THE EFFECT OF MEDICAL MARIJUANA LAWS ON THE HEALTH AND LABOR SUPPLY OF OLDER ADULTS: EVIDENCE FROM THE HEALTH AND RETIREMENT STUDY

Lauren Hersch Nicholas and Johanna Catherine Maclean

Abstract

Older adults are at elevated risk of reducing labor supply due to poor health, partly because of high rates of symptoms that may be alleviated by medical marijuana. Yet, surprisingly little is known about how this group responds to medical marijuana laws (MMLs). We quantify the effects of state medical marijuana laws on the health and labor supply of adults age 51 and older, focusing on the 55 percent with one or more medical conditions with symptoms that may respond to medical marijuana. We use longitudinal data from the Health and Retirement Study to estimate event study and differences-in-differences regression models. Three principle findings emerge from our analysis. First, active state medical marijuana laws lead to lower pain and better self-assessed health among older adults. Second, state medical marijuana laws lead to increases in older adult labor supply, with effects concentrated on the intensive margin. Third, the effects of MMLs are largest among older adults with a health condition that would qualify for legal medical marijuana use under current state laws. Findings highlight the role of health policy in supporting work among older adults and the importance of including older adults in assessments of state medical marijuana laws.
© 2019 by the Association for Public Policy Analysis and Management.

INTRODUCTION

Medical marijuana legalization is highly controversial in the United States (Anderson & Rees, 2014). Critics contend that legalizing any type of marijuana use will promote marijuana addiction and increase misuse of related substances, crime and traffic accidents, and healthcare costs. Advocates highlight the potential health benefits of medical marijuana use for patients with chronic pain and other conditions. Public support for legalization of medical marijuana has surged in recent years, with well over three-quarters of U.S. residents now supporting some form of legalization of this product for medical purposes.[1] As of December 2018, 33 U.S. states and the District of Columbia (DC) have passed laws legalizing medical use of marijuana (MMLs). State and national policymakers require a solid evidence base on both the potential costs and benefits of expanded access as they determine how best to regulate medical marijuana.

A small set of clinical trials have concluded that medical marijuana is effective in treating symptoms associated with chronic pain, nausea and vomiting, and sleep disorders, though both the number of studies and total subjects enrolled are small (Goldenberg et al., 2017; Hill, 2015; McCormick et al., 2017). Older adults experience higher prevalence of many of the health conditions with symptoms that can be effectively treated with medical marijuana (Morgan, 2003; Nahin, 2015; Unruh et al., 2008) and are more likely to use prescription medications to treat

[1] See, for example, https://www.washingtontimes.com/news/2017/apr/18/83-percent-americans-favor-legalizing-medical-weed/ (accessed July 17th, 2018).

Journal of Policy Analysis and Management, Vol. 38, No. 2, 455–480 (2019)
© 2019 by the Association for Public Policy Analysis and Management
Published by Wiley Periodicals, Inc. View this article online at wileyonlinelibrary.com/journal/pam
DOI:10.1002/pam.22122

these symptoms (NCHS, 2015). For example, 35 percent of adults age 45 years and older report back pain while 49.6 percent of adults 65 years and older suffer from arthritis (Barbour et al., 2017). Despite high rates of conditions that might respond to medical marijuana, older adults are poorly represented in medical marijuana trials. A recent National Academies of Sciences report emphasized the need for research to inform clinical decision-making related to medical marijuana use among understudied populations including older adults (McCormick et al., 2017).

Age patterns of disease suggest that the health benefits of MML passage could be concentrated among older adults. If the implementation of an MML, by promoting access to marijuana for medical use, reduces symptoms associated with work-impeding health conditions, then MMLs could enhance labor supply among the fastest growing segment of the population. Extending the work lives of older Americans is an important policy effect since this can facilitate greater retirement savings and potentially delay Social Security benefit claiming.

To date, studies of MML health and labor effects have focused on youth and working age populations, largely ignoring outcomes among older adults. Understanding the health and labor supply effects of a new treatment for this group is important because poor health is a primary reason for older adult labor force exit (Case & Deaton, 2005; Dwyer & Mitchell, 1999; Garthwaite, 2012; McGarry, 2004). The rapid growth rate in the older adult population coupled with its comparatively high rates of symptoms that may respond to medical marijuana suggest a need to understand the effects of MMLs for this demographic (Ortman, Velkoff, & Hogan, 2014).

This paper helps to address this gap by testing the effect of medical marijuana laws on several health outcomes (pain, work-limiting health conditions, self-assessed health, and depression) and measures of labor supply along both the extensive and intensive margins. We study the extent to which our results are concentrated among patients with one or more health conditions that would typically qualify a patient for medical marijuana use, isolating individuals who plausibly use marijuana gained through MMLs for medical purposes or seek medical care in response to new treatment availability (Bradford & Bradford, 2016; Sabia, Swigert, & Young, 2017).We estimate event study and differences-in-differences regression models using panel data from the 1992 to 2012 waves of the Health and Retirement Study (HRS) that control for a range of state characteristics that may predict both our outcomes and the propensity of a state to pass an MML, and for state-specific time trends.

We have three principle findings. (i) MML implementation leads to reductions in pain and improved self-assessed health among older adults including a 3.4 percent increase in the probability of reporting very good or excellent health. (ii) MML implementation increases older adult labor supply along the intensive margin; post-MML full-time employment increases by 5 percent. We do not find evidence that MMLs change the probability of any work, suggesting that the laws do not motivate retirees to return to work. (iii) Health and labor supply effects of MMLs are concentrated among older adults with medical conditions that may respond to medical marijuana. Our results can inform policymaker decisions about medical marijuana policy and broaden the clinical evidence base about medical marijuana efficacy for older adults.

BACKGROUND AND RELATED LITERATURE

Marijuana Regulation in the U.S.

Marijuana possession and distribution are illegal under U.S. federal law. The Controlled Substances Act of 1970 classifies marijuana as a Schedule I drug on a par with ecstasy and heroin, the strictest regulation category used for "Drugs with no

Table 1. State medical marijuana laws 1996 to 2013.

		MML Provisions			
State Column	Any MML (1)	Cultivation (2)	Dispensary (3)	Non-specific pain (4)	Registry (5)
Alaska	3/1999	n/a	n/a	3/1999	3/1999
Arizona	4/2011	4/2011	12/2012	4/2011	4/2011
California	11/1996	11/1996	11/1996	11/1996	n/a
Colorado	6/2001	6/2001	7/2005	6/2001	6/2001
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
Hawaii	12/2000	n/a	n/a	12/2000	12/2000
Maine	12/1999	n/a	4/2011	n/a	12/2009
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
Oregon	12/1998	12/1998	11/2009	12/1998	1/2007
Rhode Island	1/2006	1/2006	4/2013	1/2006	1/2006
Vermont	7/2004	n/a	6/2013	7/2007	7/2004
Washington	11/1998	7/2011	4/2009	11/1998	n/a

Notes: Data source is Sabia and Nguyen (2016). The following states passed MMLs after 2013: Arkansas (2016), Florida (2017), Illinois (2014), Maryland (2014), Minnesota (2014), New York (2014), North Dakota (2016), Ohio (2016), Pennsylvania (2016), West Virginia (2017), and Oklahoma (2018). We rely on the website Pro-Con (https://medicalmarijuana.procon.org/view.resource.php?resourceID = 000881, accessed July 17th, 2018) for the most recent law changes that are not included in Sabia and Nguyen (2016).

currently accepted medical use and a high potential for abuse." Schedule I status severely limits researchers' capacity to use marijuana in clinical trials, resulting in a very small number of studies restricted to low potency tetrahydrocannabinol, which is markedly weaker than the medical marijuana available to patients through home cultivation or dispensaries (Stith & Vigil, 2016; Williams et al., 2016). Existing clinical evidence is likely insufficient to inform medical marijuana policies and treatment decisions for many patients, especially older adults. For example, only 12 randomized controlled trials have tested medical marijuana's effectiveness in treating pain among a combined 721 patients of all ages (Hill, 2015).

33 states and DC implemented an MML by December 2018. To legally access marijuana, patients in these states must receive a recommendation from a medical doctor indicating their need for this medication and provide evidence of legal residence within the state. States differ in qualifying conditions for medical marijuana, but commonly include cachexia, cancer, digestive conditions, epilepsy, HIV/AIDS, glaucoma, muscle spasms, multiple sclerosis, and pain (Bradford & Bradford, 2017; Sabia, Swigert, & Young, 2017). Table 1 column 1 outlines the MML effective date for each state that has passed an MML through 2013 (Sabia & Nguyen, 2016), the last year of our study period. California passed the first state MML in 1996. This law removed criminal penalties for marijuana possession, cultivation, and use for a set of health conditions. Other early adopting states include Oregon (1998), Washington (1999), Alaska (1999), and Maine (1999).

Clinical Evidence and Medical Marijuana Use Among Older Adults

Although clinical evidence is limited, randomized control trials have found that medical marijuana is an effective treatment for symptoms associated with pain, anxiety, depression, nausea, psychosis, sleep disorders, and spasticity (Goldenberg et al., 2017; Hill, 2015; McCormick et al., 2017; Whiting et al., 2015). Pain is the most commonly reported reason for medical marijuana use (Nunberg et al., 2011; Reiman, Welty, & Solomon, 2017). The vast majority of patients surveyed reported that medical marijuana addressed their symptoms as well as prescription medications but without side effects. Respondents also reduced their prescription opioid use. Enrollees in the New Mexico Medical Cannabis Program were more likely to cease using prescription opioids and reported less pain than non-enrollee controls (Vigil et al., 2017).

Although states do not release individual-level data, our analysis of available data suggests that 20 percent to 60 percent of all registered medical marijuana users in U.S. states reporting demographic information are over age 50.[2] Recent studies using state registration data (Anderson, Hansen, & Rees, 2013; Fairman, 2016; Kaskie et al., 2017; Yi, 2015) and convenience samples (Ilgen et al., 2013; Nunberg et al., 2011) also find that older adults represent a substantial share of medical marijuana patients.

Data from the National Survey of Drug Use and Health (NSDUH) indicate that 5.8 percent of adults ages 45 to 54, 6.1 percent of adults ages 55 to 64 years, and 1.3 percent of adults age 65 years and older reported any form of marijuana use in the past month in 2014, reflecting a 48 percent, 455 percent, and 333 percent increase since 2002 (Azofeifa, 2016). Past year use rates are higher, with similar increases, from 2.9 to 9.0 percent among adults 50 to 64 years and 0.2 to 2.1 percent among adults 65 years and older (Stoner, 2016). Older adult medical marijuana use is increasingly noticed by marketers and the popular press.[3]

Economic Analyses of State Medical Marijuana Laws

A growing economic literature explores the potential harms and benefits of MMLs. We provide a brief review of the studies most relevant to our work on older adults. Wen, Hockenberry, and Cummings (2015) find that state passage of an MML leads to a 14 percent (15 percent) increase in prior month marijuana consumption (near daily use) among adults 21 years and older in the NSDUH, likely reflecting a combination of medical and recreational use. Choi (2014), also using the NSDUH, finds a similar relationship between MMLs and marijuana use among those 21 years and older. Increased use is also apparent among arrestees. Chu shows that passage of an MML leads to a 10 to 20 percent increase in arrests for marijuana-related possession and substance use disorder (SUD) treatment admissions (Chu, 2014, 2015). Effects of MMLs on marijuana-related arrests among adults aged 45 years and above range from 1.1 to 11.9 percent and are often statistically indistinguishable from zero. Anderson and Rees (2014) show that MML passage increases marijuana plant eradication by the Drug Enforcement Agency.

[2] Authors' calculation using data from 11 states (Alaska, Arizona, California, Colorado, Delaware, Hawaii, Illinois, Minnesota, Montana, Nevada, and Oregon) that, at the time of writing, require patients to register with the state to legally use medical marijuana and publicly report patient demographics.

[3] See https://mjbizmagazine.com/serving-the-senior-demographic/; https://skillednursingnews.com/2017/11/former-long-term-care-exec-bets-cannabis-demand-canada/; https://www.cbsnews.com/news/seniors-and-marijuana/; http://ualrpublicradio.org/post/marijuana-expo-brings-together-seniors-veterans-scientists-sons-arkansas; and http://www.cpr.org/news/story/more-aging-coloradans-are-turning-to-medical-marijuana-but-data-is-sparse (accessed July 16th, 2018).

There is also evidence that MML passage leads to changes in health outcomes. Sabia, Swigert, and Young (2017) find that passage of an MML leads to a 2 to 6 percent decline in the probability of being obese. The authors show that, following passage of an MML, days in poor physical and mental health decline while physical activity increases, though the effects are sensitive to the inclusion of state trends. Findings for older adults are broadly comparable to the full sample but are generally imprecise in models that include state trends. Anderson, Rees, and Sabia (2014) document that MML passage leads to a decline in completed suicides among men aged 20 to 39 years, but not for other demographic groups. Ullman (2017) shows that passage of an MML reduces work absences by 8.4 to 8.7 percent among workers aged 15 to 65 in the Current Population Survey (CPS), although effects are somewhat sensitive to specification for workers ages 50 to 65. Anderson and coauthors find that state MMLs lead to lower rates of workplace fatalities for workers age 25 to 44, but no differences for other age groups. In contrast to these beneficial health effects, Abouk and Adams (2018) show that cardiovascular deaths increase by 2.3 percent among men and 1.2 percent among women following state MMLs. Effect sizes are even larger among older adults (65 years and older).

Several studies provide evidence that MMLs lead to medicinal marijuana use. Bradford and Bradford (2016) and Bradford et al. (2018) find that elderly and disabled Medicare recipients filled fewer prescriptions to treat pain, anxiety, depression, nausea, psychosis, seizures, and sleep disorders after their states provided legal access to medical marijuana through cultivation or dispensaries. These declines are non-trivial: 5.7 percent for pain medications, 5.0 percent for anxiety medications, 5.4 percent for nausea medications, and 4.5 percent for psychosis medications (Bradford & Bradford, 2016). Bradford and Bradford (2017) and Wen and Hockenberry (2018) find similar declines in use for therapeutic substitutes following MML passage within the Medicaid population. Ozluk (2017) finds lower prescription opioid spending following MML passage in the general population. Bachhuber et al. (2014) show that passage of an MML reduces the opioid overdose death rate by 24.8 percent. Powell, Pacula, and Jacobson (2018) document that legal access to medical marijuana reduces death rates related to opioid abuse.

To the best of our knowledge, only one study explores the effect of MMLs on labor market outcomes. Sabia and Nguyen (2016) leverage data from the CPS among adults ages 18 to 64. The authors document that passage of an MML decreases wages by 2.8 percent among males ages 20 to 29 years, but passage is largely unrelated to wages among other groups and unrelated to labor supply (proxied by any work and hours worked). The authors do not find evidence that passage of an MML affects these measures among individuals aged 50 to 64.

Our study extends the MML literature in several ways. We focus on older adults, 51 years and above, the population most likely to suffer from the health conditions for which marijuana may be effective in reducing symptom burden. We study all older adults as well as the subset with health conditions that may respond to medical marijuana. We assess changes in pain and depression, conditions that could have important spillovers to labor supply. Finally, we are able to include person fixed effects as an alternative control for omitted variable bias.

MECHANISMS

Health

Medical marijuana offers a new treatment option for symptoms associated with a number of health conditions described previously. MML passage appears to promote older adults' use of medical marijuana, at least partly through substitution away

from other prescription drugs. Patient health and symptom burden should improve if medical marijuana is more effective than a patient's previous treatment program or has a less aggressive side effect profile, and worsen if marijuana is a less effective treatment. If MML passage primarily leads to increases in recreational use (Wen, Hockenberry, & Cummings, 2015), then we expect no improvement, and perhaps a decline, in health for the new recreational users.

Switching to medical marijuana may have adverse patient health effects if substitution induces patients to terminate treatments addressing a broader set of symptoms. For instance, the treatment of chronic pain is often characterized by use of both pain medication and anti-depressants (Sansone & Sansone, 2008). Healthcare providers prescribe this combination because depression and pain can co-occur, and pain medications and anti-depressants can target different pain receptors. Patients who opt to use medical marijuana may lose access to valuable secondary treatments if this use changes their relationship or frequency of follow-up care with healthcare providers. Finally, drug interactions could harm health if patients co-use marijuana with other medications (Ozluk, 2017; U.S. National Library of Medicine, 2017).

Labor Supply

Older adults may increase labor supply post-MML if their new treatment more effectively alleviates symptoms or provides similar efficacy with fewer side effects. Economic models of labor supply highlight the importance of health as a determinant (Currie & Madrian, 1999). There is substantial empirical evidence that poor health prompts older adults to reduce labor supply (Case & Deaton, 2005; Dwyer & Mitchell, 1999; Garthwaite, 2012; McGarry, 2004). Conventional prescription medications for many medical marijuana-qualifying health conditions often present patients with strong side effects that can impede work. Anti-anxiety medications' side effects include confusion, headaches, irritability, trouble concentrating, and worsening of depressive symptoms (Longo & Johnson, 2000; Stewart et al., 2003). Patients using opioid pain relievers often suffer from cardiovascular problems, central nervous system complications, impaired judgment, and respiratory problems (Chau et al., 2008; Swegle & Logemann, 2006).

While medical marijuana is generally taken to promote health, marijuana can have serious side effects that would limit work capacity such as amotivational syndrome, anxiety, depression, lethargy, difficulties with memory, and respiratory problems (Hill, 2015; Volkow et al., 2016). If older adults increase recreational marijuana use in response to easier access or perceived safety following MML passage, we expect labor supply to remain unchanged or decline. Labor supply could also decline if use of medical marijuana improves health and the increased value of leisure time prompts older adults to enter retirement. Alternatively, MMLs may lower the productivity of younger adults who are more likely to use marijuana recreationally, increasing employer demand for older workers.

Policy Spillovers

State MMLs can also influence health and labor supply outcomes through secondary channels. For example, laws may influence older adults' migration decisions and positive or negative externalities from increased marijuana use by younger workers.

DATA, VARIABLES, AND METHODS

Health and Retirement Study

We use data from the 1992 to 2012 waves of the Health and Retirement Study (HRS). We truncate the sample at the 2012 wave, which includes data collected in

2012 and 2013, to avoid confounding from passage of state recreational marijuana laws that were implemented after this time. The HRS is a nationally representative panel survey of Americans over 50 and their spouses administered biennially since 1992 to track health and labor market outcomes among older adults. Through the 2012 wave, the HRS includes 247,233 interviews with 38,008 older persons. After excluding respondents living outside the U.S. or missing state of residence and surveys completed by proxy respondents, our analysis sample includes 182,516 respondent/year observations from 34,862 respondents reporting on at least one of our outcome measures. To maximize sample size, our primary specifications use each wave's HRS as a repeated cross-section; thus, we observe respondents for different numbers of waves based on when they entered the HRS and their response patterns.

The HRS has a complex, household-level survey design including oversampling of minorities and residents of certain states. In particular, while the initial cohort was surveyed in 1992, additional "refresher" cohorts have been added over time to the HRS to maintain and improve the representativeness of the data. Because these sources of sampling are known variables that we control for in our regression models as covariates, we use the unweighted data in our main specifications. However, we conduct several sensitivity analyses to ensure that our findings are not biased by the complex HRS survey design features.

A limitation of the HRS, similar to all major surveys containing large samples of older adults and measures of health and labor supply of which we are aware, is that it does not collect information on marijuana use, either for medical or recreational purposes. The HRS is the largest study of older adult labor outcomes that also includes the detailed health information necessary to identify patients who are potentially clinically appropriate for medical marijuana. While we are unable to study outcomes among those induced to use medical marijuana in response to state laws, our results capture the net effect of these laws on older adult outcomes. We discuss the plausibility of our effect sizes later in the article.

State-Level Medical Marijuana Laws

Our source for MMLs is Sabia and Nguyen (2016). We match MML effective dates to the HRS interview on month and year. We construct an indicator variable coded one if a state has an MML in place and zero otherwise. Table 1 column 1 reports effective dates of state MMLs passed by the end of our study period (2013).

Outcome Variables

We examine four health outcomes that have some clinical support for the use of medical marijuana as a treatment option, are measured in the HRS, and have a plausible link to labor supply: (i) whether frequently troubled by pain; (ii) whether health limits the ability to work; (iii) self-assessed health (dichotomizing as very good or excellent health vs. good, fair, and poor health); and (iv) depressive symptoms (measured by an abbreviated eight-question version of the Center for Epidemiologic Studies—Depression Scale [CES-D] used in the HRS).

These HRS survey items mirror questions that healthcare providers would use to diagnose and treat pain and depression (National Institutes of Health, 2011). For example, the National Institutes of Health advise that, "Pain is a very personal and subjective experience. There is no test that can measure and locate pain with precision" (U.S. National Library of Medicine, 2017). The CES-D measures of depressive symptomatology have been validated in numerous settings (Radloff, 1977;

Turvey, Wallace, & Herzog, 1999). These HRS measures are frequently used in the economics and policy analysis literatures (Kapteyn, Smith, & Van Soest, 2008; McInerney, Mellor, & Nicholas, 2013; Tian, Robinson, & Sturm, 2005). Self-assessed health has been shown to predict, even after conditioning on observable characteristics, more objective measures of health status such as mortality and healthcare utilization (Benjamins et al., 2004; Nielsen, 2016). This measure is believed to capture aspects of mental and physical health (Apouey & Clark, 2015).

We examine four measures of labor supply: (i) any work in the past year (0/1), (ii) whether currently working full-time (0/1; working 35 or more hours per week for at least 36 weeks of the year), (iii) the natural logarithm of usual hours worked per week among those who report any work, and (iv) unconditional usual hours worked per week; respondents who report not working for pay are assigned zero hours worked.

Control Variables

We control for respondent age, race, ethnicity, marital status, number of children less than 18 years of age, household size, and education in all regressions. We include indicators of whether the respondent has reached his or her early retirement age and full retirement age for Social Security benefit claiming based on month and year of birth and interview. We account for several time-varying state characteristics that may be correlated with both the passage of an MML and our outcomes to minimize bias due to omitted policy variables: an indicator for whether a state has decriminalized marijuana (Pacula, Chiriqui, & King, 2003),[4] the beer tax per gallon from the Brewers' Almanac, the state Earned Income Tax (EITC) as a proportion of the Federal EITC, the maximum food stamp benefit for a family of four from the University of Kentucky Poverty Research Center, and the governor's (DC mayor's) political affiliation.

Qualifying Sample

If medical marijuana laws have their intended impact—allowing eligible patients to access a new, effective treatment for their symptoms—we expect to see benefits concentrated among potential medicinal users. The HRS collects longitudinal information on the majority of symptoms that qualify patients for medical marijuana under most state laws. We use these measures to identify the "qualifying sample," respondents who report one or more of (i) current cancer treatment, (ii) current glaucoma, (iii) current arthritis, or (iv) severe pain in the current or any previous wave. 100,921 observations (or 55 percent of the full sample) meet these criteria. This is a conservative approach to measuring eligibility as it fails to identify respondents with rare diagnoses such as epilepsy, HIV/AIDS, and multiple sclerosis, which are not measured in the HRS. We estimate our regressions in the full and qualifying samples.

Empirical Approach

Our primary empirical models are difference-in-differences (DD) regressions comparing respondent outcomes before versus after their states pass MMLs to those in non-MML states. A concern with analyses of state policies is that they are not randomly assigned and may be triggered by other population trends. For example, MMLs may be passed in response to growing pain prevalence in some states. To

[4] We thank Rosalie Pacula for sharing coding through 2013 for this variable.

ensure that our policy changes do not appear to be driven by pre-implementation factors, we first report event study models to test for evidence of policy endogeneity (Autor, 2003; Lovenheim, 2009). We then turn to DD models that allow us to concisely summarize MML effects.

Our event study models regress our outcomes, Y_{ist}, on a vector of dummy variables, $\Sigma Relative\ time_{st,}$ indicating time from MML implementation, and state- and respondent-level control variables. We bin our data into 24-month periods relative to the month and year of MML implementation, with all observations from non-MML states set at t = 0; this omitted category includes the 24 months prior to the law effective date in MML states.[5] Thus, we have more interviews in even-numbered years although MMLs pass in both even and odd years. We impose endpoint restrictions following Kline (2011) by pooling observations from 10 or more years prior to MML implementation into our earliest period (−10+) and all observations from eight or more years post-implementation as our final time period (+8+). States that do not pass an MML by the end of our study period are coded as zero for all bins. We estimate the following regression:

$$Y_{ist} = \alpha_0 + \rho_j \Sigma Relative\ time_{st} + X_{ist}\alpha_2 + \tau_{st}\alpha_3 + \delta_s + \gamma_t + \Omega_{st} + \in_{ist}. \quad (1)$$

Y_{ist} is a labor supply or health outcome for older adult i in state s in year t. X_{ist} is a vector of individual characteristics and τ_{st} is a vector of time-varying state characteristics. δ_s is a vector of state fixed effects that capture unobservable (to the econometrician) and time-invariant factors for each state, and γ_t is a vector of interview wave dummy variables that capture factors that affect the nation as a whole. Ω_{st} is a vector of state-specific linear HRS wave trends, where a wave includes a two-year period. These trends (linearly) capture unobservable, time-varying state factors. ϵ_{ist} is the error term. We use linear probability models (LPMs) for binary outcomes and least squares for continuous outcomes. We cluster the standard errors around the state (Bertrand, Duflo, & Mullainathan, 2004).

We estimate the following DD model to summarize treatment effects:

$$Y_{ist} = \beta_0 + \beta_1 M_{st} + X_{ist}\beta_2 + \tau_{st}\beta_3 + \delta_s + \gamma_t + \Omega_{st} + \varepsilon_{ist}. \quad (2)$$

In this specification, we report average effects of MMLs (M_{st}) in the post-period, summarizing the policy effect in a single coefficient. A robustness check leverages the panel nature of HRS to replace the state fixed effects with respondent fixed effects.

RESULTS

Summary Statistics

Table 2 reports summary statistics. In the full sample, 31 percent report experiencing pain, 29 percent report that health limits work ability, 41 percent report their health as excellent or very good, and the mean number of depressive symptoms is 1.6 (out of a maximum of 8). The medical marijuana qualifying sample, as expected, has worse health than the full sample: 43 percent report experiencing pain, 39 percent report that health limits the ability to work, 32 percent report very good or excellent

[5] The HRS is administered biennially and most interviews occur in the even-numbered year of each wave (e.g., more interviews occur in 2010 than 2011. We use survey year to match passage year to the HRS, then aggregate to two-year bins to avoid single-year cells with very small numbers of observations.)

Table 2. Summary statistics: HRS 1992 to 2012.

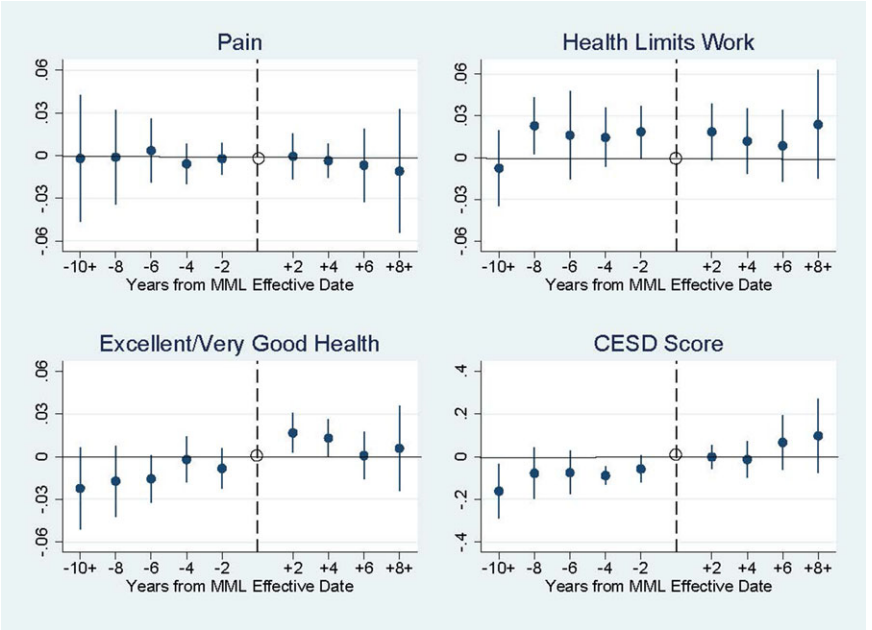
Sample	Full	Qualifying
Health Outcomes		
Pain	0.31	0.43
Health limits work	0.29	0.39
Very good/excellent health	0.41	0.32
Depressive symptoms	1.55	1.81
Labor supply outcomes		
Any work	0.39	0.31
Work full time	0.26	0.19
Hours worked/wk (conditional)	36.70	34.75
Hours worked/wk (unconditional)	14.18	10.72
Medical marijuana laws		
Any MML	0.13	0.15
Individual characteristics		
Age	68.50	67.99
White	0.80	0.80
African American	0.15	0.16
Other race	0.05	0.04
Hispanic	0.09	0.09
Less than high school	0.29	0.30
High school	0.31	0.32
Some college	0.40	0.38
Married	0.66	0.63
Not married	0.33	0.37
Number of children < 18	0.29	0.28
Household size	2.22	2.17
Early Retirement Age	0.61	0.69
Full Retirement Age	0.50	0.57
State characteristics		
Marijuana decriminalized	0.32	0.32
Beer tax ($ per gallon)	0.26	0.27
State EITC as a proportion of the federal EITC	0.12	0.13
Maximum monthly food stamp benefit, family of 4 ($)	487.96	506.20
Democratic governor	0.46	0.46
N	182,516	100,921

Notes: HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents who report one or more condition that would qualify for legal medical marijuana use.

health, and the mean number of depressive symptoms is 1.8. In the full (qualifying) sample, 39 percent (31 percent) report working and 26 percent (19 percent) report working full-time. The mean hours worked per week is 36.7 (full) and 34.8 hours (qualifying) among those respondents who report working, unconditional hours worked (including 0s for non-workers) average 14.2 in the full sample and 10.7 in the qualifying sample. 13 percent of the full sample and 15 percent of the qualifying sample reside in an MML state.

Internal Validity

The principle assumption underlying DD models, the parallel trends assumption, is that the treatment (states that pass an MML) and comparison (states that do not pass an MML) groups would have trended similarly had the treatment group not been treated. We first estimate event studies to assess the plausibility of parallel trends in our data.



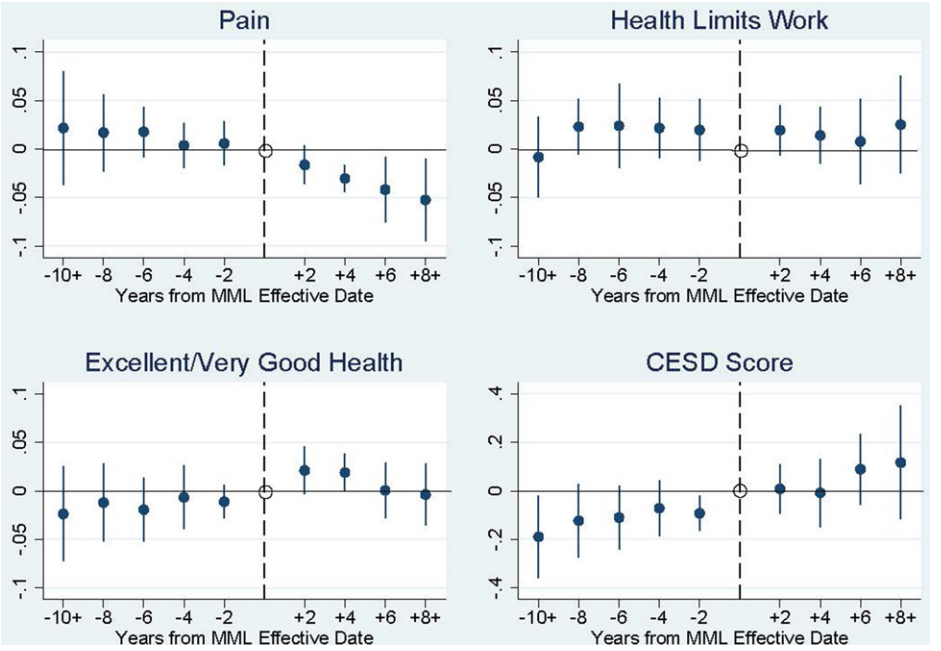
Notes: Sample includes HRS respondents 51 years and older. All models are estimated with a linear probability model (binary outcome) or least squares (continuous outcome), and control for individual and state characteristics, state fixed effects, and interview wave fixed effects. The omitted period includes the 24-month period ending with MML implementation. 95 percent confidence intervals that account for within-state clustering are reported with vertical lines. F-statistics for the joint significance of the policy leads: 0.016 (pain), 1.851 (health limits ability to work), 2.2 (excellent or very good health), and 5.2 (CES-D). F-statistics for the joint significance of the policy lags: 0.15 (pain), 0.85 (health limits ability to work), 2.46 (excellent or very good health), and 2.15 (CES-D).

Figure 1. Effect of State Medical Marijuana Laws on Older Adult Health Outcomes Using an Event Study: HRS 1992 to 2012 Full Sample.
[Color figure can be viewed at wileyonlinelibrary.com]

Results generated in event studies are reported in Figures 1 through 4. If there are no pre-trends in our outcomes, we expect to see pre-period lead estimates clustered around zero. Overall, we observe no substantial evidence of differential pre-trends in either the full or qualifying samples. While some coefficients rise to the level of statistical significance, the sign tends to work *against* our ability to identify MML effects in the post-period. For instance, in the qualifying sample, conditional hours appear to be declining in MML states (vis-a-vis non-MML states) in the pre-policy adoption period while we observe that this outcome *increases* post-MML (Figure 4). F-statistics of the joint significance of lead variables are generally small and statistically insignificant (Figures 1 through 4).

The event study analysis indicates a reduction in pain among qualifying respondents only after MML implementation (Figure 2), no change in reporting that health limits work for either sample, and some evidence of improvements in self-assessed health accompanied by increasing depressive symptoms for the full and qualifying samples (Figures 1 and 2). The event study analyses suggest no effect of MML implementation on labor supply on the extensive margin but show increases in full-time work and hours worked in both samples (Figures 3 and 4).

We also use pre-period data to estimate regression models similar to equation (2) replacing the MML variable with a time-to-MML linear trend centered around the month and year of MML implementation (or random fake date for



Notes: Sample includes HRS respondents 51 years and older with one or more medical conditions that would qualify for medical marijuana use. All models are estimated with a linear probability model (binary outcome) or least squares (continuous outcome), and control for individual and state characteristics, state fixed effects, and interview wave fixed effects. The omitted period includes the two years ending with MML passage. 95 percent confidence intervals that account for within-state clustering are reported with vertical lines. F-statistics for the joint significance of the policy leads: 0.73 (pain), 1.2 (health limits ability to work), 0.88 (excellent or very good health), and 4.6 (CES-D). F-statistics for the joint significance of the policy lags: 5.7 (pain), 0.73 (health limits ability to work), 1.13 (excellent or very good health), and 1.77 (CES-D) in the medical marijuana qualifying sample.

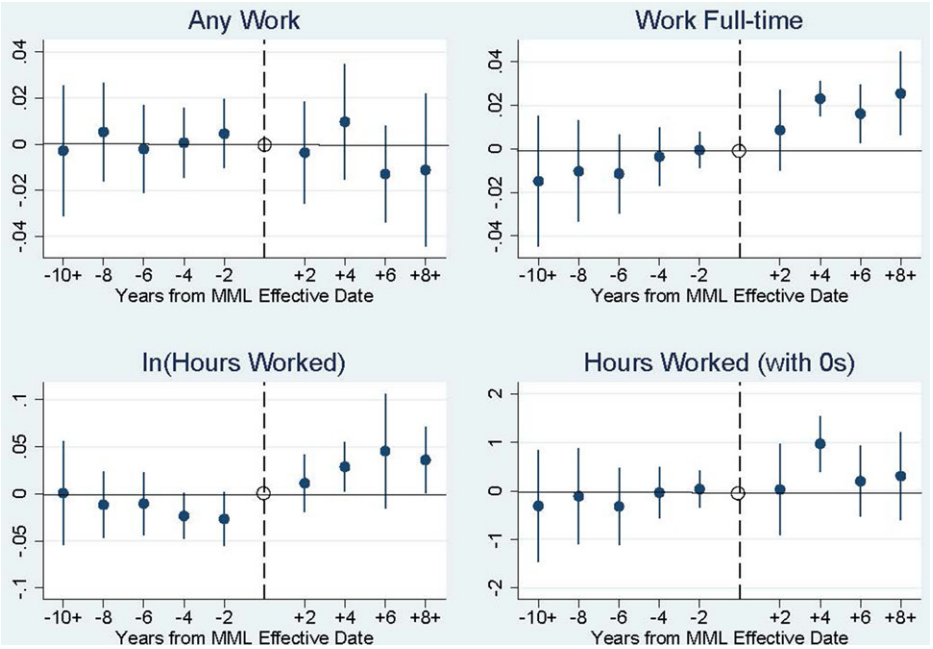
Figure 2. Effect of State Medical Marijuana Laws on Older Adult Health Outcomes Using an Event Study: HRS 1992 to 2012 Medical Marijuana Qualifying Sample. [Color figure can be viewed at wileyonlinelibrary.com]

non-MML states) and an interaction between the treatment group and the linear time-to-MML trend. We find no evidence of different pre-trends across groups for our outcomes (Tables A1 and A2), with the exception of health limits work; this outcome was improving in states that would eventually pass an MML in the pre-period.[6]

Regression Analysis of Health Outcomes

We first explore the effect of MML passage on older adult health in Table 3. Overall, we find that the health effects of MML implementation are concentrated in pain and self-assessed health; there is no evidence that MMLs are linked to reports that health limits the ability to work or depressive symptoms. The health effects are more substantial in the qualifying sample than in the full sample; MML implementation leads to a statistically significant 2.1 percentage point (4.8 percent) reduction in

[6] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.



Notes: Sample includes HRS respondents 51 years and older. All models are estimated with a linear probability model (binary outcome) or least squares (continuous outcome), and control for individual and state characteristics, state fixed effects, and interview wave fixed effects. The omitted period includes the two years ending with MML passage. 95 percent confidence intervals that account for within-state clustering are reported with vertical lines. F-statistics for the joint significance of the policy leads: 0.02 (any work), 0.93 (full-time work), 1.0 (ln(hours) worked), and 0.71 (unconditional hours worked per week). F-statistics for the joint significance of the policy lags: 3.8 (any work), 13.6 (full-time work), 1.4 (the logarithm of the conditional hours worked per week), and 6.2 (unconditional hours worked).

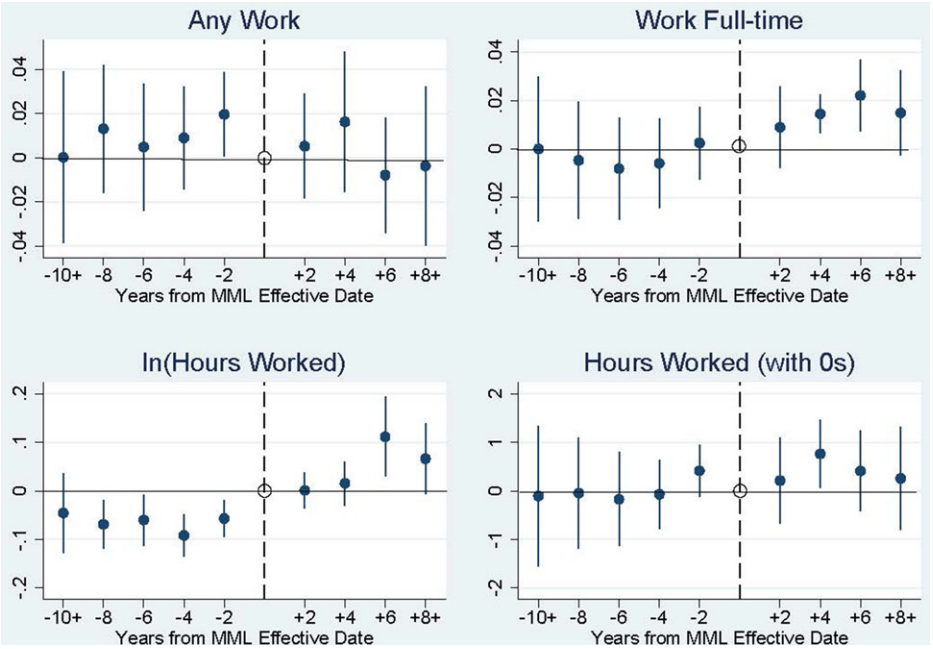
Figure 3. Effect of State Medical Marijuana Laws on Older Adult Labor Supply Outcomes Using an Event Study: HRS 1992 to 2012 Full Sample.
[Color figure can be viewed at wileyonlinelibrary.com]

reporting pain and a 2.1 percentage point (6.6 percent) increase in the probability of reporting very good or excellent health for the qualifying sample. We observe a 1.4 percentage point (3.4 percent) increase in the probability of reporting very good or excellent health for the full sample.

The pain and self-rated health results are clinically relevant and plausible in magnitude. Applying results from Azofeifa (2016) to our data implies that 3.6 percent of the full sample and 3.3 percent of the qualifying sample used marijuana for any reason during the month prior to interview. Our estimated 2.1 percentage point decline in qualifying sample members (who comprise 55 percent of the full sample) with pain and 1.4 percentage point improvement in very good/excellent health in the full sample suggests that a non-trivial share of these users receive therapeutic benefit.

Regression Analysis of Labor Supply Outcomes

Table 4 reports results on the effect of MMLs on older adult labor supply. We find no statistically significant evidence that MML implementation leads to changes on the extensive margin of labor supply. The coefficient estimates for any employment are small in magnitude and imprecise for both samples. We interpret this finding



Notes: Sample includes HRS respondents 51 years and older with one or more medical conditions that would qualify for medical marijuana use. All models are estimated with a linear probability model (binary outcome) or least squares (continuous outcome), and control for individual and state characteristics, state fixed effects, and interview wave fixed effects. The omitted period includes the two years ending with MML passage. 95 percent confidence intervals that account for within-state clustering are reported with vertical lines. F-statistics for the joint significance of the policy leads: 0.55 (any work), 0.11 (full-time work), 9.5 (ln (hours) worked), and 1.6 (unconditional hours worked). F-statistics for the joint significance of the policy lags: 3.16 (any work), 3.8 (full-time work), 2.8 (ln(hours) worked), and 2.6 (unconditional hours worked).

Figure 4. Effect of State Medical Marijuana Laws on Older Adult Labor Supply Outcomes Using an Event Study: HRS 1992 to 2012 Medical Marijuana Qualifying Sample.
[Color figure can be viewed at wileyonlinelibrary.com]

Table 3. Effect of MML passage on older adult health outcomes: HRS 1992 to 2012.

Outcome	Pain		Health limits work		Very good/excellent health		Depressive symptoms	
Sample	1	2	1	2	1	2	1	2
Prop./ mean	0.31	0.43	0.29	0.39	0.41	0.32	1.55	1.81
Any MML	0.000	−0.021**	−0.003	−0.007	0.014**	0.021*	−0.005	−0.013
	(0.006)	(0.009)	(0.010)	(0.013)	(0.006)	(0.011)	(0.022)	(0.043)
N	182,374	100,767	157,703	91,688	182,404	100,793	182,410	100,803

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents who report one or more condition that would qualify for legal medical marijuana use. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table 4. Effect of MML passage on older adult labor supply outcomes: HRS 1992 to 2012.

Outcome	Work		Work FT		Ln(Hr/wk | work)		Hr/wk (uncond.)	
Sample	1	2	1	2	1	2	1	2
Prop./mean	0.39	0.31	0.26	0.19	36.70	34.75	14.18	10.72
Any MML	0.000	0.001	0.013**	0.014***	0.038**	0.064***	0.460**	0.468*
	(0.007)	(0.011)	(0.005)	(0.003)	(0.015)	(0.017)	(0.221)	(0.271)
N	182,077	100,673	182,077	100,673	69,704	30,790	180,659	99,908

Notes: HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents who report one or more condition that would qualify for legal medical marijuana use. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked. Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Untransformed mean reported for ln(hours worked). Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

to suggest that MML implementation does not draw older workers back to the labor market. However, in both samples MMLs lead to increases in full-time work, conditional and unconditional hours worked. The magnitude of the MML effects are more substantial within the qualifying sample: 1.4 percentage points (7.3 percent) vs. 1.3 percentage points (5 percent) for full-time work; 6.4 versus 3.8 percent for hours worked conditional on working; and 0.47 (4.4 percent) vs. 0.46 (3.2 percent) unconditional hours worked.

The combination of our health and labor supply effects suggest that improved capacity to work dominates any work-impeding effects of marijuana use (recreational or medical). We hypothesize that reductions in symptoms associated with chronic health conditions and overall well-being, as measured by self-assessed health, allow older adult workers to increase the amount of time they allocate to paid employment post-MML. While the health and work effects are largest among those in the qualifying sample, the size of the labor supply response in the full sample suggests that additional mechanisms beyond improved worker health may be involved. We next consider a number of alternative explanations that could drive our results.

Endogeneity of the Qualifying Sample

Medical marijuana legalization may alter the number of HRS respondents reporting qualifying conditions, causing us to select our analysis sample on an endogenous variable. This can lead to conditional-on-positive bias in regression coefficients (Angrist & Pischke, 2009). Since HRS does not ask about marijuana use, we do not think that medical marijuana users would be deterred from reporting underlying clinical conditions, though it is possible that those exaggerating a pain problem to obtain marijuana for primarily recreational use maintain the charade for their survey response. We explore this possibility by regressing the probability of being in the qualifying sample on the MML variable and other controls in equation (2). We find no statistically or substantively significant evidence that MMLs influence the probability of reporting a qualifying condition (Table 5, panel 1).

Migration

A common empirical concern in policy analysis research is program-induced migration (Moffitt, 1992). If MMLs motivate patients to move across state lines to access legal treatments, our results may reflect changes in state composition rather

Table 5. Effect of MML passage on the probability of being in the qualifying sample and across-state migration among older adults: HRS 1992 to 2012.

Outcome	Qualifying sample	Move across state lines			
Sample	1	1	2	1	2
Prop.:	0.55	0.023	0.023	0.023	0.023
Current state any MML	−0.006 (0.007)	−0.007 (0.004)	−0.007 (0.004)	-	-
Previous state any MML	-	-	-	0.016 (0.043)	0.016 (0.043)
N	182,516	148,764	89,117	148,764	89,117

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents who report one or more condition that would qualify for legal medical marijuana use. Current state any MML = 1 if state of residence in t has an MML in place, 0 otherwise. Previous state any MML = 1 if state of residence in t-1 has an MML in place, 0 otherwise. All models are estimated with an LPM and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

than changes in resident health or labor supply. If sicker patients are moving, our estimates of the health and potentially of the labor supply effects of MMLs could be biased downward. This behavior, if present, may be considered part of the overall policy effect. We test this possibility by regressing an indicator of whether a respondent has moved across state lines since the previous interview using variants of equation (2); first regressing moves on the current state's MML status, then on the prior wave's state MML status. Table 5 shows that the probability of any move is quite low (2.3 percent in both samples) and does not appear to be influenced by state MMLs.

Effects of MMLs on Other Health Measures

We have focused on the effects of MMLs on a set of health outcomes plausibly related to work capacity and whose symptom burden can be managed by medical use of marijuana. But, the work-enhancing benefits attributable to MMLs could be muted by adverse effects of marijuana such as accidents. We test whether MML passage is related to changes in counts of activities of daily living limitations such as dressing and toileting (0 to 5); large muscle difficulties sitting, getting out of a chair, stooping or pushing (0 to 4); mobility limitations with walking and stair climbing (0 to 5); and any hospital use in the previous year. We estimate equation (2) with these alternative dependent variables and report results in Table 6. We find no statistically significant evidence that MML implementation leads to changes in these outcomes, though the coefficients on all of the disability measures are negative, which is consistent with very small improvements rather than worsening health from unintended effects of the laws.

Change in Employer Demand for Older Workers

MMLs can influence older adult employment through changes in demand for or supply of younger workers. Previous work reports that MMLs lead to increased recreational use of marijuana and reductions in productivity among younger adults (Sabia & Nguyen, 2016; Wen, Hockenberry, & Cummings, 2015). To test whether

Table 6. Effect of MML passage on additional older adult health outcomes: HRS 1992 to 2012.

Outcome	ADL count		Muscle limits		Mobility limits		Any hospital	
Sample	1	2	1	2	1	2	1	2
Prop./mean	0.28	0.41	1.26	1.66	1.04	1.40	0.24	0.30
Any MML	−0.003	−0.019	−0.007	−0.02	−0.012	−0.019	0.003	−0.0003
	(0.007)	(0.015)	(0.019)	(0.033)	(0.013)	(0.031)	(0.007)	(0.013)
N	182,282	100,757	174,915	100,748	174,908	100,745	181,889	100,529

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents who report one or more condition that would qualify for legal medical marijuana use. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. ADL count = activities of daily living limitations; muscle limitations = difficulties with large muscle activities such as sitting and standing; mobility limitations = difficulties with walking and stair climbing. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

our labor supply results are driven by younger workers, we re-estimate equation (2) with additional state-level controls for the share of adults ages 18 to 50 engaged in any work and average unconditional hours worked calculated from the Annual Social and Economic Supplement to the Current Population Survey from 1993 to 2013. Our labor supply effects are unchanged by the addition of these controls (Appendix Table A3).[7]

Effects of Specific MML Provisions

Different aspects of MMLs may have differential impacts on both medical and recreational marijuana use (Anderson & Rees, 2014; Pacula et al., 2015; Wen, Hockenberry, & Cummings, 2015). To explore such heterogeneous effects, we re-estimate equation (2) adding indicators for the following law provisions in addition to the any law indicator: (i) home or group cultivation permitted; (ii) operating dispensaries; (iii) non-specific pain included as a qualifying health condition; and (iv) patient registration required (Table 1). Cultivation, operating dispensaries, and non-specific pain as a qualifying condition may improve medical and recreational access with potential price and quality spillovers to the illegal market, while registration aims to deter program abuse by recreational users. By the end of our study period, all MML states have implemented at least one of these provisions and four states have all four in place.

We do not find clear evidence that particular law types drive our results. Dispensaries reduce pain for the qualifying sample but increase health-limiting work and conditional hours worked for the qualifying sample (Table 7). Cultivation reduces health-limiting work, but only for the full sample. None of the individual provisions significantly increase labor supply and MMLs that require patients to register with the state *reduce* the probability of working, possibly because of workplace policies that preclude use of controlled substances while working or by deterring medical use through privacy concerns or some other intangible factor(s) (Table 8).

Results are similar if we study provisions separately, though the positive coefficients on work are frequently significant for cultivation laws (results available upon

[7] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Table 7. Heterogeneity by law provision in the effect of MML passage on older adult health outcomes: HRS 1992 to 2012.

Outcome	Pain		Health limits work		Very good/ excellent health		Depressive Symptoms	
Sample	1	2	1	2	1	2	1	2
Prop./mean	0.31	0.43	0.29	0.39	0.41	0.32	1.55	1.81
Any	−0.045*	−0.04	−0.04	−0.025	0.034	−0.012	−0.232*	−0.412**
MML	(0.024)	(0.035)	(0.026)	(0.032)	(0.024)	(0.033)	(0.136)	(0.157)
Dispensary	−0.017	−0.021*	0.034***	0.043***	0.004	0.012	0.052	0.107*
	(0.010)	(0.013)	(0.007)	(0.013)	(0.013)	(0.019)	(0.046)	(0.056)
Cultivation	0.000	−0.016	−0.024*	−0.027	0.007	0.002	−0.029	−0.079
	(0.021)	(0.021)	(0.012)	(0.024)	(0.016)	(0.015)	(0.053)	(0.083)
Pain	0.056**	0.042	0.031	0.007	−0.028	0.023	0.222	0.423**
	(0.023)	(0.034)	(0.031)	(0.044)	(0.023)	(0.033)	(0.150)	(0.181)
Registration	−0.001	0.002	0.019	0.027	−0.003	0.014	0.029	−0.003
	(0.015)	(0.017)	(0.015)	(0.018)	(0.017)	(0.023)	(0.051)	(0.073)
N	182,077	100,673	182,077	100,673	182,404	100,793	180,659	99,908

Notes: HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents who report one or more condition that would qualify for legal medical marijuana use. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table 8. Heterogeneity by law provision in the effect of MML implementation on older adult labor supply outcomes: HRS 1992 to 2012.

Outcome	Work		Work FT		Ln(Hr/wk | work)		Hr/wk (uncond.)	
Sample	1	2	1	2	1	2	1	2
Prop./mean	0.39	0.31	0.26	0.19	36.70	34.75	14.18	10.72
Any MML	0.009	−0.002	0.035*	0.027	0.033	0.045	1.427*	0.401
	(0.027)	(0.047)	(0.019)	(0.020)	(0.084)	(0.126)	(0.808)	(1.362)
Dispensary	−0.003	−0.013	0.000	−0.012	0.003	−0.029*	−0.065	−0.626
	(0.009)	(0.011)	(0.009)	(0.008)	(0.017)	(0.017)	(0.400)	(0.395)
Cultivation	0.013	0.019	0.009	0.009	0.034	0.058	0.197	0.664
	(0.010)	(0.015)	(0.007)	(0.009)	(0.025)	(0.038)	(0.327)	(0.682)
Pain	−0.009	0.008	−0.025	−0.011	−0.017	−0.008	−0.841	0.165
	(0.029)	(0.051)	(0.019)	(0.020)	(0.083)	(0.133)	(0.730)	(1.447)
Registration	−0.025**	−0.035***	−0.016*	−0.012	−0.010	0.005	−0.924*	−0.756
	(0.012)	(0.013)	(0.009)	(0.008)	(0.027)	(0.034)	(0.505)	(0.613)
N	182,077	100,673	182,077	100,673	69,704	30,790	180,659	99,908

Notes: HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents who report one or more condition that would qualify for legal medical marijuana use. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked (untransformed mean reported). Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table 9. The effect of MML implementation on older adult health outcomes by sex.

Outcome	Pain		Health limits work		V. good/ex. health		Dep. Symptoms	
Sample	1	2	1	2	1	2	1	2
Men								
Prop./mean	0.26	0.40	0.27	0.34	0.42	0.33	1.32	1.55
Any MML	−0.007	−0.041**	−0.009	−0.005	0.007	0.027	−0.078***	−0.049
	(0.011)	(0.020)	(0.010)	(0.015)	(0.015)	(0.020)	(0.026)	(0.056)
N	75,368	36,933	66,791	34,103	75,387	36,947	75,373	36,938
Women								
Prop./mean	0.34	0.46	0.30	0.40	0.41	0.32	1.70	1.96
Any MML	0.005	−0.008	0.000	−0.009	0.019***	0.020**	0.051	0.005
	(0.008)	(0.011)	(0.015)	(0.021)	(0.006)	(0.008)	(0.031)	(0.062)
N	107,006	63,834	90,912	57,585	107,017	63,846	107,037	63,865

Notes: HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; with one or more condition that would qualify for legal medical marijuana use. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

request). While the adverse effect of patient registries is somewhat counter-intuitive, and raises questions about unintended consequences, we are unable to explore the ways that this law dimension reduces labor supply. This type of MML has received relatively little attention in the literature and studies that do examine patient registries report a mix of positive and negative effects (Choi, Dave, & Sabia, 2018; Pacula et al., 2015; Wen, Hockenberry, & Cummings, 2015).

Heterogeneity in MML Effects by Sex

To maximize sample size, we pool men and women in our main specifications. However, there are established sex differences in both health and labor supply. For instance, women are more likely to experience mental health problems than men (Substance Abuse and Mental Health Services Administration, 2014) and men are more likely to work than women, particularly in an older sample (Banerjee & Blau, 2016). To explore such heterogeneity, we have estimated separate regressions for men and women. Results are reported in Tables 9 (health) and 10 (labor supply). Post-MML, reported pain improves among qualifying men, but not women, in passing states. Women, but not men, experience improvements in self-assessed health post-MML. Both men and women increase labor supply on the intensive margin only.

Effect of MMLs on Individuals Not in the Qualifying Sample

We next re-estimate equation (2) using only those respondents who do not qualify for access to medical marijuana through any of the health conditions outlined earlier in the paper. Tables A4 and A5 show a decrease in health limits work, but no changes in pain, self-rated health, or labor supply among this group. These findings, especially in light of the health limits work pre-trends in Table A1, support the hypothesis that health and labor supply results are largely driven by older adults utilizing marijuana medically post-MML.[8]

[8] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Table 10. The effect of MML implementation on older adult labor supply outcomes by sex.

Outcome	Work		Work FT		Ln(Hr/wk | work)		Hr/wk (uncond.)	
Sample	1	2	1	2	1	2	1	2
Men								
Prop./mean	0.45	0.36	0.32	0.23	39.41	3.38	3.61	13.02
Any MML	−0.004	−0.011	0.008	0.008	0.044***	0.084***	0.485	0.478
	(0.009)	(0.010)	(0.008)	(0.008)	(0.015)	(0.029)	(0.426)	(0.556)
N	75,227	36,883	75,227	36,883	33,297	12,861	74,528	36,540
Women								
Prop./mean	0.35	0.29	0.21	0.17	3.53	3.50	11.76	9.40
Any MML	0.003	0.006	0.016***	0.016***	0.031	0.045*	0.439**	0.411
	(0.008)	(0.016)	(0.004)	(0.005)	(0.023)	(0.026)	(0.179)	(0.435)
N	106,850	63,790	106,850	63,790	36,407	17,929	106,131	63,368

Notes: HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked (untransformed mean reported). Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

ROBUSTNESS CHECKS

We test the sensitivity of our main DD results by considering alternative specifications and inclusion criteria. We first include respondent fixed effects to control for unobserved, time-invariant respondent characteristics. We estimate one specification of equation (2) that includes a time-from-law pre-trend in the ever-MML states to further test the pre-trends assumption underlying the DD regression and a specification with a post-law trend to explore dynamics in the response. Our main analyses control for between-state heterogeneity through the use of time-varying state characteristics, state fixed effects, and state-specific linear wave trends. While this is a standard specification within the MML literature (Anderson, Hansen, & Rees, 2013; Sabia & Nguyen, 2016) the state trends may throw away useful variation in MML effects and some of the included time-varying state-level controls may in fact be outcomes of MMLs (Sabia & Nguyen, 2016) that could lead to over-controlling bias (Angrist & Pischke, 2009). We estimate regressions models that (i) exclude state-specific linear wave trends and (ii) time-varying state-level variables.

Our health results (Table A6) show that our MML coefficient is virtually unchanged across these alternative specifications, with the exception of the models that omit the state-specific linear time trend.[9] In these specifications, coefficients are smaller in magnitude and statistically insignificant for pain and excellent/very good health. However, this specification identifies a 1.5 percentage point decline in the share of the full sample that reports that health limits work, a result also obtained in the fixed effect specification. We continue to find evidence of increases in full-time work and hours worked across the alternative specifications for labor supply (Table A7).

[9] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Tables A8 (health) and A9 (labor supply) demonstrate robustness of our DD results to alternative sample inclusion criteria. Although our models control for exogenous sampling variables, we also estimate a specification that applies HRS respondent-level weights to the data. These weights account for the complex design of the HRS and generate estimates that are representative of the community-dwelling population; nursing home residents are given a weight of zero. We next exclude California to ensure that our results are not driven by a single large, early-adopting state. Another model excludes adults older than 75, who are unlikely to change their labor supply. Finally, we restrict our sample to the original HRS cohort, respondents ages 51 to 61 and their spouses who were first interviewed in 1992 and are observed up to 11 times. The health results are virtually unchanged when we use sample weights. There is no evidence of a reduction in pain in the smaller robustness sub-samples. The improvement in self-rated health persists across all sub-samples except the no-California model, though point estimates remain broadly consistent. Point estimates for all labor supply outcomes remain consistent in direction in the weighted regressions but are smaller in magnitude and statistically insignificant. We continue to find modest increases in labor supply on the intensive margin only in all three sub-samples.

DISCUSSION

In this study, we provide new information to the current policy debate surrounding the legalization of marijuana for medical purposes through state regulations. We explore the effects of state medical marijuana laws on older adult health and labor supply outcomes, a group that has received little attention in the MML literature to date. We show that reported pain declines and overall assessments of one's health improve post-MML among older adults. For instance, post-MML, the probability of reporting one's health as very good or excellent increases by 3.4 percent. These findings suggest that access to medical marijuana through MMLs allows at least some older adults to better manage symptoms associated with health conditions that can interfere with productivity and quality of life. Second, we find that MML passage allows older adults who are currently working to increase their labor supply, but we do not find evidence that MMLs allow older adults to re-enter the labor market. Health and labor supply effects are concentrated among older adults who have one or more health condition that could be treated with medical marijuana, suggesting that the policy is impacting its intended population.

A key concern with marijuana regulation is that expanded access will promote recreational, and not medical, use of the product. The fact that we identify improvements in health outcomes that plausibly capture symptom burden (i.e., reported pain and overall health assessments) and increases in labor supply concentrated among those with medical marijuana qualifying conditions suggests that, even if some older adults do obtain recreational marijuana through medical laws, on average MML implementation confers important benefits to some older adults through the ensuing changes in health and labor supply.

Sabia and Nguyen (2016) find no change in employment propensity following passage of an MML, which is comparable to our null findings for any employment. However, while we document that older adults increase labor supply along the intensive margin post-MML, Sabia and Nguyen (2016) find no statistically significant evidence that conditional hours worked increase. We hypothesize that our focus on an older sample of workers than Sabia and Nguyen (2016) may explain this divergence in findings: We examine workers who are 50 years and older while Sabia and Nguyen (2016) examine all workers through age 64, excluding some of the older workers in our sample and including younger workers, whose response to MMLs

may be different. Older workers may be more likely to experience positive labor supply effects following health improvements, while younger workers may be more likely to have negative effects because of increased use of recreational marijuana. Our data also allow us to identify the larger increase in hours worked among the qualifying sample. Collectively, these two studies shed light on the full effects of MML passage on the labor market and highlight the potential for MMLs to have heterogenous effects across groups.

Our findings also contribute to a larger literature highlighting the role of health policies and access to medical treatments for older workers' labor supply. Pain medications may be particularly important for older workers. In addition to our results around medical marijuana access, Garthwaite (2012) found a 3.9 percentage point (10 percent) decline in labor supply among adults with joint conditions following the sudden withdrawal of Vioxx, a popular anti-inflammatory medication previously used to treat joint pain.

Our study has limitations. Our sample is vulnerable to survivor bias, as we only observe the older adults who are cognitively and physically able to complete their own interviews. Given evidence that long-term marijuana use can harm cognition, it will be important to track this outcome as MMLs mature. Our identification strategy is necessarily limited to the variation in MMLs from states implementing laws during our study period. Like all other economics studies examining MML effects of which we are aware, we lack data on medical marijuana use and our results have an intent-to-treat (ITT) interpretation. While the average treatment effect is clearly important clinically, the ITT is arguably more relevant for policy due to the complex pathways through which MMLs can lead to changes in health and labor supply. Our effect sizes are comparable to other MML ITT effects reported in the literature. Bradford and Bradford (2016) show that, post-MML, Medicare prescriptions decline by 4.5 to 5.7 percent, and Bachhuber et al. (2014) show a 24.8 percent decline in opioid-related overdoses post-MML. Finally, we lack data on some health conditions for which medical marijuana may be an effective treatment for alleviating symptoms, though all of these conditions should be captured in our self-rated health variable.

The policy debate surrounding medical marijuana legislation is fierce. Policymakers must carefully weigh costs and benefits of legalization. We find evidence of health and labor supply benefits among older adults, the demographic with the highest rate of clinical conditions that may respond to medical marijuana. In combination with findings that MMLs may reduce body weight and improve physical well-being (Sabia, Swigert, & Young, 2017), reduce suicides for some age groups (Anderson, Rees, & Sabia, 2014), lower opioid overdoses (Bachhuber et al., 2014; Powell et al., 2018), and reduce alcohol-related traffic accidents (Anderson, Hansen, & Rees, 2013), our findings suggest that there are potentially important social benefits to MMLs that must be considered in policy decisions regarding medical marijuana regulation.

The heterogenous effects of MMLs by age exhibited in our paper and others in the literature suggest that policies that more closely target access to legitimate medical users only could maximize benefits and minimize harms of these laws. Age is an easily observed characteristic that could potentially be used in policy design, i.e., to set higher ages for legal access. More comprehensive medical examinations could also better identify qualifying patients, especially among younger adults, where underlying rates of disease are lower. State and Federal laws could also be designed to include ongoing patient monitoring in ways that could support clinical research to better understand positive and negative health effects of medical marijuana use while potentially deterring recreational users from accessing medical marijuana.

LAUREN HERSCH NICHOLAS is an Assistant Professor in the Department of Health Policy and Management at Johns Hopkins University School of Public Health and

the Department of Surgery at Johns Hopkins University School of Medicine, 624 N. Broadway, Room 450, Baltimore, MD 21205 (e-mail: lauren.nicholas@jhu.edu).

JOHANNA CATHERINE MACLEAN is an Associate Professor in the Department of Economics at Temple University, 1301 Cecil B. Moore Avenue, Ritter Annex 869, Philadelphia, PA 19122 (e-mail: catherine.maclean@temple.edu). She is a Faculty Research Fellow at the National Bureau of Economics and a Research Affiliate at the Institute of Labor Economics.

ACKNOWLEDGMENTS

This work was supported by the National Institute on Aging (K01AG041763). We are grateful for support from Hopkins Population Center (NICHD R24HD042854) for use of restricted data sets in their cold room. Findings do not represent the views of the sponsor. We thank Stefanie Deluca, Brady Horn, Sean Lyons, Ian McCarthy, Dan Rees, Douglas Webber, and seminar participants at McMaster University, Cornell University, the 2016 Midwestern Health Economics Conference, the 2016 American Society of Health Economists Biennial Conference, the 2016 Association for Public Policy and Management, and the 2017 Hopkins Health, Labor & Development Economics Conference for helpful comments. We thank Micah Baum and Kevin Zhang for excellent research assistance. All errors are our own.

REFERENCES

Abouk, R., & Adams, S. (2018). Examining the relationship between medical cannabis 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. The Journal of Law and Economics, 56, 333–369.

Anderson, D. M., & Rees, D. I. (2014). The legalization of recreational marijuana: How likely is the worst case scenario? Journal of Policy Analysis and Management, 33, 221–232.

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, 2369–2376.

Angrist, J. D., & Pischke, J. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton, NJ: Princeton University Press.

Apouey, B., & Clark, A. E. (2015). Winning Big but feeling no better? The effect of lottery prizes on physical and mental health. Health Economics, 24, 516–538.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. Journal of Labor Economics, 21, 1–42.

Azofeifa, A. (2016). National estimates of marijuana use and related indicators—National survey on drug use and health, United States, 2002–2014. MMWR. Surveillance Summaries, 65.

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, 1668–1673.

Banerjee, S., & Blau, D. (2016). Employment trends by age in the United States: Why are older workers different? Journal of Human Resources, 51, 163–199.

Barbour, K. E., Helmick, C. G., Boring, M., & Brady, T. J. (2017). Vital signs: Prevalence of doctor-diagnosed arthritis and arthritis-attributable activity limitation—United States, 2013–2015. MMWR. Morbidity and Mortality Weekly Report, 66, 246–253.

Benjamins, M. R., Hummer, R. A., Eberstein, I. W., & Nam, C. B. (2004). Self–reported health and adult mortality risk: An analysis of cause-specific mortality. Social Science Medicine, 59, 1297–1306.

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

Bradford, A. C., & Bradford, W. D. (2016). Medical marijuana laws reduce prescription medication use in Medicare Part D. Health Affairs, 35, 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, 945–951.

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, 178, 667–672.

Case, A., & Deaton, A. S. (2005). Broken down by work and sex: How our health declines. In Analyses in the Economics of Aging (pp. 185–212). Chicago, IL: University of Chicago Press.

Chau, D. L., Walker, V., Pai, L., & Cho, L. M. (2008). Opiates and elderly: Use and side effects. Clinical Interventions in Aging, 3, 273.

Choi, A. (2014). The impact of medical marijuana laws on marijuana use and other risky health behaviors. American Society of Health Economists Annual Meeting. Los Angeles, CA.

Choi, A., Dave, D., & Sabia, J. J. (2018). Smoke gets in your eyes: Medical marijuana laws and tobacco use. American Journal of Health Economics, Forthcoming.

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, 481–517.

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

Dwyer, D. S., & Mitchell, O. S. (1999). Health problems as determinants of retirement: Are self-rated measures endogenous? Journal of Health Economics, 18, 173–193.

Fairman, B. J. (2016). Trends in registered medical marijuana participation across 13 US States and District of Columbia. Drug and Alcohol Dependence, 159, 72–79.

Garthwaite, C. L. (2012). The economic benefits of pharmaceutical innovations: The Case of Cox–2 Inhibitors. American Economic Journal: Applied Economics, 4, 116–137.

Goldenberg, M., Reid, M. W., IsHak, W. W., & Danovitch, I. (2017). The impact of cannabis and cannabinoids for medical conditions on health-related quality of life: A systematic review and meta-analysis. Drug and Alcohol Dependence, 174, 80–90.

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

Ilgen, M. A., Bohnert, K., Kleinberg, F., Jannausch, M., Bohnert, A. S., Walton, M., & Blow, F. C. (2013). Characteristics of adults seeking medical marijuana certification. Drug and Alcohol Dependence, 132, 654–659.

Kapteyn, A., Smith, J. P., & Van Soest, A. (2008). Dynamics of work disability and pain. Journal of Health Economics, 27, 496–509.

Kaskie, B., Ayyagari, P., Milavetz, G., Shane, D., & Arora, K. (2017). The increasing use of cannabis among older Americans: A public health crisis or viable policy alternative? The Gerontologist, 57, 1166–1172.

Kline, P. (2011). The impact of juvenile curfew laws on arrests of youth and adults. American Law and Economics Review, 14, 44–67.

Longo, L. P., & Johnson, B. (2000). Addiction: Part I. Benzodiazepines—Side effects, abuse risk and alternatives. American Family Physician, 61, 2121–2128.

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, 525–587.

McGarry, K. (2004). Health and retirement: Do changes in health affect retirement expectations? Journal of Human Resources, 39, 624–648.

McInerney, M., Mellor, J. M., & Nicholas, L. H. (2013). Recession depression: Mental health effects of the 2008 stock market crash. Journal of Health Economics, 32, 1090–1104.

Moffitt, R. (1992). Incentive effects of the US welfare system: A review. Journal of Economic Literature, 30, 1–61.

Morgan, K. (2003). Daytime activity and risk factors for late-life insomnia. Journal of Sleep Research, 12, 231–238.

Nahin, R. L. (2015). Estimates of pain prevalence and severity in adults: United States, 2012. The Journal of Pain, 16, 769–780.

McCormick, M., Abrams, D. I., Alegria, M., Checkley, W., Collins, L., Cooper, Z ... Jackson, L. (2017). The health effects of cannabis and cannabinoids: The current state of evidence and recommendations for research. Washington, DC: National Academies Press.

National Center for Health Statistics. (2015). Health, United States, 2014: with special feature on adults aged 55–64.

National Institutes of Health. (2011). Chronic pain: Symptoms, diagnosis, and treatment. NIH Medline Plus: The Magazine, 6.

Nielsen, T. H. (2016). The relationship between self-rated health and hospital records. Health Economics, 25, 497–512.

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).

Ortman, J. M., Velkoff, V. A., & Hogan, H. (2014). An aging nation: The older population in the United States. United States Census Bureau, Economics and Statistics Administration, U.S. Department of Commerce.

Ozluk, P. (2017). The effects of medical marijuana laws on utilization of prescribed opioids and other prescription drugs. Working paper. Available at SSRN: https://ssrn.com/abstract=3056791.

Pacula, R. L., Chriqui, J. F., & King, J. (2003). Marijuana decriminalization: What does it mean in the United States? National Bureau of Economic Research, Working Paper Series. Cambridge, MA: 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, 7–31.

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.

Radloff, L. S. (1977). The CES-D Scale: A self-report depression scale for research in the general population. Applied Psychological Measurement, 1, 385–401.

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

Sabia, J. J., & Nguyen, T. T. (2016). The effect of medical marijuana laws on labor market outcomes. IZA Discussion Paper Series. Bonn, Germany: IZA.

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

Sansone, R. A., & Sansone, L. A. (2008). Pain, Pain, Go Away: Antidepressants and pain management. Psychiatry, 5, 16.

Stewart, W. F., Ricci, J. A., Chee, E., Morganstein, D., & Lipton, R. (2003). Lost productive time and cost due to common pain conditions in the US workforce. JAMA, 290, 2443–2454.

Stith, S. S., & Vigil, J. M. (2016). Federal barriers to cannabis research. Science, 352, 1182–1182.

Stoner, S. (2016). Marijuana use by older adults. Seattle, WA: Alcohol and Drug Abuse Institute, University of Washington.

Substance Abuse and Mental Health Services Administration. (2014). Results from the 2013 National Survey on Drug Use and Health: Summary of national findings. Rockville, MD: Substance Abuse and Mental Health Services Administration.

Swegle, J. M., & Logemann, C. (2006). Management of common opioid-induced adverse effects. American Family Physician, 74(8).

Tian, H., Robinson, R. L., & Sturm, R. (2005). Labor market, financial, insurance and disability outcomes among near elderly Americans with depression and pain. Journal of Mental Health Policy and Economics, 8, 219.

Turvey, C. L., Wallace, R. B., & Herzog, R. (1999). A revised CES-D measure of depressive symptoms and a DSM-based measure of major depressive episodes in the elderly. International Psychogeriatrics, 11, 139–148.

U.S. National Library of Medicine. (2017). Medline Plus: Cannabidiol: U.S. National Library of Medicine.

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

Unruh, M. L., Redline, S., An, M. W., Buysse, D. J., Nieto, F. J., Yeh, J. L., & Newman, A. B. (2008). Subjective and objective sleep quality and aging in the Sleep Heart Health Study. Journal of the American Geriatrics Society, 56, 1218–1227.

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, e0187795.

Volkow, N. D., Swanson, J. M., Evins, A. E., DeLisi, L. E., Meier, M. H., Gonzalez, R., Bloomfield, M. A., Curran, H. V., & Baler, R. (2016). Effects of cannabis use on human behavior, including cognition, motivation, and psychosis: A review. JAMA Psychiatry, 73, 292–297.

Wen, H., & Hockenberry, J. M. (2018). Association of medical and adult-use marijuana laws with opioid prescribing for Medicaid enrollees. JAMA Internal Medicine, 178, 673–679.

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., ... Ryder, S. (2015). Cannabinoids for medical use: A systematic review and meta-analysis. JAMA, 313, 2456–2473.

Williams, A. R., Olfson, M., Kim, J. H., Martins, S. S., & Kleber, H. D. (2016). Older, less regulated medical marijuana programs have much greater enrollment rates than newer "medicalized" programs. Health Affairs, 35, 480–488.

Yi, E. (2015). Medical marijuana use among older adults: A systematic review. Gerontologist, 55, 672–672.

APPENDIX

Table A1. Parallel trends testing for older adult health outcomes: HRS 1992 to 2012.

Outcome	Pain		Health limits work		Very good/ excellent health		Depressive symptoms	
Sample	1	2	1	2	1	2	1	2
Proportion/ mean	0.31	0.43	0.29	0.39	0.41	0.32	1.55	1.81
MML*	−0.0008	−0.0006	0.0026*	0.0035*	0.0006	−0.0001	−0.0039	0.0002
Time trend	(0.0008)	(0.0016)	(0.0012)	(0.0013)	(0.0010)	(0.0018)	(0.0038)	(0.0035)
Time trend	−0.0022*	−0.0006	−0.0056**	−0.0059**	−0.0005	−0.0013	0.0096**	0.0214**
	(0.0010)	(0.0013)	(0.0011)	(0.0014)	(0.0006)	(0.0009)	(0.0030)	(0.0035)
N	117,132	59,195	98,464	54,483	117,125	59,195	117,125	59,197

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. Only pre-MML data are included in the sample and states that do not implement an MML by 2010 are randomly assigned a false MML implementation date. The time trend captures months from MML implementation. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table A2. Parallel trends testing for older adult labor supply outcomes: HRS 1992 to 2012.

Outcome	Work		Work FT		Ln(Hr/wk | work)		Hr/wk (uncond.)	
Sample	1	2	1	2	1	2	1	2
Proportion/ mean	0.39	0.31	0.26	0.19	36.70	34.75	14.18	10.72
MML*	0.0009	0.0000	−0.0007	0.0290	0.0013	0.0014	0.011	0.049
Time trend	(0.0010)	(0.0009)	(0.0018)	(0.0438)	(0.0017)	(0.0013)	(0.037)	(0.064)
Time trend	0.0048**	0.0065**	0.0129**	0.3256**	0.0025*	0.0048**	0.213**	0.306**
	(0.0008)	(0.0008)	(0.0017)	(0.0439)	(0.0015)	(0.0009)	(0.052)	(0.036)
N	116,968	116,968	45,647	45,687	59,133	59,133	116,134	58,704

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. Only pre-MML data are included in the sample and states that do not implement an MML by 2010 are randomly assigned a false MML implementation date. The time trend reflects months from MML implementation. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked. Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table A3. Effect of MML implementation on older adult labor supply outcomes controlling for younger worker labor supply: HRS 1992 to 2012.

Outcome	Work		Work FT		Ln(Hr/wk | work)		Hr/wk (uncond.)	
Sample	1	2	1	2	1	2	1	2
Prop./mean	0.39	0.31	0.26	0.19	36.70	34.75	14.18	10.72
Any MML	0.001	0.001	0.012***	0.013***	0.039**	0.064***	0.469**	0.458
	(0.007)	(0.011)	(0.004)	(0.003)	(0.015)	(0.017)	(0.210)	(0.289)
N	182,077	100,673	182,077	100,673	69,704	30,790	180,659	99,908

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked. Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table A4. Effect of MML implementation on older adult health outcomes among those not in the qualifying sample: HRS 1992 to 2012.

Outcome	Pain	Health limits work	Very good/ excellent health	Depressive symptoms
Sample	1	2	1	2
Proportion/mean	0.15	0.13	0.53	1.22
Any MML	0.006	−0.014**	0.007	−0.011
	(0.010)	(0.006)	(0.010)	(0.022)
N	81,607	66,015	81,611	81,607

Notes: Sample includes HRS respondents 51 years and older who do not report one or more condition that would qualify for legal medical marijuana use. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table A5. Effect of MML implementation on older adult labor supply outcomes among those not in qualifying sample: HRS 1992 to 2012.

Outcome	Work	Work FT	Ln(Hr/wk | work)	Hr/wk (uncond.)
Sample	1	2	1	2
Proportion/mean	0.49	0.36	38.50	18.50
Any MML	0.001	0.013	0.008	0.420
	(0.007)	(0.012)	(0.016)	(0.406)
N	81,404	81,404	38,914	80,751

Notes: Sample includes HRS respondents 51 years and older who do not report one or more condition that would qualify for legal medical marijuana use. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked. Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Table A6. Effect of MML implementation on older adult health outcomes: Robustness tests of alternative specifications.

Outcome	Pain		Health limits work		Very good/ excellent health		Depressive symptoms	
Sample	1	2	1	2	1	2	1	2
Proportion/mean	0.31	0.43	0.29	0.39	0.41	0.32	1.55	1.81
Baseline								
Any MML	0.000	−0.021**	−0.003	−0.007	0.014**	0.021*	−0.005	−0.013
	(0.006)	(0.009)	(0.010)	(0.013)	(0.006)	(0.011)	(0.022)	(0.043)
Person FE								
Any MML	−0.007	−0.021**	−0.016*	−0.011	0.016***	0.022*	−0.016	0.016
	(0.007)	(0.010)	(0.008)	(0.014)	(0.006)	(0.012)	(0.019)	(0.035)
Time from Law Pre-Trend								
Any MML	−0.0005	−0.021**	−0.003	−0.007	0.013**	0.022*	−0.004	−0.013
	(0.006)	(0.009)	(0.009)	(0.014)	(0.006)	(0.01)	(0.023)	(0.042)
Ever MML*	0.0000	0.0001	0.0000	−0.0001	0.0001	0.0001	−0.0004	0.0005
pre-trend	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0008)	(0.0015)
Time from Law Post-Trend								
Any MML	−0.001	−0.021**	−0.004	−0.007	0.013**	0.022*	−0.003	−0.015
	(0.0054)	(0.0090)	(0.0090)	(0.0135)	(0.0060)	(0.0119)	(0.0255)	(0.0487)
MML*	−0.0004***	−0.0002	−0.0001	0.0001	−0.0002	−0.0004	0.001	0.0017
post-trend	(0.0001)	(0.0004)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0008)	(0.0014)
Drop State*Wave Trend								
Any MML	−0.004	−0.005	−0.015**	−0.015	0.001	0.006	0.046*	0.052
	(0.007)	(0.013)	(0.008)	(0.010)	(0.007)	(0.012)	(0.024)	(0.032)
Drop State Controls								
Any MML	0.000	−0.018*	−0.002	−0.005	0.012*	0.018	−0.002	−0.012
	(0.005)	(0.009)	(0.010)	(0.013)	(0.006)	(0.011)	(0.023)	(0.042)
N	182,374	100,767	157,703	91,688	182,404	100,793	182,410	100,803

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends unless otherwise noted. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Journal of Policy Analysis and Management DOI: 10.1002/pam
Published on behalf of the Association for Public Policy Analysis and Management

Table A7. Effect of MML implementation on older adult labor supply: Robustness tests of alternative specifications.

Outcome	Work		Work FT		Ln(Hr/wk | work)		Hr/wk (uncond.)	
Sample	1	2	1	2	1	2	1	2
Proportion/mean	0.39	0.31	0.26	0.19	36.70	34.75	14.18	10.72
Baseline								
Any MML	0.000	0.001	0.013**	0.014***	0.038**	0.064***	0.460**	0.468*
	(0.007)	(0.011)	(0.005)	(0.003)	(0.015)	(0.017)	(0.221)	(0.271)
Person FE								
Any MML	−0.003	0.000	0.005	0.006	0.028	0.061**	0.295	0.471
	(0.008)	(0.013)	(0.006)	(0.007)	(0.019)	(0.025)	(0.303)	(0.363)
Time from Law Pre-Trend								
Any MML	−0.0003	0.0009	0.012***	0.014***	0.038**	0.063***	0.433*	0.471
	(0.0077)	(0.0108)	(0.0043)	(0.0031)	(0.0152)	(0.0197)	(0.2208)	(0.2937)
Ever MML* pre-trend	0.0002	0.0001	0.0002	0.0003	0.0000	0.0005	0.0114	0.0131
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0085)	(0.0097)
Time from Law Post-Trend								
Any MML	−0.0003	0.0009	0.012***	0.014***	0.038**	0.063***	0.433*	0.471
	(0.008)	(0.011)	(0.004)	(0.003)	(0.015)	(0.020)	(0.221)	(0.294)
MML * post-trend	0.0002	0.0001	0.0002	0.0003	0.0000	0.0005	0.0114	0.0131
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.009)	(0.010)
Drop State* Wave Trend								
Any MML	0.006	0.005	0.015***	0.017***	0.007	0.031	0.537*	0.558*
	(0.008)	(0.011)	(0.005)	(0.006)	(0.011)	(0.021)	(0.309)	(0.327)
Drop State Controls								
Any MML	−0.001	−0.001	0.013**	0.014***	0.039**	0.068***	0.298	0.195
	(0.007)	(0.011)	(0.005)	(0.003)	(0.015)	(0.017)	(0.474)	(0.362)
N	182,077	100,673	182,077	100,673	69,704	30,790	180,659	99,908

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked (untransformed mean reported). Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Journal of Policy Analysis and Management DOI: 10.1002/pam
Published on behalf of the Association for Public Policy Analysis and Management

Table A8. Effect of MML implementation on older adult health outcomes: Robustness tests of alternative sample inclusion criteria.

Outcome	Pain		Health limits work		Very good/ excellent health		Depressive symptoms	
Sample	1	2	1	2	1	2	1	2
Proportion/mean	0.31	0.43	0.29	0.39	0.41	0.32	1.55	1.81
Baseline								
Any MML	0.000	−0.021**	−0.003	−0.007	0.014**	0.021*	−0.005	−0.013
	(0.006)	(0.009)	(0.010)	(0.013)	(0.006)	(0.011)	(0.022)	(0.043)
N	182,374	100,767	157,703	91,688	182,404	100,793	182,410	100,803
Sample weights								
Any MML	−0.003	−0.021**	−0.011	−0.010	0.015**	0.021**	0.005	0.018
	(0.006)	(0.008)	(0.008)	(0.010)	(0.007)	(0.009)	(0.038)	(0.061)
N	172,473	96,931	149,595	88,143	172,499	96,955	172,515	96,972
Exclude CA								
Any MML	−0.002	−0.014	−0.01	−0.011	0.01	0.017	−0.019	−0.037
	(0.009)	(0.010)	(0.013)	(0.016)	(0.009)	(0.015)	(0.032)	(0.059)
N	165,195	91,906	142,903	83,748	165,217	91,926	165,227	91,937
51-75 yrs								
Any MML	0.006	−0.007	−0.009	−0.017	0.015*	0.029**	−0.013	−0.015
	(0.007)	(0.010)	(0.010)	(0.014)	(0.009)	(0.013)	(0.031)	(0.049)
N	143,001	75,972	131,685	71,947	143,032	75,989	143,028	76,000
HRS Cohort								
Any MML	−0.007	−0.001	−0.014	−0.007	0.020***	0.022*	−0.067**	−0.001
	(0.008)	(0.013)	(0.010)	(0.012)	(0.007)	(0.013)	(0.032)	(0.024)
N	92,994	54,749	88,257	51,002	93,010	54,762	93,017	54,772

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. Baseline = full analysis sample with no sample weights. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Journal of Policy Analysis and Management DOI: 10.1002/pam
Published on behalf of the Association for Public Policy Analysis and Management

Table A9. Effect of MML implementation on older adult labor supply: Robustness tests of alternative sample inclusion criteria.

Outcome	Work		Work FT		Ln(Hr/wk | work)		Hr/wk (uncond.)	
Sample	1	2	1	2	1	2	1	2
Proportion/mean	0.39	0.31	0.26	0.19	36.70	34.75	14.18	10.72
Baseline								
Any MML	0.000	0.001	0.013**	0.014***	0.038**	0.064***	0.460**	0.468*
	(0.007)	(0.011)	(0.005)	(0.003)	(0.015)	(0.017)	(0.221)	(0.271)
N	182,077	100,673	182,077	100,673	69,704	30,790	180,659	99,908
Sample weights								
Any MML	0.000	−0.005	0.006	0.007	0.021	0.036	0.281	0.123
	(0.010)	(0.010)	(0.012)	(0.007)	(0.019)	(0.021)	(0.443)	(0.330)
N	172,199	96,843	172,199	96,843	65,263	29,374	170,846	96,100
Exclude CA								
Any MML	−0.001	0.000	0.007	0.012**	0.036	0.063**	0.893***	1.760***
	(0.010)	(0.014)	(0.006)	(0.005)	(0.024)	(0.024)	(0.297)	(0.587)
N	164,960	91,826	164,960	91,826	63,034	28,180	63,113	28,232
51-75 yrs								
Any MML	0.004	0.004	0.017**	0.018***	0.033**	0.063***	1.173***	1.669***
	(0.008)	(0.012)	(0.006)	(0.005)	(0.014)	(0.016)	(0.281)	(0.389)
N	142,723	75,871	142,723	75,871	67,104	29,228	67,181	29,276
HRS Cohort								
Any MML	0.01	0.008	0.024***	0.021**	0.045**	0.057**	1.089**	0.872
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.50)	(0.54)
N	92,929	54,716	92,929	54,716	39,134	18,156	92,114	54,233

Notes: Sample includes HRS respondents 51 years and older. Sample 1 = full sample. Sample 2 = qualifying sample; respondents with one or more condition that would qualify for legal medical marijuana use. Baseline = full analysis sample with no sample weights. Ln(Hr/wk | work) = log-transformed hours worked per week conditional on any hours worked. Hr/wk (uncond.) = hours worked per week including 0s for non-workers. All models are estimated with an LPM (binary outcome) or LS (continuous outcome), and control for individual characteristics, state characteristics, state fixed effects, interview wave fixed effects, and state-specific linear time trends. Standard errors are clustered around the state and reported in parentheses. *Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent.

Journal of Policy Analysis and Management DOI: 10.1002/pam
Published on behalf of the Association for Public Policy Analysis and Management