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Heterogeneous health effects of medical marijuana legalization: Evidence from young adults in the United States

Junxing CHAY
Singapore Management University, junxingchay.2016@phdecons.smu.edu.sg

Seonghoon KIM
Singapore Management University, SEONGHOONKIM@smu.edu.sg

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Junxing Chay, Seonghoon Kim

School of Economics, Singapore Management University, Singapore

Correspondence: Junxing Chay, Duke-NUS Medical School, Singapore. Email: junxing.chay@duke-nus.edu.sg

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Abstract: Legalizing marijuana for medical purposes is a longstanding debate. However, evidence of marijuana's health effects is limited, especially for young adults. We estimate the health impacts of medical marijuana laws (MML) in the U.S. among young adults aged 18-29 years using the difference-in-differences method and data from the Behavioral Risk Factors Surveillance System. We find that having MMLs with strict regulations generate health gains, but not in states with lax regulations. Our heterogeneity analysis results indicate that individuals with lower education attainments, with lower household income and without access to health insurance coverage gain more health benefits from MML with strict regulations than from MML with lax regulations. The findings suggest greater net health gains under strict controls concerning marijuana supply and access.

Keywords: marijuana legalization, medical marijuana, mental health, physical health, self-reported general health, young adults

1 INTRODUCTION

Legalizing marijuana for medical purposes is a controversial subject. Numerous marijuana products have been marketed and used as therapeutic drugs or health supplements despite not being approved by the Food and Drug Administration (FDA) in the U.S.[1] Not only is evidence of marijuana's health effects limited (National Academies of Sciences, Engineering, and Medicine, 2017), but the potential exploitation of medical marijuana laws (MMLs) for recreational use is also a concern because of the associated harms to health and psychosocial functioning (World Health Organization [WHO], 2016).

As of December 2020, approximately 4.3 million American patients are using marijuana for medical purposes (Marijuana Policy Project [MPP], 2020). Despite its popular use, the following questions remain regarding medical marijuana legalization: Can prospective health gains from legitimate medical use be diminished or even surpassed by losses from recreational use? If so, which groups are most at risk and what role do regulations play in mitigating this adverse impact? To address these questions, this study examines the impact of MML on self-reported health measures of young adults using data from the Behavioral Risk Factors Surveillance System (BRFSS). We focus on young adults because they are especially vulnerable given that their prevalence of recreational use is higher than other age groups (Substance Abuse and Mental Health Services Administration, 2019). They are also more susceptible to long-term damage (Hall, 2015) and less likely to perceive marijuana as harmful after medical marijuana legalization (Wen, Hockenberry, & Druss, 2019). For identification, we use the difference-in-differences (DID) method exploiting variations in the timing of MML implementation across states.

We find that implementing MMLs significantly improves the health of young adults aged 18-29 living in states where universal medical and pharmaceutical standards are imposed on medical marijuana (i.e., “medicalized” MML). However, the estimated health impact of MML is small and insignificant among young adults living in states with lax access rules (i.e., “non-medical” MML). Furthermore, heterogeneous responses across population subgroups may have implications for inequality in health outcomes. We find that individuals with lower education attainment, with lower household income and without access to health insurance coverage gain more health benefits from MML with strict regulations than from MML with lax regulations.

These findings contribute to the literature in three ways. First, to the best of our knowledge, this is the first study to examine how MML affects the overall health of young adults. Several studies examine MML's impact on mortality rates due to suicide (Anderson et al., 2014; Grucza et al., 2015), traffic accidents (Anderson et al., 2013) and drug overdose (Powell, Pacula, & Jacobson, 2018; Shover et al., 2019; Smart, 2015). While informative, these extreme outcomes miss subtler health changes that are also of interest. Meanwhile, specific aspects of health, such as body weight (Sabia et al., 2017), mental health (Kalbfuß et al., 2018), and opioid addiction (Powell et al., 2018), are unlikely to reflect all potential avenues through which marijuana use can benefit or harm health. Using a broad health measure, such as self-reported general health status, is practical from a policy perspective because it summarizes net changes in health without requiring extensive knowledge about the underlying mechanisms and is widely available in several large-scale surveys. Our study is also related to the health impact of cannabis use. For example, van Ours and Williams (2011) and van Ours and Williams (2012) documented the negative mental and physical health consequences of using cannabis. Their findings are consistent with our results showing the negative (positive) health impacts of lax (strict) marijuana regulations among disadvantaged populations, which in turn illustrates the importance of drug policy on general health.

Second, this study shows substantial differences in health impacts based on the extent to which MML incorporates medical and pharmaceutical regulations. The dimensions along which MML differs range from legal definitions such as decriminalization, removal of state penalties for possession, and legal protection of dispensaries to implementation issues such as permitting home cultivation, treatment of unspecified pain, and regulating supply quality in a commercial market (Pacula & Smart, 2017). Due to the complexity of MML heterogeneity, most studies account for it by controlling for only a few provisions, for instance those concerning supply, such as dispensary operations and home cultivation (e.g., Kalbfuß et al., 2018; Pacula et al., 2015; Powell et al., 2018; Sabia et al., 2017). However, there is no a priori reason to ignore other provisions, especially those that restrict non-medical use. Following Abouk and Adams (2018), we adopt a more comprehensive MML classification originally developed by Williams et al. (2016) to assess the medical orientation of MML as a whole.

Third, this study highlights how sensitive the health of lower socioeconomic subgroups is to MML, medicalized or otherwise. Existing studies have only investigated heterogeneity by age and gender (e.g., Abouk & Adams, 2018; Smart, 2015). However, racial and ethnic differences in marijuana use (Keyes et al., 2017; Williams et al., 2019) and the fact that marijuana is not covered by health insurance have important implications for the role MML plays in persistent health disparities in the U.S (Singh et al., 2017; Zimmerman & Anderson, 2019). To our best knowledge, this study is the first to document the heterogeneous health effects of MML along with socioeconomic characteristics. The results suggest a narrowing of health inequality under “medicalized” MML. Our findings emphasize the importance of careful and rigorous policy designs in improving the general health of the young adult population.

The rest of this paper is organized as follows: Section 2 summarizes the background of MML in the U.S. and provides a brief literature review; Section 3 describes the BRFSS data; Section 4 details the empirical strategy; Section 5 reports the regression results; and Section 6 concludes the paper.

2 BACKGROUND AND LITERATURE REVIEW

The use of marijuana was illegal in the U.S. until 1996 (Marijuana Policy Project, 2016). It remains classified as a Schedule 1 drug along with heroin, ecstasy, and LSD.[2] A comprehensive review undertaken by the National Academies of Sciences, Engineering, and Medicine (2017) found mostly inconclusive evidence for marijuana's therapeutic effects and associated health risks. While strong empirical support exists for the use of marijuana to treat chemotherapy-induced nausea, chronic pain, and spasm caused by multiple sclerosis, there is also substantial evidence for risks such as bronchitis, cannabis use disorder, schizophrenia, motor vehicle crashes, and low birth weight.

Decisions to enact MML appear to be largely driven by public opinions and influential lobby groups (Cousijn et al., 2018). California was the first state to effectively remove criminal penalties for cultivation, possession and use of marijuana for qualified patients with a doctor's recommendation in 1996. Many other states gradually followed, enacting their own MML with varying provisions and conditions for medical use. As of December 2018, 33 states and the District of Columbia (D.C.) have MMLs that remove criminal penalties for possession and use of medical marijuana and allow a realistic means of access (e.g., home cultivation, dispensaries).[3] Supporting Information Section Table S1 details the dates of legalization of medical and recreational marijuana and the specific components of the marijuana programs implemented through the legislation.

Temporal and geographical variations in MML implementation present an opportunity to investigate its consequences. Marijuana use is of first-order interest in the literature. Studies on adult use tend to have insignificant findings due to unaccounted heterogeneity in laws (Pacula & Smart, 2017). However, more recent findings report positive effects on both extensive and intensive margins when narrowed to specific MML provisions or high-risk groups (Pacula et al., 2015; Smart, 2015; Wen et al., 2015). In particular, Chu (2014) finds sizable increases in illegal use based on marijuana possession arrests and admissions for marijuana abuse treatment. These findings reflect the concern that MML could encourage non-medical use through increased accessibility.

MML's influence on marijuana use can affect health through a variety of channels. In terms of its benefits, several studies find that MML leads to less pain among older adults (Nicholas and Maclean 2019), improved mental health (Kalbfuß et al., 2018), decreased body weight and obesity rates (Sabia et al., 2017), and reduced sickness absence from work (Ullman, 2017). Additionally, a reduction in prescriptions filled for diagnoses such as nausea, pain, depression and seizures suggests that marijuana is used as an alternative (Bradford & Bradford, 2017, 2018). In terms of adverse effects, there is no evidence that MML increases suicide rates (Anderson et al., 2014; Bartos et al., 2020; Grucza et al., 2015) despite marijuana's association with depression and suicide ideation and attempts (WHO, 2016). However, MML may increase the risk of cardiac death among older adults (Abouk & Adams, 2018).

In addition to increased marijuana consumption, MML can impact health through the degree to which harmful substances are substitutes or complements to marijuana. There is consistent evidence that MML decreases the use of illegal opioids (Chu, 2015; Powell et al., 2018; Smith, 2020), opioid-related deaths (Bachhuber et al., 2014; Kim et al., 2016; Powell et al., 2018; Smart, 2015) and hospitalizations (Shi, 2017). The effects of MML on alcohol consumption are mixed (Pacula et al., 2015; Santaella-Tenorio et al., 2017; Wen et al., 2015), and the effects on smoking are relatively unexplored (Choi et al., 2019).

The significant heterogeneity of health impacts across MML provisions likely reflects the heterogeneity in use. However, varying effects over a range of health outcomes make it challenging to interpret and inform policy decisions. For instance, lax regulation of dispensaries results in a greater reduction in opioid deaths (Powell et al., 2018), but the presence of dispensaries does not have an independent effect on opioid-related hospitalizations (Shi, 2017). Increased alcohol-related traffic fatalities are associated with the allowance of dispensaries (Pacula et al., 2015) but not with the actual operation of dispensaries (Santaella-Tenorio et al., 2017). There are several reasons for the lack of consistent results. First, dispensaries are associated with increased marijuana potency (Sevigny et al., 2014), which could have offsetting health effects. Second, most studies use a simple binary variable for dispensaries, which does not reflect the extent to which it is regulated or its population coverage within a state. Third, supply-side provisions such as dispensaries and home cultivation do not work in isolation. Other provisions, such as mandatory registration of medical marijuana users, supply quality regulations, and physician training for recommending marijuana, can also affect health outcomes.

To assess the health impact of MML provisions comprehensively, we investigate MML heterogeneity following Williams et al.'s (2016) classification. MML is identified as either "medicalized" or "non-medical" according to the basic tenets of medical practice, Current Good Manufacturing Practices,[4] and restrictions on controlled substances. Specifically, Williams et al. (2016) used the following seven components to classify medicalized marijuana programs: (1) physicians must have bona fide clinical relationships, (2) state licensing is required for manufacturing and dispensing, (3) testing and labeling of marijuana cannabinoid profile is required, (4) marijuana use is limited to non-smoked products, (5) supply of marijuana dispensed limited to 30-day amount with no refills, (6) a prescription drug monitoring program is operated, and (7) physician must complete training to be certified as marijuana-recommending provider. If a state meets the multiple medical components described above, the MML is considered medicalized. We applied the same methodology to classify medicalized marijuana programs of states legalized after 2016. Supporting Information Section Table S1, which is an updated version of the appendix table in Williams et al.'s (2016) study, reports the legalization status, dates, and characteristics of medical marijuana legalization laws. The last column of Panel B reports the total score, which is the number of components included in each state's medical marijuana law. Following Williams et al. (2016), we considered a state as a medicalized MML state if its score is two or above.

3 BEHAVIORAL RISK FACTOR SURVEILLANCE SYSTEM

The BRFSS is a repeated cross-sectional and nationally representative survey of U.S. residents. It is conducted annually via telephone survey.[5] Detailed questions on health conditions, health-related behaviors, use of healthcare services and basic demographic characteristics were collected from adults aged 18 and above. Supporting Information Section Table S2 summarizes respondent characteristics by states' MML status.

This study focuses on a self-assessed measure of general health of adults aged 18-29 from 50 states and D.C. over the years 1993-2018. The survey asks respondents, "Would you say that in general your health is excellent, very good, good, fair or poor?" To respect the ordinal nature of the variable, we estimate the health impact of MML using the heteroskedastic ordered probit model (see Section 4). In addition to self-assessed general health, we analyze the impact on the number of days in the past 30 days that a respondent's health has not been good, differentiating between physical health (e.g., physical illness and injury) and mental health (e.g., stress, depression, emotional problems).

4 EMPIRICAL STRATEGY

To identify the health impact of MML, we employed an ordered probit DID model.[6] Suppose the unobserved, underlying relationship between a continuous latent variable representing overall health status (y^*) as follows.

$$y^*_{ist} = \beta_0 + \beta_1 MML_{st} + \beta_2 X_{it} + \beta_3 Z_{st} + \alpha_s + \delta_t + \lambda_s t + \varepsilon_{ist} \quad (1)$$

MML_{st} is a dummy variable indicating that state s has an MML in effect at period t. The value of MML_{st} is determined daily using the exact interview date. β_1 is the causal effect of interest here, representing the impact of MML. α_s captures any time-invariant state characteristics. δ_t non-parametrically captures year-quarterly trends common across states, while $\lambda_s t$ captures any unobserved state heterogeneity that trends linearly. ε_{ist} is an error term.

X_{it} is a vector of individual and household characteristics such as age, ethnicity, gender, educational attainment, marital status, health insurance coverage, household income relative to the federal poverty level (FPL), and the presence of any child in the household. More importantly, the regression controls for time-varying health determinants at the state level that potentially correlate with the adoption of MML. Z_{st} is a vector of state characteristics that include unemployment rate, beer and cigarette excise tax rate, and Medicaid expansion status. We also control for whether recreational use is legalized to isolate the effects of MML only. Some of these controls may be affected by MML, resulting in potentially biased estimates. However, we show that including them does not materially change point estimates.

While y^*_{ist} is not observable, we can observe an ordinal health measure y_{ist}. It takes the value as 1 (poor) if $y^*_{ist} \leq \phi_1$, 2 (fair) if $\phi_1 < y^*_{ist} \leq \phi_2$, 3 (good) if $\phi_2 < y^*_{ist} \leq \phi_3$, 4 (very good) if $\phi_3 < y^*_{ist} \leq \phi_4$, 5 (excellent) if $\phi_4 < y^*_{ist}$ where ϕ_1 to ϕ_4 denote the cutoff values.

Thus, the probabilities of each ordinal response can be written as follows:

$$Pr\left(y_{ist}=1\right)=\Phi\left(\lambda_1-\beta_1 MML_{st}-\beta_2 X_{it}-\beta_3 Z_{st}-\alpha_s-\delta_t-\lambda_s t\right) \tag{2}$$

$$Pr\left(y_{ist}=k\right)=\Phi\left(\lambda_k-\beta_1 MML_{st}-\beta_2 X_{it}-\beta_3 Z_{st}-\alpha_s-\delta_t-\lambda_s t\right)$$
$$-\Phi\left(\lambda_{k-1}-\beta_1 MML_{st}-\beta_2 X_{it}-\beta_3 Z_{st}-\alpha_s-\delta_t-\lambda_s t\right)\forall k\in\left(2,3,4\right) \tag{3}$$

$$Pr\left(y_{ist}=5\right)=\Phi\left(\lambda_4-\beta_1 MML_{st}-\beta_2 X_{it}-\beta_3 Z_{st}-\alpha_s-\delta_t-\lambda_s t\right) \tag{4}$$

where $\lambda_k=\phi_k-\beta_0$.

The key identification assumption is that the counterfactual trend in health outcomes of MML states is parallel to those of non-MML states. Therefore, we include the pre-MML effects up to 5 years before MML implementation. The presence of pre-treatment effects indicates a violation of the common trend assumption. We also adopt a flexible specification for post-treatment effects in later analyses, replacing MML_{st} with a set of dummies to allow for annual effects up to 5 years after treatment.

We acknowledge that our primary dependent variable, self-reported overall health status, rated on a 5-item Likert scale, is subjective. Therefore, researchers cannot observe the true cardinal values of respondents' overall health. Because of this limitation, in the context of happiness and life satisfaction outcomes, Schröder and Yitzhaki (2017) and Bond and Lang. (2019) argue that researchers cannot identify true impacts. This logic can, in principle, be applicable to any kind of subjective measure including the self-reported health status variable. However, Kaiser and Vendrik (2020) provide evidence that this identification failure occurs only in extreme cases. In addition, Chen et al. (2019) show that using the heteroskedastic ordered probit model can overcome the identification problem addressed by Bond and Lang (2019).[7] Hence, to address the ordinal nature of the self-reported health status variable, we use the heteroskedastic ordered probit model. For other variables such as the number of days in bad health, we use the linear regression model.

We acknowledge that using the non-linear DID model can be problematic. First, the use of fixed effects in non-linear models (e.g., probit or logit) can lead to incidental parameters resulting in biased estimates. However, Greene (2004, p.144) states that the finite sample bias due to the use of fixed effects in the ordered probit model "drops off rapidly as T increases to 3 and more." Although we cannot completely rule out the possibility of the incidental parameter problem, the data length of our study is 26. This suggests that the magnitude of the bias, if any, is sufficiently small.

Second, the coefficient estimate of the DID term (in our case, β_1) in non-linear models is not likely the same as the treatment effect of intervention or policy reform we are interested in (Ai & Norton, 2003; Puhani, 2012). To address this issue, we reported not only coefficient estimates but also average marginal effects computed using the coefficient estimates following Puhani's (2012, p. 6) definition of the difference-in-differences treatment effect in non-linear models.

In the initial analysis, we use the full sample to estimate the impact of MML. This approach unrealistically assumes homogeneous effects across states. Under heterogeneous effects, the estimate simply represents the average impact of different types of MMLs. To examine the different impacts of strict and lax regulations, we conduct a series of subsample analyses. The analysis of "medicalized" MML restricts the sample to states with "medicalized" MML (Arkansas, Connecticut, D.C., Delaware, Florida, Illinois, Louisiana, Maryland, Massachusetts, Minnesota, Missouri, New Hampshire, New Jersey, New York, North Dakota, Ohio, Oklahoma, Pennsylvania, Utah, and West Virginia) and non-MML states. Similarly, the analysis of "non-medical" MML restricts the sample to states with "non-medical" MML (Alaska, Arizona, California, Colorado, Hawaii, Maine, Michigan, Montana, Nevada, New Mexico, Oregon, Rhode Island, Vermont, and Washington) and non-MML states. This approach implies that the classification of MML states does not change over time. Policy amendments over the analysis period mostly concern the allowance of dispensaries among "non-medical" MML states, which would not have affected classification (Chapman et al., 2016). It also assumes that non-MML states are the appropriate control group, which is supported by the data. Retaining the same set of non-MML states in the sample allows a clearer comparison of the impacts of the 2 types of MML.

5 RESULTS

5.1 Impact of MML on self-assessed health

Table 1 reports the effects of any MML on the self-assessed health status of young adults aged 18-29. We report the coefficient estimates using the heteroskedastic ordered probit model in Panel A. Column 1 begins with a basic specification, controlling only for year-quarter fixed effects, state fixed effects, and state-specific linear time trends. The estimated impact of MML_{st} is positive but statistically significant only at the 10% level. None of the coefficient estimates of the pre-treatment effects is statistically significant from zero, supporting the parallel trend assumption. In Column 2, we include demographic and state characteristics that are unlikely to be outcomes of MML. Subsequently, potential bad controls that may be directly affected by MML were added in Column 3. The coefficient estimates of both columns are statistically significant at the 5% level.[8]

TABLE 1. Overall impact of any MML on self-assessed health score using the heteroskedastic ordered probit model

	(1)	**(2)**	**(3)**
Panel A: Coefficient estimate			
5 years prior	0.0278	0.0263*	0.0187
	(0.0179)	(0.0159)	(0.0202)
4 years prior	0.0296	0.0210	0.0048
	(0.0260)	(0.0196)	(0.0195)
3 years prior	0.0206	0.0195	−0.0031
	(0.0136)	(0.0131)	(0.0155)
2 years prior	0.0298	0.0453**	0.0128
	(0.0270)	(0.0201)	(0.0210)
1 year prior	−0.0066	0.0039	−0.0219
	(0.0243)	(0.0181)	(0.0223)
MML	0.0539*	0.0654**	0.0485**
	(0.0286)	(0.0269)	(0.0227)
Panel B: Average marginal effect			
Pr (excellent)	0.0142*	0.0185**	0.0141**
	(0.0076)	(0.0076)	(0.0066)
Pr (very good)	0.0022*	0.0028**	0.0018**
	(0.0011)	(0.0012)	(0.0009)
Pr (good)	-0.0102*	-0.0129**	-0.0098**
	(0.0054)	(0.0053)	(0.0046)
Pr (fair)	-0.0052*	-0.0069**	-0.0050**
	(0.0028)	(0.0029)	(0.0024)
Pr (poor)	-0.0010**	-0.0015**	-0.0011**
	(0.0005)	(0.0006)	(0.0005)
Demographic and state controls	No	Yes	Yes
Other controls	No	No	Yes
Observations	872,016	870,098	730,929

Note: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. All regressions control for year-quarter and state fixed effects, and state-specific linear time trends. Demographic and state controls include age, race/ethnicity, gender, marital status, presence of children in household, Medicaid expansion status, cigarette and beer excise tax rate. Other controls include education, health insurance coverage, household income relative to FPL, unemployment rate, and whether state legalized recreational marijuana. Abbreviation: MML, medical marijuana laws.

For the convenience of interpretation and to assess the overall impact of MML after accounting for the ordinal nature of the dependent variable, we report the average marginal effects in Panel B. We find that the introduction of MML leads to an increase in the probability of reporting excellent health by 1.4−1.8pp. It also reduces the probability of reporting poor health by 1.0−1.5pp. Most of these changes are statistically significant at the 5% level. In addition, Appendix Tables 4 and 5 show that MML also reduces the number of days in bad physical mental health, respectively although the physical health impact is imprecisely estimated.[9]

Using the full model specification from Table 1, we analyze the impact of MML on self-reported health status. Table 2 presents the results for different types of MML. Columns 1 and 2 report the health impact of "medicalized" and "non-medical" MML, respectively. We find a stark difference between the 2 types of MMLs. In Column 1 of Panel A, the coefficient estimate of "medicalized" MML using the heteroskedastic ordered probit model is statistically significant at the 1% level. In contrast, "non-medical" MML appears to have no significant impact on health at all. Column 1 of Panel B indicates that "medicalized" MML increases the probability of reporting excellent or very good health, while it reduces the probability of reporting poor, fair, or good health, and the changes are all statistically significant at the 1% level. Column 2 of Panel B shows that "non-medical" MML leads to similar qualitative changes but none of the changes are statistically significant. The results reported in Table 2 demonstrate the importance of accounting for differences in regulations when evaluating MMLs.

TABLE 2. Heterogenous impact of MML on self-assessed health status using the heteroskedastic ordered probit model

	Self-reported health status	
Dependent variable	**(1)** **Medicalized MML states**	**(2)** **Non-medical MML states**
Panel A: Coefficient estimate		
5 years prior	0.0190	0.0188
	(0.0233)	(0.0242)
4 years prior	0.0247	-0.0145
	(0.0216)	(0.0263)
3 years prior	0.0142	-0.0152
	(0.0176)	(0.0239)
2 years prior	0.0347	0.0033
	(0.0248)	(0.0290)
1 year prior	-0.0134	-0.0308
	(0.0262)	(0.0344)
"Medicalized" MML	0.0612***	
	(0.0227)	
"Non-medical" MML		0.0440
		(0.0318)
Panel B: Average marginal effect		
Pr (excellent)	0.0182***	0.0126
	(0.0067)	(0.0091)
Pr (very good)	0.0021***	0.0019
	(0.0008)	(0.0014)
Pr (good)	-0.0126***	-0.0088
	(0.0046)	(0.0064)
Pr (fair)	-0.0062***	-0.0047
	(0.0023)	(0.0034)
Pr (poor)	-0.0014***	-0.0010

Dependent variable	Self-reported health status	
	(1)	(2)
	Medicalized MML states	Non-medical MML states
	(0.0005)	(0.0007)
Observations	539,219	521,244

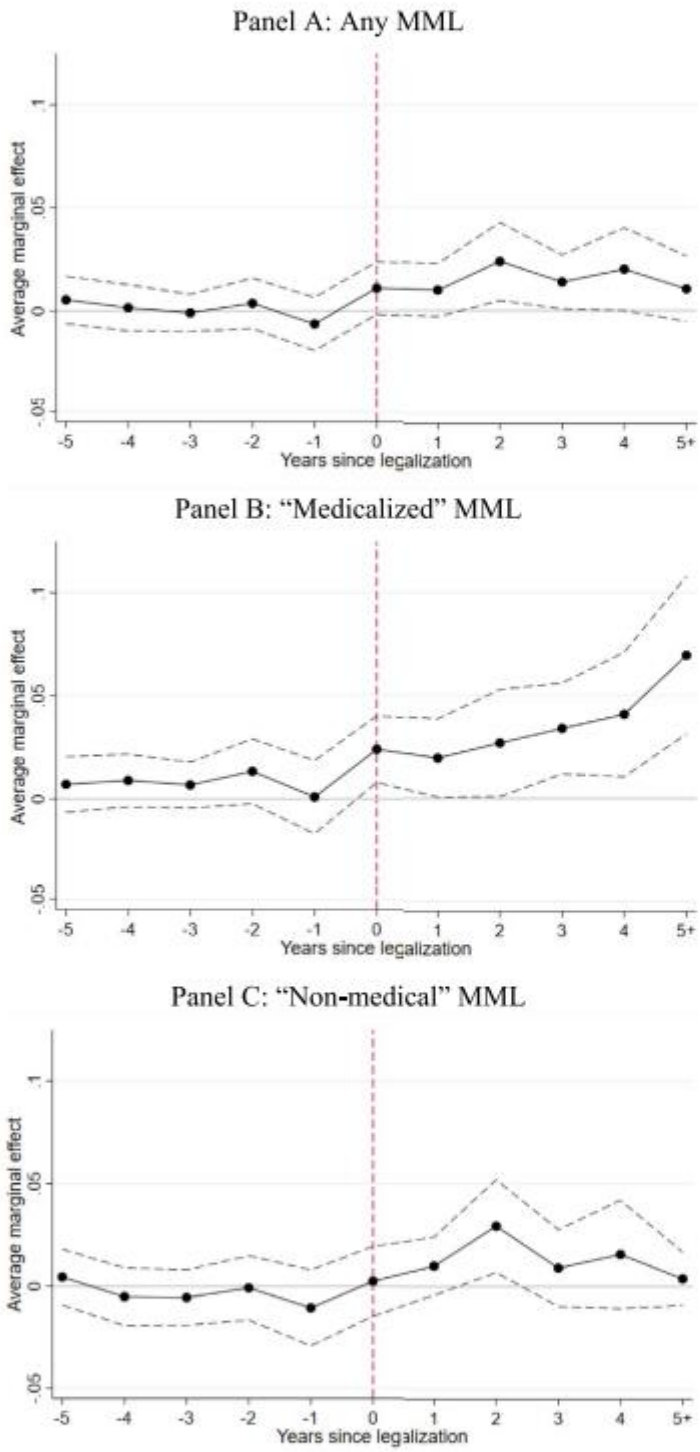
Note: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Estimates obtained from the model specification used in column 3 of Table 1. Column 1 uses non-MML states and states with "medicalized" MML. Column 2 uses non-MML states and states with "non-medical" MML. Abbreviation: MML, medical marijuana laws.

To estimate dynamic treatment effects, we replace MML_{st} in the baseline specification with dummy variables for each year before and after the MML took effect. The effects for more than 5 years before MML form the baseline and are set to zero. Figure 1 plots the results by type of MML. Solid lines represent the average marginal effects on the probability of reporting excellent health for each year before and after the MML, while dotted lines indicate 95% confidence intervals. The average marginal effects were computed using the DID estimates obtained from the heteroskedastic ordered probit model. Pre-MML effects are generally near zero for all panels, which supports causal interpretation. Panel A shows that the average health impact of any MML is slightly positive. Panels B and C reveal that this effect is largely driven by "medicalized" MML states. Self-reported health status improves considerably following the implementation of "medicalized" MML and continues to rise up to 5 years post-MML. In contrast, there is no discernible impact of "non-medical" MML, with post-MML effects being smaller in magnitude and statistically insignificant except for one year. The observed effects for "medicalized" MML do not appear to be predominantly driven by one state. Excluding any "medicalized" MML state from the analysis yields similar effects (see Supporting Information Section Figure S1).

Our baseline estimates are also robust to more flexible state-specific time trends, restriction to only "medicalized" MML states. The regression results are presented in Supporting Information Section Table S6. Using state-specific quadratic trends produces a similar estimated effect, although the coefficient estimate is statistically significant only at the 10% level. Considering only "medicalized" MML states is equivalent to an event study design. Regression on the restricted sample yielded a similar result.

To address concerns related to strong distributional assumptions under the ordered probit model, we estimated the effects of MML using a linear probability model on four dependent dummy variables: excellent, very good or better, good or better, and fair or better health (see Supporting Information Section Table S7 and Supporting Information Section Figure S2). The estimates yield similar conclusions that "medical" MML has a greater and more sustained health improvement compared to "non-medical" MML.

FIGURE 1: Dynamic impact of medical marijuana laws (MML) on the probability of reporting excellent health. *Notes*: Solid circles represent the average marginal effect on the probability of reporting excellent health for each year before and after the MML. Dotted lines indicate 95% confidence intervals. Standard errors are clustered at the state-level. The average marginal effects were computed using the DID estimates obtained from the heteroskedastic ordered probit model specification (column 3 of Table 1). Panel B uses non-MML states and states with "medicalized" MML. Panel C uses non-MML states and states with "non-medical" MML



5.2 Heterogeneity analysis

We first examine demographic heterogeneity over the distribution of health status following the implementation of different MML types. Table 3 reports the results by ethnicity, showing significant improvements under "medicalized" MML for Whites, but not for Blacks and Hispanics. We find that "medicalized" MML increases the probability of reporting excellent health by 2.2pp among non-Hispanic Whites, and the change is statistically significant at the 1% level. In column 4, we find that "non-medical" MML improves health of non-Hispanic Blacks but the estimate is statistically significant only at the 10% level.

TABLE 3. Overall impact of MML on self-assessed health status by race/ethnicity

Dependent variable: Self-reported health status						
Group	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	White non-Hispanic		**Black non-Hispanic**		**Hispanic**	
Panel A: Coefficient estimate						
"Medicalized" MML	0.0680***		0.0379		0.0647	
	(0.0252)		(0.0606)		(0.117)	
"Non-medical" MML		0.0581		0.132*		0.0406
		(0.0399)		(0.0771)		(0.0574)
Panel B: Average marginal effect						
Pr (excellent)	0.0224***	0.0186	0.0111	0.0376*	0.0167	0.0104
	(0.0082)	(0.0127)	(0.0180)	(0.0222)	(0.0301)	(0.0146)
Pr (very good)	0.0010***	0.0012	0.0023	0.0081*	0.0060	0.0041
	(0.0004)	(0.0008)	(0.0038)	(0.0048)	(0.0109)	(0.0058)
Pr (good)	-0.0157***	-0.0132	-0.0074	-0.0250*	-0.0100	-0.0063
	(0.0058)	(0.0090)	(0.0120)	(0.0147)	(0.0192)	(0.0089)
Pr (fair)	-0.0062***	-0.0052	-0.0050	-0.0171*	-0.0106	-0.0070
	(0.0023)	(0.0036)	(0.0081)	(0.0101)	(0.0192)	(0.0098)
Pr (poor)	-0.0015***	-0.0013	-0.0011	-0.0037*	-0.0021	-0.0012
	(0.0006)	(0.0009)	(0.0017)	(0.0022)	(0.0037)	(0.0017)
Observations	388,377	370,376	68,040	48,359	53,571	64,075

Note: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with "medicalized" MML. Even columns use non-MML states and states with "non-medical" MML. Abbreviation: MML, medical marijuana laws.

Table 4 reports heterogeneity by educational attainment. Column 1 of Panel A shows that less-educated individuals appear to be better off under "medicalized" MML, while we do not see any significant change under "non-medical" MML. Column 1 of Panel B indicates that "medicalized" MML increases the probabilities of reporting excellent and very good health, while it reduces the probabilities of reporting good, fair, and poor health. In contrast, individuals with postsecondary education benefit from both types of MML, albeit more substantially under "non-medical" MML. The observation that more-educated individuals experienced positive health impact from "non-medical" MML than less educated individuals is consistent with the efficient producer hypothesis, which states that more-educated individuals have higher returns to health investment because they have better understanding of health benefits and risks associated with their actions (Grossman, 1972). The findings of our study show that more-educated individuals are less likely to misuse marijuana to the extent of affecting their health negatively affected when marijuana is more accessible (i.e., under non-medical MML).

TABLE 4. Overall impact of MML on self-assessed health status by education attainment

Dependent variable: Self-reported health status				
Group	**(1)**	**(2)**	**(3)**	**(4)**
	High school or lower		**Post-secondary**	
Panel A: Coefficient estimate				
"Medicalized" MML	0.0883**		0.0523*	
	(0.0355)		(0.0292)	
"Non-medical" MML		-0.0056		0.0993***
		(0.0455)		(0.0365)
Panel B: Average marginal effect				
Pr (excellent)	0.0215***	-0.0013	0.0172*	0.0317***
	(0.0084)	(0.0106)	(0.0098)	(0.0113)
Pr (very good)	0.0072***	-0.0005	-0.0005*	-0.0004***
	(0.0027)	(0.0040)	(0.0003)	(0.0001)
Pr (good)	-0.0148***	0.0009	-0.0116*	-0.0218***
	(0.0057)	(0.0072)	(0.0066)	(0.0078)
Pr (fair)	-0.0112***	0.0007	-0.0042*	-0.0078***
	(0.0044)	(0.0061)	(0.0024)	(0.0028)
Pr (poor)	-0.0027***	0.0002	-0.0008*	-0.0016***
	(0.0011)	(0.0014)	(0.0005)	(0.0006)
Observations	195,798	193,433	314,190	289,377

Note: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by *p < 0.1, **p < 0.05, ***p < 0.01. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with "medicalized" MML. Even columns use non-MML states and states with "non-medical" MML. Abbreviation: MML, medical marijuana laws.

Table 5 reports heterogeneity by household income relative to the relevant FPL. Columns one and two indicate that individuals with lower household income benefit 4-5 times more from "medicalized" MML than from "non-medical" MML. However, we observe little difference in the estimated health impact between "medicalized" MML and "non-medicalized" MML among higher income groups (Columns 4-6).

TABLE 5. Overall impact of MML on self-assessed health status by household income

Dependent variable: Self-reported health status						
Group	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	<200% FPL		**200-400% FPL**		**>400% FPL**	
Panel A: Coefficient estimate						
"Medicalized" MML	0.1010**		0.0243		0.0792**	
	(0.0489)		(0.0351)		(0.0362)	
"Non-medical" MML		0.0213		0.0394		0.0821
		(0.0336)		(0.0554)		(0.0533)
Panel B: Average marginal effect						
Pr (excellent)	0.0232**	0.0047	0.0071	0.0118	0.0288**	0.0289
	(0.0112)	(0.0074)	(0.0102)	(0.0165)	(0.0131)	(0.0186)
Pr (very good)	0.0090**	0.0019	0.0009	0.0016	-0.0030**	-0.0024
	(0.0042)	(0.0030)	(0.0012)	(0.0022)	(0.0013)	(0.0015)
Pr (good)	-0.0149**	-0.0030	-0.0053	-0.0088	-0.0189**	-0.0194
	(0.0072)	(0.0047)	(0.0075)	(0.0123)	(0.0086)	(0.0124)
Pr (fair)	-0.0136**	-0.0029	-0.0023	-0.0039	-0.0058**	-0.0059

Dependent variable: Self-reported health status

Group	(1)	(2)	(3)	(4)	(5)	(6)
	<200% FPL		200-400% FPL		>400% FPL	
	(0.0067)	(0.0046)	(0.0033)	(0.0054)	(0.0026)	(0.0039)
Pr (poor)	-0.0038**	-0.0007	-0.0004	-0.0007	-0.0011**	-0.0011
	(0.0017)	(0.0011)	(0.0006)	(0.0010)	(0.0005)	(0.0007)
Observations	165,261	167,932	170,445	166,529	174,282	148,349

Note: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with "medicalized" MML. Even columns use non-MML states and states with "non-medical" MML. Abbreviation: MML, medical marijuana laws.

Table 6 reports heterogeneity by health insurance status. Consistent with the heterogeneity pattern by household income in Table 5, we find that uninsured individuals gain more health benefits from "medicalized" MML than from "non-medical" MML. However, none of the coefficient estimates in Columns 1 and 2 are statistically significant at the 5% level. As in the case of higher income groups, we observe little difference in the estimated health impact between "medicalized" MML and "non-medical" MML among individuals with access to health insurance coverage.

TABLE 6. Overall impact of MML on self-assessed health status by health insurance status

Dependent variable: Self-reported health status

Group	Uninsured		Insured	
	(1)	(2)	(3)	(4)
Panel A: Coefficient estimate				
"Medicalized" MML	0.1070*		0.0542***	
	(0.0651)		(0.0208)	
"Non-medical" MML		0.0116		0.0647*
		(0.0432)		(0.0339)
Panel B: Average marginal effect				
Pr (excellent)	0.0260*	0.0019	0.0173***	0.0191*
	(0.0155)	(0.0108)	(0.0066)	(0.0102)
Pr (very good)	0.0101*	0.0008	0.0008***	. 0015*
	(0.0059)	(0.0047)	(0.0003)	(0.0008)
Pr (good)	-0.0172*	-0.0012	-0.0120***	-0.0135*
	(0.0102)	(0.0070)	(0.0045)	(0.0072)
Pr (fair)	-0.0154*	-0.0012	-0.0050***	-0.0059*
	(0.0092)	(0.0070)	(0.0019)	(0.0032)
Pr (poor)	-0.0036*	-0.0003	-0.0011***	-0.0012**
	(0.0020)	(0.0015)	(0.0004)	(0.0006)
Observations	107,357	108,061	402,631	374,749

Note: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with "medicalized" MML. Even columns use non-MML states and states with "non-medical" MML. Abbreviation: MML, medical marijuana laws.

The results reported in Tables 4-6 suggest that health benefit from medical marijuana legalization among low-educated, low-income, and uninsured individuals is mitigated in states predisposed to greater non-medical use. However, we acknowledge that the cost of medical marijuana usage on a regular basis can be high and it is generally not covered under health insurance. Possible explanations for the larger benefit of medicalized MML among the low socio-economic status (SES) group are: 1) medical marijuana may still be cheaper and more accessible than other pharmaceutical drugs (Kruger and Kruger, 2019) and 2) lower SES individuals may benefit more from medicalized MML than higher SES individuals as they face a steeper health production function due to their lower overall health status. Our findings imply the importance of government regulations required to avoid the misuse of marijuana and maximize its medical benefits.

Figure 2 presents the heterogeneous dynamic treatment effect estimates of "medicalized" MML by computing the average marginal effects on the probability of reporting excellent health. As in Figure 1, we replace MML_{st} in the baseline specification with dummy variables for each year before and after the MML took effect. Graphical evidence is consistent with the regression results reported in Tables 3-6.[10] The corresponding figures for the "non-medical" MML impact are presented in Supporting Information Section Figure 5. Our findings on demographic heterogeneity are also robust to a more flexible model specification based on a series of linear probability models (Supporting Information Section Tables S8-S11).

6 CONCLUDING REMARKS

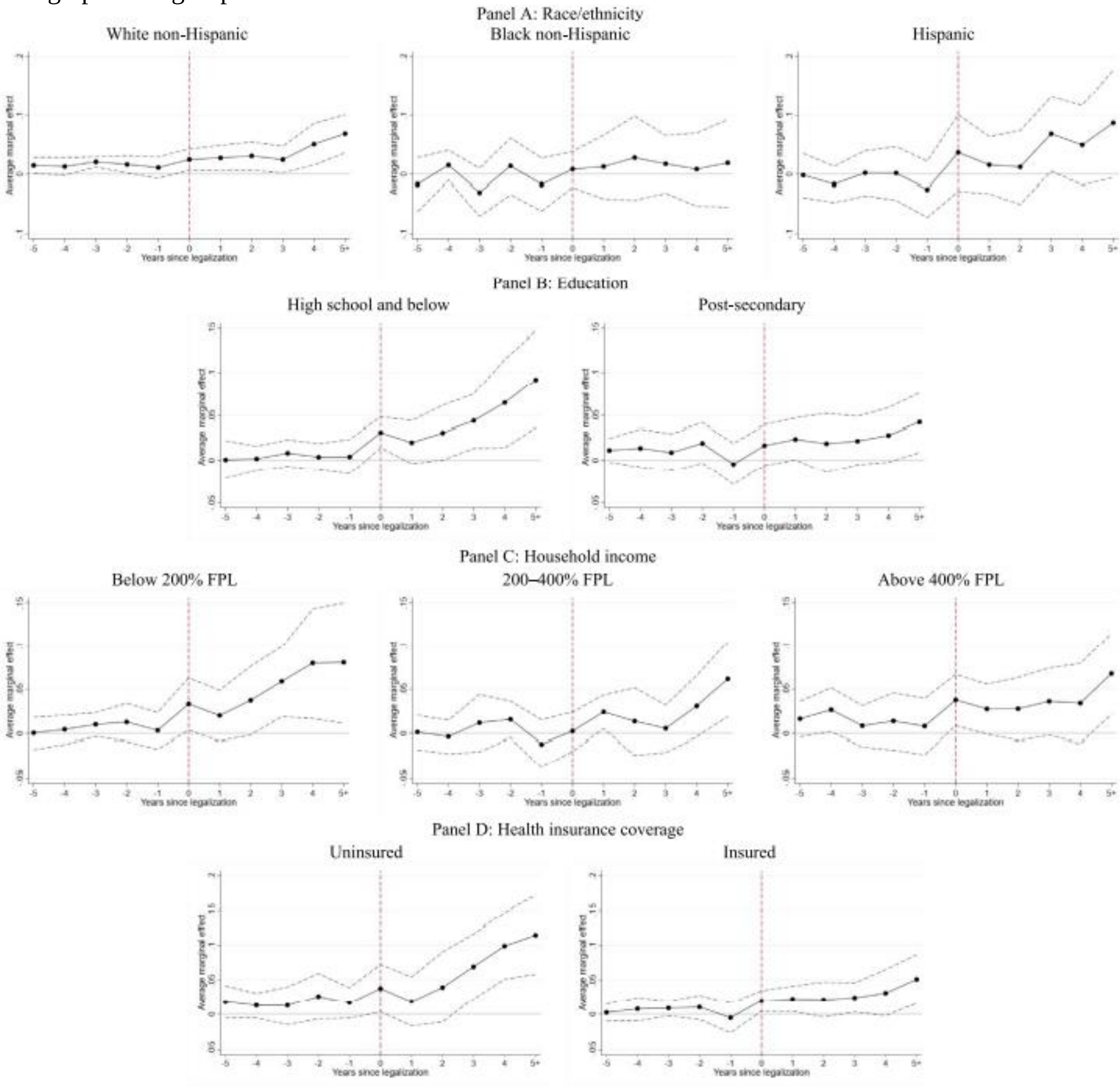
This study finds that MMLs that incorporate more medically oriented regulations improve the self-assessed health of young adults aged 18-29 relative to states without MML. Our findings suggest that future research on health outcomes should consider a wider range of MML provisions. Our heterogeneity analysis results indicate that individuals with lower education attainments, with lower household income and without access to health insurance coverage gain more health benefits from MML with stricter regulations than from MML with lax regulations.

These findings highlight the importance of government regulations for avoiding health crises, such as the current opioid epidemic in the U.S. Like opioids, marijuana offers potential therapeutic benefits when used in a controlled manner and consistent with established medical principles. Evidence from this study suggests greater net health gains under stricter controls concerning supply and access of marijuana. Drawing parallels to how the opioid epidemic developed, state governments may also do well to err on the side of caution when liberalizing marijuana. We still have little knowledge of medical marijuana's propensity for misuse and addiction or its long-term effects. If the rate of marijuana liberalization outpaces understanding of its risks, the U.S. may be in danger of another costly health crisis.

This study has two limitations. First, Shover et al. (2019) document that the previously existing negative association between MMLs and opioid overdose mortality is reversed when using more recent data. They argue that, as medicalized marijuana programs tend to occur later than non-medical marijuana programs, the association between medicalized marijuana laws and opioid deaths is likely to be spurious. By the same token, it is possible that our estimate of the treatment effect of medicalized marijuana programs is biased by other simultaneous changes in general health status correlated with the timing of the introduction of medicalized marijuana programs. Although we provide evidence of parallel pre-reform trends and control for state-specific time trends and other controls, further research is warranted to strengthen the causal interpretation of our findings. Second, our analysis is based on a sample of young adults aged 18-29. Although we focus on this age group owing to potential long-term consequences of marijuana use, this limits the generalizability of the findings to older populations.

FIGURE 2: Impact of "medicalized" medical marijuana laws (MML) on the probability of reporting excellent health by demographic characteristics. *Notes*: Solid circles represent the average marginal effect

on the probability of reporting excellent health for each year before and after the “medicalized” MML compared to no MML. Dotted lines indicate 95% confidence intervals. Standard errors are clustered at the state-level. The average marginal effects were computed using the DID estimates obtained from the heteroskedastic ordered probit model specification (column 3 of Table 1) estimated for a given demographic subgroup.



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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at https://www.cdc.gov/brfss/annual_data/annu al_data.htm

ENDNOTES

[1] Only a few marijuana-derived and synthetic marijuana-related products, such as Epidiolex (cannabidiol), Marinol (dronabinol), Syndros (dronabinol), and Cesamet (nabilone), have been approved for treating specific forms of epilepsy and chemo-induced nausea.
[2] See the U.S. Drug Enforcement Administration website (https://www.dea.gov/drug-scheduling) for more information.
[3] We use the BRFSS data up to 2018. Thus, we consider MML up to 2018. As of November 2020, 36 states and the D.C. implemented MML.
[4] The main regulatory standard set by the FDA to certify pharmaceutical quality.
[5] Cellular phone lines were included from 2011 onwards. All estimates use the sampling weights provided.
[6] Courtemanche and Zapata (2014) also used the ordered probit DID model to estimate the health impact of the Massachusetts healthcare reform. We closely follow their discussion of the ordered probit DID model.
[7] We allow the variance to be modeled as a function of age, race/ethnicity, gender, educational attainment dummies, marital status, and the presence of any child in the household.
[8] We acknowledge that the coefficient estimate of the two-year anticipation effect prior to MML is statistically significant at 5% level in Column 2. However, the corresponding estimates in Columns 1 and 3 are statistically insignificant. Supporting Information Section Table 3 shows that the baseline result remains robust to different lengths of anticipation effect except that the estimate of the 1-year lagged effect is statistically significant at 5% level in Column 4.
[9] Similar to Kalbfuß et al. (2018), we find significant anticipatory effects on mental health up to 2 years prior to MML.
[10] We also find similar results for days of bad physical and mental health (see Supporting Information Section Figures S3 and S4). However, the estimates are less precise and the difference between “medicalized” and “non-medical” MML are less obvious.

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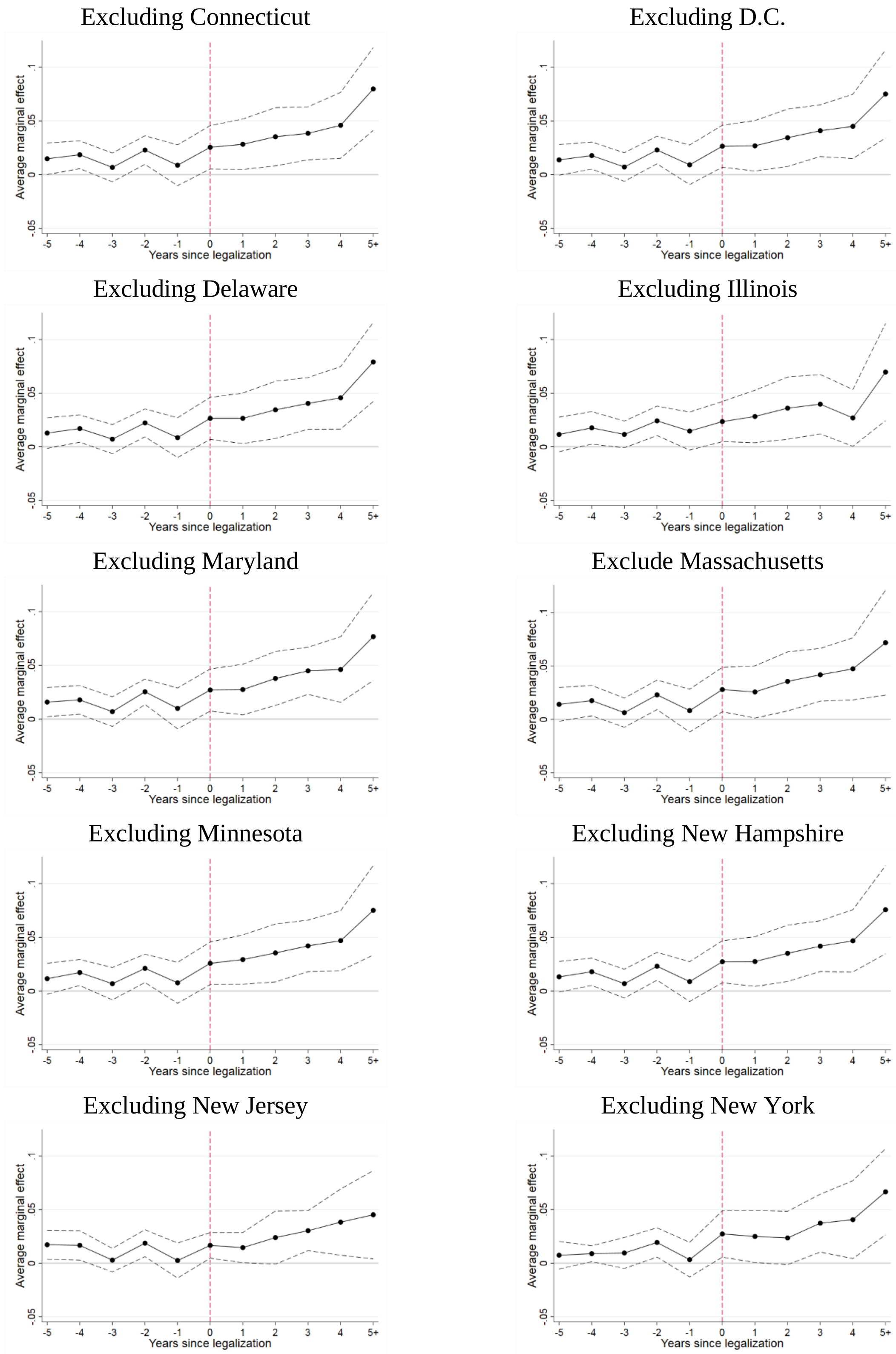
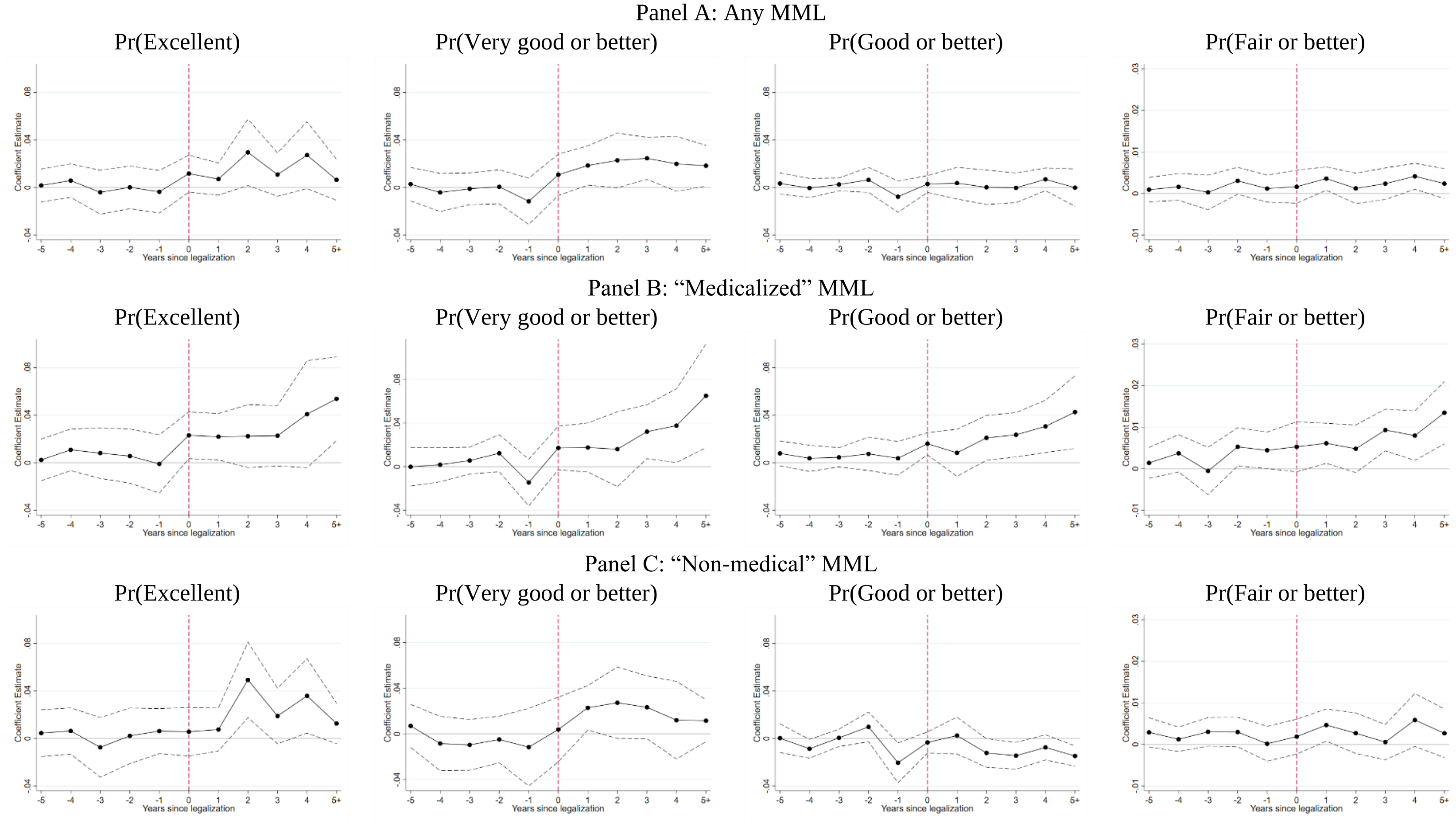
Figure S1: Impact of “Medicalized” MML on the probability of reporting excellent health



Notes: Solid circles represent the average marginal effect on the probability of reporting excellent health for each year. Dotted lines indicate 95% confidence intervals. Standard errors are clustered at the state-level. The average marginal effects were computed using the DID estimates obtained from the heteroskedastic ordered probit model specification. We excluded states that legalized MML after 2015 due to the short post-reform periods only in this analysis.

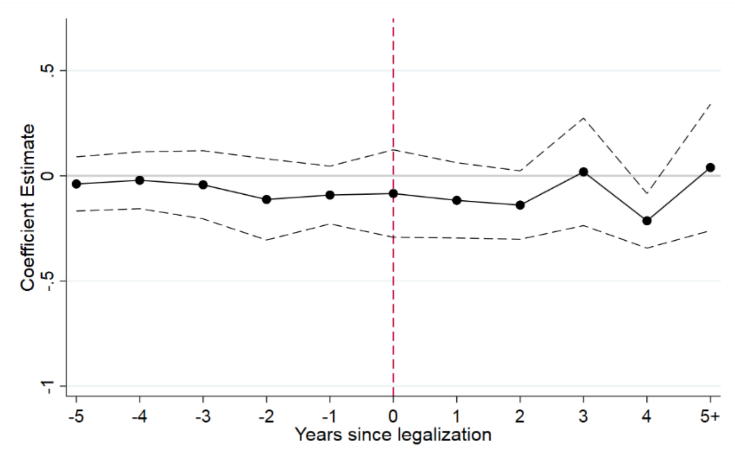
Figure S2: Dynamic impact of MML on self-assessed health status using the linear specification



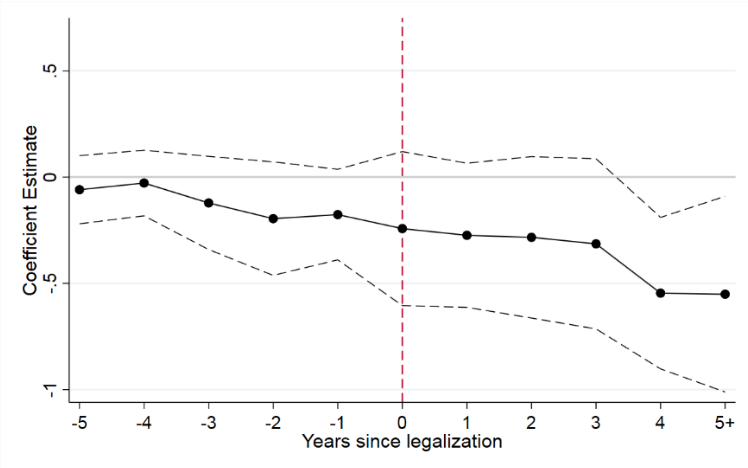
Notes: Solid circles represent point estimates. Dotted lines indicate 95% confidence intervals. Standard errors are clustered at the state-level. Estimates obtained from the linear regression specification with the same control variables used in column 3 of Table 1. Panel B uses non-MML states and states with “medicalized” MML. Panel C uses non-MML states and states with “non-medical” MML

Figure S3: Impact of MML on days in bad physical health

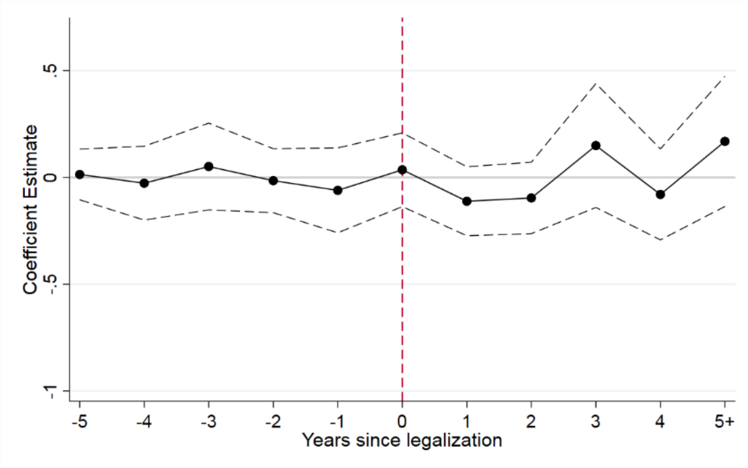
Panel A: Any MML



Panel B: "Medicalized" MML



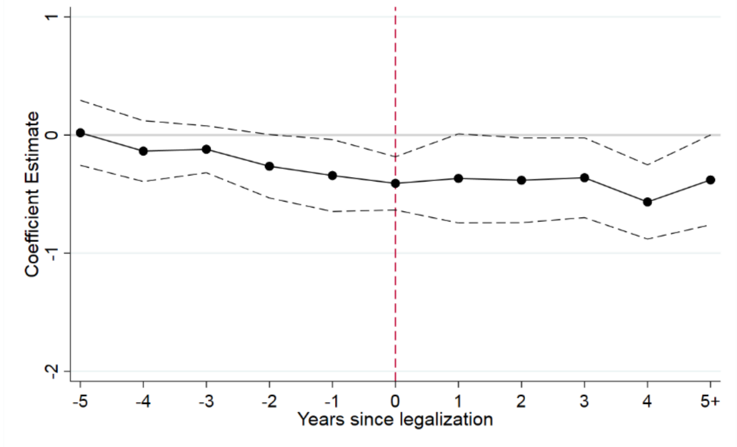
Panel C: "Non-medical" MML



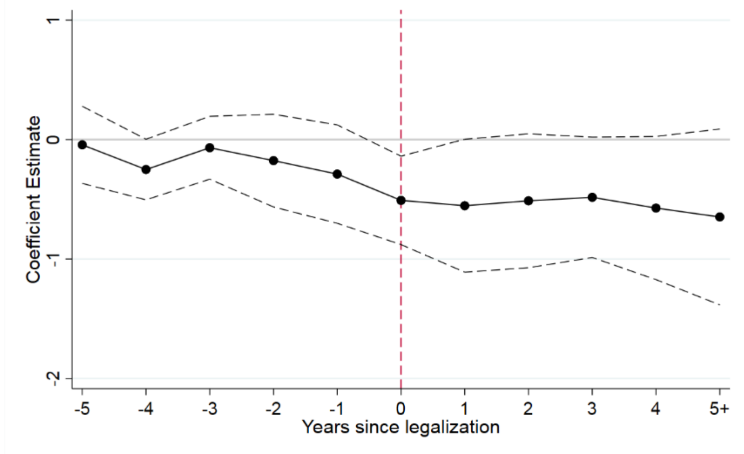
Notes: Solid circles represent point estimates. Dotted lines indicate 95% confidence intervals. Standard errors are clustered at the state-level. Estimates obtained from the heteroskedastic ordered probit model specification used in column 3 of Table 1. Panel B uses non-MML states and states with "medicalized" MML. Panel C uses non-MML states and states with "non-medical" MML.

Figure S4: Impact of MML on days in bad mental health

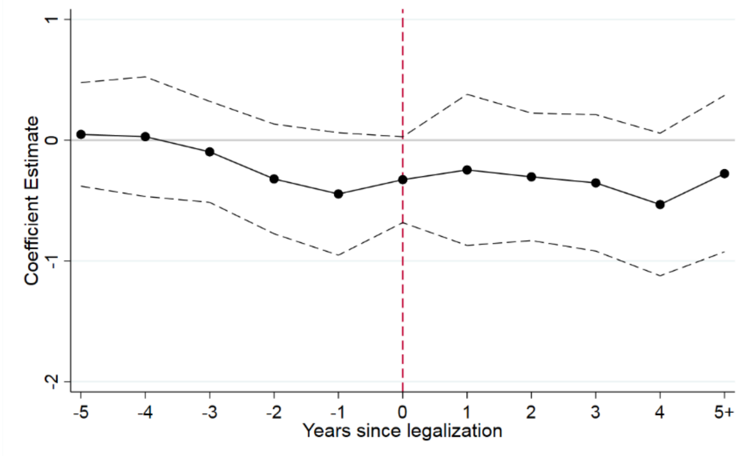
Panel A: Any MML



Panel B: "Medicalized" MML

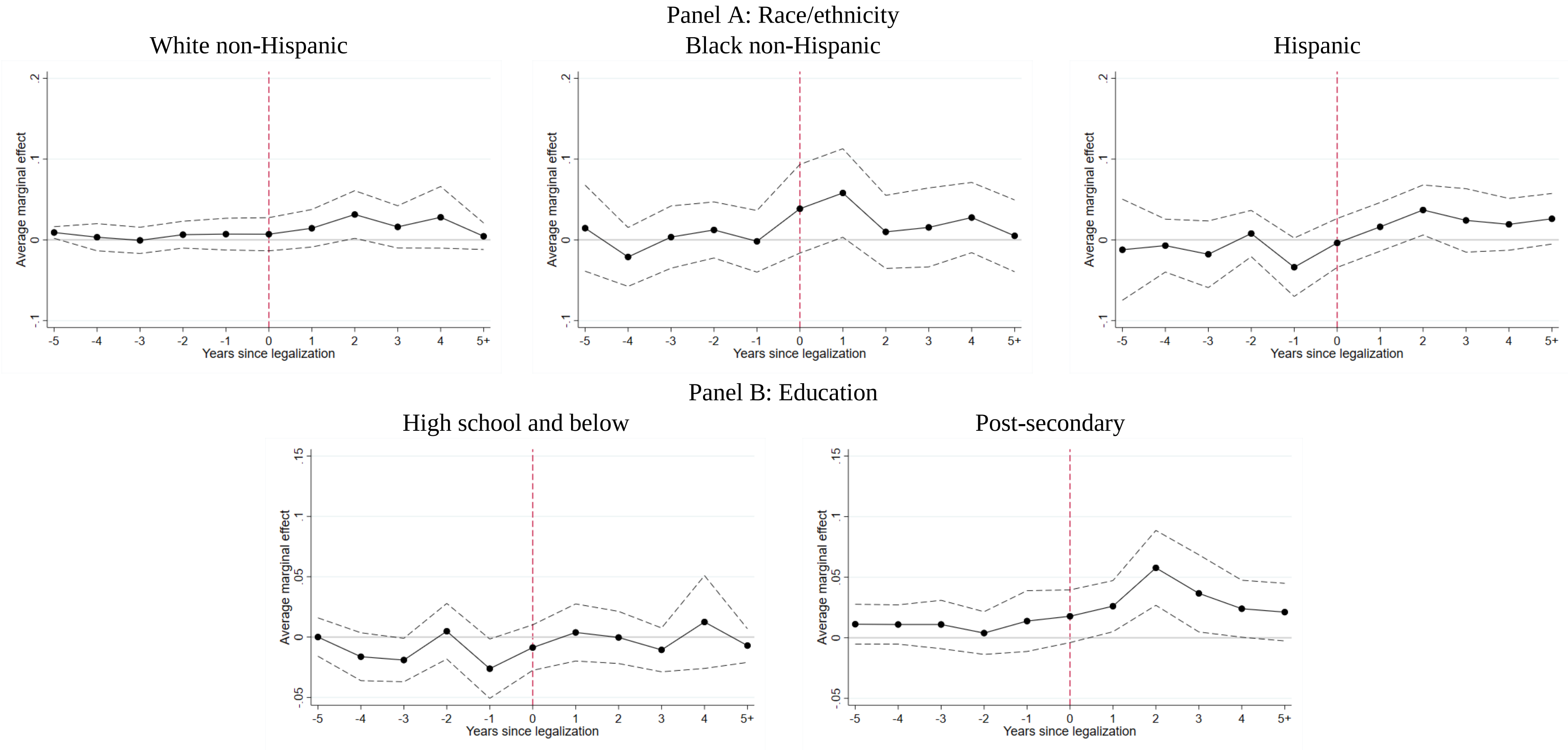


Panel C: "Non-medical" MML



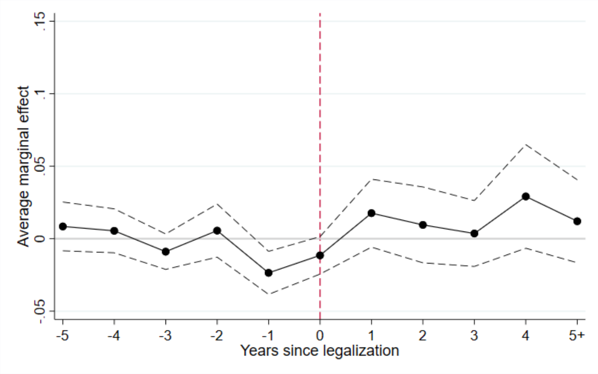
Notes: Solid circles represent point estimates. Dotted lines indicate 95% confidence intervals. Standard errors are clustered at the state-level. Estimates obtained from the linear regression specification with the control variables used in column 3 of Table 1. Panel B uses non-MML states and states with "medicalized" MML. Panel C uses non-MML states and states with "non-medical" MML.

Figure S5: Impact of “non-medical” MML on the probability of reporting excellent health by demographic characteristics

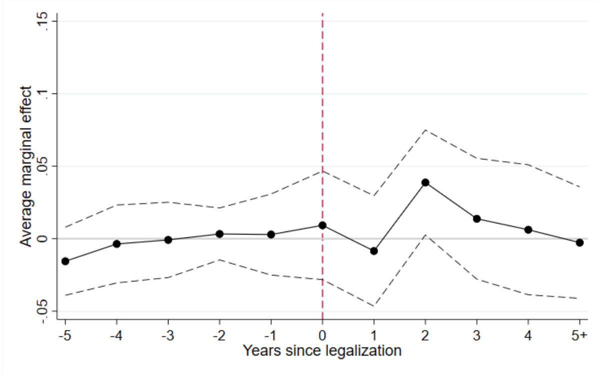


Panel C: Household income

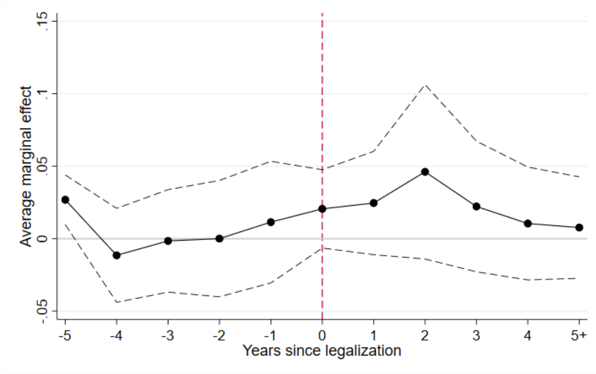
Below 200% FPL



200–400% FPL

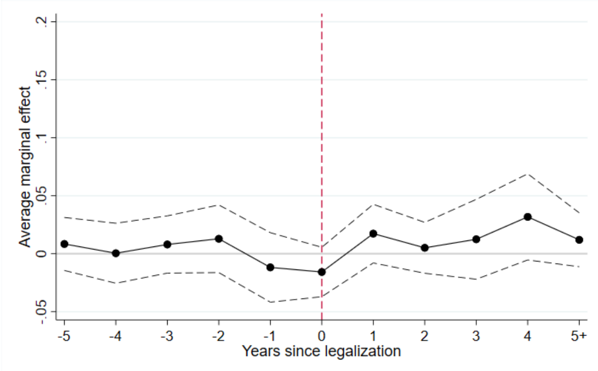


Above 400% FPL

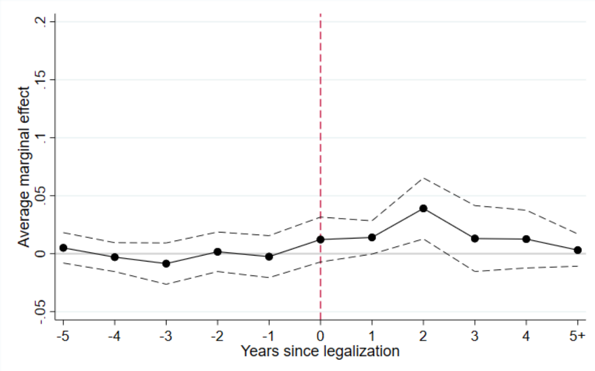


Panel D: Health insurance coverage

Uninsured



Insured



Notes: Solid circles represent the average marginal effect on the probability of reporting excellent health for each year before and after the "non-medicalized" MML compared to no MML. Dotted lines indicate 95% confidence intervals. Standard errors are clustered at the state-level. The average marginal effects were computed using the DID estimates obtained from the heteroskedastic ordered probit model specification estimated for a given demographic subgroup.

Table S1. State Medical Marijuana Laws, Program Regulations, and Medical Characteristics

Panel A. Legalization Dates of State Medical Marijuana Laws

State	Route of Passage	Statutory Language Reviewed	Date of medical marijuana legalisation	Date of recreational marijuana legalisation
Alaska	Voters	Measure 8 (1998); SB 94 (1999)	4 Mar 1999	24 Feb 2015
Arizona	Voters	Proposition 203 (2010)	10 Dec 2010	-
Arkansas	Voters	Issue 6 (2016); 007-16-17 Ark. Code R. § 1	9 Nov 2016	-
California	Voters	Proposition 215 (1996); SB 420 (2003)	6 Nov 1996	9 Nov 2016
Colorado	Voters	Ballot Amendment 20 (2000); HB 1284; SB 109 (2010)	30 Jul 2001	10 Dec 2012
Connecticut	Legislature	HB 5389 (2012), Regulations 21a-408-1	1 Oct 2012	-
Delaware	Legislature	SB 17 (2011)	1 Jul 2011	-
District of Columbia	Legislature	Title 22c Regulations 2014; L18-0210 (2010)	27 Jul 2010	26 Feb 2015
Florida	Voters	Amendment 2 (2016); HB 1455 (2021)	3 Jan 2017	-
Hawaii	Legislature	SB 642 (2013)	14 Jul 2000	-
Illinois	Legislature	HB 1 (2013)	1 Jan 2014	-
Louisiana	Legislature	Act 874 (1991); SB 271 (2016)	29 June 2015	-
Maine	Voters	Rules 144c122-2 (2013)	22 Dec 1999	30 Jan 2017
Maryland	Legislature	HB 881/SB 923 (2014); Title 10 Draft Regulations April 2014	1 Jun 2014	-
Massachusetts	Voters	Question 3 (2012); Regulations 105 CMR 725 (2013)	1 Jan 2013	15 Dec 2016
Michigan	Voters	Proposal 1 (2008); Michigan Medical Marijuana Act 2008	4 Dec 2008	6 Dec 2018
Minnesota	Legislature	SF 2470 (2014)	30 May 2014	-
Missouri	Voters	Amendment 2 (2018); HB 2321; 19 CSR 30-95.070 (2020)	6 Dec 2018	-
Montana	Voters	SB 423 (2011)	2 Nov 2004	-
Nevada	Voters	SB 374 (2013)	1 Oct 2001	1 Jan 2017
New Hampshire	Legislature	HB 573 (2013); Ch. 126-W (2014)	23 Jul 2013	-
New Jersey	Legislature	SB 119 (2009)	10 Oct 2010	-
New Mexico	Legislature	SB 523 (2007) Medical Cannabis Program	1 Jul 2007	-
New York	Legislature	A6357 (2014); proposed regulations Dec 18, 2014	5 Jul 2014	-
North Dakota	Voters	Measure 5 (2016); NDCC Chapter 19-24.1; NDAC Chapter 33-44-01	8 Dec 2016	-
Ohio	Legislature	HB 523 (2016)	8 Sep 2016	-
Oklahoma	Voters	SQ 788 (2018)	25 Aug 2018	-
Oregon	Voters	HB 3460 (2013); Oregon Medical Marijuana Act (2012)	3 Dec 1998	1 Jul 2015
Pennsylvania	Legislature	SB 3 (2016)	17 May 2016	-
Rhode Island	Legislature	SB 185 (2009)	3 Jan 2006	-
Utah	Legislature	Prop 2 (2018); HB 3001 2018	1 Dec 2018	-
Vermont	Legislature	SB 17 (2011); Act 155 (S.247) (2014)	1 Jul 2004	1 Jul 2018
Washington	Voters	SB 5073 (2011)	3 Nov 1998	9 Dec 2012
West Virginia	Legislature	SB 386 (2017); SB 1037; HB 2568; SB 339 (2020)	19 Apr 2017	-

Panel B. Characteristics of State Medical Marijuana Laws

State	Basic tenets of medical practice and Current Good Manufacturing Practices				Components of restrictive models for controlled substances			Total score
	Doctor-Patient Relationship	Manufacturing / Dispensing	Testing / Labelling	Excluding Smoked Products	Refill Limitations	Prescription monitoring program	Physician Training	
Alaska	✓	✗	✗	✗	✗	✗	✗	1
Arizona	✓	✗	✗	✗	✗	✗	✗	1
Arkansas	✓	✓	✓	✗	✗	✓	✗	4
California	✗	✗	✗	✗	✗	✗	✗	0
Colorado	✓	✗	✗	✗	✗	✗	✗	1
Connecticut	✓	✓	✓	✗	✓	✓	✗	5
Delaware	✓	✓	✓	✗	✗	✗	✗	3
District of Columbia	✓	✓	✓	✗	✗	✗	✗	3
Florida	✓	✓	✓	✗	✗	✓	✓	5
Hawaii	✗	✗	✗	✗	✗	✗	✗	0
Illinois	✓	✓	✓	✗	✗	✗	✗	3
Louisiana	✓	✓	✓	✓	✓	✓	✗	6
Maine	✓	✗	✗	✗	✗	✗	✗	1
Maryland	✓	✓	✓	✗	✓	✗	✓	5
Massachusetts	✓	✗	✗	✗	✗	✓	✓	3
Michigan	✗	✗	✗	✗	✗	✗	✗	0
Minnesota	✓	✓	✓	✓	✓	✗	✗	5
Missouri	✓	✗	✓	✗	✗	✗	✗	2
Montana	✓	✗	✗	✗	✗	✗	✗	1
Nevada	✗	✗	✗	✗	✗	✗	✗	0
New Hampshire	✓	✓	✓	✗	✗	✗	✗	3
New Jersey	✓	✓	✓	✗	✓	✗	✗	4
New Mexico	✗	✗	✗	✗	✗	✗	✗	0
New York	✓	✓	✓	✓	✓	✓	✓	7
North Dakota	✓	✓	✓	✗	✗	✓	✗	4
Ohio	✓	✓	✓	✓	✗	✓	✓	6
Oklahoma	✓	✗	✓	✗	✗	✓	✗	3
Oregon	✗	✗	✗	✗	✗	✗	✗	0
Pennsylvania	✓	✓	✓	✓	✓	✓	✓	7
Rhode Island	✗	✗	✗	✗	✗	✗	✗	0

Utah	✓	✓	✓	✓	✓	✓	✓	7
Vermont	✓	×	×	×	×	×	×	1
Washington	×	×	×	×	×	×	×	0
West Virginia	✓	✓	✓	✓	✓	✓	✓	7

Sources: Williams et al. (2016), Marijuana Policy Project. State-by-State Medical Marijuana Laws; Marijuana laws in the United States. Ballotpedia: The encyclopedia of American Politics.

Notes: We borrowed the classification of Williams et al. (2016) for states introducing MML up to 2016. For states introducing MML after 2016, we followed Williams et al.'s methodology to classify medicalized MML status. The total score (last column) is the total score is defined as the number of components included in each state's medical marijuana law. Following Williams et al. (2016), we consider a state as a medicalized MML state if this score is 2 or above.

Table S2. Summary of respondent characteristics, 1993–2018

	No MML	Any MML	"Medicalized" MML	"Non-medical" MML
	(1)	(2)	(3)	(4)
Panel A: Control variables				
Age	23.4	23.4	23.4	23.4
	(.029)	(.029)	(.049)	(.035)
Male	.514	.517	.523	.511
	(.001)	(.003)	(.002)	(.002)
Non-Hispanic White	.656	.582	.522	.632
	(.053)	(.053)	(.086)	(.037)
Non-Hispanic Black	.157	.100	.057	.136
	(.025)	(.016)	(.012)	(.014)
Hispanic	.140	.225	.305	.159
	(.060)	(.053)	(.080)	(.025)
Married	.365	.328	.352	.308
	(.009)	(.009)	(.009)	(.009)
Childless	.525	.548	.517	.573
	(.011)	(.013)	(.013)	(.008)
High school or lower	.478	.450	.475	.428
	(.007)	(.010)	(.007)	(.011)
Below 200% FPL	.335	.325	.374	.283
	(.012)	(.022)	(.023)	(.012)
200–400% FPL	.333	.287	.281	.292
	(.006)	(.013)	(.024)	(.009)
Above 400% FPL	.332	.388	.345	.425
	(.010)	(.014)	(.009)	(.018)
Health insurance coverage	.731	.759	.745	.771
	(.024)	(.011)	(.008)	(.018)
Panel B: Dependent variables				
Pr(excellent or very good health)	.621	.622	.603	.637
	(.013)	(.007)	(.004)	(.007)
Pr(good health)	.294	.290	.302	.280
	(.007)	(.004)	(.002)	(.005)
Pr(fair or poor health)	.085	.088	.095	.083
	(.006)	(.004)	(.004)	(.003)
Number of days with bad physical health	2.00	2.21	2.27	2.16
	(.031)	(.025)	(.032)	(.022)
Number of days with bad mental health	3.93	4.12	4.16	4.09
	(.078)	(.050)	(.084)	(.066)
Number of states	17	34	20	14
Observations	384685	503298	248404	254894

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. States are classified as “Any MML” if they have an effective MML as of 2018. States with an MML in effect as of 2018 are further classified as “medicalized” or “non-medical” are based on Williams et al. (2016). FPL denotes the federal poverty level.

Table S3. Overall impact of any MML on self-assessed health score
With different lengths of anticipation

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Coefficient Estimate						
5 years prior	.0187					
	(.0202)					
4 years prior	.0048	-.0006				
	(.0195)	(.0167)				
3 years prior	-.0031	-.0090	-.0088			
	(.0155)	(.0180)	(.0167)			
2 years prior	.0128	.0066	.0068	.0093		
	(.0210)	(.0183)	(.0142)	(.0140)		
1 years prior	-.0219	-.0282	.0280*	-.0252*	-.0274**	
	(.0223)	(.0211)	(.0167)	(.0146)	(.0131)	
MML	.0485**	.0416*	.0419**	.0450**	.0423**	.0495***
	(.0227)	(.0216)	(.0198)	(.0212)	(.0193)	(.0192)
Panel B. Average Marginal Effect						
Pr(excellent)	. 0141**	.0121*	.0122**	.0131**	.0123**	.0144***
	(.0066)	(.0063)	(.0058)	(.0062)	(.0056)	(.0055)
Pr(very good)	. 0018**	.0016*	.0016**	.0017**	.0016**	.0019***
	(.0009)	(.0008)	(.0007)	(.0008)	(.0007)	(.0007)
Pr(good)	-.0098**	-.0084*	-.0085**	-.0091**	-.0085**	-.0100***
	(.0046)	(.0043)	(.0040)	(.0042)	(.0039)	(.0038)
Pr(fair)	-.0050**	-.0043*	-.0043**	-.0047**	-.0044**	-.0051**
	(.0024)	(.0023)	(.0021)	(.0022)	(.0021)	(.0020)
Pr(poor)	-.0011**	-.0010*	-.0010**	-.0010**	-.0010**	-.0011**
	(.0005)	(.0005)	(.0004)	(.0004)	(.0004)	(.0004)
Demographic and state controls	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	730,929	730,929	730,929	730,929	730,929	730,929

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. All regressions control for year-quarter and state fixed effects, and state-specific linear time trends. Demographic and state controls include age, race/ethnicity, gender, marital status, presence of children in household, Medicaid expansion status, cigarette and beer excise tax rate. Other controls include education, health insurance coverage, household income relative to FPL, unemployment rate, and whether state legalized recreational marijuana.

Table S4. Overall impact of any MML on days in bad physical health

	(1)	(2)	(3)
5 years prior	-0.048	-0.048	-0.047
	(0.058)	(0.062)	(0.066)
4 years prior	-0.047	-0.046	-0.030
	(0.067)	(0.075)	(0.067)
3 years prior	-0.104	-0.131*	-0.056
	(0.073)	(0.075)	(0.082)
2 years prior	-0.006	-0.043	-0.127
	(0.076)	(0.084)	(0.097)
1 years prior	-0.098	-0.114*	-0.109
	(0.060)	(0.068)	(0.070)
MML	-0.109	-0.128*	-0.110
	(0.067)	(0.072)	(0.081)
R-squared	0.003	0.011	0.015
Mean outcome	2.160	2.155	2.141
Demographic and state controls	No	Yes	Yes
Other controls	No	No	Yes
Observations	859386	843275	708649

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. All regressions control for year-quarter and state fixed effects, and state-specific linear time trends. Demographic and state controls include age, race/ethnicity, gender, marital status, presence of children in household, Medicaid expansion status, cigarette and beer excise tax rate. Other controls include education, health insurance coverage, household income relative to FPL, unemployment rate, and whether state legalized recreational marijuana.

Table S5. Overall impact of any MML on days in bad mental health

	(1)	(2)	(3)
5 years prior	-0.053	-0.058	0.019
	(0.129)	(0.139)	(0.140)
4 years prior	-0.127	-0.184	-0.136
	(0.112)	(0.124)	(0.128)
3 years prior	-0.095	-0.167	-0.121
	(0.124)	(0.132)	(0.100)
2 years prior	-0.275**	-0.311**	-0.262*
	(0.125)	(0.135)	(0.137)
1 years prior	-0.273**	-0.364***	-0.341**
	(0.122)	(0.132)	(0.156)
MML	-0.319**	-0.381**	-0.401***
	(0.134)	(0.146)	(0.144)
R-squared	0.008	0.024	0.030
Mean outcome	4.155	4.148	4.148
Demographic and state controls	No	Yes	Yes
Other controls	No	No	Yes
Observations	859060	841895	708308

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. All regressions control for year-quarter and state fixed effects, and state-specific linear time trends. Demographic and state controls include age, race/ethnicity, gender, marital status, presence of children in household, Medicaid expansion status, cigarette and beer excise tax rate. Other controls include education, health insurance coverage, household income relative to FPL, unemployment rate, and whether state legalized recreational marijuana.

Table S6. Robustness checks for the impact of MML on self-assessed health status using the heteroskedastic ordered probit model

	(1)	(2)
Panel A: Coefficient Estimate		
5 years prior	0.026	0.010
	(0.021)	(0.024)
4 years prior	0.018	0.016
	(0.021)	(0.016)
3 years prior	0.016	-0.013
	(0.024)	(0.026)
2 years prior	0.032	0.033
	(0.028)	(0.023)
1 years prior	0.001	-0.027
	(0.031)	(0.026)
MML	0.072*	0.051***
	(0.041)	(0.018)
Panel B: Average Marginal Effect		
Pr(excellent)	.0208*	.0155***
	(.0120)	(.0057)
Pr(very good)	.0027*	.0014***
	(.0015)	(.0005)
Pr(good)	-.0144*	-.0106***
	(.0083)	(.0039)
Pr(fair)	-.0074*	-.0051***
	(.0043)	(.0019)
Pr(poor)	-.0017*	-.0012***
	(.0009)	(.0004)
State-specific trend	Quadratic	Linear
Sample	All states	“Medicalized” MML states
Observations	730,929	248,404

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. Controls include state and year-quarter fixed effects, state-specific quadratic time trends, age, race/ethnicity, gender, education, marital status, presence of children in household, Medicaid expansion status, unemployment rate beer excise tax rate, health insurance coverage, household income relative to FPL, and whether state legalized recreational marijuana.

Table S7. Heterogenous impact of MML on self-assessed health status using the linear probability model

Coefficient:	(1) Any MML	(2) Medicalized MML	(3) Non-medical MML
Dependent variable:			
Pr(excellent)	.0132*	.0170**	.0160
	(.0075)	(.0075)	(.0101)
Pr(very good or better)	.0183*	.0147	.0155
	(.0094)	(.0091)	(.0136)
Pr(good or better)	.0016	.0117*	-.0041
	(.0036)	(.0059)	(.0028)
Pr(fair or better)	.0021	.0044*	.0027**
	(.0013)	(.0025)	(.0012)
Observations	730,929	539,219	521,244

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Estimates obtained from the model specification used in column 3 of Table 1. Column 1 uses all states. Column 2 uses non-MML states and states with "medicalized" MML. Column 2 uses non-MML states and states with "non-medical" MML.

Table S8. Impact of MML on self-assessed health status by race/ethnicity, using the linear probability model

	(1)	(2)	(3)	(4)	(5)	(6)
Group:	White non-Hispanic		Black non-Hispanic		Hispanic	
Coefficient:	Medicalized	Non-medical	Medicalized	Non-medical	Medicalized	Non-medical
Dependent variable:						
Pr(excellent)	.0308***	.0240	-.0200	.0040	.0093	.0062
	(.0097)	(.0150)	(.0241)	(.0207)	(.0292)	(.0189)
Pr(very good or better)	.0139	.0150	.0264	.0774***	.0082	.0165
	(.0087)	(.0155)	(.0266)	(.0279)	(.0421)	(.0245)
Pr(good or better)	.0077	.0033	.0190	.0173	.0275	-.0020
	(.0066)	(.0035)	(.0170)	(.0181)	(.0238)	(.0172)
Pr(fair or better)	.0020	.0021*	.0095*	.0111	.0071	.0055
	(.0026)	(.0012)	(.0049)	(.0078)	(.0117)	(.0092)
Observations	388,377	370,376	68,040	48,359	53,571	64,075

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with "medicalized" MML. Even columns use non-MML states and states with "non-medical" MML.

Table S9. Impact of MML on self-assessed health status by education attainment, using the linear probability model

	(1)	(2)	(3)	(4)
Group:	High school or lower		Post-secondary	
Coefficient:	Medicalized	Non-medical	Medicalized	Non-medical
Dependent variable:				
Pr(excellent)	.0244***	.0073	.0165*	.0301*
	(.0107)	(.0116)	(.0095)	(.0153)
Pr(very good or better)	.0216	-.0018	.0080	.0344***
	(.0147)	(.0232)	(.0106)	(.0102)
Pr(good or better)	.0109	-.0157**	.0115	.0086**
	(.0108)	(.0070)	(.0070)	(.0041)
Pr(fair or better)	.0069	.0030	.0028	.0031**
	(.0049)	(.0033)	(.0027)	(.0012)
Observations	195,798	193,433	314,190	289,377

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with "medicalized" MML. Even columns use non-MML states and states with "non-medical" MML.

Table S10. Impact of MML on self-assessed health status by household income, using the linear probability model

	(1)	(2)	(3)	(4)	(5)	(6)
Group:	< 200% FPL		200–400% FPL		> 400% FPL	
Coefficient:	Medicalized	Non-medical	Medicalized	Non-medical	Medicalized	Non-medical
Dependent variable:						
Pr(excellent)	.0250	<.0001	.0201*	.0209	.0164	.0334
	(.0166)	(.0079)	(.0116)	(.0128)	(.0026)	(.0039)
Pr(very good or better)	.0238	.0040	-.0126	.0204	.0342***	.0247
	(.0185)	(.0172)	(.0139)	(.0290)	(.0111)	(.0165)
Pr(good or better)	.0218**	.0017	.0030	-.0148**	.0107	.0027
	(.0092)	(.0073)	(.0082)	(.0073)	(.0084)	(.0072)
Pr(fair or better)	.0085	.0084*	.0030	-0.0012	.0022	.0005
	(.0061)	(.0042)	(.0033)	(.0020)	(.0026)	(.0016)
Observations	165,261	167,932	170,445	166,529	174,282	148,349

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with “medicalized” MML. Even columns use non-MML states and states with “non-medical” MML.

Table S11. Impact of MML on self-assessed health status by health insurance status, using the linear probability model

	(1)	(2)	(3)	(4)
Group:	Uninsured		Insured	
Coefficient:	Medicalized	Non-medical	Medicalized	Non-medical
Dependent variable:				
Pr(excellent)	.0405	.0336**	. 0148*	.0166
	(.0246)	(.0155)	(.0088)	(.0114)
Pr(very good or better)	.0242	-.0137	. 0126	.0270**
	(.0231)	(.0228)	(.0082)	(.0126)
Pr(good or better)	.0218*	-.0160	. 0086	.0010
	(.0119)	(.0135)	(.0067)	(.0039)
Pr(fair or better)	-.0028	-.0014	.0068**	.0044**
	(.0047)	(.0047)	(.0030)	(.0011)
Observations	107,357	108,061	402,631	374,749

Notes: Cluster-robust standard errors at the state-level are reported in parentheses. Statistical significance denoted by * p<0.1, ** p<0.05, *** p<0.01. Estimates obtained from the model specification used in column 3 of Table 1. Odd columns use non-MML states and states with “medicalized” MML. Even columns use non-MML states and states with “non-medical” MML.