Estimating the effect of recreational cannabis legalization on labor market outcomes, labor supply and leisure preferences

Julian Sauvage

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Abstract: This article investigates the effect of Recreational Marijuana Laws (RMLs) on time use trends and labor market outcomes. I use a difference-in-differences research design, exploiting variation in the timing of legalization, to estimate the effect of RMLs on labor market outcomes and time-use trends. I further investigate how the model differs when treatment is assigned based on retail availability of marijuana as opposed to legalization. I then investigate whether heterogenous treatment effects emerge based on age, gender, and student status. I find that the varying the treatment time affects the model implications, though effects remain mostly marginal in aggregate. Among students specifically, I find larger and more significant effects on time-use, specifically post-RML students tend to work approximately 3 additional hours weekly, and report spending between 5-8 fewer hours on leisure activities per week.

Support for the legalization of marijuana amongst adults in the United States has increased steadily in the last 50 years, up to 67% in 2019 (Pew Research Center, 2019). This shift in public sentiment has been reflected in the state-level trends in legalization policy. Medical marijuana laws (MMLs) have been implemented in 39 states, as well as the District of Columbia, allowing state-licensed physicians to be prescribe medical marijuana to patients. Moreover, recreational marijuana laws (RMLs) have been implemented in 18 states, as well as DC, allowing direct sale to consumers and thereby broadening its accessibility at the state-level. I use data from the American Time Use Survey (ATUS) and the Current Population Survey (CPS) to I investigate the effect of these policies on labor market outcomes and trends in time use among working-age adults (18-65). In particular, I examine whether these policy changes have a measurable effect on labor force participation, time spent on work, time spent on leisure, and time spent searching for a job when an individual is unemployed.

Background

Through the course of the 20th century, particularly in the latter half, marijuana became one of the most heavily regulated drugs in the United States. Since 1970, marijuana has been a classified as a Schedule 1 drug in the United States, alongside other drugs such as heroin and methamphetamines. While it remains federally illegal, it has become a controversial and hotly contested political issue, and as the federal government has lessened its enforcement policies states have begun taking the issue into their own hands. As early as 1996, California passed the first medical marijuana policy. In 2012, Colorado and Washington became the first states to legalize the recreational use of marijuana at the state-level, reflecting a general shift in public sentiment regarding marijuana in the United States. Since then, 16 additional states as well as the District of Columbia have implemented similar policies. That said, RMLs do not inherently increase marijuana availability or appeal. Even after recreational marijuana is legalized in a state, it still does not become legal for retailers to carry and sell. Retail accessibility typically takes several years, or even longer depending on the jurisdiction. For instance, although the District of Columbia passed recreational legalization policy in 2014, it remains illegal to sell marijuana in DC.

In general, recreational marijuana legalization (RML) allows the legal sale, consumption, and possession of marijuana. These policies are associated with significant increases in the consumption of marijuana amongst adults, with estimates ranging from a 20-30% increase in "recent consumption", and even larger effects have been measured in some communities (Cerda et al, 2020). Yet, how these consumption increases are reflected in behavior and labor market outcomes remains uncertain.

Literature Review

Although the first RML was put in place over 10 years ago, the literature examining the general effects of recreational legalization remain very limited. This is likely attributable to the limited sample of states that have installed RML policies. There is a relatively small literature studying the effect of MMLs on labor market outcomes, however far fewer have examined RMLs. The lack of empirical research on the effect of RMLs is particularly concerning since only about 2% of individuals residing in MML states are eligible for medical marijuana, thus existing studies of MMLs may not adequately reflect the effect of RMLs (Abouk et al., 2021).

Since few studies examine the impact of RMLs on labor-market outcomes and time-use trends, studies focused on MMLs form the foundation for much of the on-going research regarding the effect of RML adoption. Sabia and Nguyen find no evidence suggesting that MMLs affect individual employment status nor hours worked, but they do find a small hourly wage decrease among males aged 20-29 years old. Although MMLs do not appear to have a significant effect on labor market outcomes amongst the general population, they nonetheless have a significant and measurable impact on the narrow subset of individuals who are more likely to be eligible. Focusing on adults older than 50, Nicholas and Maclean finding improvements in self-assessed health as well as labor supply amongst older adults (Nicholas & Maclean, 2019). In a similar vein, Ullman (2017) finds that MMLs resulted in an 8% decrease in sick days, and Ghimire and Maclean (2020) show that worker's compensation claims decline post-MML, particularly amongst older adults.

While existing research has suggested that MMLs do not have a significant effect on labor market outcomes, this does not preclude the existence of effects specific to RMLs. As previously noted, relatively few individuals are eligible for medical marijuana, whereas RMLs allow all adults to enter the market. Abouk et al. highlight that the "marginal user [induced] to consume marijuana" likely differs between an RML, and an MML, due to their differing effects on individual access (Abouk et al. 2021). Moreover, RMLs might have broader impacts based on variation in effects on pricing, social acceptance, and advertising (Cerda et al., 2019). It has been well-established that RMLs significantly increase consumption of marijuana in the post-treatment period (Cerda et al., 2020; Maclean, Ghimire, & Nicholas, 2020). Utilizing a large sample of respondents to the National Survey of on Drug Use and Health, Cerda and co-authors document a 28% increase in past-month marijuana use amongst adults post-RML, and a 25% increase in substance abuse disorders related to marijuana use (Cerda et al., 2020).

Of particular relevance to this study are several papers that investigate how shifts in marijuana policy have affected time-use trends. Chu and Gershenson find that college students in post-MML states spend approximately 20% less time on education-related activities, and 20%

more time on leisure activities, relative to their non-MML counterparts (Chu & Gershenson, 2018). Although we might expect that this same pattern exists among working adults, that does not appear to be the case. Jergins uses the American Time Use Survey to examine the effect of MMLs, for the most part confirming Sabia and Nguyen's aforementioned finding, namely that MMLs do not significantly affect labor market outcomes. One study found that adolescents in Washington who worked were in fact relatively more likely to consume marijuana compared to their non-working counterparts (Graves et al., 2019). One potential explanation is that working adolescents have income and are exposed to a broader range of individuals.

A small body of literature examines the direct effect of marijuana use directly on labor market outcomes. Williams and Van Ours use the National Longitudinal Survey of Youth to examine whether the duration and prevalence of marijuana use affect labor market outcomes. They find that "early adopters" of marijuana accept jobs more readily, and at a lower wage rate, compared to those who do not consume it consistently (Williams & Van Ours, 2019).

MMLs do not appear to significantly affect labor market outcomes amongst the general population, and few significant effects have emerged in the (albeit limited) literature on RMLs. However, there are certainly mechanisms by which RMLs could affect labor market outcomes. Sabia and Nguyen argue that the effects of marijuana legalization are "theoretically ambiguous" because marijuana use is "likely to have competing health and human capital effects" (Sabia & Nguyen, 2018). It may be negatively related to human capital due to marijuana's association with amotivation and diminished cognition, amongst other negative effects noted in the literature (Volkow et al., 2016; van Ours and Williams 2011). The deleterious psychological effects of marijuana use are difficult to observe in data but may explain why some authors have found that marijuana use leads to diminished acquisition of human capital and education (Chu &

Gershenson 2016; van Ours & Williams, 2015). On the other hand, there is strong evidence that MMLs, and consequently RMLs, may induce health benefits for some groups, either by acting as pain relief, or as a substitute for more dangerous alternatives such as opioids (Chan et al., 2020; Bradford & Bradford, 2016). One more potential mechanism to consider is that RMLs may change the relative value of leisure time, though the direction of any resulting effect is not endogenously determined and remains ambiguous.

Most studies of RMLs have focused on a single state, or a jurisdiction therein; no studies have been published yet investigating whether the effect of RMLs are reflected in American time-use trends. This article contributes to the literature by examining whether RMLs produce noticeable changes in time-use behavior, and if so, do they affect labor market outcomes. Another important consideration that has up until now been largely ignored is that the impact of RMLs may be blunted by the disconnect

Data and Methodology

The primary data source used for this analysis is the American Time Use Survey (ATUS) from 2003 to 2019. The ATUS is a survey on a sample of CPS respondents administered 2 to 5 months after they complete their final CPS survey. Individuals are asked to record their time use allocation on the “diary day”, the day immediately prior to the date of the survey. Respondents report their time spent on a range of potential activities, starting at 4 a.m. the previous day and ending at 4 a.m. on the interview day, ultimately forming a 24-hour “time diary”. Activities are classified into one of 17 broad time-use categories, each of which is composed of 2 tiers of increasing specificity. After the final sampling stage, individuals are assigned a weight that accounts for the sampling methodology and corrects for non-response, such that the sample is a nationally representative after weighting (BLS, 2018).

The ATUS is administered year-round, such that we have an equal distribution of surveys over the weeks and months in any particular year. Within each week, 10% of surveys are administered per weekday, and 25% are administered on each weekend day. This characteristic is vital to consider because the type of day accounts for significant variation in time-use trends amongst employed individuals. Thus, a variable identifying whether the survey was administered on a weekend or weekday is included in all time-use regressions. Time-use may also vary seasonally, so I include the time fixed-effect component in the following analyses accounts for the month of survey administration, in addition to the year.

There are two primary limitations associated with using the ATUS. First, the survey does not collect information specifically regarding drug use. It asks individuals to report their combined tobacco and drug use, but with no separability between categories. Thus, this analysis will quantify the Intent-To-Treat (ITT) effect, under the assumption that the RML treatment is assigned randomly.

Dependent Variables

There are two types of outcome variables in the following analysis, labor market indicators and time use measures. The first set of variables are binary, indicating whether an individual is in the *Labor Force*, and if they are *Employed* or *Unemployed*. To be explicit, these variables are constructed such that they are equal to 1 if the respondent is in labor force/employed/unemployed, and 0 otherwise. These variables are based on individuals' reported status in the American Time Use Survey Respondent dataset.

Summary Statistics for DVs

Variable	Mean	Sd	NotNA
	male: 0		
Labor Force	0.608	0.488	117978
Employed	0.564	0.496	117978
Unemployed	0.044	0.205	117978
Work Hours	16.134	27.237	117978
Leisure Hours	114.746	28.096	117978
Job Search Hours	0.133	1.973	117978
Age	48.214	18.128	117978
	male: 1		
Labor Force	0.741	0.438	92608
Employed	0.693	0.461	92608
Unemployed	0.048	0.213	92608
Work Hours	24.61	32.96	92608
Leisure Hours	117.139	31.156	92608
Job Search Hours	0.218	2.623	92608
Age	46.635	17.396	92608

The second set of outcome variables are measures of individual time use in weekly hours. We use weekly hours to ease interpretation of results, for reference noting that Americans work on average 40 hours a week. *Market Work* represents the time spent at a job or another income-generating activity, conditional on being employed. *Job Search* represents time spent searching for a job, conditional on being unemployed. *Leisure* represents time spent on leisure activities such as relaxing, socializing, watching tv, etc.; a more detailed breakdown of which activities compose the *Leisure* variable is available in the appendix.

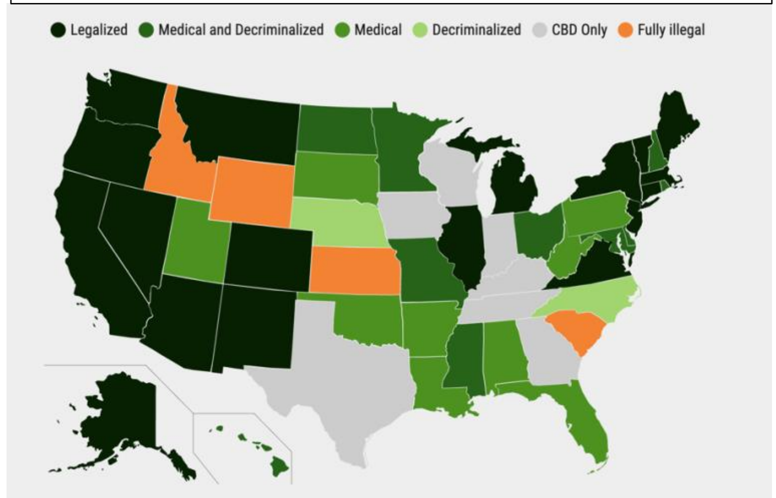
Model Specification

I will use a two-way fixed-effect framework, based on a difference-in-difference identification strategy. Following a similar methodology as Jergins (2022), I will estimate the following model specification:

$$y_{ist} = \beta_0 + \beta_{RML} RML_{st} + \gamma X_{ist} + \pi Recession_{st} + \delta_t + \theta_s + \varepsilon_{ist}$$

Individuals are indexed by subscript *i*, states are indexed by subscript *s*, and *t* denotes the year/month that the survey was administered. y_{ist} represents the outcome of interest, namely time spent on an activity of interest or labor market status. RML_{st} is a binary variable equal to one if the state *s* had legalized recreational marijuana at time *t*. Data on the timing of legalization was collected from the Marijuana Policy Project. X_{ist} is a vector of individual and state characteristics including gender, age, race, marital status, and education, as well as variables controlling for survey characteristics such as the day of the week that the survey was administered. Following Jergins (2022), I include a $Recession_{st}$ variable, which is a state-specific indicator variable that is equal to 1 from January 2008 to June 2009, and 0 otherwise,

FIGURE 1: Geographic Variation in Treatment Status



allowing for state-specific variation in individual behavior and state trends related to the recession. δ_t is a set of year-by-month time fixed-effects which account for omitted variables that are time-varying national changes that have a consistent effect across all states, while θ_s is a state fixed-effect which will control for time-invariant state-level covariates that are not otherwise observed in the model. The primary coefficient of interest is β_{RML}, which represents the impact of state RMLs on individual outcomes.

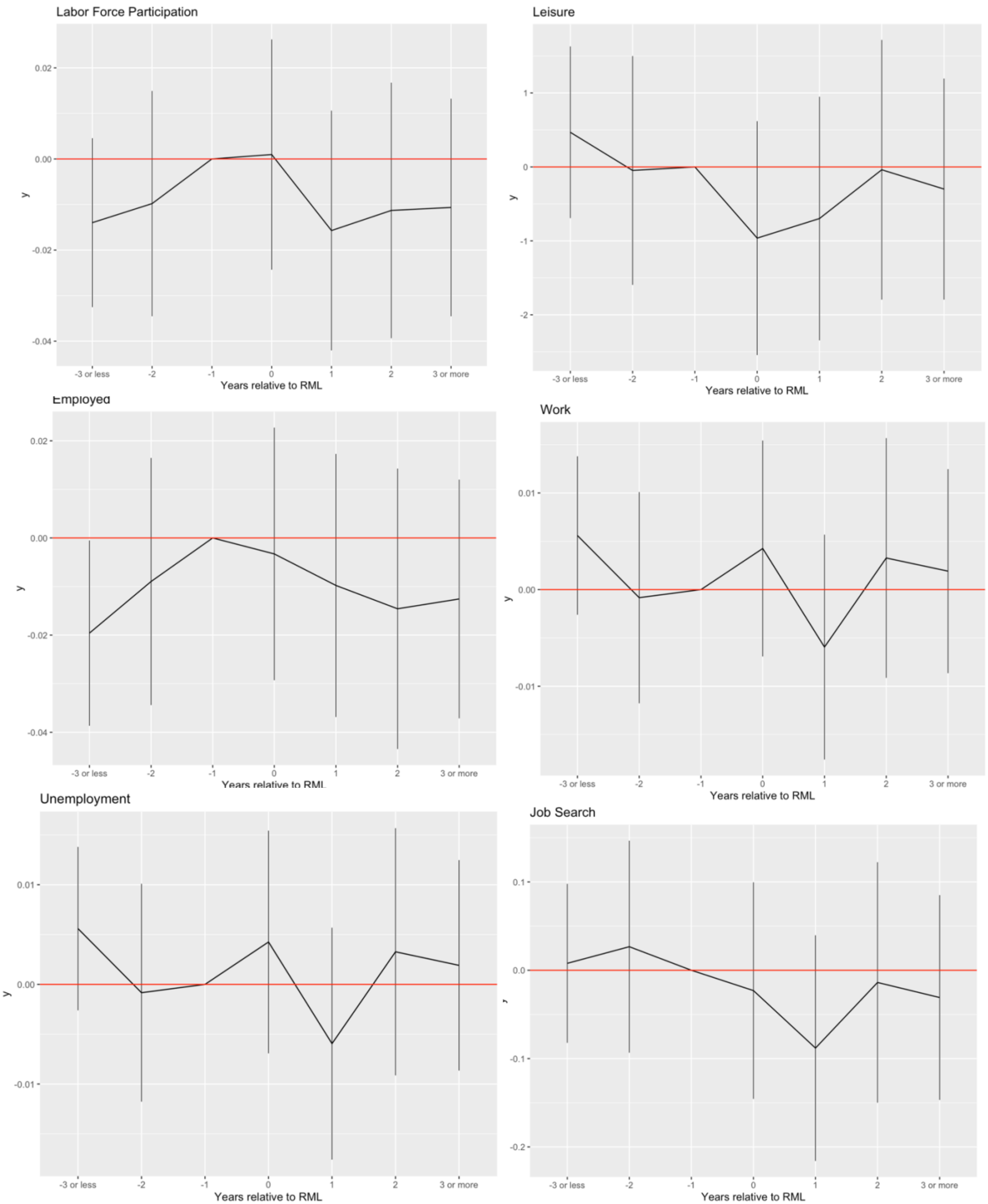
The analysis will proceed as follows; I begin by regressing the time-use outcome variables linearly on the richest possible model specification. The binary labor force indicators will be estimated using a Probit model, again using all relevant independent variables. I will then subset the sample by age and gender to account for heterogenous effects, treatment uptake, and treatment levels within groups (Jergins, 2022; Van Ours & Williams, 2015). Finally, I will examine whether fitting the model based on the date of retail availability, as opposed to the date of legalization itself, produces a model that better reflects the data at hand.

The identifying assumption of the model is that after controlling for time and state fixed effects, the time-use trends between the treated states (those who have adopted RMLs) and control states (those who have not adopted RMLs) are parallel. This relies on the premise that trends in the outcome variables are independent of the factors that determine if/when a state adopts an RML; this seems reasonable since we can safely assume that policy is not determined directly by citizens, though it is not totally implausible that outcome variables and RML uptake may be correlated due to some underlying relationship related to political behavior. In Figure 1, we can see the geographic concentration of RML states, while Table A.1 in the appendix shows the timing of medical and recreational legalization based on state. The lack of geographic variation in treated states should be controlled by the model specification. The set of control observations will be limited to individuals residing in states which did not adopt RMLs during the study period to preclude comparisons between groups that were both already treated, which can lead to biased estimators when treatment effects are heterogenous (Roth et al., 2022; Callaway & Sant'Anna, 2020).

To test the parallel trends assumption, we regress the dependent variables on an indicator variable and both fixed effects. In a perfect world with full experimental control and true randomness we would like to see that there are no significant differences in outcomes prior to the new policy, and then post-treatment we see some divergence in outcomes based on treatment status. In the figure below, I report the coefficients associated with the year relative to dismissal. Following Jergins (2022), I assign states that are never treated to the omitted reference category, which in this case is the year immediately prior to treatment (year = -1). The figure below plots the coefficients associated with the periods around the treatment.

Reassuringly, the figures below indicate that no coefficient estimates are significantly different from 0, suggesting the parallel trends assumption holds. Unfortunately, we do not see a clear treatment effect in the post-treatment periods, however effects may be obscured by the heterogeneity of the data.

FIGURE 2: Pre/Post-treatment trends of Dependent Variables



Results

The analysis will proceed as follows; I begin by regressing the time-use outcome variables linearly on the richest possible model specification. The binary labor force indicators will be estimated using a Probit model, again using all relevant independent variables. I will then subset the sample by age and gender to account for heterogenous effects, treatment uptake, and treatment levels within groups (Jergins, 2022; Van Ours & Williams, 2015). Finally, I will examine whether fitting the model based on the date of retail availability, as opposed to the date of legalization itself, produces a model that better reflects the data at hand.

Tables 1-3 report the main results of this analysis. In particular, Table 1 records the effect of RMLs on the entire sample, along with the inclusion of age and gender variables. To further understand how the effect of these policies may vary according to common demographic variables, Tables 2 and 3 specify the coefficient associated with RMLs among men and women respectively, to allow for heterogenous treatment effects based on covariates. These tables are further broken down based on age group. All models include fixed effects based on time and location. The reported coefficient on *RML* is the difference-in-difference

Table 1: The effect of RMLs on Labor Outcomes and Time Use

	Work	**Leisure**	**Job Search**	**Employed**	**Unemployed**	**Labor Force**
RML	0.18	−0.45	−1.15*	0.00	−0.02	−0.01
	(0.30)	(0.31)	(0.58)	(0.02)	(0.03)	(0.02)
Age	0.66***	−0.78***	0.41***	0.14***	−0.00	0.13***
	(0.02)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
Age^2	−0.01***	0.01***	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	5.14***	4.47***	1.36***	0.38***	0.05***	0.43***
	(0.11)	(0.11)	(0.18)	(0.01)	(0.01)	(0.01)
Race						
Black	−0.17	2.88***	−0.07	−0.18***	0.27***	−0.10***
	(0.17)	(0.17)	(0.24)	(0.01)	(0.01)	(0.01)
Asian	0.78**	−1.15***	0.34	−0.19***	−0.06*	−0.23***
	(0.28)	(0.28)	(0.53)	(0.02)	(0.03)	(0.02)
Other	−0.19	0.90*	−0.70	−0.20***	0.15***	−0.17***
	(0.35)	(0.36)	(0.50)	(0.02)	(0.03)	(0.02)
Married	−1.05***	−3.39***	−1.03**	0.01	−0.10***	−0.03**
	(0.14)	(0.15)	(0.32)	(0.01)	(0.02)	(0.01)
Have Child	−1.95***	−2.94***	0.05	0.08***	0.16***	0.15***
	(0.23)	(0.23)	(0.32)	(0.01)	(0.02)	(0.01)
*Married*Have Child*	2.28***	−1.30***	0.05	0.01	−0.26***	−0.09***
	(0.22)	(0.23)	(0.43)	(0.01)	(0.02)	(0.01)
Number of Children	−0.14	−2.28***	−0.21	−0.11***	0.00	−0.12***
	(0.08)	(0.08)	(0.11)	(0.00)	(0.01)	(0.00)
Education	0.16***	−0.60***	0.43***	0.09***	−0.04***	0.08***
	(0.02)	(0.02)	(0.04)	(0.00)	(0.00)	(0.00)
Employed	35.69***	−20.04***				
	(0.13)	(0.13)				
Recession	0.01	−0.01	0.01	−0.00	0.00	−0.00
	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
Intercept	−37.64***	174.24***	−0.27**	−2.78***	−0.89***	−2.33***
	(1.15)	(1.05)	(0.11)	(0.05)	(0.08)	(0.05)
Time FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.45	0.32	0.14			
Log Likelihood				−104044.00	−35441.73	−95861.08
Num. obs.	210586	210586	9577	210586	210586	210586

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

estimator, and for the time-use models (Work, Leisure, Job Search) it can be understood as the approximate change in hours worked per week post-RML. In Table 1, the coefficient associated with our Labor Force indicator models can be understood as the change in employment/unemployment rate, and that of labor force participation. In Tables 2 and 3, the RML coefficient is the change in probability that a group's respondent has the associated labor force status following an RML.

Table 1 suggests that following an RML, average hours spent searching for a job, conditional on being unemployed, falls a little over one hour per week. Looking at Table 2 we can see that RMLs do not appear to shift job search time amongst unemployed men. On the other hand, in Table 3 we see that amongst women aged 18-30 there is a highly significant decrease in time spent job searching post-RML. An opposite but nonetheless significant effect appears amongst women aged 30 to 40. These counter-intuitive effects may suggest that our results on job search time-use were biased based on the low number of unemployed persons in our sample.

Table 2: The effect of RMLs on Labor Outcomes and Time Use - Men

	Work	Leisure	Job Search	Employed	Unemployed	Labor Force
	OLS	*OLS*	*OLS*	*probit*	*probit*	*probit*
Panel A: Men 18-30						
RML	−0.624	−0.015	−0.684	0.011	−0.124	−0.077
	(1.809)	(1.493)	(2.054)	(0.092)	(0.122)	(0.103)
N	9,414	11,966	1,102	11,966	11,966	11,966
Panel B: Men 30-40						
RML	0.286	−2.082*	−2.788	−0.089	−0.079	−0.206**
	(1.244)	(1.099)	(5.742)	(0.089)	(0.129)	(0.103)
N	16,087	17,604	680	17,604	17,604	17,604
Panel C: Men 40-50						
RML	1.194	−1.196	1.902	0.078	0.038	0.109
	(1.261)	(1.128)	(3.709)	(0.086)	(0.124)	(0.099)
N	17,022	19,149	725	19,149	19,149	19,149
Panel D: Men 50-65						
RML	−0.589	1.087	0.136	−0.022	−0.070	−0.055
	(1.225)	(1.034)	(3.241)	(0.057)	(0.103)	(0.058)
N	17,173	24,339	953	24,339	24,339	24,339

*p<0.1; **p<0.05; ***p<0.01

Table 3: The Effect of RMLs on Labor Outcomes and Time Use - Women

	Work	Leisure	Job Search	Employed	Unemployed	Labor Force
	OLS	*OLS*	*OLS*	*probit*	*probit*	*probit*
Panel A: Women 18-30						
RML	0.775	0.239	−4.032***	−0.020	0.0001	−0.027
	(1.653)	(1.200)	(1.306)	(0.077)	(0.109)	(0.082)
N	10,424	15,423	1,354	15,423	15,423	15,423
Panel B: Women 30-40						
RML	−0.244	−0.668	4.351**	0.023	0.054	0.034
	(1.142)	(0.857)	(1.859)	(0.060)	(0.103)	(0.062)
N	16,536	22,883	1,112	22,883	22,883	22,883
Panel C: Women 40-50						
RML	−0.573	0.552	−2.295	0.018	0.030	0.033
	(1.241)	(0.986)	(2.341)	(0.065)	(0.111)	(0.069)
N	16,685	21,983	936	21,983	21,983	21,983
Panel D: Women 50-65						
RML	−0.375	1.186	2.921	−0.027	0.061	−0.009
	(1.191)	(0.881)	(2.455)	(0.049)	(0.094)	(0.050)
N	18,414	29,571	944	29,571	29,571	29,571

*p<0.1; **p<0.05; ***p<0.01

In Table 2, the only significant effects that emerge are associated with a decrease in leisure time amongst men aged 30-40, and an approximate 20% decrease in their probability of being in the labor force. This effect is large but imprecisely estimated, the 95% confidence interval suggests the effect falls between a 10-30% decrease in the probability that 30–40 year-old men are in the labor force.

One reason why negligible or counter-intuitive effects may be arising in the previous regressions is that the RMLs do not immediately change the effective accessibility or consumption behavior of marijuana. There is typically a temporal gap between when legalization occurs and when marijuana enters the legal market. In Table 4, we see how the models presented in Table 1 change when the difference-in-difference estimator is associated with retail availability rather than solely the existence of RMLs.

Table 4: The effect of Retail Availability on Labor Outcomes and Time Use

	Work	**Leisure**	**Job Search**	**Employed**	**Unemployed**	**Labor Force**
Retail	-0.68^{*}	0.45	-1.27	0.02	-0.04	0.01
	(0.33)	(0.34)	(0.66)	(0.02)	(0.04)	(0.02)
Age	0.66^{***}	-0.78^{***}	0.41^{***}	0.14^{***}	-0.00	0.13^{***}
	(0.02)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
Age^2	-0.01^{***}	0.01^{***}	-0.00^{***}	-0.00^{***}	-0.00^{***}	-0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	5.14^{***}	4.47^{***}	1.37^{***}	0.38^{***}	0.05^{***}	0.43^{***}
	(0.11)	(0.11)	(0.18)	(0.01)	(0.01)	(0.01)
Race						
Black	-0.17	2.88^{***}	-0.07	-0.18^{***}	0.27^{***}	-0.10^{***}
	(0.17)	(0.17)	(0.24)	(0.01)	(0.01)	(0.01)
Asian	0.79^{**}	-1.16^{***}	0.32	-0.19^{***}	-0.06^{*}	-0.23^{***}
	(0.28)	(0.28)	(0.53)	(0.02)	(0.03)	(0.02)
Other	-0.19	0.90^{*}	-0.70	-0.20^{***}	0.15^{***}	-0.17^{***}
	(0.35)	(0.36)	(0.50)	(0.02)	(0.03)	(0.02)
Married	-1.05^{***}	-3.39^{***}	-1.04^{**}	0.01	-0.10^{***}	-0.03^{**}
	(0.14)	(0.15)	(0.32)	(0.01)	(0.02)	(0.01)
Have Child	-1.95^{***}	-2.95^{***}	0.05	0.08^{***}	0.16^{***}	0.15^{***}
	(0.23)	(0.23)	(0.32)	(0.01)	(0.02)	(0.01)
*Married*Have Child*	2.28^{***}	-1.30^{***}	0.05	0.01	-0.26^{***}	-0.09^{***}
	(0.22)	(0.23)	(0.43)	(0.01)	(0.02)	(0.01)
Number of Children	-0.14	-2.27^{***}	-0.21	-0.11^{***}	0.00	-0.12^{***}
	(0.08)	(0.08)	(0.11)	(0.00)	(0.01)	(0.00)
Education	0.16^{***}	-0.60^{***}	0.43^{***}	0.09^{***}	-0.04^{***}	0.08^{***}
	(0.02)	(0.02)	(0.04)	(0.00)	(0.00)	(0.00)
Employed	35.69^{***}	-20.04^{***}				
	(0.13)	(0.13)				
Recession	0.01	-0.01	0.01	-0.00	0.00	-0.00
	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
(Intercept)	-31.51^{***}	165.63^{***}	-13.97^{***}	-3.09^{***}	-0.92^{***}	-2.68^{***}
	(0.97)	(1.00)	(1.70)	(0.05)	(0.08)	(0.05)
Time FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.45	0.32	0.14			
Log Likelihood				-104043.60	-35441.46	-95861.13
N	210586	210586	9577	210586	210586	210586

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

We can see the introduction of retail availability appears to have a negative effect on hours worked across the entire population. In Appendix tables A1 and A2, we have the results for the models based on the sub-samples stratified by gender and age, as were seen in Tables 2 and 3. These show particularly significant decreases in weekly hours worked amongst women aged 30-40 and men aged 50-65, though no other effects stand out, and there is no evidence suggesting that retail availability significantly affects labor force status across any of our sub-groupings.

Student-Specific Effects

Research on RMLs/MMLs have typically found small or insignificant effects, except for amongst student populations. As previously mentioned, Chu and Gershenson found that students increased leisure time by approximately 20% following MMLs and decreased their education time-use consequently. The final regression herein captures the effect of RMLs and retail availability on students specifically. I expect that these results will yield the most significant estimates as college students are more likely than average to use marijuana and tend to increase their consumption following legalization (Kerr et al., 2017). The student-specific regression results are reported in Table 5 below.

Table 5: Effects of RML and Retail Availability on Student Time Use

	Work Models		Leisure Models		Education Models	
	RML	Retail	RML	Retail	RML	Retail
RML	2.36		-3.75^{**}		1.09	
	(1.52)		(1.44)		(1.32)	
Retail		3.69^{*}		-6.35^{***}		2.19
		(1.69)		(1.60)		(1.47)
Age	1.88^{***}	1.88^{***}	-4.17^{***}	-4.17^{***}	-0.65^{**}	-0.53^{*}
	(0.27)	(0.27)	(0.24)	(0.24)	(0.24)	(0.22)
Age^2	-0.02^{***}	-0.02^{***}	0.05^{***}	0.05^{***}	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Race						
Black	1.51	1.51	-1.12	-1.12	0.44	0.38
	(0.81)	(0.81)	(0.76)	(0.76)	(0.70)	(0.70)
Asian	-7.74^{***}	-7.68^{***}	-0.16	-0.25	8.57^{***}	8.70^{***}
	(1.09)	(1.09)	(1.03)	(1.03)	(0.95)	(0.94)
Other	-3.97^{*}	-3.93^{*}	1.68	1.59	0.51	0.52
	(1.57)	(1.57)	(1.49)	(1.49)	(1.37)	(1.37)
Male	3.89^{***}	3.89^{***}	3.20^{***}	3.20^{***}	0.14	0.15
	(0.53)	(0.53)	(0.51)	(0.51)	(0.47)	(0.47)
Recession	-0.23^{***}	-0.23^{***}	0.12^{*}	0.12^{*}	0.02	0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Constant	-46.29^{***}	-46.34^{***}	203.36^{***}	203.34^{***}	8.31	9.14
	(5.55)	(5.55)	(5.21)	(5.21)	(4.83)	(4.79)
R^2	0.15	0.15	0.25	0.25	0.16	0.16
Adj. R^2	0.13	0.13	0.23	0.24	0.14	0.14
Num. obs.	11195	11195	11195	11195	11195	11195

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

We can see that students tend to work more post-RML and following retail availability. In both models, students spend significantly less time on Leisure activities, and education time-use appears unaffected. Time spent on leisure activities falls by approximately 3 hours per week following RMLs, and more than 6 hours following retail availability. The 95% confidence interval for leisure time post-Retail relates a decrease of between 5 and 8 hours in weekly leisure time. These results contradict Chu and Gershenson's findings, which held that time spent on leisure increased significantly amongst students following legalization. It is possible that these differences arise based on differing time-use-activity coding schemes, but that seems unlikely to explain the sign reversal and large coefficient differences. Chu and Gershenson also did not account for variation in students' time spent working in their analysis, which may have led to the dissimilarity in results. These results are robust, though somewhat imprecise, and remain significant in the presence of clustered standard errors by state.

Discussion

For the most part, the results reported above suggest that labor outcomes are largely independent of recreational marijuana legalization. Although some relationships bear highlighting once more. Post-RML we see that across the entire population, individuals tend to spend less time searching for jobs. This is particularly true for women aged 18-30, although we see the opposite relationship with women aged 30-40. These results are likely due to small sample sizes and can be discounted. We also see that while RMLs do not affect labor force in aggregate, they appear to have a strong negative effect on labor force participation among men aged 30-40. This result is very imprecise but nonetheless suggests that men are more likely to leave the labor force compared to their counterparts in non-RML states, though the mechanism explaining that relationship is beyond the scope of this paper. Due to the limited sample of states that have passed RMLs, it is possible that this result is driven by systematic variation in state-specific trends in labor force participation.

While RMLs do not appear to affect time spent working, the existence of retail availability does produce a somewhat significant negative relationship. This appears to be largely driven by relative decreases in working hours among men aged 50-65 and women aged 30-40. We also see negative effects, that are smaller in magnitude and do not rise to the level of significance, in other sub-groups. Another significant effect that emerges when we examine sub-groups is that men tend to spend less time on leisure following the retail availability of marijuana, which is a similar effect to those we find among students.

The clearest effects that we see from RMLs are when we look at student time-use. Following legalization, students tend to work more hours and report less leisure time, though time spent on education appears unaffected. These relationships are magnified when we focus on the retail availability rather than the date of legalization itself, suggesting that student working hours are increasing in the availability of marijuana and vice versa for leisure time. The negative relationship between marijuana availability and leisure time seems quite counter-intuitive but several potential explanations exist. Sabia and Nguyen (2018) note that if leisure time is more valuable when accompanied by marijuana consumption, it may elicit changes in labor supply as well. Under the simplifying assumption that individuals choose their leisure time such that they derive a fixed utility from leisure, and that leisure utility per hour is higher after marijuana consumption, this would explain the relationship that appears here. Moreover, if students are more motivated to work for income when marijuana is available to purchase, they may substitute away from their “excess” leisure time.

Taken together with the findings of Graves and co-authors, namely that working adolescents were more likely to use marijuana than their non-working counterparts (Graves et al., 2018), it seems that income becomes relatively more valuable after legalization, and students are motivated to work additional hours. This doesn’t fully account for the large decrease in weekly hours spent on leisure, but nonetheless provides some rationale. Another potential explanation is that students are hesitant to honestly report their leisure time-use when some of that time is spent on illicit activities, such as using drugs, and thus under-report their time spent on leisure. If this type of behavior exists, it would suggest that leisure reported is decreasing in the total time spent consuming marijuana. If students tended to report that they were doing school-related activities when they were actually consuming marijuana, this would account for the positive but muddled relationship between RML/retail availability and education time-use.

Conclusion

This study considers the effect of recreational marijuana legalization on labor market outcomes and time-use among Americans. We take RMLs as an exogenous shock to individuals' behavior, to identify the intent-to-treat estimator, estimating the effect of recreational marijuana availability on outcomes. Cognizant that an RML does not immediately increase availability in most states, I complement the initial analysis by investigating how the model differs when we assess the treatment to be imposed on the date of retail availability as opposed to the date of legalization. All models are shown in aggregate and then within groups based on age and gender to allow for heterogenous treatment effects across groups.

Ultimately, both the RML and Retail models tend to find largely insignificant effects relating marijuana availability and labor market outcomes. Although some marginal effects emerge when focusing on sub-groups. However, when we examine the effect among students, a population particularly at-risk for marijuana use, we see more significant effects and can derive more precise estimates. In particular, after marijuana becomes legal, students tend to work more and report less time spent on leisure. After marijuana becomes available recreationally, students spend 3 more hours working on average, and decrease leisure time reported by 6 hours. These results contradict some prior findings but are nonetheless robust and bear further attention in future research.

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Appendix

States with Legalized Medical Use[2, 3]	Population[1]	States with Legalized Recreational Use	Population
Alaska (1999)	731,545	Alaska (2015)	731,545
Arizona (2010)	7,278,717	California (2018)	39,512,223
Arkansas (2016)	3,017,804	Colorado (2012)	5,758,736
California (1996)	39,512,223	Illinois (2019)	12,671,821
Colorado (2000)	5,758,736	Maine (2016)	1,344,212
Connecticut (2012)	3,565,287	Massachusetts (2018)	6,892,503
Delaware (2011)	973,764	Michigan (2019)	9,986,857
Florida (2016)	21,477,737	Nevada (2016)	3,080,156
Hawaii (2000)	1,415,872	Oregon (2015)	4,217,737
Illinois (2014)	12,671,821	Vermont (2018)	623,989
Louisiana (2015)	4,648,794	Washington (2012)	7,614,893
Maine (1999)	1,344,212	District of Columbia (2015)	705,749
Maryland (2014)	6,045,680	**Total Population**	**93,140,421**
Massachusetts (2013)	6,892,503	**% of US Population**	**28.4%**
Michigan (2008)	9,986,857		
Minnesota (2014)	5,639,632		
Missouri (2018)	6,137,428		
Montana (2004)	1,068,778		
Nevada (2001)	3,080,156		
New Hampshire (2013)	1,359,711		
New Jersey (2010)	8,882,190		
New Mexico (2007)	2,096,829		
New York (2014)	19,453,561		
North Dakota (2016)	762,062		
Ohio (2016)	11,689,100		
Oklahoma (2019)	3,956,971		
Oregon (1999)	4,217,737		
Pennsylvania (2016)	12,801,989		
Rhode Island (2006)	1,059,361		
Utah (2020)	3,205,958		
Vermont (2004)	623,989		
Washington (1998)	7,614,893		
West Virginia (2020)	1,792,147		
Washington DC (2010)	705,749		
Total Population	**221,469,793**		
% of US Population	**67.5%**		

Leisure Time Activities:

Lawn, Garden, and Houseplants, Animals and Pets, Socializing, Relaxing, and Leisure, Playing Games, Sports, Exercise, and Recreation, Telephone Calls, Hobbies, Household and personal mail, Reading/Writing for personal interest

Table A1: The Effect of Retail on Labor Outcomes and Time Use - Men

	Work	Leisure	Job Search	Employed	Unemployed	Labor Force
Panel A: Men 18-30						
Retail	−1.720	1.328	−1.026	−0.063	−0.149	−0.187
	(2.070)	(1.689)	(2.384)	(0.106)	(0.145)	(0.118)
R^2	0.231	0.214	0.482			
Log Likelihood				-5,309.059	-3,211.751	-3,866.941
N	9,414	11,966	1,102	11,966	11,966	11,966
Panel B: Men 30-40						
Retail	0.302	-2.213^{*}	−3.135	0.004	−0.070	−0.064
	(1.420)	(1.259)	(6.701)	(0.105)	(0.149)	(0.123)
R^2	0.341	0.243	0.529			
Log Likelihood				-4,683.414	-2,578.402	-3,021.615
N	16,087	17,604	680	17,604	17,604	17,604
Panel C: Men 40-50						
Retail	−0.970	1.089	−1.826	−0.026	−0.024	−0.057
	(1.458)	(1.305)	(4.384)	(0.100)	(0.149)	(0.113)
R^2	0.343	0.228	0.556			
Log Likelihood				-5,991.697	-2,803.452	-4,438.347
N	17,022	19,149	725	19,149	19,149	19,149
Panel D: Men 50-65						
Retail	-3.656^{***}	0.303	−3.266	−0.024	−0.065	−0.054
	(1.413)	(1.197)	(4.348)	(0.066)	(0.122)	(0.068)
R^2	0.342	0.205	0.382			
Log Likelihood				-12,798.380	-3,747.585	-11,799.730
N	17,173	24,339	953	24,339	24,339	24,339
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A2: The Effect of Retail on Labor Outcomes and Time Use - Women

	Work	Leisure	Job Search	Employed	Unemployed	Labor Force
Panel A: Women 18-30						
Retail	0.472	0.077	-3.367^{**}	0.010	−0.007	−0.005
	(1.844)	(1.362)	(1.474)	(0.091)	(0.127)	(0.096)
R^2	0.211	0.188	0.386			
Log Likelihood				-8,520.770	-4,149.188	-7,401.193
N	10,424	15,423	1,354	15,423	15,423	15,423
Panel B: Women 30-40						
Retail	-3.249^{**}	1.298	−2.298	0.054	0.101	0.083
	(1.288)	(0.971)	(2.101)	(0.070)	(0.119)	(0.073)
N	16,536	22,883	1,112	22,883	22,883	22,883
R^2	0.303	0.217	0.437			
Log Likelihood				-12,315.730	-4,099.242	-11,088.390
Panel C: Women 40-50						
Retail	−0.875	1.819	−0.837	−0.035	0.149	0.007
	(1.434)	(1.140)	(2.529)	(0.076)	(0.126)	(0.080)
R^2	0.309	0.192	0.465			
Log Likelihood				-11,404.160	-3,589.941	-10,246.840
N	16,685	21,983	936	21,983	21,983	21,983
Panel D: Women 50-65						
Retail	−2.104	0.944	0.714	0.016	−0.098	0.0003
	(1.348)	(1.018)	(2.735)	(0.058)	(0.118)	(0.059)
R^2	0.296	0.139	0.392			
Log Likelihood				-17,800.010	-3,957.641	-17,173.940
N	18,414	29,571	944	29,571	29,571	29,571
Note:						*p<0.1; **p<0.05; ***p<0.01