not allowed. MML passage also appears to prolong SSDI claiming spells as SSDI terminations decline post-law.

We use reduced form methods to study the effects of MMLs on disability claiming. An appeal of the reduced form approach is that it does not place restrictions on the possible mechanisms through which a treatment variable may influence the outcome; this attribute is of particular value in our study as we expect MMLs to influence disability claiming through a range of pathways, which may operate in offsetting ways. While some workers may experience improved symptom control that reduces their need for disability benefits after MML passage, these improvements were overshadowed by behaviors that triggers an increase in applications and greater benefit receipt tenure due to fewer terminations.

Our findings suggest that medical marijuana may not be an effective medication for disabled workers. At least if work capacity is the metric used to measure treatment effectiveness. As noted earlier, the available economic MML studies focus on general samples of respondents and thus the extent to which these findings (which show some improvements in health post-MML) need not apply to disabled workers who, by definition, are in worse health. The reduction in terminations for medical reasons could indicate that marijuana worsens symptoms, leading to extended claims. However, the longer receipt period is also in line with medical marijuana extending life through improved pain control or reduced overdoses on pain-reducing medications (Bachhuber et al., 2014; Powell et al., 2018). Alternatively, the change in terminations may simply reflect lower SSA staff availability for continuing reviews due to the need to process larger numbers of new applications. Recreational use of marijuana obtained following passage of an MML may reduce reduce the returns to labor market participation for marginally disabled workers, leading to a claim or extending an existing claim. Overall, our findings are in line with a demand-side explanation: disabled individuals who use marijuana medically do not see improvements in their capacity to work and those individuals who use marijuana obtained through MMLs for recreational use face depresses labor market opportunities. The acts of seeking a recommendation from a medical marijuana doctor and/or purchasing marijuana through dispensaries potentially changes knowledge of/attitudes towards disability claiming. We view our findings as an important first step in understanding the relationship between medical marijuana and disability claiming. We encourage further work on this question.

Our effects are intent-to-treat (ITT) and it therefore worthwhile to consider if our estimated effect sizes are of reasonable magnitude. Comparison of our estimates, which reflect a 5% increase in applications and a 10% decrease in medical terminations, with findings from the literature on medical use of marijuana (Bradford & Bradford, 2016; Bradford et al., 2018; Wen & Hockenberry, 2018) and recreational marijuana use (Chu, 2014, 2015; Wen et al., 2015) suggests that our effects are not outrageously large. However, we note that an estimate of the treatment-on-the treated would be useful, although, from a policy perspective, an ITT is also a very valuable object. Put differently, the MML is the lever available to the policy maker, not other aspects of marijuana use.

Our findings add to the growing literature that evaluates the overall effects of expanded access to medical marijuana through MMLs. This literature documents that such expansions in access lead to both benefits and costs. Policy makers should consider both when establishing MMLs. The optimal law likely varies across states based on state demographics, underlying health status, labor market conditions, and so forth. From a broader regulatory perspective, our findings highlight the importance of considering policy spillovers. Previous researchers have examined such spillovers in the context of, for example, MMLs, minimum wages, retirement ages, and workers compensation benefits (Page, Spetz, & Millar, 2005; Duggan et al., 2007; McInerney & Simon, 2012; Reich & West, 2015; Bradford & Bradford, 2016, 2017; Hudson & Moriya, 2017). Overall, these studies document that optimal policy requires considering not only the 'first order' effects but also secondary effects. Failure to do so can lead to an inaccurate estimates of policy costs and benefits.

Table 1: Characteristics of non-disability claimants and disability claimants

Sample:	Non-claimants	Claimants
Age	40.29	48.60
Male	0.490	0.482
Female	0.510	0.518
White	0.783	0.721
Non-white	0.217	0.279
Hispanic origin	0.169	0.121
College education	0.308	0.0857
Less than college education	0.692	0.914
Married	0.530	0.326
Not married	0.470	0.674
In the labor force	0.785	0.0950
Not in the labor force	0.215	0.905
Poverty	0.127	0.334
Wage and salary earnings ($)	34172.7	1063.1
Any difficulties with daily activities	0.0494	0.615
Observations	115,983	5,681

Notes: Dataset is ASEC to the CPS 2013. The unit of observation is a CPS respondent. Data are weighted by the ASEC sample weights. Difficulties with daily activities include difficulty with hearing, vision, memory, mobility, physical health, and own personal care.

Table 2: State medical marijuana laws implemented between 1996 and 2013

State	MML	MML Provisions			
		Cultivation	Dispensary	Non-specific pain	Registry
	(1)	(2)	(3)	(4)	(5)
First MML before 2001					
Alaska	3/1999	n/a	n/a	3/1999	3/1999
Colorado	6/2001	6/2001	7/2005	6/2001	6/2001
Hawaii	12/2000	n/a	n/a	12/2000	12/2000
Maine	12/1999	n/a	4/2011	n/a	12/2009
California	11/1996	11/1996	11/1996	11/1996	n/a
Oregon	12/1998	12/1998	11/2009	12/1998	1/2007
Washington	11/1998	7/2011	4/2009	11/1998	n/a
First MML In 2001 or later					
Arizona	4/2011	4/2011	12/2012	4/2011	4/2011
Connecticut	5/2012	n/a	8/2014	n/a	5/2012
DC	7/2010	n/a	7/2013	n/a	7/2010
Delaware	7/2011	n/a	n/a	7/2011	7/2011
Massachusetts	1/2013	n/a	n/a	n/a	1/2013
Michigan	12/2008	12/2008	12/2009	12/2008	n/a
Montana	11/2004	11/2004	4/2009	11/2004	n/a
Nevada	10/2001	10/2001	n/a	10/2001	10/2001
New Hampshire	7/2013	n/a	n/a	7/2013	7/2013
New Jersey	10/2010	n/a	12/2012	10/2010	10/2010
New Mexico	7/2007	n/a	6/2009	n/a	7/2007
Rhode Island	1/2006	1/2006	4/2013	1/2006	1/2006
Vermont	7/2004	n/a	6/2013	7/2007	7/2004

Notes: Data source: Sabia and Nguyen (2018) and ProCon (http://medicalmarijuana.procon.org/view.resource.php?resourceID=000881; accessed August 2nd, 2017). The effect of having any MML in place is identified in our empirical models using variation offered by states passing their first law between 2001 and 2013. The following states passed an MML after 2013: Arkansas (2016), Florida (2017), Illinois (2014), Maryland (2014), Missouri (2018), Minnesota (2014), North Dakota (2016), New York (2014), Ohio (2016), Oklahoma (2018), Pennsylvania (2016), Utah (2018), and West Virginia (2017).

Table 3: Summary statistics

Sample:	All states	MML states	Non-MML states
Applications per 10,000 non-elderly			
All claims	145.1	134.2	163.3
SSDI	88.47	81.15	100.7
SSI only	56.76	53.22	62.74
New beneficiaries per 10,000 non-elderly			
All claims	49.61	48.39	51.66
SSDI	29.97	29.10	31.41
SSI only	19.67	19.32	20.26
Terminations per 10,000 non-elderly			
All claims	5.040	4.641	5.708
SSDI	1.407	1.350	1.503
SSI only	3.685	3.342	4.265
MMLs			
Any MML	0.226	0.360	0
Control variables			
Decriminalize marijuana	0.204	0.301	0.041
HIFA waiver	0.076	0.121	0
Age	36.56	36.90	35.99
Male	0.489	0.490	0.488
Female	0.511	0.510	0.512
White	0.799	0.802	0.795
African American	0.127	0.110	0.157
Other race	0.074	0.089	0.048
Hispanic	0.152	0.169	0.122
Born outside the U.S.	0.135	0.167	0.083
No college education	0.749	0.734	0.775
College education	0.251	0.266	0.225
Observations	663	377	286

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. Data are weighted by the state eligible adult population.

Table 4: Effect of MML passage on disability claiming outcomes

Outcome:	All disability	SSDI	SSI only
Mean value	145.1	88.47	56.76
Applications	7.28**	3.78*	3.46***
	(2.78)	(1.98)	(1.17)
Mean value	49.61	29.97	19.67
New beneficiaries	1.75	0.58	1.15*
	(1.81)	(1.31)	(0.59)
Mean value	5.040	1.407	3.685
Terminated claims	-0.52*	-0.26**	-0.27
	(0.27)	(0.12)	(0.24)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 5: Effect of specific MML provisions on applications

Outcome:	All disability	SSDI	SSI only
Mean value	145.1	88.47	56.76
Panel A			
MML	6.01	2.80	3.17**
	(3.72)	(2.86)	(1.19)
Home cultivation	2.54	1.96	0.57
	(4.32)	(3.32)	(1.28)
Linear combination	8.55**	4.76*	3.74**
of MML + provision	(3.63)	(2.63)	(1.47)
Panel B			
MML	7.87***	4.04**	3.79***
	(2.42)	(1.88)	(0.93)
Dispensaries	-1.49	-0.67	-0.84
	(2.91)	(2.17)	(1.14)
Linear combination	6.38	3.37	2.95*
of MML + provision	(3.86)	(2.65)	(1.71)
Panel C			
MML	2.10	-0.40	2.47
	(6.62)	(3.92)	(2.84)
Pain qualifying condition	6.41	5.17	1.23
	(7.19)	(4.52)	(2.97)
Linear combination	8.51***	4.77**	3.69***
of MML + provision	(2.96)	(2.25)	(1.20)
Panel D			
MML	7.21**	3.48	3.67***
	(2.99)	(2.14)	(1.19)
Patient registry	0.12	0.47	-0.34
	(3.54)	(2.58)	(1.24)
Linear combination	7.32**	3.95	3.33**
of MML + provision	(3.40)	(2.39)	(1.38)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. Each panel reports selected results from a separate regression. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 6: Effect of specific MML provisions on new beneficiaries

Outcome:	All disability	SSDI	SSI only
Mean value	49.61	29.97	19.67
Panel A			
MML	1.81	0.64	1.16
	(2.48)	(1.81)	(0.73)
Home cultivation	-0.14	-0.12	-0.03
	(3.22)	(2.35)	(0.91)
Linear combination	1.68	0.52	1.13
of MML + provision	(2.36)	(1.69)	(0.77)
Panel B			
MML	1.17	0.23	0.93*
	(1.82)	(1.35)	(0.54)
Dispensaries	1.46	0.90	0.54
	(1.77)	(1.28)	(0.56)
Linear combination	2.63	1.12	1.47*
of MML + provision	(2.29)	(1.62)	(0.78)
Panel C			
MML	-0.95	-1.61	0.64
	(3.64)	(2.54)	(1.27)
Pain qualifying condition	3.34	2.71	0.62
	(3.92)	(2.77)	(1.36)
Linear combination	2.39	1.10	1.27**
of MML + provision	(1.86)	(1.36)	(0.61)
Panel D			
MML	2.18	1.13	1.04
	(1.51)	(1.00)	(0.71)
Patient registry	-0.69	-0.87	0.17
	(1.95)	(1.29)	(0.83)
Linear combination	1.49	0.26	1.21
of MML + provision	(2.27)	(1.66)	(0.74)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. Each panel reports selected results from a separate regression. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 7: Effect of specific MML provisions on terminated claims

Outcome:	All disability	SSDI	SSI only
Mean value	5.040	1.407	3.685
Panel A			
MML	-0.68*	-0.71**	-0.42***
	(0.32)	(0.10)	(0.28)
Home cultivation	0.39	0.32***	0.08
	(0.27)	(0.10)	(0.23)
Linear combination	-0.32	-0.10	-0.23
of MML + provision	(0.26)	(0.11)	(0.24)
Panel B			
MML	-0.33	-0.25*	-0.10
	(0.32)	(0.13)	(0.26)
Dispensaries	-0.46	-0.01	-0.43*
	(0.31)	(0.12)	(0.22)
Linear combination	-0.80**	-0.26*	-0.53**
of MML + provision	(0.33)	(0.15)	(0.26)
Panel C			
MML	-0.55	-0.40**	-0.19
	(0.80)	(0.18)	(0.71)
Pain qualifying condition	0.04	0.17	-0.09
	(0.79)	(0.20)	(0.70)
Linear combination	-0.51**	-0.22*	-0.28
of MML + provision	(0.25)	(0.13)	(0.20)
Panel D			
MML	-0.26	-0.07	-0.20
	(0.24)	(0.11)	(0.24)
Patient registry	-0.41	-0.30**	-0.10
	(0.28)	(0.12)	(0.27)
Linear combination	-0.67*	-0.37***	-0.30
of MML + provision	(0.34)	(0.10)	(0.29)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. Each panel reports selected results from a separate regression. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 8: Effect of MML passage on applications using different samples

Outcome:	All disability	SSDI	SSI only
Sample mean	141.7	86.58	55.28
Years 2001-2017	4.15	2.97*	1.08
	(2.70)	(1.71)	(1.26)
Observations	867	867	867
Sample mean	152.2	92.80	59.45
Drop treated controls	6.98*	4.28*	2.68*
	(3.52)	(2.49)	(1.50)
Observations	559	559	559
Sample mean	153.9	94.87	59.55
Event-study sample	5.16*	3.53	1.61**
	(3.06)	(2.47)	(0.80)
Observations	452	452	452

Notes: Dataset is SAMWD 2001 to 2013 unless otherwise noted. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 9: Effect of MML passage on new beneficiaries using different samples

Outcome:	All disability	SSDI	SSI only
Sample mean	47.74	28.75	59.17
Years 2001-2017	0.34	-0.16	0.44
	(1.27)	(0.75)	(0.60)
Observations	867	867	867
Sample mean	51.18	31.12	19.69
Drop treated controls	1.28	0.59	0.68
	(1.89)	(1.31)	(0.67)
Observations	559	559	559
Sample mean	50.55	30.87	19.62
Event-study sample	2.47	1.53	0.93
	(1.66)	(1.04)	(0.69)
Observations	452	452	452

Notes: Dataset is SAMWD 2001 to 2013 unless otherwise noted. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 10: Effect of MML passage on terminated claims using different samples

Outcome:	All disability	SSDI	SSI only
Sample mean	6.175	1.659	4.586
Years 2001-2017	-1.41***	-0.29*	-1.13***
	(0.45)	(0.15)	(0.33)
Observations	867	867	867
Sample mean	5.409	1.437	4.024
Drop treated controls	-0.69**	-0.26*	-0.43
	(0.30)	(0.13)	(0.26)
Observations	559	559	559
Sample mean	5.385	1.450	3.983
Event-study sample	-0.71**	-0.21**	-0.51*
	(0.28)	(0.09)	(0.27)
Observations	452	452	452

Notes: Dataset is SAMWD 2001 to 2013 unless otherwise noted. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 11: Effect of MML passage on applications using different specifications

Outcome:	All disability	SSDI	SSI only
Mean value	145.1	88.47	56.76
Drop time-varying	7.21**	4.04*	3.12*
state-level controls	(3.47)	(2.03)	(1.71)
Include division-by-year	9.12***	4.95***	3.46***
fixed effects	(2.68)	(1.78)	(1.17)
Include state-specific	7.45	4.60	2.86**
linear time trends	(5.07)	(3.81)	(1.42)
Logarithm of rate	0.06**	0.05	0.07***
	(0.03)	(0.03)	(0.03)
Sample mean	113005.7	66731.0	46091.9
Untransformed count	4749.38**	851.45	3836.13***
	(2220.26)	(1568.59)	(1400.01)
Sample mean	146.0	91.83	54.12
Unweighted	7.24	4.66	2.58
	(5.29)	(3.68)	(1.78)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 12: Effect of MML passage on new beneficiaries using different specifications

Outcome:	All disability	SSDI	SSI only
Mean value	49.61	29.97	19.67
Drop time-varying	2.01	0.92	1.07
state-level controls	(3.19)	(2.12)	(1.12)
Include division-by-year	1.40	0.61	1.15*
fixed effects	(1.85)	(1.28)	(0.59)
Include state-specific	4.44**	3.09**	1.34**
linear time trends	(1.93)	(1.32)	(0.66)
Logarithm of rate	0.02	-0.00	0.05
	(0.05)	(0.05)	(0.04)
Sample mean	40209.3	23277.7	16837.4
Untransformed count	3299.15*	1276.61	1979.36**
	(1673.57)	(934.69)	(865.31)
Sample mean	50.07	31.28	18.79
Unweighted	1.11	0.76	0.36
	(2.22)	(1.71)	(0.61)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 13: Effect of MML passage on terminated claims using different specifications

Outcome:	All disability	SSDI	SSI only
Mean value	5.040	1.407	3.685
Drop time-varying	-0.45	-0.23**	-0.23
state-level controls	(0.27)	(0.09)	(0.25)
Include division-by-year	-0.24	-0.26**	0.02
fixed effects	(0.40)	(0.10)	(0.34)
Include state-specific	-0.47	-0.18	-0.32
linear time trends	(0.36)	(0.13)	(0.32)
Logarithm of rate	-0.06	-0.13**	-0.02
	(0.05)	(0.06)	(0.07)
Sample mean	3889.3	1107.9	2806.7
Untransformed count	194.95	2.86	183.49
	(285.92)	(119.37)	(191.78)
Sample mean	4.991	1.455	3.571
Unweighted	0.06	-0.28**	0.33
	(0.47)	(0.12)	(0.39)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 14: Effect of MML passage on cross state migration

Sample:	Full sample	Low income sample
Mean value	0.028	0.036
MML	0.0006	0.0011
	(0.0008)	(0.0013)
Observations	663	663

Notes: Dataset is the ACS 2001-2013. Outcome is an indicator variable for a past-year across state move. Low income sample includes only ACS respondents with family income at or below 250% FPL. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 15: Effect of MML passage on disability claiming outcomes controlling for a border state with an MML

Outcome:	All disability	SSDI	SSI only
Mean value	145.1	88.47	56.76
Applications	7.08**	3.72*	3.31***
	(2.88)	(2.05)	(1.13)
Mean value	49.61	29.97	19.67
New beneficiaries	1.99	0.76	1.21**
	(1.73)	(1.23)	(0.59)
Mean value	5.040	1.407	3.685
Terminated claimsL	-0.51*	-0.25*	-0.27
	(0.27)	(0.13)	(0.23)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. All models estimated with OLS and control for any MML, an inidcator variable for whether a state borders another state with an MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 16: Effect of MML passage on SSI applications and new beneficiaries, excluding disabled children counts

Outcome:	Applications	New beneficiaries
Mean value	33.79	10.28
MML	3.00**	1.06**
	(1.17)	(0.50)
Observations	663	663

Notes: Dataset is SAMWD 2001 to 2017. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 17: Effect of MML passage on concurrent applications, new beneficiaries, and terminated claims

Outcome:	Applications	New beneficiaries	Terminated claims
Mean value	42.46	10.40	0.330
MML	2.76**	0.23	-0.03
	(1.13)	(0.55)	(0.04)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2017. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 18: Effect of MML passage on new beneficiaries using different lag structures

Outcome:	All disability	SSDI	SSI only
Mean value	145.1	88.47	56.76
One year lag	0.94	0.24	0.68
	(1.70)	(1.23)	(0.58)
Two year lag	1.36	0.59	0.76
	(2.02)	(1.46)	(0.66)
Three year lag	0.42	-0.31	0.70
	(2.23)	(1.59)	(0.72)
Four year lag	0.53	-0.18	0.70
	(1.98)	(1.47)	(0.64)
Observations	663	663	663

Notes: Dataset is SAMWD 2001 to 2013. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state eligible adult population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 19: Correlates of passing an MML

Outcome	MML
Sample proportion	0.226
Decriminalize marijuana	-0.05
	(0.09)
HIFA waiver	0.11
	(0.11)
Age	0.10
	(0.06)
Female	1.34
	(3.87)
African American	-0.04
	(2.17)
Other race	0.99
	(1.53)
Hispanic	0.52
	(2.90)
College education	-1.10
	(1.25)
Born outside the U.S.	3.01
	(2.82)
F-test of joint significance of time-varying state-level controls	0.96
p-value	0.48
Observations	663

Notes: The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state non-elderly population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 20: Effect of MML passage on unemployment insurance benefit claiming

Outcome	Unemployment insurance initial claims per 100,000 non-elderly adults
Mean value	1072.6
MML	11.15
	(65.29)
Observations	663

Notes: Unemployment insurance initial claims drawn from the Department of Labor Unemployment Insurance Database 2001-2013. The unit of observation is a state-year. All models estimated with OLS and control for any MML, state characteristics, state fixed effects, and year fixed effects. Data are weighted by the state non-elderly population. Standard errors are clustered at the state level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

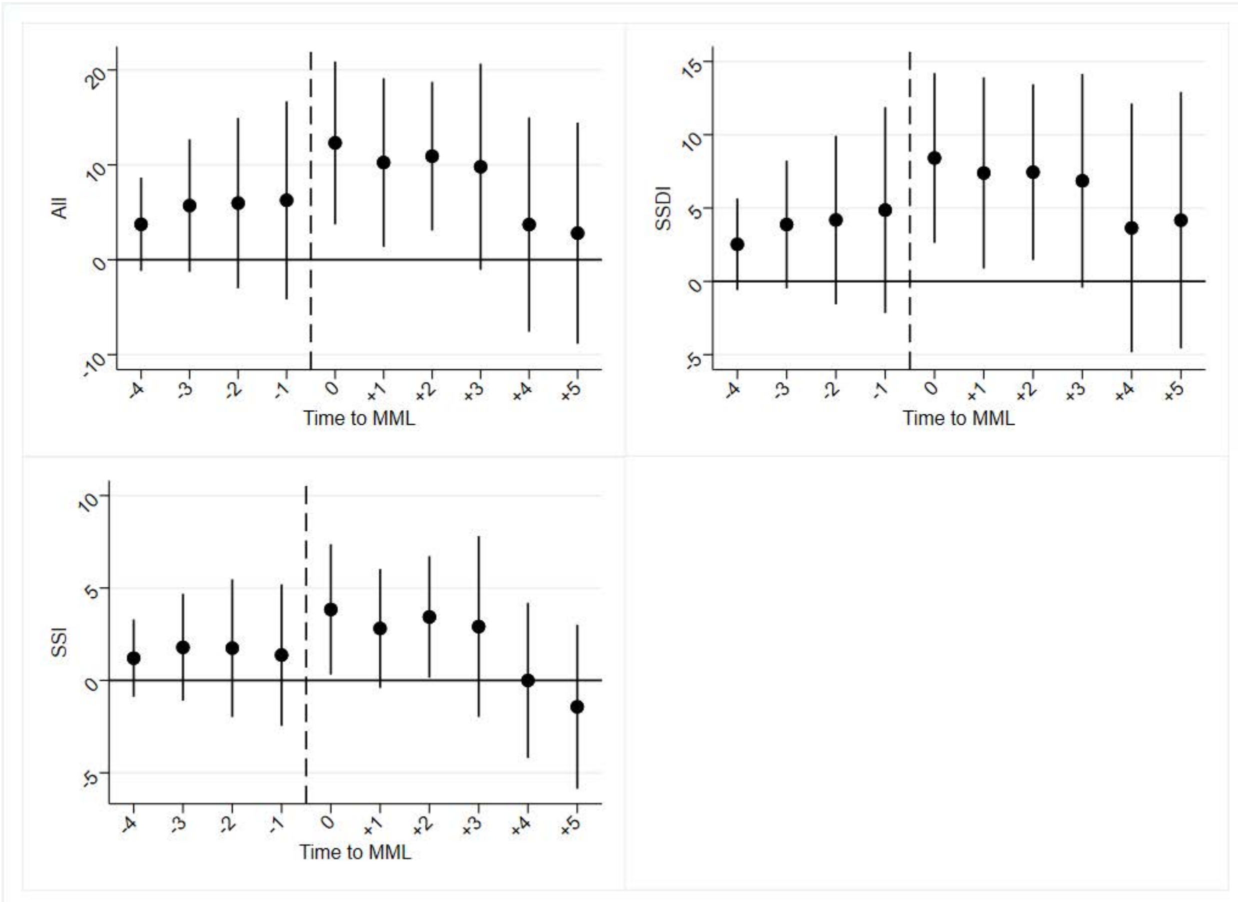

Figure 1: Applications event-study results

Notes: Dataset is SAMWD 2001-2013. Coefficients are estimates from event study models controlling for time-varying state characteristics, state fixed effects, and year fixed effects. The omitted category is eight years prior to law passage. Non-adopting states coded as zero for all event-time indicators. Observations more than five years in advance/following law passage excluded (among the sample of states that adopted the law).

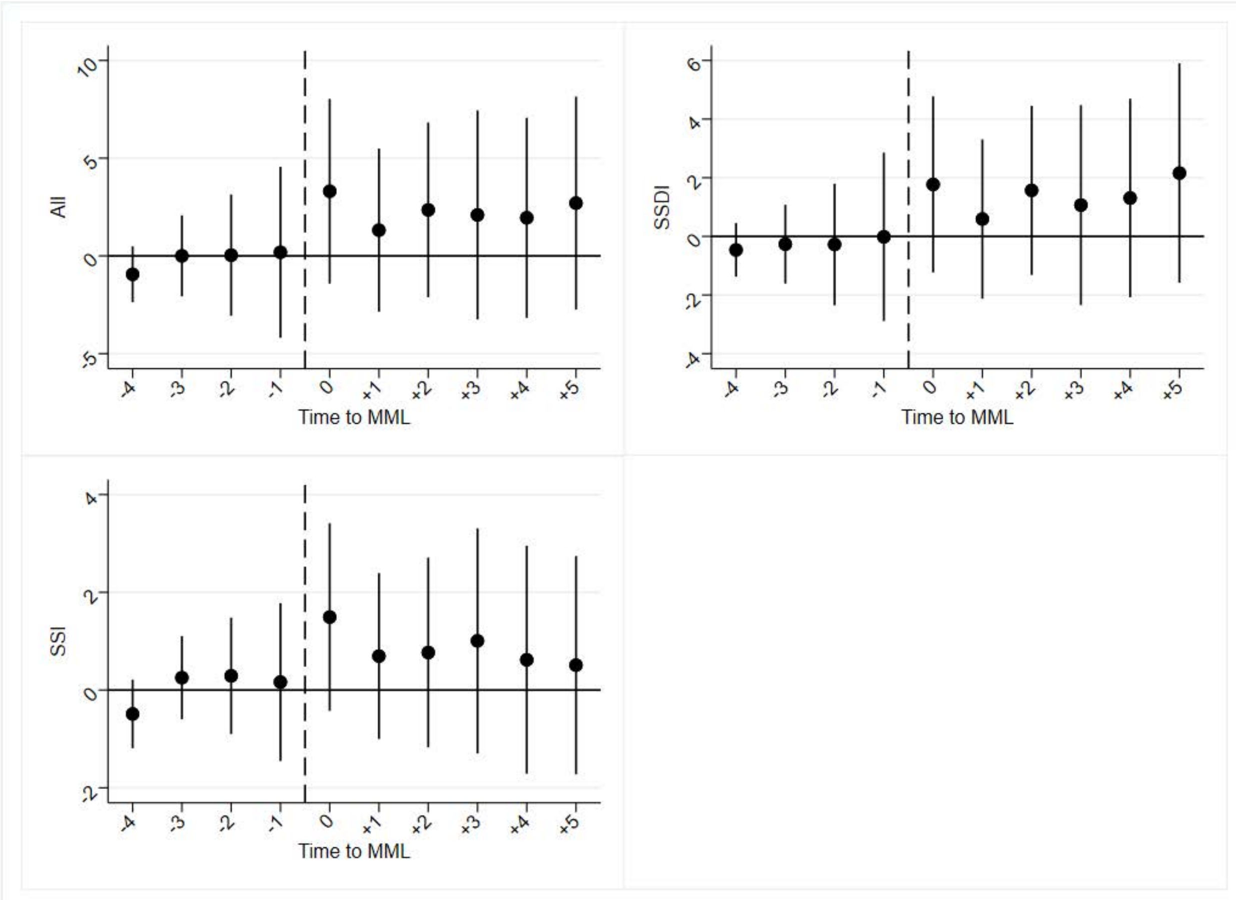

Figure 2: New beneficiaries event-study results

Notes: Dataset is SAMWD 2001-2013. Coefficients are estimates from event study models controlling for time-varying state characteristics, state fixed effects, and year fixed effects. The omitted category is eight years prior to law passage. Non-adopting states coded as zero for all event-time indicators. Observations more than five years in advance/following law passage excluded (among the sample of states that adopted the law).

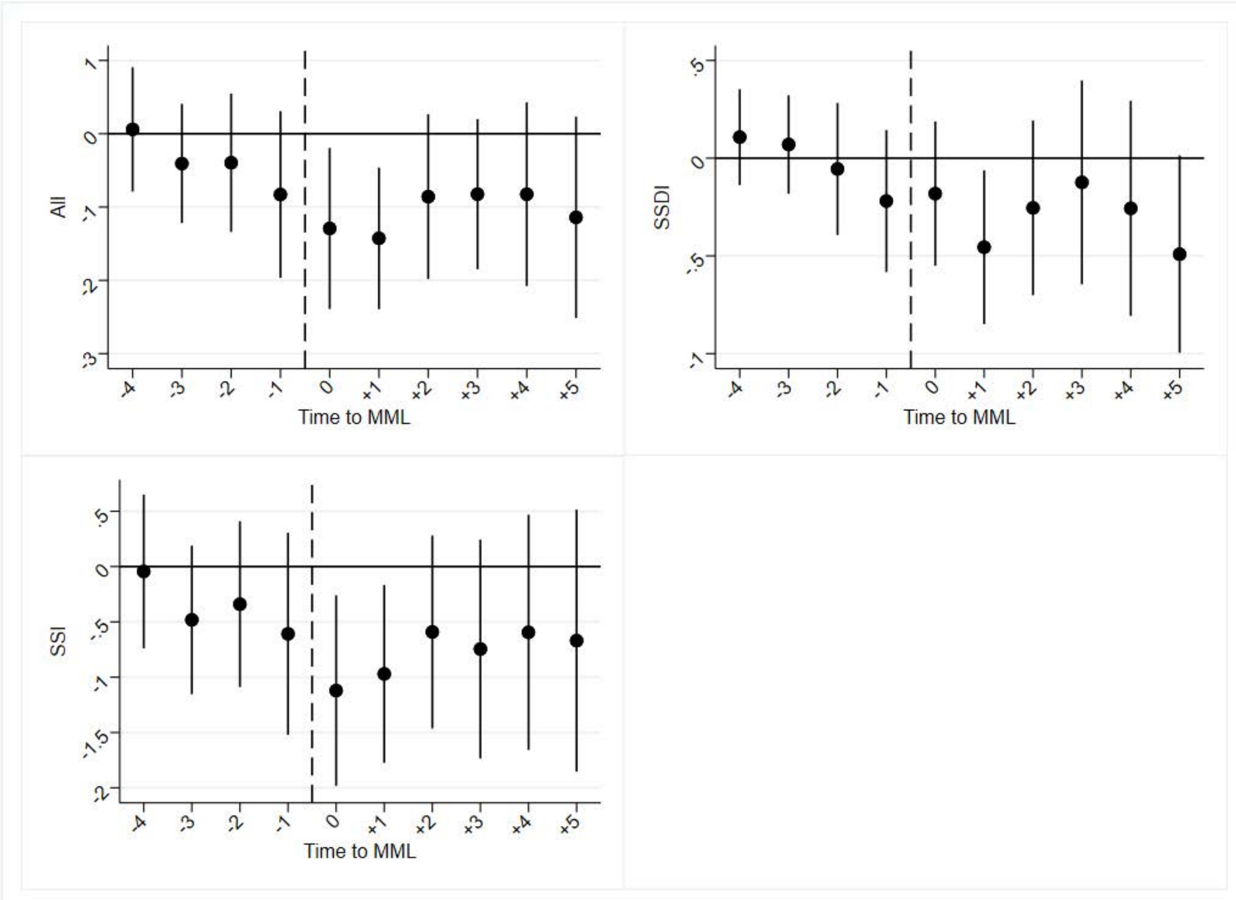

Figure 3: Terminated claims event-study results

Notes: Dataset is SAMWD 2001-2013. Coefficients are estimates from event study models controlling for time-varying state characteristics, state fixed effects, and year fixed effects. The omitted category is eight years prior to law passage. Non-adopting states coded as zero for all event-time indicators. Observations more than five years in advance/following law passage excluded (among the sample of states that adopted the law).

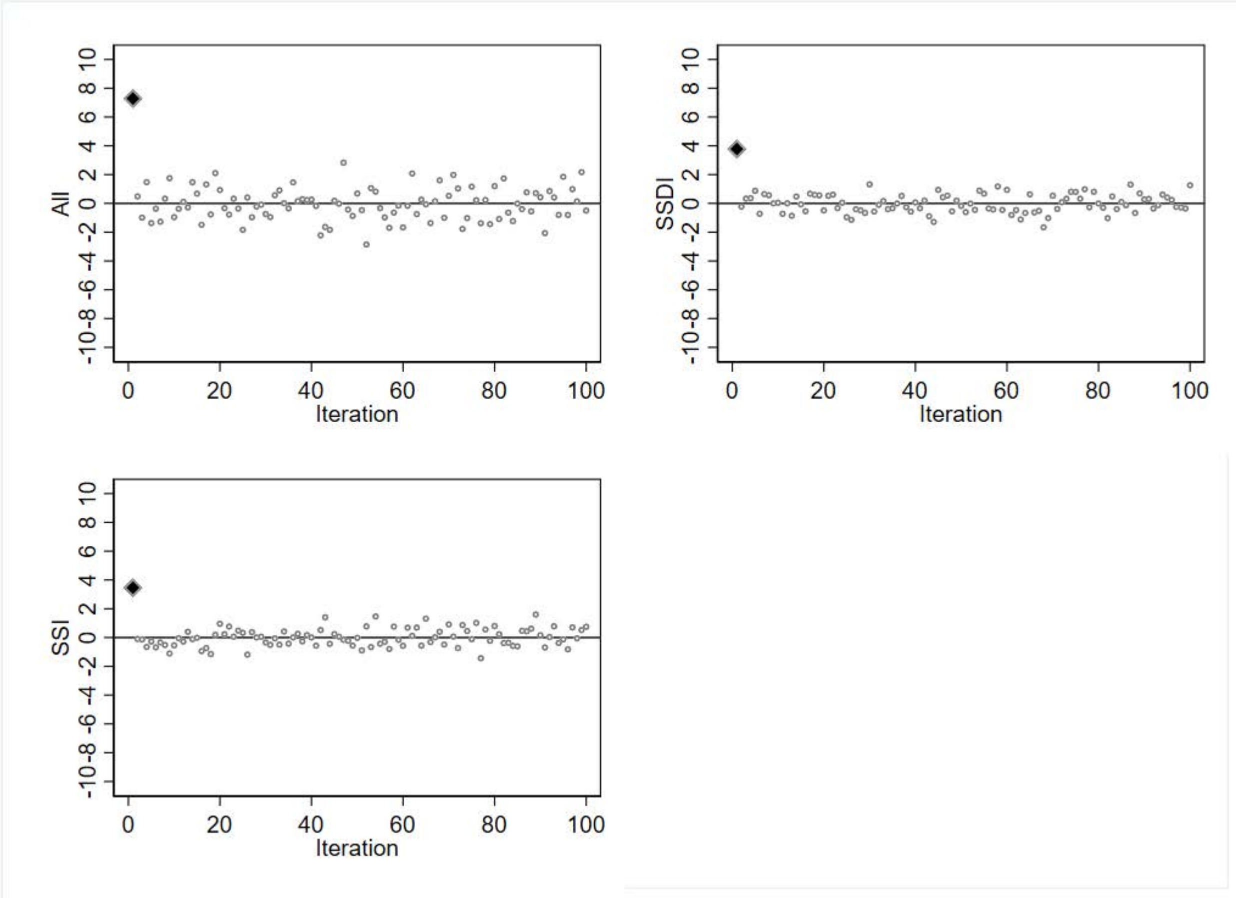

Figure 4: Applications placebo testing results

Notes: Dataset is SAMWD 2001-2013. The large diamond is the coefficient estimate from the main DD model. Circles represent placebo estimates in which we randomly re-assign state MMLs across states. See text for more details.

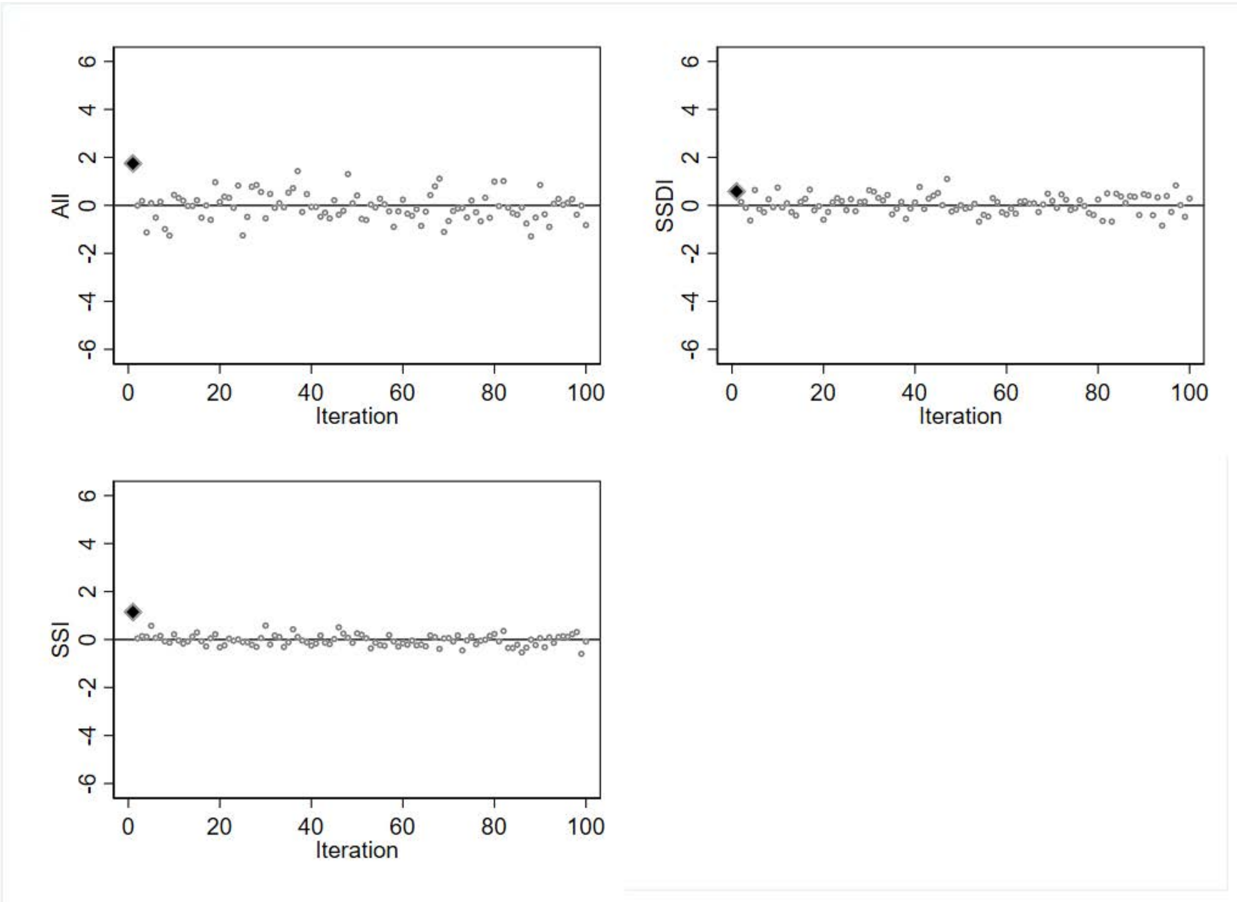

Figure 5: New beneficiaries placebo testing results

Notes: Dataset is SAMWD 2001-2013. The large diamond is the coefficient estimate from the main DD model. Circles represent placebo estimates in which we randomly re-assign state MMLs across states. See text for more details.

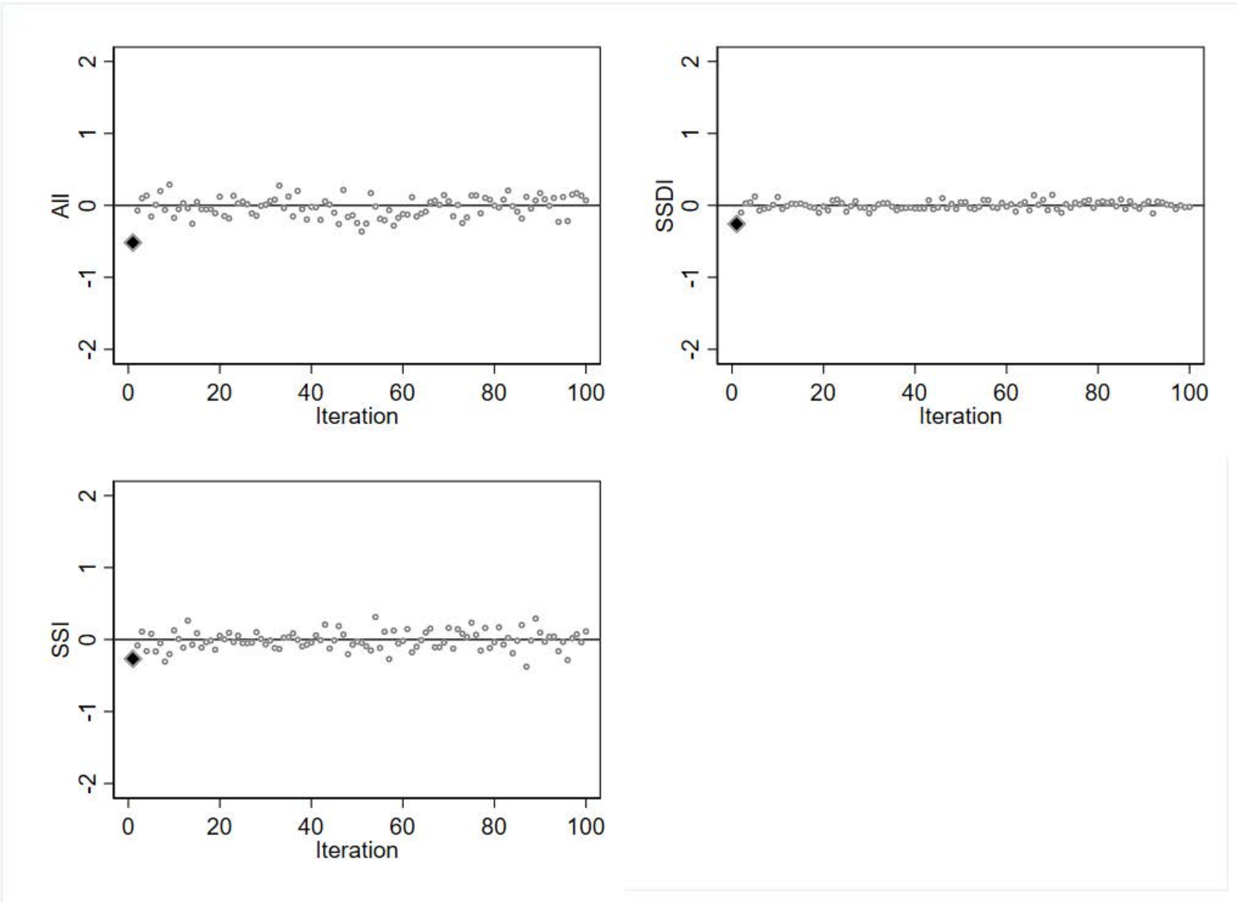

Figure 6: Terminated claims placebo testing results

Notes: Dataset is SAMWD 2001-2013. The large diamond is the coefficient estimate from the main DD model. Circles represent placebo estimates in which we randomly re-assign state MMLs across states. See text for more details.

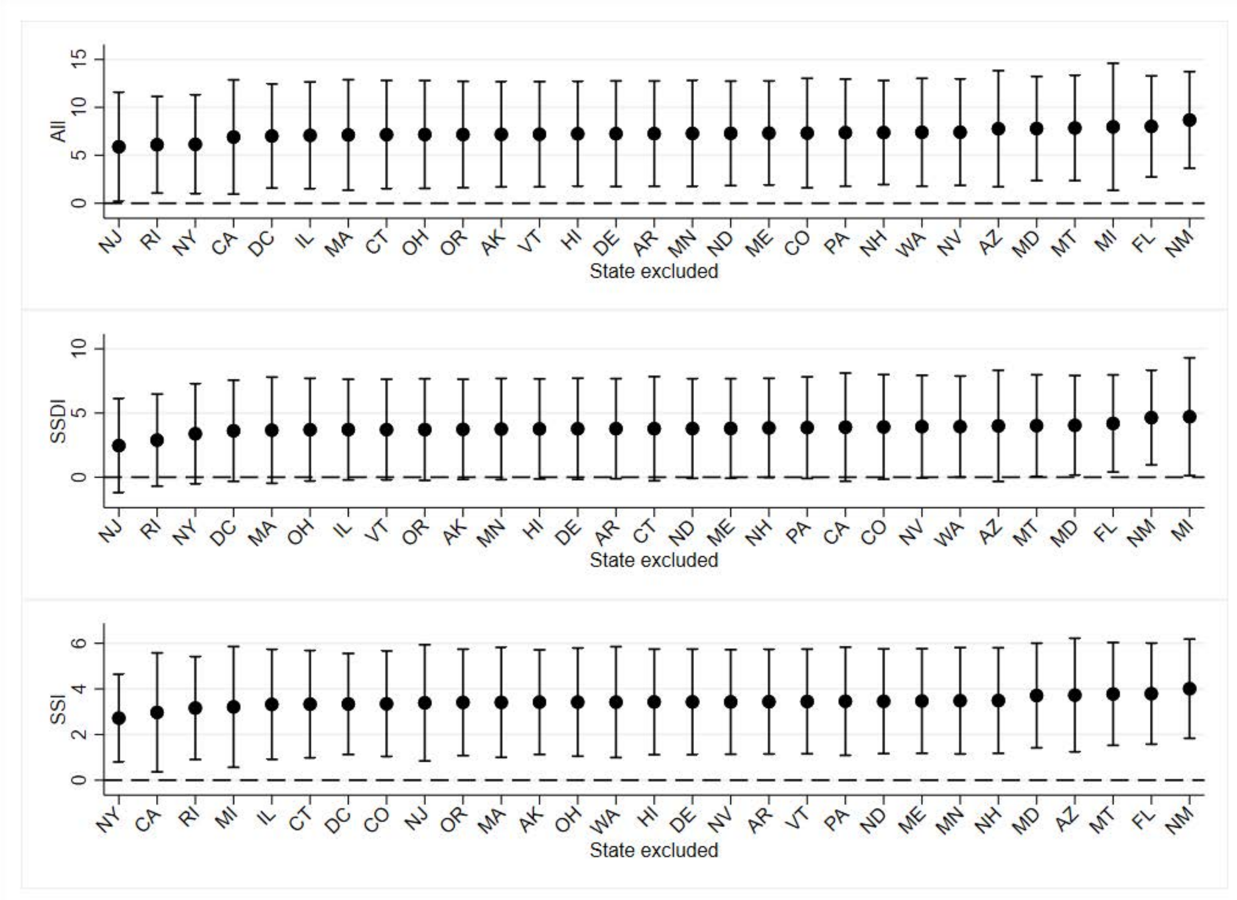

Figure 7: Applications placebo testing results

Notes: Dataset is SAMWD 2001-2013. Coefficient estimates are generated in regression models that exclude the state listed on the x-axis. 95% confidence intervals are reported with vertical solid lines. See text for more details.

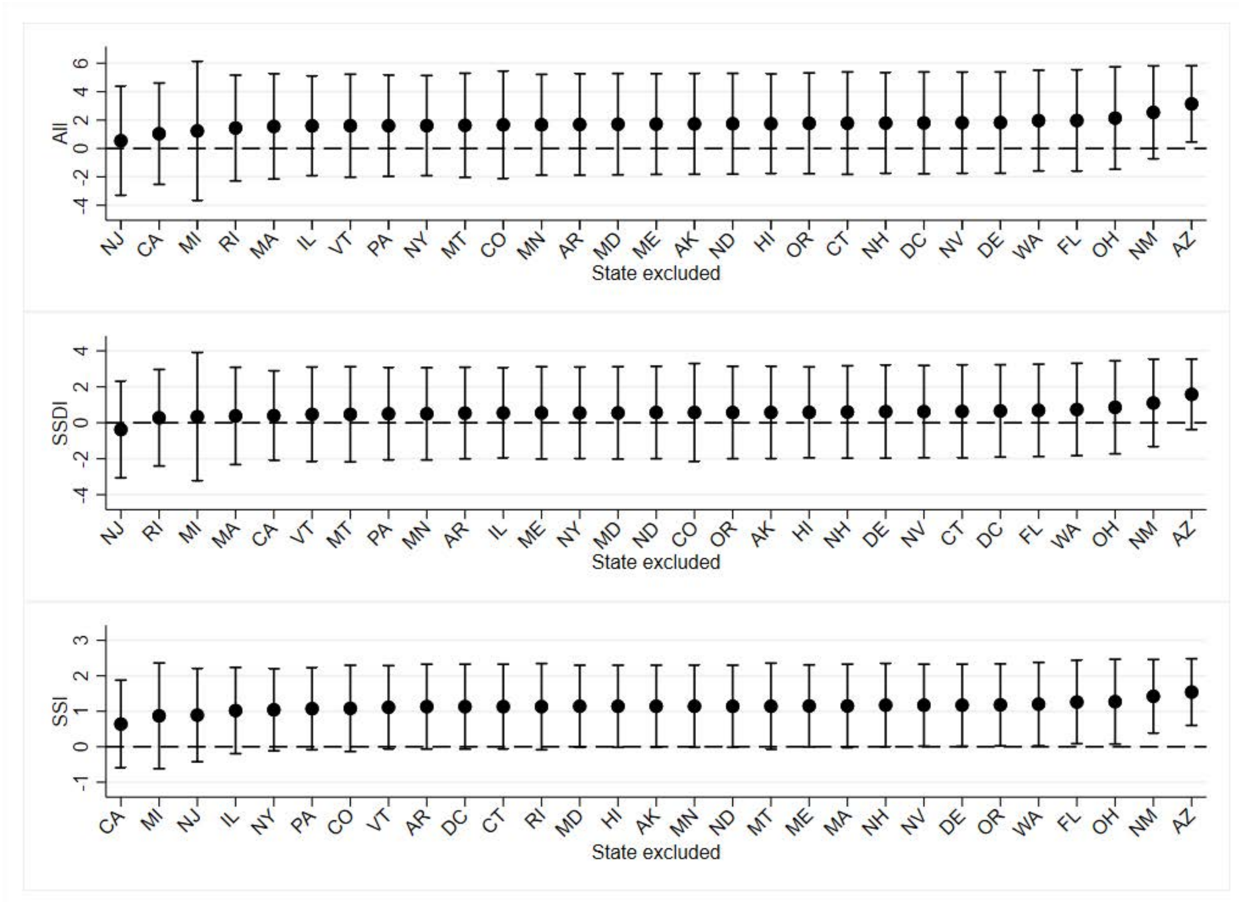

Figure 8: New beneficiaries placebo testing results

Notes: Dataset is SAMWD 2001-2013. Coefficient estimates are generated in regression models that exclude the state listed on the x-axis. 95% confidence intervals are reported with vertical solid lines. See text for more details.

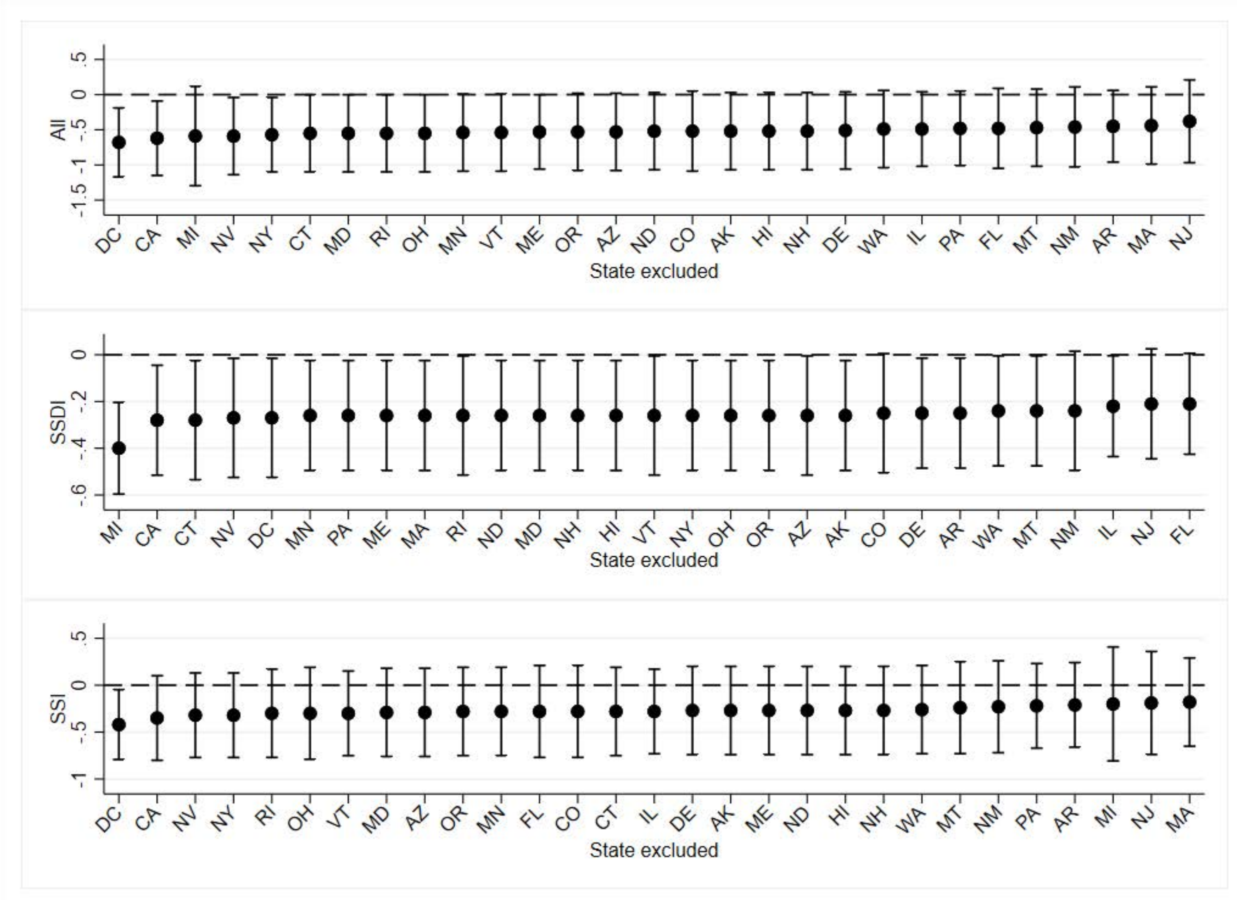

Figure 9: Terminated claims placebo testing results

Notes: Dataset is SAMWD 2001-2013. Coefficient estimates are generated in regression models that exclude the state listed on the x-axis. 95% confidence intervals are reported with vertical solid lines. See text for more details.

References

Abouk, R., & Adams, S. (2018). Examining the Relationship between Medical Marijuana Laws and Cardiovascular Deaths in the US. *International Journal of Drug Policy*, *53*, 1–7.

Anderson, D. M., Hansen, B., & Rees, D. I. (2013). Medical marijuana laws, traffic fatalities, and alcohol consumption. *Journal of Law and Economics*, *56*(2), 333–369.

Anderson, D. M., Rees, D. I., & Sabia, J. J. (2014). Medical marijuana laws and suicides by gender and age. *American Journal of Public Health*, *104*(12), 2369–2376.

Anderson, D. M., Rees, D. I., & Tekin, E. (2018). Medical marijuana laws and workplace fatalities in the United States. *International Journal of Drug Policy*, *60*, 33 - 39. Retrieved from `http://www.sciencedirect.com/science/article/pii/S0955395918301968` doi: https://doi.org/10.1016/j.drugpo.2018.07.008

Atherly, A., Dowd, B. E., Coulam, R. F., & Guy, G. (2012). The effect of HIFA waiver expansions on uninsurance rates in adult populations. *Health Services Research*, *47*(3pt1), 939–962.

Autor, D. H., & Duggan, M. G. (2006). The growth in the Social Security Disability rolls: A fiscal crisis unfolding. *The Journal of Economic Perspectives*, *20*(3), 71–96.

Bachhuber, M. A., Saloner, B., Cunningham, C. O., & Barry, C. L. (2014). Medical cannabis laws and opioid analgesic overdose mortality in the united states, 1999-2010. *JAMA Internal Medicine*, *174*(10), 1668–1673.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-in-differences Estimates? *Quarterly Journal of Economics*, *119*(1).

Bradford, A. C., & Bradford, W. D. (2016). Medical marijuana laws reduce prescription medication use In Medicare Part D. *Health Affairs*, *35*(7), 1230-1236.

Bradford, A. C., & Bradford, W. D. (2017). Medical marijuana laws may be associated with a decline In the number of prescriptions for Medicaid enrollees. *Health Affairs*, *36*(5), 945–951.

Bradford, A. C., & Bradford, W. D. (2018). The Impact of Medical Cannabis Legalization on Prescription Medication Use and Costs under Medicare Part D. *The Journal of Law and Economics*, *61*(3), 461–487.

Bradford, A. C., Bradford, W. D., Abraham, A., & Adams, G. B. (2018). Association between US state medical cannabis laws and opioid prescribing in the Medicare Part D population. *JAMA Internal Medicine*, *In press*.

Burkhauser, R. V., Fisher, T. L., Houtenville, A. J., & Tennant, J. R. (2014). Is the 2010

Affordable Care Act minimum standard to identify disability in all national datasets good enough for policy purposes? *Journal of Economic and Social Measurement*, *39*(4), 217–245.

Burns, M., & Dague, L. (2017). The effect of expanding Medicaid eligibility on Supplemental Security Income program participation. *Journal of Public Economics*, *149*, 20–34.

Butikofer, A., & Skira, M. M. (2016). Missing work is a pain: The effect of cox-2 inhibitors on sickness absence and disability pension receipt. *Journal of Human Resources*, 0215–6958R1.

Chu, Y.-W. L. (2014). The effects of medical marijuana laws on illegal marijuana use. *Journal of Health Economics*, *38*, 43–61.

Chu, Y.-W. L. (2015). Do medical marijuana laws increase hard-drug use? *The Journal of Law and Economics*, *58*(2), 481–517.

Currie, J., & Madrian, B. C. (1999). Health, health insurance and the labor market. *Handbook of Labor Economics*, *3*, 3309–3416.

Duggan, M., Singleton, P., & Song, J. (2007). Aching to retire? The rise in the full retirement age and its impact on the social security disability rolls. *Journal of Public Economics*, *91*(7), 1327–1350.

Freedman, V. A., Crimmins, E., Schoeni, R. F., Spillman, B. C., Aykan, H., Kramarow, E., ... others (2004). Resolving inconsistencies in trends in old-age disability: Report from a technical working group. *Demography*, *41*(3), 417–441.

Furtado, D., Papps, K. L., & Theodoropoulos, N. (2019). *Who Goes on Disability When Times Are Tough? The Role of Social Costs of Take-Up Among Immigrants.* (Institute for the Study of Labor (IZA))

Garthwaite, C. (2012). The economic benefits of pharmaceutical innovations: The case of cox-2 inhibitors. *American Economic Journal: Applied Economics*, *4*(3), 116-137.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political economy*, *80*(2), 223–255.

Hill, K. P. (2015). Medical marijuana for treatment of chronic pain and other medical and psychiatric problems: A clinical review. *Journal of the American Medical Association*, *313*(24), 2474–2483.

Hudson, J. L., & Moriya, A. S. (2017). Medicaid expansion for adults had measurable welcome mateffects on their children. *Health Affairs*, *36*(9), 1643–1651.

Joy, J. E., Watson, S. J., & Benson, J. A. (1999). *Marijuana and medicine: Assessing the science base* (Tech. Rep.). National Academies Press.

Keiser, L. R. (2010). Understanding street-level bureaucrats' decision making: Determining eligibility in the Social Security Disability Program. *Public Administration Review*, *70*(2), 247–257.

Kilby, A. (2015). *Opioids for the masses: Welfare tradeoffs in the regulation of narcotic pain medications.*

King, M., Ruggles, S., Alexander, J. T., Flood, S., Genadek, K., Schroeder, M. B., ... Vick, R. (2018). *Integrated Public Use Microdata Series, Current Population Survey: Version 6.0. [Machine-readable database]* (Tech. Rep.). Minnesota Population Center.

Lovenheim, M. F. (2008). How far to the border?: The extent and impact of cross-border casual cigarette smuggling. *National Tax Journal*, *7–33*.

Lovenheim, M. F. (2009). The effect of teachers unions on education production: Evidence from union election certifications in three midwestern states. *Journal of Labor Economics*, *27*(4), 525–587.

Lynch, M. E., & Campbell, F. (2011). Cannabinoids for treatment of chronic non-cancer pain; a systematic review of randomized trials. *British Journal of Clinical Pharmacology*, *72*(5), 735744.

McInerney, M., & Simon, K. (2012). The effect of state Workers Compensation program changes on the use of federal Social Security Disability Insurance. *Industrial Relations: A Journal of Economy and Society*, *51*(1), 57–88.

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., & Medicine. (2017). *The health effects of cannabis and cannabinoids: The current state of evidence and recommendations for research* (Tech. Rep.). National Academies Press.

Nicholas, L. H., & Maclean, J. C. (2019). The Impact of Medical Marijuana Laws on the Labor Supply and Health of Older Adults: Evidence from the Health and Retirement Study. *Journal of Policy Analysis and Management*(22688).

Nunberg, H., Kilmer, B., Pacula, R. L., & Burgdorf, J. R. (2011). An analysis of applicants presenting to a medical marijuana specialty practice in California. *Journal of Drug Policy Analysis*, *4*(1). (Article 1)

Ozluk, P. (2017). *The effects of medical marijuana laws on utilization of prescribed opioids and other prescription drugs.*

Pacula, R. L., Chriqui, J. F., & King, J. (2003). *Marijuana Decriminalization: What does it mean in the United States?* (NBER Working Paper Series). National Bureau of

Economic Research.

Pacula, R. L., Powell, D., Heaton, P., & Sevigny, E. L. (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.

Page, M. E., Spetz, J., & Millar, J. (2005). Does the minimum wage affect welfare caseloads? *Journal of Policy Analysis and Management*, *24*(2), 273–295.

Pei, Z., Pischke, J.-S., & Schwandt, H. (2018). Poorly measured confounders are more useful on the left than on the right. *Journal of Business & Economic Statistics*(1-12).

Powell, D., Pacula, R. L., & Jacobson, M. (2018). Do medical marijuana laws reduce addictions and deaths related to pain killers? *Journal of Health Economics*, *58*, 29-42.

Reich, M., & West, R. (2015). The effects of minimum wages on food stamp enrollment and expenditures. *Industrial Relations: A Journal of Economy and Society*, *54*(4), 668–694.

Reiman, A., Welty, M., & Solomon, P. (2017). Cannabis as a substitute for opioid-based pain medication: Patient self-report. *Cannabis and Cannabinoid Research*, *2*(1), 160–166.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., & Sobek, M. (2018). *IPUMS USA: Version 8.0 [dataset]* (Tech. Rep.). IPUMS USA.

Sabia, J. J., & Nguyen, T. T. (2018). The effect of medical marijuana laws on labor market outcomes. *The Journal of Law and Economics*, *61*(3), 361396.

Sabia, J. J., Swigert, J., & Young, T. (2017). The effect of medical marijuana laws on body weight. *Health Economics*, *26*(1), 6-34.

Social Security Administration. (2018a). *Annual Statistical Report on the Social Security Disability Insurance Program, 2017* (Tech. Rep. No. 13-11826). Social Security Administration.

Social Security Administration. (2018b). *SSI Annual Statistical Report, 2017* (Tech. Rep.). Author. Retrieved from `https://www.ssa.gov/policy/docs/statcomps/ssi_asr/index.html`

Troutt, W. D., & DiDonato, M. D. (2015). Medical cannabis in arizona: Patient characteristics, perceptions, and impressions of medical cannabis legalization. *Journal of Psychoactive Drugs,*, *47*(4), 259266.

Ullman, D. (2017). The effect of medical marijuana on sickness absence. *Health Economics*, *26*(10), 1322–1327.

University of Kentucky Center for Poverty Research. (2018). *UKCPR National Welfare Data,* *1980-2017* (Tech. Rep.). http://www.ukcpr.org/data: Gatton College of Business and Economics, University of Kentucky.

Vigil, J. M., Stith, S. S., Adams, I. M., & Reeve, A. P. (2017). Associations between medical cannabis and prescription opioid use in chronic pain patients: A preliminary cohort study. *PloS one*, *12*(11), e0187795.

Wen, H., & Hockenberry, J. M. (2018). Association of medical and adult-use marijuana laws with opioid prescribing for Medicaid enrollees. *JAMA Internal Medicine*, *In press*.

Wen, H., Hockenberry, J. M., & Cummings, J. R. (2015). The effect of medical marijuana laws on adolescent and adult use of marijuana, alcohol, and other substances. *Journal of Health Economics*, *42*, 64–80.

Whiting, P. F., Wolff, R. F., Deshpande, S., Di Nisio, M., Duffy, S., Hernandez, A. V., ... others (2015). Cannabinoids for medical use: a systematic review and meta-analysis. *Journal of the American Medical Association*, *313*(24), 2456–2473.