Dissertation

Essays on Behavioral Change Caused by Exogenous Shocks

Department of Economics

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THREE ESSAYS IN APPLIED MICROECONOMICS ON THE BEHAVIORAL CHANGES CAUSED BY EXOGENOUS SHOCKS

AN ABSTRACT

SUBMITTED ON THE FIRST DAY OF DECEMBER 2020

TO THE DEPARTMENT OF ECONOMICS

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

OF THE SCHOOL OF LIBERAL ARTS

OF TULANE UNIVERSITY

FOR THE DEGREE

OF

DOCTOR OF PHILOSOPHY

BY

Sanjukta Basu

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Abstract

People living through changes in their surroundings react to it unexpectedly. Exogenous political, economic and legal changes impact individual behavior in an unpredictable manner. This dissertation uses three papers to give evidence of exogenous shocks affecting individual behavior. First, I study the impact of an economic change. Using business cycle indicators, I show that a change in the employment status of parents causes them to invest higher time with their children instead of exploring new job opportunities in the early months of unemployment. The short term impact of unemployment is favorable for child development even though literature has shown that long term unemployment is detrimental to child well-being. Second, I explore the impact of a spillover of a policy intended to save energy. The Daylight Savings Time was implemented during the World Wars to conserve energy. Over the decades, its impact on energy conservation has diminished. My research shows that there are clear evidences of serious disruption in daily lives of those subjected to the clock change twice a year, causing higher stress and lower sleep in the early weeks of the time change. Third, I study the legalization of medical marijuana on consumption of marijuana and alcohol patterns, as well as criminal behavior among those subjected to it. The results show that even though there is a slight increase in marijuana and alcohol consumption among adults, there is no evidence to support that it encourages teenagers to explore marijuana consumption. There is also no evidence of any change in criminal behavior.

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Dedication

To the extraordinary women in my life who served as inspirations,

My mother Dr. Tinku Basu

My grandmothers,

Manju Bhattacharjee and Shukla Bose

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Declaration

I, Sanjukta Basu, declare that this dissertation and the work presented in it are my own and has been generated by me as the result of my own original research. I confirm that this work was done wholly or mainly while in candidature for a PhD degree at the Department of Economics in the School of Liberal Arts at Tulane University.

I corroborate that

- No part of this dissertation has previously been submitted for a degree or any other qualification at this University or any other institution;
- Where I have consulted the published work of others, this is always clearly attributed;
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- None of this work has been published before submission;

Sanjukta Basu

December 1, 2020

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I would like to thank my former department chair, Dr. James Alm and current department chair Dr. Douglas N. Harris for giving me the opportunity to study in this prestigious institute. I am very grateful to all the faculty and staff members of the Department of Economics that have taken some time to discuss and enrich my work. Particularly valuable were the corridor chats; the weekly seminars; and the informal meetings. Tulane University has provided me with a very stimulating environment in what concerns the extraordinary quality of its academic staff, and that experience will leave marks beyond this thesis.

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This thesis would not have ever been completed without the support and motivation of the wonderful people in my life.

Introduction

Human beings are habitual creatures. They are accustomed to follow their schedules and daily routines. Exogeneous changes have the potential to disrupt these routines. My study focuses on how individuals' lives are affected by exogeneous changes in the economic, political and legal atmosphere. My dissertation consists of three papers.

First, I study the impact of economic changes. Through this paper, I show that a change in employment status, caused by a change in the business cycle, affects parental daily time schedules, that is spent in various activities including childcare. I use state level unemployment rate as an indicator for economic changes. For time use information, I use the American Time Use Survey database. My study focuses on the short-term impact of unemployed parents in their time investment. Parental unemployment has long term detrimental impact on children well-being, however, in the short-run, children benefit from unemployed parents as they get more time investment from them. When unemployed, parents spend more time with their children than looking for a new job in the short run. The income effect of unemployment is negligible as parents tend to use their savings and smooth consumption.

My second paper focuses on an archaic policy. I study how Daylight Savings Time (DST), a policy implemented during the World War I, changes sleep pattern, moods and various intensity of activities engaged by individuals in the modern world. Some states in the US like California, Louisiana, Oregon, etc., and the European

Union have been discussing the removal of daylight savings time due to its harmful impact on health and no benefit of energy conservation. I use the American Time Use Survey database and focus on respondents interviewed a week before and after the fall and spring DST. I compare two states - Arizona which never had DST, and New Mexico which always had DST using a difference-in-differences estimation method. Both states are geographically and climatically similar making them suitable for comparison. I find that DST significantly disrupts daily schedules and changes moods of those who are affected by it, however, the impact fades out in subsequent weeks.

Third, I study how the legalization of medical marijuana changes the consumption of marijuana and other licit and illicit drugs, and influence criminal behavior. This is a joint study with Siobhan Innes-Gawn and Mary Penn. We use the National Longitudinal Survey of Youth 1997, which is a self-reported survey on criminal and drug abuse behaviors. As of January 2019, 33 states and the District of Columbia have approved laws permitting the medical use of marijuana. We use a difference-in-differences approach. State medical marijuana laws are very different from each other in terms of the possession and consumption limit, presence of state dispensary and the various diseases it is allowed to be used for treatment. We incorporate these difference in our analyses. The results show that there is a slight increase in marijuana and alcohol consumption but no change in criminal behavior. The magnitude of increase is very small indicating that this policy has negligible negative impact on society.

The three papers are attached below.

Chapter 1

Effect of Parental Employment Status on Child Care

By Sanjukta Basu

Abstract

Parents spend a significant amount of time and income on raising children. Existing literature shows that parental unemployment has detrimental long-term effects on child development. My study focuses on the short-term impact of unemployed parents in their time investment. Using an instrumental variable approach and the American Time Use Survey (ATUS), I study if individuals who were laid-off or have been unemployed reallocate the time that was spent at work by spending more time with their children. I find that when unemployed, parents spend more time with their children than looking for new employment opportunities in the short-run. The short-run effects of unemployment are opposite of long-run effects and favorable for children. This behavior is consistent among all races and sexes.

Keywords: Unemployment; Non-market Production; Time diary; Childcare.

JEL: D13, J13.

1.1 Introduction

Changes in business cycle can cause unemployment to rise, forcing workers to quit the labor market, thus affecting their daily time schedules. This paper attempts to analyze how unemployment, in the short run, affects daily time schedules of parents. I used state-level unemployment rate as an indicator for the business cycle change. Using an instrumental variable (IV) approach, I studied if individuals who were laid-off or have been unemployed, reallocate their time, earlier spent at work, on other activities such as household chores, leisure, child care and job search. I find a 32 percentage points rise in time spent with children when parents become unemployed due to an economic slowdown, and only a 4-percentage point increase in time spent on exploring new employment opportunities. My study emphasizes on the behavioral change of those unemployed for a few months. I conclude that parents tend to focus on their children more than looking for new jobs when unemployed in the short run. The results are more intriguing when we focus on various demographics separately.

Time and income spent by parents are the two key ingredients for producing children (Becker (1988)). I define parental time as the time spent by parents with their children, and parental income as the income spent on purchasing goods and services for the children. Higher parental income implies access to high quality market goods such as education, health care and toys. Children also require adequate time investment from their parents for their stable growth and development. It helps in forming bonds, monitoring growth, and providing stability in a child's life. An efficient combination of income and time provides an appropriate environment for child development. Parents want to furnish such pertinent atmosphere in the household.

A sudden loss in employment results with individuals having more time and less income. An unexpected lay-off is equivalent to a reduction in opportunity cost because the wage rate equals the opportunity cost of parent's time. The opportunity cost of parent's time does not, of course, equals zero as the parent can also engage in alternative productive activities such as household chores or other income-generating hobbies. A reduction in the opportunity cost of a parent's time can be separated into income effect and substitution effect. If the lay-off is considered to be short-term and perceived as temporary by the unemployed individuals, the effect on permanent income will be negligible. Parents will use their savings to smoothen consumption in the near future after being unemployed (this is in accordance to Franco Modigliani's Life Cycle Hypothesis). So, I can ignore the income effect and conclude that the total effect of short-term unemployment is driven by the substitution effect, causing parents to spend more time with their children without changing parental income.

Consequently, it is surprising that we find unemployment has little effect on the amount of time parents spend with their children using the OLS method.[1] The OLS estimates indicate that a change in business cycle conditions, given by a unit increase in the state level unemployment rate, is associated with 0.02 percentage points higher parental time with their children.

Studying the descriptive statistics, I find very little difference between the employed and unemployed parents in their allocation of time on child care. One might imagine, given that the unemployed will have more time at their hands, they will spend extra time with their children. However, they do not do so. This is because unemployed individuals are different from employed workers and hence, have distinct demand for leisure. This preference for leisure might carry over to their allocation of time for childcare. When previously employed individuals lose their jobs, their behavior might be different.

The IV approach allows me to evaluate how those, who are more likely to be unemployed due to an economic slowdown, change their time allocation when unemployed. If I could perform a randomized control trial experiment where employed workers are unexpectedly unemployed, I could observe the effect of unemployment

[1]The OLS estimates are very small in magnitude and statistically insignificant at conventional levels for most demographics. These analyses were conducted but excluded from the paper.

on the allocation of time for childcare and other activities. Since such an experiment is not possible, I propose the use of an instrumental variable to account for the possibility that employment status is endogenous.

The IV estimation method allows me to analyze the above relationship effectively. The underlying intuition is that the effect of loosing employment on parental time is basically the effect of business cycle conditions (the IV), as measured by the state level unemployment rate, on parental time allocation (the outcome). Employed workers will not respond to business cycle conditions if their employment status is unaffected. The IV estimates are higher in magnitude and statistically significant at conventional levels. The effect of the business cycle conditions (the instrument) on the treatment (employment status), that is the "first-stage regression" has statistically significant estimates which are high in magnitude.[2] In my analyses, using the IV strategy helps me recover a stronger effect of the treatment on the outcome which was not possible with the OLS approach. Therefore, I use the IV estimation technique for this study.

My paper's contribution to the existing literature is three-fold. First, this study confirms earlier empirical estimates of the effect of unemployment on the amount of time spent on childcare with a larger dataset and using an IV estimate. The resultant hypothesis is testing if individuals who became unemployed due to the declining business cycle increase the time they spent with their children. Aguiar *et al.* (2013) finds that after the 2008 recession, unemployment rose and the foregone work hours were re-distributed among other activities. They found a five percent increase in child care time. Similar behavior was observed by Edwards (2011). Both these papers used the ATUS, but were constrained by a smaller dataset. Results from my study show that parents increase the time they spend with their children during unemployment by

[2]These regression estimates are not included in the paper. However, the first stage regressions are strong and statistically significant at conventional levels. I also use the Hausman specification tests. These results are discussed in more detail in the paper.

32 percentage points. This is relatively higher than the results found by other studies and consistent with the findings of Mork *et al.* (2014). Time spent on job search is 4 percentage points higher. Fathers increase their contribution to the household by spending more time on chores. Second, I find that in the short-run, parents try to compensate the loss in parental income by spending more time with their children to maintain similar level of care. Third, I find happier parents choose to spend more time with their children. Juster (1985) and Guryan *et al.* (2008) find that parents feel spending time with their children can be enjoyable and therefore, spend more time with them when stressed. Such a behavior may not be in the best-interest of the child. However, my estimates show that only black fathers respond to higher levels of stress by reducing parental time. Finally, and more importantly, I find that temporary economic slowdown comes with benefits. In the short run, parents can smoothen their consumption by using their savings and hence are not worried about new employment opportunities in the near future. My results corroborate this hypothesis. I find unemployment encourages parents to spend more time with their children than looking for new jobs.

1.2 Background

Becker (1988) calls children self-produced goods using market goods and services, and parental time by each family. Some parents may choose not to have any children and spend none of these resources while some children may need more resources than others. The cost of a child, in terms of time and income, differs with children and parents. Each family or individual chooses the quantity of time and market goods to spend on their children. Higher parental income ensures that the child has access to good and nutritious food, quality education and better health facilities. Letablier *et al.* (2009) provides evidence that expenditure on children account for 20-30 percent of household budgets. Raising children is costly. Parental time is also essential for raising children. Becker (1988) argues that mothers' time is a major part of child care and this is the main reason why mothers invest more time with their children than at labor market.

Child care and development is a subject of concern for parents as well as policy makers. A loss of employment affects both - parental income and parental time. Involuntary or voluntary unemployment would result in a rise in disposable time but a fall in family income, both of which will have a significant effect on child development. A fall in household/parental income can lead to a loss of quality goods such as private schooling or health care, and socio-economic downgrade of the family, both of which influence child development. However, in the short-run the effect of fall in income is negligible as parents are more likely to smoothen their consumption using their savings. The gain in time resulting from unemployment which is more difficult to smooth, would be allocated to various activities including child care. As documented by Aguiar *et al.* (2013), after the 2008 recession, when unemployment rate rose, foregone work hours were re-distributed among other activities including child care. Parental time is expected to rise as a result of unemployment as seen by Edwards (2011). Mork *et al.* (2014) finds that chronic or long-term unemployment can lead to a deterioration of home environment due to household conflicts, and thus may lead to a fall in the time spent with children. My study finds the opposite effect in case of short-term unemployment.

To summarize, a change in unemployment status can alter parental time. However, due to a lack of household data on time use information in the past, this relationship was difficult to explore. With the existence of the ATUS database, it is now possible to test whether unemployment influences parental time. and to what extent.

Loss of jobs (causing long-term unemployment) can have adverse effects on worker's health (Sullivan & Von Wachter (2009)), mental well being (Eliason & Storrie

(2009)), marital stability (Eliason (2011)) as well as socio-economic status (Stevens (1997) and Jacobson *et al.* (1993)), all of which can affect their parental behavior and influence the child negatively. Many studies have highlighted the negative impact of long-term unemployment on child care. According to Ström (2002), parental unemployment is positively associated with higher risks of children accidents. Page *et al.* (2019) shows that an increase in local unemployment rate is associated with a significant increase in incidences of injuries and severe emotional difficulties among children. Chronic unemployment can lead to feelings of depression and humiliation creating a strain on parental behavior towards children. Such children are more likely to suffer from long periods of hospitalization, less likely to graduate high school and face unemployment (Christoffersen (2000)). Pedersen *et al.* (2005) shows that high prevalence of psychosomatic symptoms and chronic illness is common among children living in families with lower labor market participation. Parental unemployment has long term impact on children as seen in Oreopoulos *et al.* (2008). The authors find that adult earnings of children, with unemployed parents during their developing years, are 9 percent lower than otherwise.

Following the argument made by Becker (1988) that parental time and income are the two inputs for producing children, I assume that parent's utility is affected by the care they provide to their children (Appendix 1.7 shows the derivation and the analyses in detail). To simplify the model, I use a Cobb Douglas utility function. However, I have replicated the results using different specifications such as constant elasticity of substitution function. Equation 1.1 depicts how parental care affects their utility. Parents' utility consists of the care they provide to their children ($C(X_c, L_c)$), in addition to their own leisure (L_p) and consumption of market goods and services (X_p).

$$U_p = U(C(X_c, L_c), X_p, L_p) \tag{1.1}$$

Production function of childcare is a function of parental time (L_c) and parental income (X_c). Let this function be Cobb Douglas in nature as given below where a and b are constants giving the share of time and income spent by parents on children, respectively.

$$C(X_c, L_c) = X_c L_c = abXL \tag{1.2}$$

Parents' maximize their utility (defined in equation 1.3), which incorporates the production of childcare given to their children subject to the budget constraint given by equation 1.4.

$$U_p = [C(X_c L_c)]^{\alpha} X_p^{\beta} L_p^{(1-\alpha-\beta)} = AX^{(\alpha+\beta)} L^{(1-\beta)} \tag{1.3}$$

$$24w - wL - X + I = 0 \tag{1.4}$$

Total available parental time is less than 24 hours as parents are expected to spend some amount of total available time on their own leisure and other activities like household chores. Total available parental time is effectively 24 hours minus time at work (t), leisure time (L_p) and time spent in any other activities. I assume that time spent at other activities is negligible. Parents earn non-wage income, I, in addition to wage income earned at a rate of w per hour. They substitute between parental time in caring for their children and the time they spent at work (to earn income to buy consumption goods for them and their children). To provide a certain level of childcare, parents choose an optimum X_c^* and L_c^*. This is obtained by maximizing parental utility (equation 1.3), which incorporates production of childcare, subject to the budget constraint (equation 1.4) faced by parents.

$$L^* = \frac{(24w + I)(1 - \beta)}{(1 + \alpha)w} \tag{1.5a}$$

$$X^* = \frac{(24w + I)(\alpha + \beta)}{(1 + \alpha)} \tag{1.5b}$$

Employed parents consume at the equilibrium point where the marginal rate of substitution between parental income and time coincide with the wage rate. These results are consistent with other functional forms of the utility function such as constant elasticity of substitution.

Besides the two determinants mentioned above, there are many other factors which affect child care development such as parental education (Guryan *et al.* (2008)) and household and neighborhood characteristics. Some of these determinants are influenced by state unemployment rate changes. These factors are included in the production function and hence detailed analyses is beyond the scope of this study. For this paper, I will focus on the effect of state unemployment levels on changes in parental time with children.

1.3 Data

The data is taken from the American Time Use Survey (ATUS) and the Labor force participation data, both of which are administered by the Bureau of Labor Statistics (BLS). I use the unemployment rate which is an important indicator for measuring the current state of the business cycle and economic performance. It is a useful statistic because it serves to measure changes over time. Low unemployment rate suggests business cycle growth and higher levels depict an economic recession. Data on time diaries is obtained from the ATUS. It is a self-reported data which covers individual level information across state and over time. ATUS contains detailed information regarding the amount of time an individual spends engaging in various activities. I have divided a typical parental day into five groups: time with children; time at work; time for leisure; time doing household chores; and time spent searching for a job. The aggregate data covers 50 states over the time period of 2004 and 2015.

Table 1.1 gives the descriptive statistics of the labor force participation variables. Mean unemployment rate has been high at 6.25 percent, and the labor force participation has been slightly less than two thirds of the total working population (65 percent). Labor force participation is higher for men (71 percent) than that for women (59 percent), and the respective unemployment rate is also higher for men (6.58 percent) than that for women (5.89 percent). Similarly, we see a huge difference in the unemployment rate of the two races as well. Though the labor force participation rate between the two races differs slightly with white population having a higher rate, the difference between their unemployment rate is much larger. The white population has an average unemployment rate of 5.45 percent and the black population faces an average unemployment of 12.17 percent. It is important to notice that the two demographics face very different labor market conditions.

There is a statistically significant difference between the mean of time spent by parents, as a ratio of total time, in various activities when employed versus unemployed (table 1.2). Employed parents spend 24 percent of their time with their children and 16 percent at their workplace. Unemployed parents spend 5 percentage points more time with their children and 1.3 percentage points more at leisure as compared to employed parents. Unemployed parents also spend more time working on household chores and looking for new employment. The characteristics of this sample of observation is given in table 1.3. There is a significant difference between unemployed and employed parents. Unemployed parents are slightly younger and less educated. They have lower spousal income than employed parents. Fifty percent of unemployed parents have employed spouses while 63 percent of employed parents have working spouses.

1.4 Empirical strategy

Parents change their daily schedules as a response to a change in their employment status. Changes in the business cycle affect employment status of workers by either gaining employment or getting laid-off. Employment status affects time diaries by impacting working hours. During a boom period, employment opportunities are lucrative and the opportunity cost of spending time with the children can be huge in terms of foregone wages. Thus, a business cycle change can influence the employment status, hence substituting time spent at work with other activities like child care and job search. This is tested using the Instrumental Variable (IV) estimation method where I use the business cycle indicator as an instrument for employment status to find the effect on the time an individual tend to spend with their children. Business cycle changes are reflected by changes in the unemployment rate prevailing in the economy.[3] The second stage equation is represented as follows

$$Time\_A_{istj} = \alpha + \gamma Emp_{ist} + \rho Z_{ist} + \tau_j + \epsilon_{istj} \tag{1.6}$$

The first stage is given below

$$Emp_{ist} = \nu + \beta Unemp_{st} + \lambda Z_{ist} + \eta_s + \delta_t + \mu_{ist} \tag{1.7}$$

where Emp_{ist} gives the employment status of individual i at year t and state s; coded 1 if employment status is unemployed but looking for a job or laid-off; $Unemp_{st}$ gives the state of the business cycle in state s and over year t - namely

[3]To study if the business cycle changes directly impact individual time allocations, I use an OLS estimation method to estimate the effect of state level unemployment rate on time diaries. I study how state level unemployment rate changes the time spent by parents on five different activities. The OLS estimates are very small in magnitude and statistically insignificant for most demographics. For this reason, I have excluded them from the paper.

the state unemployment rate; $Time\_A_{istj}$ is the time spent engaging in one of the five activities, A, as a percentage of total time available in a day (namely, time with children, time at work, time doing household chores, time for leisure and time spent searching for new employment opportunities), by individual i living in state s, over year t and on day j of the week; Z_{ist} gives individual characteristics such as age, family income level, educational achievement (the respondent's highest completed level of education), and spousal employment status, coded as 1 if spouse/partner is employed; η_s gives the state fixed effects; δ_t gives the time fixed effects; τ_j gives the days of the week; and ϵ_{istj} gives the error term in the second stage equation; μ_{ist} gives the error term in the first stage equation.

Various endogenous test such as the Hausman-specification test shows that we can reject the null, which says variables are exogenous, at conventional levels for specifications using time with children, time at leisure and time searching for job as outcome variables. This result is consistent across all different analyses, races and sexes that I conducted over the course of my study.

Further, to understand the extent to which a change in the business cycle effects various demographics, separate regressions were run for each by segregating individuals as per their race and sex.

1.5 Results

Figures 1.1 and 1.2 give the time trend of the national unemployment rate for various demographics. Both figures mirror a typical business cycle change graph with adjacent peaks and valleys. The unemployment rate for all demographics has been lowest in 2007 and then peaking in 2010. Comparing the two sexes, the unemployment rate has been fairly similar with the rate for men being slightly higher than that for women. However, figure 1.2 shows that the unemployment rates are starkly different for the two races. An unfavorable business cycle is more adverse for the black demographics who are already suffering from low employment opportunities. The national average is closer to the white population unemployment rate. Nevertheless, consistent with the previous figure, unemployment rate is lowest in 2007 before reaching its peak in 2010, just after the global financial crises, and then falling again. Due to the difference in the labor market for each demographic, I study the races and sexes individually.

Tables 1.4, 1.5 and 1.6 give the estimates for all the six demographics. I find that parents spend the greater share of their newly acquired time with their children than looking for new job opportunities. Table 1.4 shows, for the whole sample, unemployed parents spend 12 percentage points less time at their work or any work-related activities such as socializing and engaging in income-generating hobbies, crafts and services. Parents lose their main or secondary job where they are subjected to report. Time spent on these work declines significantly in magnitude. However, time spent in other work related or income-generating activities like crafts and services increases. These estimates are statistically significant at 1 percent level. When parents loose their main employment (or source of income), they continue to spend the same or more time in work-related gatherings to explore future networks, or engage in their hobbies or services which may provide any additional income.

When unemployed, parents spend 32 percentage points more time with their children and 3.8 percentage points more time looking for new employment. The sign of the estimates are consistent across all demographics, and statistically significant at conventional levels. The magnitude of these estimates differ across various demographic groups. White mothers increase their time with their children by 31 percentage points and job search time by 2.8 percentage points as a response to being unemployed, while white fathers increase their time with their children by 28 percentage points but increase job search time by 5 percentage points (table 1.5).

White fathers contribute 23 percentage points more time to household chores. This magnitude is large and statistically significant at 1 percent level. Such a behavior is not replicated by mothers when unemployed. White parents lower leisure time by 23 and 29 percentage points for fathers and mothers, respectively, but black parents do not.

Black parents, in general, face a higher level of state unemployment rate than white parents (table 1.6). Similar to white parents, they also increase their time with their children when subjected to a business cycle downturn. Black unemployed fathers spend 13 percentage points more time with their children than their employed counterparts. The magnitude of response of black mothers differ much from their white counterparts. Black mothers spend only 15 percentage points more time with their children when subjected to unemployment. These parents spend more time looking for new employment when compared to similar white parents. Mothers and fathers spend 4 and 6 percentage points, respectively in this activity. However, they still prefer to spend a larger portion of their gained time with their children. Black fathers, similar to their white counterparts, increase their time engaged in household chores by 11 percentage points. Leisure is another important activity which occupies a significant time of the day. However, unlike white parents, black parents do not change their time allocation to leisure. For both races, unemployment status shifts parental priority from career to family and children.

Black mothers reduce time at work by 13 percentage points while white mothers do not reduce hours at work significantly at conventional levels (table 1.5). This is an interesting observation seen among the two demographics who also differ in their employment characteristics. Even though more white mothers are employed (93 percent) as compared to black mothers (86 percent) and they earn higher mean wages, time spent at work when employed is 4 percentage points lower for white mothers as compared to black mothers. White mothers spend less time at work when they are employed as compared to black mothers. This difference is statistically significant at 1 percent level of significance.[4]

Appendix 1.7 gives the regression estimates for each demographic including the estimates of control variables.

Anticipated versus Unanticipated Unemployment

An individual can become unemployed for multiple reasons, and the reason for unemployment can impact their time diaries. To explore this, I compare workers who are unemployed for one of the following reasons: being laid-off, voluntarily resigned, new or re-entrants in the labor market and temporary or seasonal workers.

I used the state-level unemployment rate as an IV for the employment status of individuals. One would assume that the cause for unemployment plays a significant role in deciding time allocation by parents. Temporary or seasonal workers are expecting unemployment in the near future. They can plan their daily schedules accordingly. These workers will work more hours before their contract ends and spend greater hours at leisure and other activities after their contract ends. These parents may not be looking for new employment aggressively. On the other hand, laid-off workers face unexpected unemployment. They are unprepared for the change in their daily schedule, and hence their reaction to a job loss is predicted to be different from parents with expected unemployment. These parents are expected to actively look for new employment to compensate for the sudden loss in income. Other types of workers, such as new/re-entrants, have voluntarily entered the labor force and remain unemployed while they look for a job.

My study focuses on the short-run effect of unemployment, and it does not support the above hypothesis. Individuals facing unemployment in the short run are not worried about new jobs and tend to continue to focus on family welfare. Thus,

[4]The descriptive statistics given by race and sex are not shown in the paper.

corroborating the previous argument for no or negligible income effect. The cause for unemployment affects the time they chose to spend with their children slightly.

Table 1.7 shows that the interaction between employment status and the cause for unemployment is statistically significant at conventional levels. In this section, I do not provide the results for each demographics due to the problem of missing data for questions regarding the type of unemployment. Separating the regressions for each demographic reduces the observation size significantly giving unreliable regression estimates. Hence, I have used the whole sample and used a dummy variable depicting race and sex, respectively.

Workers, who are unemployed due to being new/re-entrants in the labor market, reduce parental time by 40 percentage points. Effectively, the gain in parental time for children with such type of unemployed parents is 8 percentage points (estimate from employment status + new/re-entrants + interaction between the two terms). Unemployed parents who are laid-off spend 38 percentage points (effectively 6.7 percentage points) less time with their children. Seasonally or temporary unemployed parents spend 38 percentage points (effectively 5 percentage points) less and voluntarily resigned parents spend 39 percentage points (effectively 5.02 percentage points) less time with their children. Leisure time increases for all types of unemployed parents by 45 percentage points. Individuals who are presumed to be more worried about their employment status (for example, laid-off and new/re-entrants) tend to spend more time with their children as compared to workers who have more control over their employment status (seasonal and voluntarily resigned workers).

Workers who are unemployed due to being new/re-entrants spend 1.5 percentage points less time searching for jobs (effectively 2.4 percentage points more time than other workers). Laid off workers spend 1.8 percentage points more time in job search (or effectively 5.5 percentage points more time than other workers). Seasonal workers and those who have voluntarily resigned do not deviate much from the group average.

Time spent by parents engaging with their children differs slightly due to the cause of unemployment but time spent at job search does not differ for different types of workers.

Long-term versus short-term unemployment

Parents unemployed for a long term are expected to behave differently than parents who have been unemployed in the short term. The ATUS records individuals who have been unemployed for more than four weeks. The data also provides the current population survey collected 2-5 months before the ATUS interviews which asked the respondents' employment status in the last 4 weeks before the interview. Based on the two sources of information, the data provides those individuals who have been unemployed for at least a total of 3-6 months. I consider this medium-term unemployment instead of long-term unemployment because long-term unemployment, as measured in the existing literature, consists of years of unemployment. There is a small subset of the sample that responded to this question which explains the lower number of observations. I used state-level unemployment rates as an instrument for the employment status of individuals. A dummy variable is used to depict those individuals who have been unemployed for more than 3-6 months.

Very few demographics are affected by medium-term unemployment. White mothers spent 8 percentage points less parental time when unemployed for a few months. Time allocation to leisure is 8.1 percentage points more for this demographic in such conditions. Time allocated to engaging in job search is higher by 4 percentage points for white fathers. Black fathers are more likely to spend greater time with their children (11 percentage points), this behavior is not reflected among black mothers, when unemployed for longer time. Black mothers are more likely to spend greater time for job search when faced with a medium-term unemployment. Being unemployed for a few months versus immediate unemployment causes very limited behavioral changes from each demographic. Some demographics, like white mothers are more likely to increase leisure time while others, like black mothers, increase job search time. This section further supports the negligible income effect argument in the short and medium run.

Mood indicators

Unemployment can cause emotional distraught leading to stress and decline in mental well-being (Eliason & Storrie (2009), Baum *et al.* (1986) and Turner (1995)). Parents, who face sudden unemployment, are concerned about the lack of adequate income, financial stability of their families and payment of their children's expenses. Such factors can affect parental behavior towards their children by either spending less time with them or being psychologically distressed.

This section discuses the effect of self-reported mood indicators, namely happiness, sadness and stress, on the amount of time parents spend with their children as a percentage of total time in a day. The mood indicators are reported on a discrete scale with 0 being the lowest. This data ia available for only three years in my sample - 2010, 2012 and 2013. I use the unemployment rate as an IV for parental employment status and incorporate interaction between employment status and the level of mood reported by parents in the regression analyses.

I find that a small subset of the 6 demographics studied here, is affected by these indicators. Happier parents tend to share their happiness by spending an additional 4.8 percentage points time with their children. This result is consistent with white parents but not black parents. White parents spend an additional 4 percentage points more time with their children when they report 1 unit higher on the happiness scale. White fathers and mothers increase parental time by 5 percentage points, respectively.

It is interesting to find that black parents respond to parental time when they report a high value on the sadness scale. Fathers and mothers spend 1.9 and 2.2

percentage points less time, respectively, with their children when they report to be upset. I do not observe such behavior among white parents. Lastly, I also find that only stressed black fathers reduce parental time by 2.8 percentage points. All other demographics are non-responsive to higher levels of stress.

Elasticities

Time allocation to certain activities are more elastic than others when the employment conditions of parents change. More formally, I estimate the elasticity of time use category A when employed with respect to when unemployed using the following expression

$$e^A = \hat{\beta}^A \frac{\tau^A_{empt}}{\tau^A_{unempt}} \tag{1.8}$$

where τ^A_{empt} gives average time allocated to activity A when employed; τ^A_{unempt} gives average time allocated to activity A when unemployed; $\hat{\beta}^A$ denotes the estimated responsiveness of time use in activity A to changes in the employment status. Using the estimates of the employment status variable from tables 1.4, 1.5 and 1.6 for all six demographics, I find the elasticities for each demographic shown in table 1.8.

Elasticity of parental time is 0.27 for all individuals. It is slightly higher for white parents (0.29) and much lower for black parents (0.14). Parental time is inelastic in nature. Also, elasticity is higher for mothers than fathers when I analyze each race separately. For the entire population, elasticity is higher for fathers than mothers. Allocation of time to work is highly elastic for all demographics but much higher for men than women. Elasticity of job search is perfectly inelastic. Time allocation to household chores is inelastic also but statistically significant for only fathers. Leisure is also inelastic and statistically significant at 1 percent level for all demographics except black parents.

1.6 Conclusion

Patterns of daily time schedules show that there is a behavioral response of parents to the conditions of business cycle. Downturns in business cycle will force unemployed parents, theoretically, to spend more time searching for new job opportunities. My paper attempts to find evidence to test the hypothesis that business cycle changes causes parents, when unemployed, to spend a larger share of their time searching for new employment. Using the unemployment rate as an indicator for business cycle conditions, I look at the effect of its change on the total amount of time, as a percentage of total time in a day, individuals spend engaging in various activities such as leisure, household chores, job search and with their children. Parents can spend time with their children by helping them in household chores, assisting in school work, reading and listening, and child care.

My results show that parents, when unemployed due to a business cycle downturn, spend only 3 percentage points more time looking for new employment. The larger share (32 percentage points) of their excess time is spent with their children engaging in child care and other child productive activities. My data allows me to focus on individuals who have been unemployed for a short period of time. In the short run, parents are more focused towards their children's welfare than looking for new employment. This result is consistent in sign but not magnitude across various demographics.

Though the regression estimates seems large in magnitude, the important implication is the direction or the sign of these estimates. When parents lose their employment, children welfare takes a higher priority than looking for new jobs. Unemployed fathers also spend more time engaging in household chores. White unemployed parents significantly reduce their leisure time. Such a change is not seen among black parents. Demographic characteristics also play an important role in determining parental time.

This study reflects an interesting aspect of parental behavior in terms of the time they spend in various activities. Unexpectedly, parents focus a lot more on children when unemployed instead of looking for new employment in the short run. The amount of time parents spend with their children is positively related to child care. However, my results cannot provide evidence to show how changes in parental time is associated with the long-term well-being of children. A broader implication of my study is that an economic slowdown, or specifically a loss in employment, comes with costs and some unexpected benefits. The gain in disposable time by losing employment seems to expand parental time, possibly because parents now have more energy, greater social interaction or less money to spend on professional child care. In the short run, they seem to focus on their children more than job search.

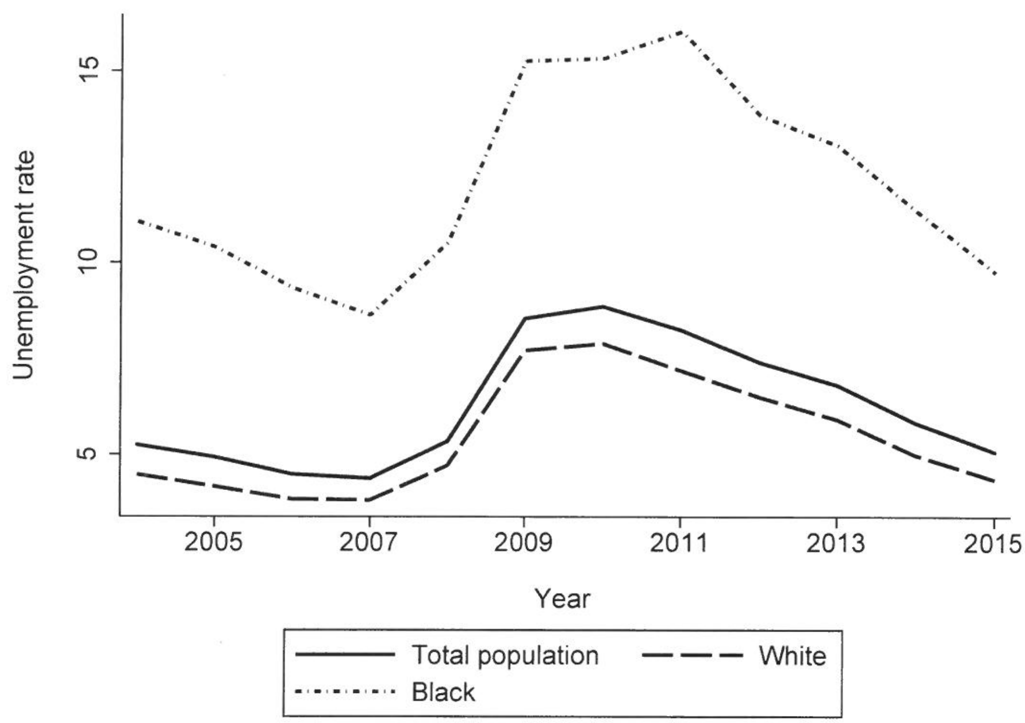
Employed parents are more likely to substitute parental time for work and compensate for their time with income spent on professional child care. When unemployed, the opportunity cost of spending time with children falls. While income effect is negligible in the short-run, substitution effect is the driving force. I find evidence to suggest that loss of employment causes potential changes in household dynamics. Parents are likely to spend more time with children and fathers contribute more in household chores while continuing to look for new employment opportunities. Short-run unemployment might actually be beneficial for children even though long-run is not.

Short-run business cycle changes may be a blessing in disguise to strengthen the bond between parents and children. These results create a vital need to explore these relationships and provide suitable policy measures at the school level where parents can be educated, appropriately, regarding the importance of their time in the welfare and future development of their children, so that they do not wait for an economic slowdown or temporary unemployment to spend more time with their children.

Figure 1.1: Time Trend of National Average Unemployment Rate

Source: Bureau of Labor Statistics.

Figure 1.2: Time Trend of National Average Unemployment Rate: White and Black Population



Source: Bureau of Labor Statistics.

Table 1.1: Description Statistics: Unemployment rate

Variable	Observations	Mean	Std. Dev
All individuals			
Unemployment rate	612	6.25	2.12
Labor force rate	612	65.65	4.19
Men			
Unemployment rate	612	6.58	2.41
Labor force rate	612	71.81	4.21
Women			
Unemployment rate	612	5.89	1.90
Labor force rate	612	59.86	4.44
All White individuals			
Unemployment rate	612	5.45	1.99
Labor force rate	612	66.10	4.71
White Men			
Unemployment rate	612	5.75	2.30
Labor force rate	612	72.63	4.75
White Women			
Unemployment rate	612	5.11	1.72
Labor force rate	612	59.82	5.35
All Black individuals			
Unemployment rate	507	12.17	3.98
Labor force rate	507	63.96	5.23
Black Men			
Unemployment rate	441	13.36	4.70
Labor force rate	441	66.56	5.99
Black Women			
Unemployment rate	428	11.40	3.81
Labor force rate	428	60.96	4.78

Source: Bureau of Labor Statistics. Unit of observation: state/year.

Table 1.2: Descriptive Statistics: Time Allocated to Various Activities

	When employed			When unemployed			Mean Difference
		Section 1			Section 2		Section 3
Variable	N	Mean	Std. Dev.	N	Mean	Std. Dev.	
Children	408,314	0.247	0.431	29,428	0.296	0.457	-0.049***
Work	408,314	0.168	0.374	29,428	0.007	0.081	0.161***
Leisure	408,314	0.327	0.469	29,428	0.340	0.474	-0.013***
Chores	408,314	0.257	0.437	29,428	0.326	0.469	-0.069***
Job Search	408,314	0.001	0.026	29,428	0.031	0.173	-0.038***

Source: American Time Use Survey. Unit of observations: Ratio of time spent in activity given in column 1 divided by total time in a day in minutes.
Notes: Section 1 gives the mean and standard deviations of time spent on various activities of individuals who are employed. Section 2 gives the above information of individuals who are unemployed. The last column shows the difference between the mean time spent by employed and unemployed individuals engaging in activities given in column 1. $***p < 0.01$ for the difference in mean. The mean difference between the two are statistically significant.

Table 1.3: Descriptive Statistics: Control variables

	When employed			When unemployed			Mean
		Section 1			Section 2		Section 3
Variable	N	Mean	Std. Dev.	N	Mean	Std. Dev.	Difference
Age (in years)	408,314	40.215	9.149	29,428	37.291	10.425	2.924***
Below high school	408,314	0.059	0.235	29,428	0.167	0.373	-0.109***
High school	408,314	0.216	0.412	29,428	0.298	0.457	-0.082***
College	408,314	0.725	0.446	29,428	0.535	0.499	0.190***
Single	408,314	0.257	0.437	29,428	0.454	0.498	-0.197***
Spousal employment status	408,314	0.636	0.481	29,428	0.495	0.500	0.142***
Spousal income (weekly in log)	408,003	6.409	3.909	29,391	5.016	4.314	1.393***

Source: American Time Use Survey. Unit of observations: Years for age, percentage for education level, marital status and spousal employment, log of income for spousal income.
Notes: Section 1 gives the mean and standard deviations of the control variables of individuals who are employed. Section 2 gives the above information of individuals who are unemployed. The last column shows the difference between the mean value of the control variables, given in column 1, for employed and unemployed individuals. $***p < 0.01$ for the difference in mean. The mean difference between the two are statistically significant.

Table 1.4: Estimates from an IV Estimation: All Individual

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
All individuals					
Employment status					
1 if unemployed	0.318***	-0.127**	-0.286***	0.0567	0.0388***
	(0.0559)	(0.0544)	(0.0577)	(0.0437)	(0.00318)
Observations	437742	437742	437742	437742	437742
All men					
Employment status					
1 if unemployed	0.276***	-0.276***	-0.214***	0.163**	0.0518***
	(0.0763)	(0.0681)	(0.0734)	(0.0735)	(0.00706)
Observations	172037	172037	172037	172037	172037
All women					
Employment status					
1 if unemployed	0.252***	-0.0189	-0.268***	0.00706	0.0285***
	(0.0552)	(0.0498)	(0.0540)	(0.0418)	(0.00571)
Observations	265705	265705	265705	265705	265705

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.
Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for all individuals, only men and only women respectively in the three sections. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.5: Estimates from an IV Estimation: White

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
White individuals					
Employment status					
1 if unemployed	0.352***	-0.195***	-0.286***	0.0876*	0.0414***
	(0.0619)	(0.0706)	(0.0575)	(0.0468)	(0.00417)
Observations	367333	367333	367333	367333	367333
White men					
Employment status					
1 if unemployed	0.286***	-0.340***	-0.228***	0.231***	0.0511***
	(0.0769)	(0.0782)	(0.0755)	(0.0840)	(0.00813)
Observations	148465	148465	148465	148465	148465
White women					
Employment status					
1 if unemployed	0.308***	-0.0673	-0.288***	0.0190	0.0283***
	(0.0604)	(0.0615)	(0.0570)	(0.0449)	(0.00560)
Observations	218868	218868	218868	218868	218868

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.
Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of white population - all individuals, only men and only women respectively in the three sections. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.6: Estimates from an IV Estimation: Black

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Black individuals					
Employment status					
1 if unemployed	0.173***	-0.0978*	-0.129**	0.00531	0.0486***
	(0.0417)	(0.0499)	(0.0653)	(0.0556)	(0.0101)
Observations	41667	41667	41667	41667	41667
Black men					
Employment status					
1 if unemployed	0.129**	-0.241***	-0.0657	0.115**	0.0629***
	(0.0626)	(0.0783)	(0.0897)	(0.0528)	(0.0142)
Observations	11715	11715	11715	11715	11715
Black women					
Employment status					
1 if unemployed	0.154***	-0.132***	-0.0740	0.00965	0.0416***
	(0.0520)	(0.0509)	(0.0485)	(0.0555)	(0.00936)
Observations	29952	29952	29952	29952	29952

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.
Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of black population - all individuals, only men and only women respectively in the three sections. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.7: Anticipated Versus Unanticipated Unemployment: IV Estimates

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.443***	-0.135	-0.452***	0.111*	0.0337***
	(0.110)	(0.105)	(0.0835)	(0.0643)	(0.00672)
New/re-entrants	0.0379**	-0.0151	-0.0313*	0.00315	0.00535***
	(0.0176)	(0.0128)	(0.0179)	(0.0138)	(0.00207)
New/re-entrants × Employment status	-0.401***	0.00668	0.454***	-0.0446	-0.0152*
	(0.112)	(0.0999)	(0.0883)	(0.0646)	(0.00805)
Laid-off	0.0100	0.00340	-0.0203**	0.00368	0.00325***
	(0.0121)	(0.0155)	(0.0103)	(0.0105)	(0.00101)
Laid-off × Employment status	-0.386***	-0.0452	0.456***	-0.0432	0.0182*
	(0.110)	(0.111)	(0.0816)	(0.0661)	(0.0105)
Temporary job ended	-0.0118	-0.0151	0.00231	0.0197	0.00485*
	(0.0256)	(0.0159)	(0.0198)	(0.0248)	(0.00264)
Temporary job ended × Employment status	-0.381***	-0.0213	0.452***	-0.0566	0.00658
	(0.105)	(0.111)	(0.0927)	(0.0762)	(0.00887)
Resigned	-0.00557	0.00986	-0.0249	0.0132	0.00746*
	(0.0229)	(0.0187)	(0.0210)	(0.0164)	(0.00433)
Resigned × Employment status	-0.396***	-0.0375	0.446***	-0.0115	-0.00158
	(0.117)	(0.112)	(0.0938)	(0.0706)	(0.0116)
Observations	437742	437742	437742	437742	437742

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The table gives the estimates for the whole population. I use marital status, age, race, sex, spousal employment status, family income and education level as control variables. Equation 1.6 was modified to include dummy variables for various reasons of unemployment. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level.

Table 1.8: Elasticities

	Children	Work	Leisure	HH chores	Job Search
All individual	0.266***	-3.208***	-0.275***	0.045	0.001***
All men	0.230***	-6.972***	-0.206***	0.128**	0.001***
All women	0.210***	-0.477	-0.258***	0.006	0.001***
White individuals	0.294***	-4.926***	-0.275***	0.069*	0.001***
White men	0.234***	-8.892***	-0.219***	0.183***	0.001***
White women	0.257***	-1.700	-0.277***	0.015	0.001***
Black individuals	0.144***	-2.471*	-0.124*	0.004	0.001***
Black men	0.108**	-6.088***	-0.063	0.091**	0.001***
Black women	0.129***	-3.334***	-0.071	0.008	0.001***

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey.
Notes: The table gives the elasticities for different samples of the population as given in the rows. I estimate the elasticity of time use category A when employed with respect to when unemployed using the following expression $e^A = \hat{\beta}^A \frac{\tau^A_{empt}}{\tau^A_{unempt}}$. Here, τ^A_{empt} gives average time allocated to activity A when employed; τ^A_{unempt} gives average time allocated to activity A when unemployed; $\hat{\beta}^A$ denotes the estimated responsiveness of time use in activity A to changes in the employment status. I use the estimates of the employment status variable from tables 1.4, 1.5 and 1.6 for all six demographics.

1.7 Appendix

Parental Resource Allocation: Theoretical Analyses

Simple 3 good model: Parental time with children, leisure time, market goods

Parents allocate their time between work and non-work activities. Individuals earn a wage rate of w for every hour spent at work. They earn a utility from consuming goods and services bought from the income earned, and the time they spend with their children and on their leisure. Parental utility function, U_p, consists of the time they spend with their children (C_t), time spent on their personal leisure (L_p)and total goods and services consumed by them (X).

$$U_p = U(C_t, X, L_p) \tag{A.1}$$

where C_t is the time spent with children, X is the total amount of goods and services consumed by the parents, and L_p is the time spent on leisure by parents. Parents face the following budget constraint

$$wt = P_x X$$

Let P_x = price of consumption goods = 1 and t = total working hours, the budget constraint becomes

$$t = 24 - L_p - C_t$$
$$w(24 - L_p - C_t) = X$$

$$24w - wL_p - wC_t - X = 0 \tag{A.2}$$

where total time spent at work is the difference between total time available, which is 24 hours, and the time spent in other non-income earning activities (L_p and C_t), and assuming the price of consumption goods to be unity. I maximize parental utility U_p (equation A.1) subject to their budget constraint (equation A.2) using the Lagrange's multiplier. For simplicity, I assume the parental utility function, U_p to be Cobb-Douglas with unit elasticity.

$$U_p = U(C_t, X, L_p) = C_t^{\alpha} X^{\beta} L_p^{1-\alpha-\beta} \tag{A.3}$$

Using Lagrange's optimization, I obtain the following equilibrium values

$$L_p^* = 24(1 - \alpha - \beta) \tag{A.4a}$$
$$C_t^* = 24\alpha \tag{A.4b}$$
$$X^* = 24w\beta \tag{A.4c}$$

Integrating Production of Child Care in Parents' Utility

Becker (1988) discussed how time and income spent by parents are essential for production of children. Parents care about their children and their wellbeing. Their utility consists of the amount of goods and services they consume, the time they spent at leisure and their children's wellbeing (in terms of childcare they provide). In this section, I assume that parents' utility is affected by the amount of care they provide to their children in terms of income and time spent on them. I modify equation A.1 to

$$U_p = U(C(X_c, L_c), X_p, L_p) \tag{A.5}$$

where $C(X_c, L_c)$ gives the production function of childcare given by parents which is a function of the goods and services consumed by their children, X_c and the parental time spent with them, L_c. Also, parental consumption of goods and services is given by X_p and their leisure is depicted by L_p. For this model, I assume that parents spend a fixed share of their income on X_c and a fixed share of their non-working hours on their children, L_c. Therefore,

$$X_c + X_p = X \quad \& \quad L_c + L_p = L \tag{A.6}$$

I assume $X_c = aX$ and $L_c = bL$ where $0 < a, b < 1$. This implies $X_p = (1-a)X$ and $L_p = (1-b)L$. Let the production function of childcare also be Cobb-Douglas in nature with the following expression

$$C(X_c, L_c) = X_c L_c = abXL \tag{A.7}$$

Now, the new utility function of parents' is defined as below

$$U_p = U(C(X_c, L_c), X_p, L_p) = [C(X_c L_c)]^{\alpha} X_p^{\beta} L_p^{(1-\alpha-\beta)} = AX^{(\alpha+\beta)} L^{(1-\beta)} \tag{A.8}$$

Maximizing the utility function of parents given by equation A.8 subjected to a new modified budget constraint given as,

$$24w - wL - X = 0 \tag{A.9}$$

The equilibrium values are as follows

$$L^* = \frac{24(1-\beta)}{(1+\alpha)} \tag{A.10a}$$

$$X^* = 24w\frac{(\alpha+\beta)}{(1+\alpha)} \tag{A.10b}$$

Optimum consumption of parents

$$L_p^* = (1-b)\frac{24(1-\beta)}{(1+\alpha)} \; ; \; X_P^* = 24w(1-a)\frac{(\alpha+\beta)}{(1+\alpha)}$$

Optimum consumption of children

$$L_c^* = b\frac{24(1-\beta)}{(1+\alpha)} \; ; \; X_c^* = 24wa\frac{(\alpha+\beta)}{(1+\alpha)}$$

Including Non-Wage Income

In the previous two sections, I analyzed a model for parental behavior which focused only on parental wage income. The primary and only source of income, for parents, was wage income, earning at a rate of w per hour. In this section, I explore the conditions under which parents earn both wage and non-wage income which is a lump sum amount given by I. Parental utility function remains the same as given in equation A.8. The budget constraint is modified to include a non-wage income along with a wage income. Here, the non-wage income is independent of their employment status. Non-wage income can be obtained from savings, spousal income and gifts and bequests or family income for which an individual does not spend any hours working. The budget constraint changes to

$$24w - wL - X + I = 0 \tag{A.11}$$

The new optimum values are

$$L^* = \frac{(24w + I)(1 - \beta)}{(1 + \alpha)w} \tag{A.12a}$$

$$X^* = \frac{(24w + I)(\alpha + \beta)}{(1 + \alpha)} \tag{A.12b}$$

Consumption of goods and services increases while the change in hours spent on leisure is ambiguous when wage rate, w, increases. When parents lose their jobs and become unemployed, the whole 24 hours of time is divided into own leisure and parental time.

Estimates from the IV regressions for various demographics

This section gives the regression estimates for each demographic including the estimates of control variables. The estimates show that single white parents spend less time with their children by 1.3 and 1.9 percentage points for mothers and fathers, respectively. Such a behavior is not seen among black parents. They do not change their parental time in the absence of a spouse or partner. Single white fathers allocate less time for work but more for household chores (table 1.13). Black single fathers do not change their time allocation for work significantly at conventional levels (table

1.16) but spends greater time doing household chores by 2.5 percentage points. White single mothers spend more time looking for employment (table 1.14) while black single mothers spend less time engaging in household chores and more time at leisure (table 1.17).

Higher educational achievement causes higher allocation to parental time with children. Here the omitted group is that with a college degree. There is a direct relationship between educational achievement and parental time. Parents with higher educational degree spend more time with their children. More education also allows parents to spend lesser number of hours at work as they earn a higher wage. Table 1.10 shows that all high school graduate fathers with no college degree spent 6 percentage points less time with their children while those with lower educational qualification spend 9 percentage points less time with their children when compared to college graduate fathers. Less educated mothers are more likely to be engaged in household chores than those with more education. Mothers with less than a high school degree spend 9.6 percentage points less time with their children and 4.2 percentage points more engaging in household chores (table 1.11).

White (table 1.13) and black fathers (table 1.16) have similar parental behavior when I compare their educational qualification but the magnitude of the estimates differ. With only a high school degree, black and white fathers spend 3 and 6.5 percentage points less time with their children, respectively. However, those with lower education level spend 3.5 and 9.7 percentage points less parental time as compared to college graduates for black and white fathers, respectively. Less educated white fathers also spend less time engaging in household chores - a behavior not mimicked by black fathers. Additionally, more educated fathers spend less time searching for new employment opportunities as compared to those with lower education. This behavior is seen among black fathers also. Similar trend is seen among white (table 1.14) and black (table 1.17) mothers, but with different magnitudes for the regression estimates.

There is a 3.5 percentage points drop in parental time when educational qualification falls from college graduates to high school level and an additional 2 percentage points from high school level to below for black mothers. The corresponding estimates for white mothers are 6.5 and 11 percentage points, respectively.

Spousal employment status acts as an important factor in determining parental time allocation with their children. Individuals supported by employed spouses should have more time to spend with their children. Such behavior is seen among white parents but not among black parents. White parents spend more time with their children and engaging in household chores; and lesser hours at work when they have an employed spouse. They also lower job search time when supported by employed partners (table 1.12). Black mothers are not affected by their partners' employment status when allocating time in different activities except with their children (table 1.17). Black fathers only increases hours spent on household chores when they have an employed partner (table 1.16).

Family income plays a significant role in defining parental time. It specifies the purchasing power and the standard of living of the household. In my analysis, annual family income is divided into four categories - those receiving annually less than \$30000, between \$30000 and \$50000, between \$50000 and \$100000, and more than \$100000. As families move to higher income brackets, they spend more time with their children. Families in the lowest income bracket spend 2.5 percentage points less time with their children (table 1.9). Individuals in the next higher income bracket spends 1 percentage points less time with their children. Individuals with family income between \$50000 and \$100000 spend 1.3 percentage points more time with their children, and individuals with family income above \$100000 spends 5 percentage points more time with their children.

A similar trend is seen among white parents (table 1.12). At the lowest income bracket, white mothers spend 3.5 percentage points less time with their children and at the highest income bracket of family income, they spend 4.8 percentage points more time with their children (table 1.14). White fathers behave in a similar manner. The corresponding estimates for this demographic are -2 and 5 percentage points, respectively (table 1.13).

Black parents living in a rich household spend more time with their children as compared to black parents living in a poor household (table 1.15). Black fathers allocate 4.6 percentage points more time when they live in the lowest income bracket household. In the middle income range, they increase the time with their children by 4 percentage points. Fathers belonging to the highest income bracket (above $100000) spend 7 percentage points more time with their children (table 1.16). Surprisingly, black mothers are not affected significantly by their household income level (table 1.17). The coefficient estimates of all income groups are statistically insignificant at conventional levels except for the lower-middle income group. Black mothers living in a household with a family income of $30000-$50000 allocate 2.5 percentage points more time with their children than their counterparts.

Table 1.9: All individuals

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.318***	-0.127**	-0.286***	0.0567	0.0388***
	(0.0559)	(0.0544)	(0.0577)	(0.0437)	(0.00318)
Age	-0.00891***	0.00176***	0.00367***	0.00339***	0.0000882***
	(0.000153)	(0.000130)	(0.000136)	(0.000106)	(0.0000119)
Below HS	-0.106***	0.0427***	0.0662***	0.000496	-0.00335***
	(0.00575)	(0.00336)	(0.00509)	(0.00466)	(0.000704)
High School	-0.0671***	0.0175***	0.0512***	-0.000434	-0.00120***
	(0.00307)	(0.00237)	(0.00251)	(0.00182)	(0.000295)
single	-0.00147	-0.0293***	-0.0161***	0.0469***	-0.0000911
	(0.00396)	(0.00258)	(0.00318)	(0.00195)	(0.000393)
Family income <30K	-0.0256***	-0.0124*	0.0261***	0.0117*	0.000164
	(0.00676)	(0.00698)	(0.00677)	(0.00605)	(0.000639)
Family income 30-50k	-0.0105**	-0.00216	0.0118**	-0.0000548	0.000998**
	(0.00450)	(0.00383)	(0.00484)	(0.00394)	(0.000487)
Family income 50-100K	0.0136***	-0.00189	-0.00630	-0.00617	0.000727**
	(0.00406)	(0.00338)	(0.00441)	(0.00391)	(0.000347)
Family income >100k	0.0493***	0.000537	-0.0324***	-0.0177***	0.000311
	(0.00347)	(0.00292)	(0.00390)	(0.00401)	(0.000368)
Spousal emp status					
1 if employed	0.0122***	-0.0421***	-0.0301***	0.0611***	-0.00111***
	(0.00270)	(0.00160)	(0.00190)	(0.00158)	(0.000318)
Observations	437742	437742	437742	437742	437742

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the whole population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.10: All Men

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.276***	-0.276***	-0.214***	0.163**	0.0518***
	(0.0763)	(0.0681)	(0.0734)	(0.0735)	(0.00706)
Age	-0.00701***	0.00144***	0.00350***	0.00202***	0.0000557**
	(0.000179)	(0.000146)	(0.000206)	(0.000118)	(0.0000271)
Below HS	-0.0905***	0.0499***	0.0648***	-0.0220***	-0.00220*
	(0.00487)	(0.00456)	(0.00533)	(0.00396)	(0.00115)
High School	-0.0619***	0.0164***	0.0480***	-0.000505	-0.00200***
	(0.00430)	(0.00384)	(0.00347)	(0.00314)	(0.000526)
single	-0.0245***	-0.0208***	0.00353	0.0405***	0.00126
	(0.00450)	(0.00338)	(0.00425)	(0.00344)	(0.000909)
Family income <30K	-0.0153*	-0.00956	0.0278***	-0.00542	0.00242**
	(0.00908)	(0.00822)	(0.00781)	(0.00696)	(0.00123)
Family income 30-50k	-0.00609	-0.0127**	0.0136*	0.00443	0.000770
	(0.00654)	(0.00648)	(0.00750)	(0.00604)	(0.000890)
Family income 50-100K	0.0223***	-0.0219***	-0.0161**	0.0155***	0.000248
	(0.00708)	(0.00593)	(0.00737)	(0.00574)	(0.000622)
Family income >100k	0.0586***	-0.0235***	-0.0457***	0.0110*	-0.000407
	(0.00737)	(0.00615)	(0.00776)	(0.00577)	(0.000609)
Spousal emp status					
1 if employed	-0.00395*	-0.0193***	-0.00349	0.0273***	-0.000635
	(0.00238)	(0.00256)	(0.00246)	(0.00229)	(0.000418)
Observations	172037	172037	172037	172037	172037

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all men population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.11: All Women

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.252***	-0.0189	-0.268***	0.00706	0.0285***
	(0.0552)	(0.0498)	(0.0540)	(0.0418)	(0.00571)
Age	-0.00986***	0.00169***	0.00325***	0.00485***	0.0000664***
	(0.000218)	(0.000148)	(0.000170)	(0.000134)	(0.0000147)
Below HS	-0.0966***	0.0110*	0.0476***	0.0422***	-0.00410***
	(0.00750)	(0.00636)	(0.00704)	(0.00665)	(0.00108)
High School	-0.0603***	0.00780***	0.0422***	0.0112***	-0.000947***
	(0.00336)	(0.00295)	(0.00308)	(0.00210)	(0.000319)
single	-0.0155***	0.00934**	0.0168***	-0.0118***	0.00110***
	(0.00506)	(0.00394)	(0.00389)	(0.00385)	(0.000352)
Family income <30K	-0.0311***	-0.0126*	0.0299***	0.0137**	0.000138
	(0.00670)	(0.00712)	(0.00799)	(0.00623)	(0.000813)
Family income 30-50k	-0.00895	0.00101	0.00756	-0.000448	0.000831*
	(0.00581)	(0.00433)	(0.00533)	(0.00459)	(0.000462)
Family income 50-100K	0.0127**	0.00489	-0.00447	-0.0139***	0.000797***
	(0.00509)	(0.00389)	(0.00502)	(0.00421)	(0.000305)
Family income >100k	0.0485***	0.00719*	-0.0306***	-0.0258***	0.000648*
	(0.00442)	(0.00411)	(0.00465)	(0.00546)	(0.000371)
Spousal emp status					
1 if employed	0.00144	-0.0209***	-0.0139***	0.0339***	-0.000492
	(0.00379)	(0.00302)	(0.00388)	(0.00364)	(0.000331)
Observations	265705	265705	265705	265705	265705

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all women population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.12: All White individuals

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.352***	-0.195***	-0.286***	0.0876*	0.0414***
	(0.0619)	(0.0706)	(0.0575)	(0.0468)	(0.00417)
Age	-0.00913***	0.00164***	0.00377***	0.00364***	0.0000817***
	(0.000182)	(0.000125)	(0.000151)	(0.000123)	(0.0000141)
Below HS	-0.117***	0.0539***	0.0681***	-0.00200	-0.00333***
	(0.00629)	(0.00352)	(0.00517)	(0.00563)	(0.000835)
High School	-0.0711***	0.0200***	0.0513***	0.00125	-0.00145***
	(0.00312)	(0.00244)	(0.00259)	(0.00225)	(0.000294)
single	0.00178	-0.0286***	-0.0243***	0.0510***	0.000136
	(0.00444)	(0.00248)	(0.00396)	(0.00255)	(0.000436)
Family income <30K	-0.0291***	-0.00848	0.0283***	0.00920	0.0000658
	(0.00740)	(0.00876)	(0.00726)	(0.00704)	(0.000726)
Family income 30-50k	-0.0165***	-0.00206	0.0183***	-0.000310	0.000582
	(0.00477)	(0.00452)	(0.00512)	(0.00415)	(0.000474)
Family income 50-100K	0.0104**	-0.00349	0.0000143	-0.00775*	0.000799**
	(0.00420)	(0.00389)	(0.00486)	(0.00454)	(0.000366)
Family income >100k	0.0453***	-0.000783	-0.0241***	-0.0207***	0.000331
	(0.00390)	(0.00339)	(0.00408)	(0.00460)	(0.000409)
Spousal emp status					
1 if employed	0.0129***	-0.0427***	-0.0309***	0.0618***	-0.00112***
	(0.00294)	(0.00200)	(0.00223)	(0.00220)	(0.000345)
Observations	367333	367333	367333	367333	367333

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all white population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.13: All White Men

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.286***	-0.340***	-0.228***	0.231***	0.0511***
	(0.0769)	(0.0782)	(0.0755)	(0.0840)	(0.00813)
Age	-0.00726***	0.00159***	0.00352***	0.00207***	0.0000700**
	(0.000265)	(0.000135)	(0.000253)	(0.000125)	(0.0000282)
Below HS	-0.0973***	0.0579***	0.0689***	-0.0272***	-0.00238**
	(0.00473)	(0.00504)	(0.00560)	(0.00448)	(0.00120)
High School	-0.0647***	0.0199***	0.0498***	-0.00254	-0.00257***
	(0.00443)	(0.00398)	(0.00380)	(0.00351)	(0.000491)
single	-0.0196***	-0.0202***	-0.00420	0.0427***	0.00127
	(0.00533)	(0.00400)	(0.00482)	(0.00341)	(0.000890)
Family income <30K	-0.0208**	-0.00353	0.0295***	-0.00790	0.00274**
	(0.00895)	(0.00976)	(0.00867)	(0.00782)	(0.00138)
Family income 30-50k	-0.0113*	-0.00956	0.0182**	0.00200	0.000646
	(0.00654)	(0.00680)	(0.00744)	(0.00631)	(0.000842)
Family income 50-100K	0.0166**	-0.0202***	-0.0104	0.0137**	0.000175
	(0.00739)	(0.00632)	(0.00668)	(0.00603)	(0.000777)
Family income >100k	0.0510***	-0.0207***	-0.0381***	0.00841	-0.000636
	(0.00725)	(0.00647)	(0.00603)	(0.00562)	(0.000779)
Spousal emp status					
1 if employed	-0.00265	-0.0182***	-0.00402	0.0253***	-0.000454
	(0.00282)	(0.00261)	(0.00269)	(0.00243)	(0.000420)
Observations	148465	148465	148465	148465	148465

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all white men population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.14: All White Women

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.308***	-0.0673	-0.288***	0.0190	0.0283***
	(0.0604)	(0.0615)	(0.0570)	(0.0449)	(0.00560)
Age	-0.0101***	0.00137***	0.00341***	0.00525***	0.0000521***
	(0.000213)	(0.000143)	(0.000161)	(0.000141)	(0.0000138)
Below HS	-0.112***	0.0214***	0.0474***	0.0476***	-0.00398***
	(0.00933)	(0.00644)	(0.00799)	(0.00841)	(0.00105)
High School	-0.0652***	0.00899***	0.0412***	0.0159***	-0.000886***
	(0.00362)	(0.00272)	(0.00309)	(0.00214)	(0.000314)
single	-0.0135***	0.00869**	0.00802*	-0.00462	0.00145***
	(0.00520)	(0.00374)	(0.00458)	(0.00378)	(0.000420)
Family income <30K	-0.0358***	-0.0114	0.0363***	0.0110	-0.00000397
	(0.00745)	(0.00858)	(0.00786)	(0.00729)	(0.000867)
Family income 30-50k	-0.0162**	0.000298	0.0169***	-0.00146	0.000426
	(0.00654)	(0.00469)	(0.00566)	(0.00470)	(0.000502)
Family income 50-100K	0.0106**	0.00291	0.00267	-0.0171***	0.000963***
	(0.00482)	(0.00441)	(0.00566)	(0.00474)	(0.000366)
Family income >100k	0.0474***	0.00521	-0.0223***	-0.0311***	0.000720*
	(0.00506)	(0.00482)	(0.00501)	(0.00597)	(0.000403)
Spousal emp status					
1 if employed	-0.00154	-0.0220***	-0.0119***	0.0357***	-0.000390
	(0.00411)	(0.00276)	(0.00399)	(0.00370)	(0.000395)
Observations	218868	218868	218868	218868	218868

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all white women population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.15: All Black individuals

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.173***	-0.0978*	-0.129**	0.00531	0.0486***
	(0.0417)	(0.0499)	(0.0653)	(0.0556)	(0.0101)
Age	-0.00777***	0.00177***	0.00382***	0.00199***	0.000192***
	(0.000346)	(0.000291)	(0.000382)	(0.000321)	(0.0000629)
Below HS	-0.0580***	0.00401	0.0528***	0.00637	-0.00520**
	(0.00980)	(0.0103)	(0.0115)	(0.0122)	(0.00257)
High School	-0.0425***	0.00856	0.0411***	-0.00597	-0.00126
	(0.00556)	(0.00593)	(0.00661)	(0.00801)	(0.00104)
single	0.00742	-0.0148**	-0.00888	0.0180**	-0.00172
	(0.00933)	(0.00625)	(0.00837)	(0.00832)	(0.00185)
Family income <30K	0.0118	-0.00756	-0.0152	0.0109	0.0000253
	(0.00979)	(0.0103)	(0.0106)	(0.00956)	(0.00184)
Family income 30-50k	0.0203**	0.0122	-0.0213**	-0.0162	0.00503**
	(0.00941)	(0.0110)	(0.0105)	(0.0102)	(0.00214)
Family income 50-100K	0.0175*	0.0143	-0.0302**	-0.00289	0.00123
	(0.00938)	(0.0112)	(0.0123)	(0.0128)	(0.00140)
Family income >100k	0.0360***	0.0153	-0.0553***	0.00163	0.00238
	(0.0132)	(0.0115)	(0.0143)	(0.0134)	(0.00164)
Spousal emp status					
1 if employed	0.00101	-0.0144**	0.00361	0.0113	-0.00150
	(0.00650)	(0.00674)	(0.00680)	(0.00704)	(0.00220)
Observations	41667	41667	41667	41667	41667

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all black population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.16: All Black Men

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.129**	-0.241***	-0.0657	0.115**	0.0629***
	(0.0626)	(0.0783)	(0.0897)	(0.0528)	(0.0142)
Age	-0.00428***	-0.000621	0.00269***	0.00222***	-0.00000547
	(0.000490)	(0.000519)	(0.000511)	(0.000489)	(0.000147)
Below HS	-0.0349*	-0.0126	0.0506***	-0.00377	0.000706
	(0.0183)	(0.0152)	(0.0177)	(0.0155)	(0.00543)
High School	-0.0315***	-0.0107	0.0244**	0.0168*	0.00101
	(0.0118)	(0.0111)	(0.00988)	(0.00993)	(0.00308)
single	-0.0136	-0.0214	0.00940	0.0257**	-0.0000673
	(0.0108)	(0.0141)	(0.0162)	(0.0100)	(0.00343)
Family income <30K	0.0463***	-0.0297**	-0.0237	0.00760	-0.000531
	(0.0154)	(0.0133)	(0.0218)	(0.0159)	(0.00573)
Family income 30-50k	0.0406**	-0.0208	-0.0378*	0.0165	0.00150
	(0.0158)	(0.0134)	(0.0224)	(0.0155)	(0.00561)
Family income 50-100K	0.0380**	-0.0280**	-0.0391*	0.0291**	0.00000483
	(0.0163)	(0.0133)	(0.0234)	(0.0144)	(0.00427)
Family income >100k	0.0698***	-0.0290*	-0.0658**	0.0223	0.00279
	(0.0207)	(0.0173)	(0.0298)	(0.0195)	(0.00403)
Spousal emp status					
1 if employed	0.00645	-0.0158	-0.00267	0.0172*	-0.00520
	(0.0108)	(0.0144)	(0.0172)	(0.0105)	(0.00325)
Observations	11715	11715	11715	11715	11715

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all black men population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Table 1.17: All Black Women

	(1) Children	(2) Work	(3) Leisure	(4) HH chores	(5) Job search
Employment status					
1 if unemployed	0.154***	-0.132***	-0.0740	0.00965	0.0416***
	(0.0520)	(0.0509)	(0.0485)	(0.0555)	(0.00936)
Age	-0.00872***	0.00214***	0.00374***	0.00264***	0.000205***
	(0.000385)	(0.000325)	(0.000410)	(0.000444)	(0.0000685)
Below HS	-0.0550***	0.0127	0.0353***	0.0133	-0.00628**
	(0.0131)	(0.0115)	(0.0103)	(0.0154)	(0.00314)
High School	-0.0356***	0.0114**	0.0347***	-0.00788	-0.00261**
	(0.00641)	(0.00529)	(0.00779)	(0.00842)	(0.00127)
single	0.00349	0.00627	0.0157*	-0.0245**	-0.000978
	(0.0126)	(0.0117)	(0.00802)	(0.0105)	(0.00170)
Family income <30K	0.00163	0.00489	-0.0168	0.00925	0.00102
	(0.0135)	(0.0105)	(0.0120)	(0.0118)	(0.00170)
Family income 30-50k	0.0257**	0.0126	-0.0245**	-0.0192	0.00545***
	(0.0119)	(0.0134)	(0.0109)	(0.0133)	(0.00193)
Family income 50-100K	0.0181	0.0206*	-0.0296**	-0.0104	0.00132
	(0.0114)	(0.0123)	(0.0120)	(0.0159)	(0.00140)
Family income >100k	0.0223	0.0168	-0.0520***	0.0103	0.00249*
	(0.0139)	(0.0146)	(0.0119)	(0.0170)	(0.00147)
Spousal emp status					
1 if employed	0.0153*	-0.0140	-0.00730	0.00687	-0.000839
	(0.00840)	(0.0104)	(0.00709)	(0.00857)	(0.00201)
Observations	29952	29952	29952	29952	29952

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Bureau of Labor Statistics and American Time Use Survey. Dependent variable: Ratio of time spent in one of the five activities to total time available in a day.

Notes: The columns show the estimated coefficients from equation 1.6. The table gives the estimates for the sample of all black women population. The standard errors are given in parenthesis under the coefficient estimates. They are robust and clustered at state level. I use marital status, age, race, family income, education level and spousal employment status as control variables.

Chapter 2

Does the Daylight Savings Time Causes People to Change More than their Clock?

By Sanjukta Basu

Abstract

Daylight-Saving Time (DST) has a long and controversial history, regarding both its implementation and main intent. This paper attempts to take advantage of the natural experiment created by DST twice a year to study how individuals are affected by an arbitrary change in clock. I study how individuals' respond to the DST by adjusting their daily schedules when the clock changes. I compare two states - Arizona which never had DST, and New Mexico which always had DST using a difference-in-differences estimation method. Both states are geographically and climatically similar making them suitable for comparison. Main findings - first, New Mexicans reduce sedentary activities, such as sleeping and relaxing, during spring and increase in fall. Second, New Mexicans claim to experience high stress after the spring DST implementation. Third, the effect of DST fades out in subsequent weeks. I conclude that clock change twice a year seriously affects those who are impacted by it when compared to similar counterparts living in the same geographical latitude.

Keywords: Day-light Savings; Time diary; Daily schedules.

JEL: J22, D13.

2.1 Introduction

The First World War created a law which forced citizens to change their clocks twice a year. This law was known as the Daylight Savings Time in the USA. Canada first introduced the concept as early as 1908 in some provinces. Germany and Austria were the first to implement DST throughout their countries. The main intent of the law, which is to conserve energy, have been lost over the years but its spillover effects continues. My paper studies some of its spillover effects by analyzing the impact of time change on individuals subjected to it. People living in regions which follow DST adapts to the time change twice a year. My study analyzes how DST impacts these individuals and how long it takes to adapt.

DST has been in discussion among policymakers in the recent past. After the results of an on-line poll, the European Union is in consideration to remove DST. Many states in the US, like Florida, California, Oregon and Louisiana, are also taking measures to re-evaluate the need of DST in their constituencies.

My paper is appropriate in the current policy environment. I study how the change in clocks, bi-annually, changes people's behavior in the first few days. Though the clock changes by one hour only, everyone is forced to re-adjust their internal clock twice a year as a result. I study how daily time schedules change for individuals who are subjected to it. I also study if there is any change in their mood or well-being indicators. This is the first paper which studies the impact of DST on individual behavior and by using the metabolic equivalent (MET) values associated with various activities engaged.

In the US, all states except Arizona and Hawaii change their clocks twice a year to follow the daylight savings time. Indiana did not have daylight savings before 2006. They adopted the policy in 2006 and started changing the clock twice a year. I use the American Time Use Survey (ATUS) for analyzing the impact of DST. I use Arizona and New Mexico as sample states. Arizona and New Mexico are neighboring states with very similar climatic and geographic conditions. They are within the same latitude. The average weather is very hot and dry in the lowlands and cooler in the mountainous regions. Arizona enacted the DST exemption status in 1968 and has not observed DST since then. Historically, New Mexico has always had DST. The state implemented the clock change policy in 1966 when the Uniform Time Act was introduced in the country. Both states are situated on the same latitudinal position in the northern hemisphere ensuring they have similar sun rise, sun set times and weather conditions throughout the year. They differ in their DST policy.[1]

My sample of study is limited to those respondents who were interviewed within a week, before and after the change in time due to DST, both spring and fall. However, to study how the effect of DST changes over subsequent weeks, I also increase the sample of study to 14 days and 21 days before and after the clock change.

I use a difference-in-differences estimation technique where Arizona is treated as a control state and New Mexico as a treatment state due to the presence of the DST law. I test two different types of variables - daily schedules divided into three groups based on the metabolic equivalent values, and mood indicators. I find New Mexicans increase time spent in sedentary activities such as sleeping and relaxing by 70 minutes, vigorous-intensive activities, such as hiking and jogging by 160 minutes, and decrease light intensive activities after the fall DST change. The spring DST causes a decrease in sleeping/relaxing time by 78 minutes and no statistical change in other more intensive activities. New Mexican also claim to be less stressed in the fall and more stressed in the spring as compared to Arizonians. The impact of DST fades out completely after a week of the clock change. It takes seven days to adjust to the new time both in the spring and fall.

[1]I compare these two states instead of including all 50 states because using a difference-in-differences technique with only 2 control groups and a large number of treatment groups violates the assumption of large groups of each type. Such a problem leads to incorrect signs of the coefficient estimates and error in statistical significance. Hence, for a clean identification strategy, I compare two states which are similar in geographical conditions but different DST laws.

Given the unique condition of Indiana, this serves as a fascinating case study. Indiana implemented DST in 2006 after a long political debate. Kotchen & Grant (2011) found that DST does not support energy conservation. My study explores the other effects of the law when comparing with the 47 states which always had DST since 1966. I use a triple difference empirical approach and other 47 DST states for comparison. Here, I find that Indiana citizens have experienced a decline in sleeping time in the fall and an increase in the spring after implementing DST when compared to other such states. This behavior is consistent in the working population but not the elderly. The newly implementation of DST in Indiana makes its citizens disrupt their regular routines much more than states which always followed this clock change for decades.

Daylight savings impact people differently based on how they are affected. A one hour change in clock causes a much larger impact in daily schedules, sleep patterns and mood indicators. Many studies have concluded that the underlying reason for implementing DST, which is energy savings, is no more relevant in today's time but its spillover effect is large.

2.2 Background

Daylight saving time (DST), also known as Summer Time in some countries, is the practice of advancing clocks during the summer months so that evening daylight lasts longer. Typically, regions that use daylight saving time adjust clocks forward one hour close to the start of spring and adjust them backward in the autumn/fall to standard time. These regions follow the standard time during the winter months. DST has been used in the USA and in many European countries since the World War I.

The DST plan was formally adopted in the USA in 1918 when standard time zones were established. After the war ended, it was repealed in 1919. During World War II, year-round DST was instituted again from February 1942 to September 1945. After World War II, there was no federal law regarding DST, and states and regions were free to choose whether to observe DST or not. This caused confusion, especially in many industries such as broadcasting, transportation and others which required to coordinate with other countries. In 1966, the Uniform Time Act established a system of uniform (within each time zone) Daylight Saving Time throughout USA and its possessions, exempting only those states in which the legislatures voted to keep the entire state on standard time.[2]

DST is used to match activity peaks of a population with the daylight hours. The major underlying purpose of implementing and extending DST in USA and other European countries is energy conservation. Energy use and the demand for electricity for lighting homes is directly related to the times when people go to bed at night and rise in the morning. If time is pushed back in the summer months, DST would trim electricity usage because less electricity will be used for lighting and appliances during long summer days. It was assumed that a significant amount of energy consumed by lighting and appliances occurred in the evening when families were home. By moving the clock ahead one hour, the amount of electricity consumed each day decreased.

Recent research in the field of energy, has shown that DST does not reduce energy consumption but can increase it instead. Aries & Newsham (2008) conducted a literature survey on the effect of DST on saving energy around the globe. They found mixed evidence. They conclude that while some studies are able to show no significant reduction in energy use, others concluded a slight but statistically significant reduction in energy consumption. They also show that some studies found a rise in fuel consumption and recreational traffic. Kotchen & Grant (2011) takes advantage of a natural experiment in the state of Indiana to provide the first empirical

[2]http://www.webexhibits.org/daylightsaving/e.html

estimates of DST effects on electricity consumption. They found that DST increased residential electricity demand.

Economists have shied away from the discussion of DST resulting in a lack of abundant literature. However, other fields of study have been analyzing the role of DST on various aspects of the economy. Kotchen & Grant (2011) shows that the role of DST in energy consumption is inefficient. However, the influence of DST extends much beyond energy consumption to sleep pattern (Harrison (2013)), health (Lahti *et al.* (2010) and Sipilä *et al.* (2016)), traffic (Varughese & Allen (2001)), and leisure and labor productivity.

Varughese & Allen (2001) shows that there was significant increase in automobile accidents for the Monday immediately following the spring DST. The authors believe sleep deprivation is a major reason behind the increase in road fatalities. Lahti *et al.* (2010) showed that transition into and out of DST cause minor jet lag symptoms such as sleep disruption, cardiac rhythm fragmentation and change in fatigue. They show that though social timing changes instantly, bodily timing changes more slowly. They found that the impact of DST, though mild, is significant for patients suffering from seasonally affecting disorder, bipolar disorder or chronic sleep loss. Harrison (2013) suggested that increased sleep fragmentation and sleep latency presents a cumulative effect of sleep loss, at least for a week after the clock change. There is very little evidence of extra sleep on the night of fall DST even though it is seen as an extra hour gained.

Other studies in the medical literature show that disruption in sleep pattern detriments well-being (Short *et al.* (2013) and Gallicchio & Kalesan (2009)). Sipilä *et al.* (2016) finds DST transitions is associated with an increase in ischemic stroke hospitalizations during the first two days after transitions but not during the entire following week. Foerch *et al.* (2008) show that transition to or from DST is associated with an immediate shift in the time pattern of stroke onset.

Hamermesh *et al.* (2008) and Hamermesh *et al.* (2006) show that the effect of DST goes beyond those who are subjected to it directly. Individuals who live in regions that do not have DST are also affected as they alter their timing of work to synchronize activities more closely with those subjected to DST. My study aims to provide a holistic impact of daylight savings on individuals who are subjected to it as well as those who are not using individual data.

DST has been a topic of discussion for policymakers currently. Netherlands gathered a petition for DST abolition in March 2017, joined later by Finland in January 2018. Finland had called for its abolition across the EU in January 2018, after gathering a petition of more than 70,000 people calling on its government to stop the practice earlier in the same year. In March 2017, Netherlands petitioned for the same to the European transport commissioner.[3] The European Parliament voted on February 8, 2018, to ask the European Commission to re-evaluate DST in Europe. An online consultation, ran by the Commission, showed that more than 80 percent of the participants do not want to change clocks anymore.[4] This online poll received the highest number of responses ever in any Commission public consultation. Based on the results, the Commission proposed to eliminate the bi-annual clock changes in the European Union in 2019.

Not far behind the European Union, certain states in the US have joined the discussion on abolition of DST. The Florida senate passed the Sunshine Protection Act in March 2018 to keep the daylight saving time all year-round and abolish the bi-annual clock change.[5] In November 2018, California also voted to allow the state to make the DST year round and remove the bi-annual clock change. The Louisiana State Legislature approved a resolution in May 2018 to study whether Daylight Saving Time or standard time is best for the state. Recently, Oregon, Idaho and Washington

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[3]http://www.euronews.com/2018/03/22/no-change-likely-to-eu-clock-change-rules-despite-strong-opposition

[4]http://europa.eu/rapid/press-release_IP-18-5302_en.htm

[5]https://www.nytimes.com/2018/03/08/us/daylight-saving-time-florida.html

have introduced bills in their respective legislatures to end the twice a year clock changes.[6] In 2015, a house bill was filed to end DST in the state of Washington, however, it was defeated.

2.3 Data

Data on time diaries is obtained from the American Time Use Survey (ATUS). The dataset is limited to observations recorded a week before and after the daylight savings time change, both in the fall and the spring for the states of Arizona and New Mexico. I drop all observations which do not meet the above requirement. To study how the effect of DST changes over the subsequent weeks, I increase the sample of study by including respondents interviewed up till 21 days before and after the clock change.

The American Time Use Survey (ATUS) is administered by the Bureau of Labor Statistics (BLS) from 2003 to 2017. It measures the amount of time people spend in different activities from 4 AM of the previous day to 4 AM of the interview day (Hofferth & Sobek (2018)). It is a nationally representative survey done via telephone interviews to a selected sample of Current Population Survey (CPS) respondents. Since ATUS respondents were interviewed in CPS before, I can identify individuals' state of residence, sociodemographic and socioeconomic characteristics.

The main advantage of this dataset is that ATUS contains detailed information regarding the amount of time an individual spends engaging in various activities. Along with the time diaries, the data also provides the metabolic equivalent (MET) value associated with the ATUS primary activity codes. This is an activity-level variable. Tudor-Locke *et al.* (2009) linked MET value with each activity collected in the ATUS data. Based on this information, I can measure the level of activity

[6] https://www.argusobserver.com/news/daylight-savings-bills-lawmaker-hopeful-for-coordination/article_47d6e102-2cd7-11e9-a172-4fcbdc7cfbf3.html

an individual does, more accurately, in a certain amount of time and categorize by their level of strenuousness. I categorize activities into three main groups: sedentary (MET value is below 1.5) (Mansoubi *et al.* (2015)); light intensity activities (MET value between 1.5-3); and moderate to vigorous intensity activities (MET value above 3). In this sample, seventy eight percent of the time spent in sedentary activities are allocated to sleeping/sleepiness and relaxing/watching movies and television. Light intensity activities mainly consists of household chores, caring for children and driving. Moderate to vigorous intensity activities includes physical exercise such as jogging and playing sports, interior and exteriors cleaning and repairing and all other strenuous tasks.

2.4 Empirical Strategy

First, I study the change in time spent in activities grouped by their MET value as a result of the daylight savings time. Daily activities are grouped into three groups based on the MET value - sedentary (MET value $<$ 1.5), light intensity activities (MET value between 1.5 and 3.0) and medium to vigorous intensity activities (MET value $>$ 3.0). I use the following equation

$$duration(metcategory)_{ijst} = constant + \beta Post * treated_{it} + \rho X_i + \gamma_t + \delta_s + \eta_j + \epsilon_{ist} \quad (2.1)$$

where, $duration(metcategory)_{ijst}$ gives the total time spent doing activities which has a MET value defined as sedentary (met value below 1.5), light (met value between 1.5 and 3.0) or medium to vigorous activity (above 3.0), for individual i, interviewed on day j, for state s and year t. Other variables include $Post * treated_{ist}$ is the interaction term and the coefficient of interest depicting the DID estimate; X_i indicates individual characteristics: age, race, sex, education level and employment status; γ_t gives the year fixed effects; δ_s gives the state fixed effects; η_j gives the dummy for the day of the week, j of the interview; and ϵ_{ijst} gives the error term.

Second, to study the change in the self-reported well-being indicators, I use the following difference-in-differences equation. ATUS provides the self-reported mood indicators scaled from 0-6 where 0 is the lowest scale for the particular emotion and 6 is the highest. This data is reported for only three years in the dataset - 2010, 2012 and 2013.

$$w_{ijst} = constant + \beta Post * treated_{it} + \rho X_i + \gamma_t + \delta_s + \eta_j + \epsilon_{ijst} \tag{2.2}$$

where w_{ijst} indicates the change in welfare indicator variable - namely happy, sad, stress and tired. All these scales are measured from 0 to 6. With 0 being the lowest and 6 highest. Rest of the terms are same as equation 2.1.

2.5 Results

Metabolic Equivalent

Table 2.1 gives the regression estimates for equation 2.1 focusing only on Arizona (as the control state) and New Mexico (as the treated state). The fall DST change causes citizens in New Mexico to increase sedentary activities by 70 minutes and moderate to vigorous-intensive tasks by 160 minutes and reduce light activities by 104 minutes as compared to Arizona. These estimates are statistically significant at conventional levels. The fall DST shifts the clock behind allowing people to feel like they now have a longer day suddenly. The sun rises earlier, and it gets darker sooner than a few days before. People take advantage of an extra hour in the morning by sleeping and relaxing. They feel more energized due to extra sleep and it is reflected in the increased time they choose to spend on vigorous-intensity activities like exercise. The higher time spent on other activities is compensated by reducing time engaged in light-intensity work like household chores.

In spring, the clock change causes a fall in time spent engaging in sedentary activities such as sleeping and relaxing by 78 minutes. This estimate is statistically significant at one percent level of significance. Light and vigorous activities increase by 24 and 21 minutes, respectively. However, these estimates are statistically insignificant at conventional level. As the clock is moved forward, people now wake up earlier than usual even though the clock time is the same as before. This change creates an illusion of a smaller day even when the day has not changed. People feel more tired as a result of losing sleep. DST in the spring does not affect time engaged in other activities. The hour lost is compensated through a loss in sleep.

Overall, any change in time, as given in row 3, reduce light intensive activities by 50 minutes. It has no effect on sedentary or vigorous tasks.

Mood Behavior

Table 2.2 gives the estimates from equation 2.2. Mood indicators are only collected for 3 years in my data explaining the small number of observations. I find that the fall time change makes people happier, less sad and stressed as compared to those interviewed a week before the time change. Individuals report almost 3 points higher on the happiness scale, 3 points lower on stress and sadness scale after the time change. These estimates are statistically significant at 1 percent level of significance. Individuals also report to be less tired, but this estimate is statistically insignificant at conventional levels. The illusion of a longer day in the fall makes people feel more relaxed and happy.

The springtime change causes people to lose 1 hour from their day. These individuals report to be less happy, more sad, stressed and tired as compared to those interviewed before the time change. All estimates except the one for stress scale are statistically insignificant at conventional levels. The spring DST causes individuals to report 2 points higher on the stress scale. The sudden fall in the perceived number of hours in a day takes a while for people to adjust making them feel more stressed and less happy.

Working Population

Working population have a more inflexible daily schedule due to office commitments, childcare routines, etc. I use equation 2.1 to study the impact of DST on the working population of New Mexico as compared to those in Arizona. I find that the fall DST change increases sedentary activities by 90 minutes and moderate to vigorously intensive activities by almost 3 hours. However, there is a decline in chores which are categorized as light-intensive (MET value between 1.5 to 3.0) by little less than 3 hours. These estimates are statistically significant at 1 percent level of significance (Table 2.3).

In the spring, the DST causes a fall in sedentary activities by approximately 2 hours and has little to negligible impact on time spent on more intense chores. These estimates are statistically significant at conventional levels. These results support the pre-assumption that individuals subjected to the fall DST feel more relaxed and energized due to the extra hour they perceive to receive in the day. They relax and sleep more while intensifying their exercise routine. I find the opposite effect in the spring. People lose relaxing and sleeping time but does not change time spent on more intensive activities which may be more unchangeable in their daily schedule.

Comparing with table 2.1, working population feel more disrupted due to DST as compared to the whole population. New Mexican workers change their daily routines by a lot as compared to Arizonian in the same demographic.

How long does it take for the effect of DST to fade out?

The previous section provided evidence to support how a sudden change in the clock time impacts daily schedules. Now the question arises if given time to adjust to daylight savings time, are individuals expected to ease into the new schedule? To test this, I increase the interval of study before and after DST by one and two weeks respectively to observe how individuals respond in the subsequent weeks after the change. I compare people's daily routines 7, 14 and 21 days before and after DST change, respectively.

Metabolic Equivalent

After the fall DST, time spent engaging in sedentary activities increased by 70 minutes, in light intensity tasks like shopping and easy household chores declined by 104 minutes and in vigorous exercise increased by 161 minutes in New Mexico as compared to Arizona (table 2.1). This behavior is seen in the 7 day interval, that is, when I compare the schedules 7 days before and after DST. As I increase the time interval to a 14 or 21 day period before and after DST, impact of the clock change completely fades out immediately. It significantly declines in magnitude and loses its statistical significance when I increase the interval of study from a 7 day period. This result is consistent for all three categories of activities.

Similar results are seen during the spring DST. Only time spent engaging in sedentary activities such as sleeping and relaxing declines by 78 minutes in New Mexico as compared to Arizona in the first 7 days with respect to the last 7 days before the clock change. There is statistically no change in sleeping habits in a 14 or 21 day interval. The magnitude of the estimate also falls in subsequent weeks. There is no change in the time spent engaging in other higher intensive activities such as shopping, vacuuming or vigorous exercise after the DST change in any period of study.

There is no change in the daily routines among New Mexicans as compared to Arizonians in subsequent weeks after DST, thus, supporting the theory that the impact of DST is only temporary. The change in daily schedules experienced by the population in New Mexico due to following the DST law fades out after the first 7 days. New Mexicans completely adjusts their routine a week after DST (fall or spring).

Mood Indicators

I find similar results for the mood indicators. There are statistically significant changes in various mood indicators such as happy, sad, stress and tired in the first 7 days after DST in New Mexico citizens, which fades out eventually in subsequent weeks.

The fall DST causes people in New Mexico to report to be happier, less sad and stressed in the 7 day interval as compared to Arizonians (table 2.2). These estimates are statistically significant at one percent level of significance. As I increase the period of focus from 7 to 21 days, individual's response to the stress and tired scale is no more statistically significant. However, New Mexicans continue to report to be happier in the 14 and 21 day interval. These estimates decline in magnitude and is statistically significant at 10 percent level. Responders also report to be less sad in the 14 day interval. This estimate is smaller than that seen for the 7 day period but is statistically significant at 10 percent level.

In the spring, DST only affects the stress level of the responders. New Mexicans report to have statistically higher stress in the 7 day interval after the clock change as compared to people in Arizona. This result fades out as I increase the interval of study around DST. The estimate is no more statistically significant at 14 or 21 day period. None of the other mood indicators have statistically significant estimates. People adjust their mood and stress more rapidly in the spring as compared to the fall time change.

As seen before, the impact of DST on most mood indicators also fade out in subsequent weeks when I compare Arizona and New Mexico. However, New Mexicans report to be happier even after 21 days after the fall DST.

Working Population

The effect of DST fades out in the same way among the working population as seen for all demographics. In the fall, New Mexico respondents report to spend 90 minutes more time on sedentary activities, 170 minutes less on light intensity activities and 174 minutes more on strenuous exercises in the 7 day interval (table 2.3). These estimates are statistically significant at conventional levels. Light intensity activity declines by 43 minutes in the 14 day interval and 41 minutes in the 21 day interval. These estimates are significant at 5 percent level of significance. There is no statistically significant change in longer intervals for sedentary or high intensive tasks. The impact of the fall DST fades out completely for the working population after the first 7 days for all kinds of activities except those categorized as light intensity in terms of MET equivalent values.

In the spring, only sleeping pattern significantly reduces at one percent level of statistical significance by 102 minutes in the 7 day period. Light and high intensity tasks are unaffected during this time. In the 14 day period, time spent engaging in only light intensity activities such as shopping, vacuuming and other household chores reduces by 35 minutes. This estimate is statistically significant at 10 percent level. Other activities are unaffected. In the 21 day interval, all effects of spring DST cease to exist showing that New Mexicans completely adjust to the clock change with respect to their neighboring state. This demographic does not experience any residual effect of DST in the spring.

2.6 Case Study: Indiana

Indiana along with Arizona and Hawaii chose not to adopt Daylight Savings time when the Uniform Time Act was passed in 1966 in the United States. While Arizona and Hawaii have continued with their chosen policy since then, Indiana's history with time has been long and complicated. After World War II, the federal government lifted the mandate of DST but some states chose to follow. Indiana was officially in the Central time zone, but in the late 40s, some communities chose to follow the daylight-savings time all year-round, thus aligning themselves with the Eastern time zone.

In 1949, the Indiana Senate, after much mayhem, passed a bill which would keep the state on Central time zone and outlaw daylight-savings time. However, the law had no enforcement powers and was ignored by the communities which followed the daylight-savings time all year. A non-binding statewide referendum was conducted in 1956. It asked voters their preference on Eastern versus Central time and the use of daylight-savings time.[7] Those in favor of Central time won with a slight majority but it was clear that not many were in favor of changing the clock twice a year.

A law was passed in 1957 to make Central time the official time of the state but permit any community to switch to DST during the summer. This law was very unpopular and repealed in 1961.

The Uniform DST was passed by the federal government in 1966 allowing any state to exempt themselves as long as the whole state is exempted. During this time, Congress also shifted federal authority over time zones to the Department of Transportation. Between 1968-72, the Indiana General Assembly passed a legislation which would permit Indiana to exempt some counties from following DST if others want to pursue it. This amendment was finally approved and signed by President Richard Nixon in 1972.[8]

This system remained unchanged till the political climate of Indiana changed in 2005. Governor Mitch Daniels argued that the state was losing economic and business opportunities because neighboring states could not keep track of the Indiana time. After multiple defeats, the DST bill of Indiana was finally passed in April 2005. Beginning on April 2 2006, Indiana became the 48th state to observe daylight

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[7]https://www.indystar.com/story/news/politics/2018/11/27/indianapolis-indiana-time-zone-history-central-eastern-daylight-savings-time/2126300002/

[8]https://www.indystar.com/story/news/politics/2018/11/27/indianapolis-indiana-time-zone-history-central-eastern-daylight-savings-time/2126300002/

saving time statewide. The state sets their clocks back an hour in the fall to Eastern Standard Time and ahead one hour in the spring to Eastern Daylight Time.[9]

I compare Indiana with other states which always had DST (namely all states besides Hawaii and Arizona) to study if the implementation of the DST law in 2006 influenced the daily schedules of its residents. For this analyses, I use a triple difference model to study how the implementation of the Indiana DST law in 2006 leads to a difference in daily scheduling of respondents living in Indiana as compared to those living in states which always had DST.

$$duration(metcategory)_{ijst} = constant + \beta Post{*}treated{*}DSTyr_{st} + \rho X_i + \gamma_t + \delta_s + \eta_j + \epsilon_{ist} \tag{2.3}$$

where, $duration(metcategory)_{ijst}$ gives the total time spent doing activities which has a MET value defined as sedentary (met value below 1.5), light (met value between 1.5 and 3.0) or medium to vigorous activity (above 3.0), for individual i, interviewed on day j, for state s and year t. Other variables include $Post{*}treated{*}DSTyr_{st}$ is the interaction term and the coefficient of interest depicting the DDD estimate; X_i indicates individual characteristics: age, race, sex, education level and employment status; γ_t gives the year fixed effects; δ_s gives the state fixed effects; η_j gives the dummy for the day of the week, j of the interview; and ϵ_{ijst} gives the error term.

The coefficient of interest is β which measures the DDD estimate. The triple difference arises due to comparing the outcome variables before and after the implementation of the DST law in Indiana. The comparison to before and after the clock change in the fall/spring provides the double difference and the further comparison to other states which always had DST since 1966 provides the triple difference.

[9]https://www.indystar.com/story/news/2019/03/08/why-indiana-observes-daylight-saving-time-statewide/3092875002/

Table 2.4 gives the estimates for equation 2.3. I find that after the fall DST change, there is a decline in time spent in sedentary activities such as sleeping and relaxing by 111 minutes. Time spent in engaging in light intensity activities also decline by a little less than 2 hours. These estimates are statistically significant at conventional levels. Responders in Indiana significantly changed their routine after the DST implementation in 2006. There is no significant change in time spent engaging in moderate to vigorous intensive activities after the fall DST change. In the spring, time spent engaging in sedentary activities increase after DST implementation in 2006 in Indiana by 149 minutes as compared to other DST states. These estimates are statistically significant at conventional levels. Due to the implementation of the DST policy in 2006, people living in Indiana were able to coordinate with their neighboring states more efficiently. Therefore, I find a significant change in the sleeping/relaxing patterns in both fall and spring.

The working group in Indiana, between the ages of 15-65 years, react in the similar manner to the DST implementation in 2006 as seen for the whole population. Table 2.5 shows that in the fall, Indiana's working population spends less time in sedentary and light intensive activities by approximately 2 hours each, and increase time spent at vigorous intensive activities at almost 3 hours. These estimates are statistically significant at conventional levels. The implementation of the DST law in Indiana causes people to lose time spent in sleeping and relaxing when compared to other states which always had DST. In the spring, there is an increase in time spent in sedentary activities by more than 3 hours in Indiana as compared to other DST states. This estimate is statistically significant at one percent level of significance. Time spent at vigorous tasks also increases by 2 hours which is statistically significant at 10 percent level of significance.

Focusing on the elderly, table 2.6 shows that the implementation of DST in 2006 causes them to increase their sedentary activities by 165 minutes after the clock change in the fall. There is a decline in light intensive activities by 2 hours. Due to a lack of enough observations in the treated group, I am unable to estimate the coefficient for column 3, that is, the time spent engaging in moderate to vigorously intensive activities. In the spring, DST implementation in 2006 causes Indiana elderly to increase engagement in light intensive activities by 4.5 hours and decrease more rigorous tasks by a little less then 4.5 hours. There is no impact on sedentary activities.

Compared to other states which had DST since 1966, the implementation of the law in Indiana in 2006 is large in magnitude and statistically significant. Indiana is an interesting case study. It is the only state to implement DST in the recent times when other states are involved in serious discussion of repealing it. I include this analyses to highlight how the policy impacts those who are newly introduced to it. Implementing the DST policy in Indiana caused more disruption in the daily lives of its citizen as compared to those who have been changing their clocks for decades. This shows that as the change in clock becomes a recurring phenomenon, people are more adjusting than those who are first introduced to it. Hence, people who have migrated from non-DST regions to DST regions are expected to be more affected than those who have lived in DST regions for significantly long time.

2.7 Conclusion

A government policy passed decades ago, forces every citizen in some countries, around the world, to change their clocks twice a year; once in spring and then again in fall. In the spring, the clock moves one hour forward. We lose one hour in the day. In the fall, the clock moves one hour back. We gain one extra hour. This is a practice of advancing clocks during summer months so that evening daylight lasts longer, while sacrificing normal sunrise times. The policy was introduced in the US during the

World War I to conserve energy during wartime and give longer daylight. Existing literature (such as Kotchen & Grant (2011) and Aries & Newsham (2008)) shows that contrary to the intent of the policy, DST has not been successful in reducing energy consumption in the modern world.

My research attempts to study how the change in time caused by DST disrupts the lives of people subjected by it. I use various outcome variables such as sleep pattern, working hours, exercise pattern, well-being and mood indicators such as happiness, sadness, tiredness and stress scale. I classify daily activities into groups based on their MET values - sedentary (MET Value < 1.5), light-intensive (MET Value (1.5-3.0)) and moderate to vigorously intensive activities (MET Value > 3.0). I use the ATUS and a difference-in-differences approach to study the DST change in the USA. A typical difference-in-differences inference assumes a large number of treated and control groups. Due to the presence of only 2 control states, Arizona and Hawaii, and 48 states with DST, I focus on studying the impact of this law on New Mexico while comparing with its neighboring state Arizona. New Mexico always followed DST since the Uniform Time Act of 1966 and Arizona never did.

These two states are geographically similar and belong to the same latitudinal position. I find significant difference in behavior of individuals in New Mexico as compared to Arizona after DST. The fall DST causes individuals in New Mexico to spend more than 1 hour engaging in sedentary activities such as sleeping and relaxing as compared to those in Arizona. In the spring, there is a fall in time spent in relaxing and sleeping by 78 minutes. Fall DST causes individuals to be happier, less sad and stressed while spring DST increases stress but does not impact happiness or sadness scale. The impact on the working population is more severe than the whole population. Interestingly, I also observe that the impact of DST fades out in New Mexico in the following weeks after the clock change. This is true during the spring and fall. Daily schedules return back to pre DST period and any mood changes also disappear in subsequent weeks.

Indiana is the only state in recent past who has adopted the DST law in 2006. Most states in the US are discussing its repeal. This makes Indiana an interesting case study. I analyze how people in Indiana changed their daily schedules when compared with the other 47 states which always had DST after the implementation of the law in 2006. I use a triple difference approach. I find that the fall DST change causes people to decrease the time spent in sleeping/relaxing by 111 minutes and increase in spring by 2.5 hours. Indiana's attempt to adjust with their neighboring states after implementing the law is higher than a 1 hour clock change. The elderly in Indiana do not change their sleeping schedules in the spring when compared to other states after implementing DST. However, they do adjust their sleeping pattern in the fall as a result of DST after 2006. The working population adjust their sleeping schedules in both spring and fall. The case of Indiana is truly intriguing as the DST causes the working population to decrease sedentary activities but entices the elderly to spend more time relaxing in the fall. In the spring, the working population increases their sleeping time but the elderly do not change time spent in sedentary activities.

DST is an archaic law which does not produce the intended impact on energy consumption. However, it disrupts individuals' daily life twice a year causing them to change their schedules and adjust to the new clock. Individuals are forced to reprogram their internal clock twice a year. Some state governments, such as Florida, California, Oregon, etc., are discussing the removal of DST. While in Europe, the European Commission was asked to re-evaluate the DST in the spring of 2018. An on-line survey of citizens showed high support to remove DST. These instances show that individuals subjected to this policy wants it removed or repealed. My study makes a case in favor of the repeal of the DST law in the USA.

Even though the DST causes only a one hour change in the clock twice a year, its cumulative impact is much larger and longer. People subjected to it responds to the clock change by involuntarily changing their daily schedules by more than one hour. There is a disruption in time spent in relaxing and sleeping, engaging in light chores or errands and exercise routines. Although, it seems that people are more happier during the fall transition than the spring, the resultant change in clock in spring makes them miserable as a whole. It takes at least a week for people to adjust back into their regular routine and absorb the presumed loss/gain in time. There is no reason to subject citizens to change their clocks and as a result their biological clocks twice a year. The benefits of the DST law has long been outweighed by its drawbacks. There is no economical, political or physical advantage of continuing with the policy. It is time to change it.

Table 2.1: Change in Types of Activities given by the MET Value: Comparing Arizona and New Mexico

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.>3.0
post_fall=1 × dst_states=1	70.58**	-104.1***	161.5***
	(32.28)	(20.63)	(58.24)
Observations	873	1818	224
post_spring=1 × dst_states=1	-78.97**	24.28	21.00
	(34.41)	(22.06)	(58.24)
Observations	852	1725	210
post_all=1 × dst_states=1	-5.493	-49.54***	43.33
	(23.18)	(15.08)	(36.49)
Observations	1725	3543	434

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.
Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona is the control state which never had DST and New Mexico is the treatment state with DST.

Table 2.2: Respondents' Mood Change when Subjected to DST: Comparing Arizona and New Mexico

	Happy	Sad	Stress	Tired
post_fall=1 × dst_states=1	2.868***	-2.846***	-2.926***	-1.724
	(0.925)	(0.769)	(1.044)	(1.090)
Observations	107	107	106	107
post_spring=1 × dst_states=1	-1.084	0.320	2.067**	0.190
	(1.043)	(0.721)	(0.937)	(1.027)
Observations	85	85	85	85
post_all=1 × dst_states=1	0.623	-0.718	-0.533	-0.0889
	(0.566)	(0.517)	(0.632)	(0.625)
Observations	192	192	191	192

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.

Notes: Dependent variable is the mood scales which are given between 0 - 6. Higher the number on the scale, the respondents feel more strongly about the corresponding emotion. In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona is the control state which never had DST and New Mexico is the treatment state with DST.

Table 2.3: Change in Types of Activities given by the MET Value for the Working Population: Comparing Arizona and New Mexico

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.> 3.0
post_fall=1 × dst_states=1	89.98***	-170.6***	174.6**
	(33.98)	(22.69)	(76.44)
Observations	733	1566	172
post_spring=1 × dst_states=1	-102.9***	26.47	-1.115
	(35.40)	(22.75)	(71.56)
Observations	728	1493	144
post_all=1 × dst_states=1	15.36	-83.02***	66.64
	(24.86)	(16.22)	(45.93)
Observations	1461	3059	316

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.

Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. Working population consists of individuals between the age group of 15-65 years. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona is the control state which never had DST and New Mexico is the treatment state with DST.

Table 2.4: Change in Types of Activities given by the MET Value: Case Study of Indiana

	MET Val.<1.5	MET Val. (1.5-3.0)	MET >3.0
post_fall=1 × treated=1 × yr_2006=1	-111.5***	-117.1***	116.8
	(34.29)	(23.94)	(73.41)
Observations	31878	66079	8170
post_spring=1 × treated=1 × yr_2006=1	149.1***	36.23	90.31
	(36.36)	(29.53)	(58.29)
Observations	33582	68718	8394
post_all=1 × treated=1 × yr_2006=1	8.637	-72.52***	88.60**
	(24.75)	(17.97)	(44.91)
Observations	65460	134797	16564

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.

Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). Indiana did not adopt DST till 2006. I use a triple difference to study if there has been any change in the respondents of Indiana due to the adoption of the policy as compared to all other states who always had DST as control groups. In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables.

Table 2.5: Change in Types of Activities given by the MET Value for the Working Population: Case Study of Indiana

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.> 3.0
post_fall=1 × treated=1 × yr_2006=1	-133.6***	-110.3***	176.0**
	(37.79)	(26.26)	(85.88)
Observations	25272	56177	5508
post_spring=1 × treated=1 × yr_2006=1	198.0***	-17.39	134.0*
	(40.60)	(32.25)	(73.32)
Observations	27243	59225	5952
post_all=1 × treated=1 × yr_2006=1	15.40	-89.00***	163.1***
	(27.12)	(19.57)	(55.53)
Observations	52515	115402	11460

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.
Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). Indiana did not adopt DST till 2006. I use a triple difference to study if there has been any change in the respondents of Indiana due to the adoption of the policy as compared to all other states who always had DST as control groups. In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. Working population consists of individuals between the age group of 15-65 years. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables.

Table 2.6: Change in Types of Activities given by the MET Value for the Older population: Case Study of Indiana

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.> 3.0
post_fall=1 × treated=1 × yr_2006=1	165.0*	-126.1**	0
	(91.73)	(50.37)	(.)
Observations	7073	10592	1425
post_spring=1 × treated=1 × yr_2006=1	24.49	276.6***	-255.7**
	(80.92)	(68.32)	(107.4)
Observations	6904	10387	1256
post_all=1 × treated=1 × yr_2006=1	91.63	-11.02	-320.7***
	(59.06)	(39.31)	(88.58)
Observations	13977	20979	2681

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.

Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). Indiana did not adopt DST till 2006. I use a triple difference to study if there has been any change in the respondents of Indiana due to the adoption of the policy as compared to all other states who always had DST as control groups. In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. Older population consists of individuals above the age of 65 years. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. The missing coefficient in row 1 is due to the lack of sufficient observations in post DST sample. There was no observations recorded which met the criteria in this category.

2.8 Appendix

All 50 States: Comparing all DST States with Non-DST States

Due to the lack of sufficient number of control groups, it is difficult to obtain reliable regression estimates for all 50 states. In this section, I show the regression coefficient when I include all 50 states instead of comparing only Arizona and New Mexico. I use equations 2.1 and 2.2 for all 50 states. Here Arizona, Hawaii and Indiana before 2006 serve as control states and rest serve as treated states. Arizona and Hawaii never had ant DST policy and Indiana adopted DST after 2006. I use two cases here. Case 1: comparing Arizona with New Mexico. Case 2: comparing all DST states with all non-DST states.

Metabolic Equivalent

Table 2.7 shows the estimates from equation 2.1. I compare these results with table 2.1, which gives the regression estimates when we compare Arizona and New Mexico only. In the fall, individuals subjected to DST reduce time spent in sedentary activities such as sleeping, relaxing, watching TV, etc. by 50 minutes, and in light intensive activities such as strolling, household chores, etc. by 68 minutes. However, individuals increase their moderate to vigorously intensive activities such as jogging, swimming or hiking by 65 minutes. These estimates are statistically significant at one percent level (table 2.7).

The clock moves forward in the spring and people lose one hour. My results show that people reduce 30 minutes of sedentary activities and 50 minutes of moderate to vigorously intensive activities after the time change in spring but increase 40 minutes of light intensive activities. The coefficient estimate for sedentary and light-intensity activities matches in sign with table 2.1.

The sign of the coefficient for all 50 states, and New Mexico and Arizona comparison differ only for the sedentary activities in the fall and vigorously intensive activities in the spring. In the fall, time spent in sleeping and relaxing decline by 50 minutes when I compare all DST states with all non-DST states but increases by 70 minutes in New Mexico when I compare with Arizona. Theoretically, an extra hour in the morning should increase relaxing time. One hour shift in the clock gives an illusion of a longer day and people are more likely to spend relaxing. The results of table 2.7 seems unreliable. Similarly, sign of the coefficient estimate for vigorously-intensive activities are different in the two cases. However, this estimate is statistically insignificant at conventional levels in the Arizona and New Mexico comparison but significant at 5 percent level of significance in case 2.

Mood Behavior

Table 2.8 gives the regression estimates from equation 2.2. I find that the fall time change makes people happier, more stressed and tired but less sad. In the spring, people also report to be more happy and tired but less sad and stress. However, none of the regression estimates are statistically significant at conventional levels. I am unable to conclude if and how the respondents moods are influenced by the change in clock.

Comparing these results with case 1, I find New Mexicans are more happy, less sad, stress and tired in the fall when compared to Arizonian (table 2.2). All estimates except that for tired are statistically significant at conventional levels. Even though the sign for the coefficient estimates for happiness and sadness scale are same in the two cases, the magnitudes are very small for all 50 states. Similarly, New Mexicans claimed to be statistically more stressed than Arizonians after the spring DST. All DST states do not show any such behavioral change as compared to non-DST states.

Working vs Older Population

Due to the availability of data, I can compare the working and the elderly population for all DST versus non-DST states. I am unable to make the same comparison for Arizona and New Mexico because the number of observations are too small for any statistical power.

Working population (those within the age of 15-65 years) are expected to follow a daily routine which is fairly rigid due to a work schedule. I expect these individuals to behave differently than those who are retirees and hence have less flexible routines. Table 2.9 gives the estimates from equation 2.1 for the working population (those within the age of 15-65 years). The fall DST change causes a decline in time spent engaging in sedentary activities by 35 minutes and light intensive activities by 77 minutes but increases vigorously intensive activities by 75 minutes. In the spring, time moves 1 hour forward causing individuals to reduce sedentary activities and increase light-intensity activities by 38 and 33 minutes, respectively. Any time change, given by row 3, causes a fall in time spent engaging in sedentary activities by 46 minutes, light to moderate intensity activities by 22 minutes and gain in vigorous exercise time by 48 minutes. These regression estimates are statistically significant at conventional levels.

Table 2.10 gives the regression estimates for the older population (those above 65 years of age). I find that these individuals are more susceptible to DST than the working population. In fall, this demographic lose 166 minutes of sedentary activities and gain almost an hour of light-intensive activities. The spring clock change leads to a gain in light intensive activities by 83 minutes and a fall in moderate to vigorously intensive activities by 2 hours. Row 3 shows that any change in clock reduces sedentary activities by a little more than 1 hour and vigorous intensive chores by 1 hour, and gains light-intensive tasks by 77 minutes. All regression estimates are statistically significant at conventional levels.

My results show that although the working demographic has a more rigid routine, the older population, who are more likely to be retirees, are affected more due to the clock change. This could be due to them being older and suffering from health complications as a result of age causing them to adjust more slowly to the clock change than the working population who are much younger. It is more difficult for the older population to adjust to the time change and continue with their daily schedules after DST.

Disabled Population

In this section, I look closely at those individuals who have reported to have a disability. I include all individuals who have responded affirmatively to possess any difficulty such as serious vision or hearing impairment, restrictive mobility (such as walking and climbing stairs), cognitive struggle (such as remembering, concentrating or making decision), or any other physical or mental condition which lasted over 6 months and requires the individual to seek assistance for their own personal needs. I find that these individuals increase light intensive activity by 2 hours in the fall (table 2.11). This estimate is statistically significant at conventional levels. The change in sedentary and vigorous chores are statistically insignificant. In the spring, they increase light intensity tasks by 2 hours and moderate to vigorously intensive tasks by almost 3 hours. Row 3 shows that any change in DST, whether spring or fall causes a decline in sedentary activities by 131 minutes, and an increase in light and moderate to vigorous activities by 108 and 134 minutes, respectively. These regression estimates are statistically significant at conventional levels.

Using all 50 states increases the number of observations but due to a very small number of control groups, the typical difference-in-differences inference assumption of a large number of treated and control groups is violated. However, the above analysis does give evidence to support the significant impact of DST on various demographics.

Table 2.7: Change in Types of Activities given by the MET Value

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.>3.0
post_fall=1 × dst_states=1	-50.27***	-68.84***	65.27***
	(14.10)	(9.619)	(25.17)
Observations	32597	67603	8361
post_spring=1 × dst_states=1	-30.78**	39.84***	-50.97**
	(15.01)	(10.60)	(23.93)
Observations	34217	70087	8561
post_all=1 × dst_states=1	-49.56***	-15.98**	11.73
	(10.04)	(6.965)	(16.93)
Observations	66814	137690	16922

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.
Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona, Hawaii and Indiana (before 2006) are the control states, whereas the rest of the states (including Indiana after 2006) are seen as treatment states with DST.

Table 2.8: Respondents' Mood Change when Subjected to DST

	Happy	Sad	Stress	Tired
post_fall=1 × dst_states=1	0.176	-0.486	0.617	0.0755
	(0.397)	(0.342)	(0.435)	(0.481)
Observations	3564	3575	3580	3574
post_spring=1 × dst_states=1	0.434	-0.0217	-0.377	0.421
	(0.427)	(0.365)	(0.464)	(0.508)
Observations	3741	3746	3751	3752
post_all=1 × dst_states=1	0.172	-0.133	0.226	0.221
	(0.277)	(0.237)	(0.301)	(0.331)
Observations	7305	7321	7331	7326

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.
Notes: Dependent variable is the mood scales which are given between 0 - 6. Higher the number on the scale, the respondents feel more strongly about the corresponding emotion. In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona, Hawaii and Indiana (before 2006) are the control states, whereas the rest of the states (including Indiana after 2006) are seen as treatment states with DST.

Table 2.9: Change in Types of Activities given by the MET Value for the Working Population

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.>3.0
post_fall=1 × dst_states=1	-35.81**	-77.17***	74.58**
	(15.08)	(10.28)	(29.39)
Observations	25907	57559	5659
post_spring=1 × dst_states=1	-38.38**	33.95***	2.106
	(16.28)	(11.44)	(30.00)
Observations	27775	60420	6060
post_all=1 × dst_states=1	-46.26***	-22.96***	48.68**
	(10.79)	(7.463)	(20.61)
Observations	53682	117979	11719

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.

Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. Working population consists of individuals between the age group of 15-65 years. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona, Hawaii and Indiana (before 2006) are the control states, whereas the rest of the states (including Indiana after 2006) are seen as treatment states with DST.

Table 2.10: Change in Types of Activities given by the MET Value for the Older Population

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.>3.0
post_fall=1 × dst_states=1	-166.2***	56.05**	115.6
	(41.71)	(27.88)	(81.06)
Observations	7163	10746	1448
post_spring=1 × dst_states=1	-29.49	83.04***	-120.5***
	(35.73)	(25.58)	(41.39)
Observations	7021	10580	1296
post_all=1 × dst_states=1	-64.32**	77.53***	-59.18*
	(26.24)	(18.62)	(33.98)
Observations	14184	21326	2744

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.
Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. Older population consists of individuals above the age of 65 years. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona, Hawaii and Indiana (before 2006) are the control states, whereas the rest of the states (including Indiana after 2006) are seen as treatment states with DST.

Table 2.11: Change in Types of Activities given by the MET Value for the Disabled Population

	MET Val.<1.5	MET Val. (1.5-3.0)	MET Val.>3.0
post_fall=1 × dst_states=1	-93.16	120.4***	7.585
	(58.26)	(41.89)	(96.30)
Observations	2859	3480	409
post_spring=1 × dst_states=1	9.875	120.4***	176.3**
	(54.69)	(45.06)	(83.89)
Observations	2689	3316	407
post_all=1 × dst_states=1	-131.9***	108.5***	134.9**
	(36.40)	(31.67)	(54.67)
Observations	5548	6796	816

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Time Use Survey.

Notes: Dependent variable is the time spent in minutes on activities when divided into either of the three groups of activities based on the MET value. The three groups are defined as - sedentary activities (MET value < 1.5), light intensive activities (MET value between 1.5-3.0) and moderate to vigorously intensive activities (MET value > 3.0). In the fall, the clock moves back by 1 hour. In the spring, the clock moves forward by 1 hour. For row 3, I combine all individuals who have been subjected to any time change - fall or spring. Disabled population consists of individuals who have reported to have any of the following disability - serious vision or hearing impairment, restrictive mobility (such as walking and climbing stairs), cognitive struggle (such as remembering, concentrating or making decision), or any other physical or mental condition which lasted over 6 months and requires the individual to seek assistance for their own personal needs. The standard errors are given in the parenthesis under the coefficient estimates. I use age, sex, race, education level and employment status as control variables. Here, Arizona, Hawaii and Indiana (before 2006) are the control states, whereas the rest of the states (including Indiana after 2006) are seen as treatment states with DST.

Chapter 3

The Highs and Lows of Medical Marijuana Legalization

By Sanjukta Basu, Siobhan S. Innes-Gawn and Mary H. Penn

Abstract

We estimate the impact of legalizing medical marijuana on the consumption of marijuana, alcohol and criminal behavior using data from the National Longitudinal Survey of Youth 1997 (NLSY97). We apply a difference-in-differences approach to study the effect of medical marijuana legalization on individual-level consumption of substances and other criminal behaviors. We incorporate the state-level institutional variation in medical marijuana laws in our analyses in much details than the existing literature presents. We test the impact of this variation on individual-level behaviors using self-reported data. Results show that there is a slight increase in marijuana and alcohol consumption but no change in criminal behavior. The magnitude of increase is very small indicating that this policy has negligible negative impact on society.

Keywords: medical marijuana laws; crime; substance use.
JEL: K42, I18.

3.1 Introduction

There has been an ongoing debate of the social consequences of legalizing medical marijuana since California first legalized the drug in 1996. Since then, more states and the District of Columbia have followed suit and legalized medical marijuana. This paper attempts to determine the effect of legalizing medical marijuana on crime and the consumption of marijuana and alcohol. The impact of legalizing medical marijuana potentially has large social implications, yet there are few empirical papers on this topic that determine the links between legalizing the drug, substance use, and crime. We study this underlying relationship using a difference-in-differences model and data from the National Longitudinal Survey of Youth 1997 (NLSY97). We find that the effect of medical marijuana legalization (MML) causes a very slight increase in marijuana and alcohol consumption but no change in criminal behavior. According to our results, MML does not have any negative side-effects on the society.

There are many reasons why a state may choose to legalize medical marijuana. States may legalize medical marijuana if the benefits of the drug outweigh the costs. Recent studies show that marijuana is a viable alternative to many pain medications and is more cost effective. Hill (2015) reports findings from 28 randomized clinical trials from 1948 to 2015 and finds that marijuana use for "chronic pain, neuropathic pain and spasticity due to multiple sclerosis is supported by high-quality evidence." Bradford & Bradford (2016) finds that legalizing medical marijuana leads to a decrease in prescription medication use in Medicare Part D. The decrease is due to prescriptions for which medical marijuana could be used as an alternative. This reduction in spending is estimated to be $165.2 million annually from 2010 to 2013.

Despite these benefits to legalizing medical marijuana, there are also potential drawbacks such as if the law increase other substance use or crime rates. If the laws do increase crime rates, then this could lead to an increase in spending on criminal justice system (costs associated with police funding and incarceration), crime career costs (opportunity costs associated with an individual's choice to commit crime rather than have a legal job), and intangible costs (indirect costs for victims). McCollister *et al.* (2010) reports that the act of robbery has an average cost of $\$42,310$, motor vehicle theft has an average cost of $\$10,772$ and stolen property has a total cost of $\$7,974$.

Additionally, if legalizing medical marijuana increases marijuana, alcohol or other illegal substance use, then states may be wary of passing such legislation (Wood *et al.* (2003)). If we find any effects for medical marijuana laws, we might expect the impact to be even larger if states pass recreational marijuana laws.

There are many possible mechanisms through which legalizing medical marijuana could increase crime rates. If legalization escalates the number of marijuana users, this may lead to a general social acceptance of drug use, which further increases usage. Therefore, if marijuana is a gateway drug, then hard drug use may start to rise. As hard drug use increases, individuals may commit crimes to support their drug addictions. Alternatively, if the laws do not increase the number of marijuana users, then crime may increase if facilities growing marijuana are targeted for robberies (Morris *et al.* (2014)). Finally, crime rates may decrease due to fewer individuals buying from illegal sources. If former illegal sources are now legally growing marijuana, this may also decrease crime associated with selling and growing marijuana "on the street." As marijuana becomes a legitimate business, crimes associated with "street deals" and gang violence may decrease.

We use the NLSY97 data and focus on those states which have legalized medical marijuana until 2014. This is because the last round of survey was in 2015. We classify states into two groups based on their state characteristics defined by the law in terms of their physical availability, legal protections provided to patients and caregivers, patient qualification requirements, and financial access to the medical marijuana treatment. These groups are - strict and permissive. We use a difference-in-differences approach to study the effect of MML on criminal behavior, marijuana and alcohol consumption.

This paper contributes to the literature in numerous ways. First, we find that the MML slightly increases consumption of marijuana and alcohol but has no impact on criminal behavior. Second, we use a longer time period that includes individual data on crime and substance use, not merely state level aggregates. The nature of our dataset allows individuals to report actual crimes they commit and does not rely on the individual being caught. Therefore, assuming the respondents are honest, (this is an anonymous survey), our crime and substance usage reports may be more accurate. Fourth, we use the state MML characteristics in our specification to incorporate the differences in the law. We find that state characteristics of the law has significant impact on some MML induced behaviors. Finally, we find that MML is discouraging young adults and teenagers (between the age of 12-20 years) from consuming marijuana but encourages over 21 year olds.

3.2 Background

As of January 2019, the use of marijuana for medicinal purposes had been legalized in 33 states and the District of Columbia. The first state to remove criminal penalties for marijuana use, possession, and cultivation was California in 1996 with the Compassionate Use Act (Anderson *et al.* (2013)). The law removed criminal penalties for physicians who recommended marijuana for medical purposes. Following California, Alaska, Oregon, and Washington passed medical marijuana laws in 1998 with successful ballot measures.[1] In Alaska, the law became effective in March 1999. In December 2000, Hawaii was the first state to legalize by state legislature. Since then, other states have followed (see table 3.1 for the timeline). States have used different methods to enact these laws, such as ballot measures (Alaska in 1998,

[1]https://medicalmarijuana.procon.org/view.resource.php?resourceID=000881.

Nevada in 2000, and Arkansas in 2016) and state legislation (Vermont in 2004, New Jersey in 2010, and Connecticut in 2012).

In addition to the 33 states mentioned in table 3.1, 14 other states have more restrictive medical CBD (cannabidiol) laws allowing the use of products rich in CBD and low in THC (tetrahydrocannabinol) for medicinal consumption.[2] This is a non-psychoactive component of cannabis. Three states (Idaho, Nebraska and South Dakota) do not allow cannabis products in any form to be purchased or consumed for any reason. At the federal level, cannabis remains a prohibited substance by the Controlled Substances Act of 1970.

There is considerable variation in medical marijuana laws among the states, including its possession, cultivation, distribution, the approved medical conditions for which it can be prescribed and other particulars specified in the law. Table 3.2 shows the variation in some of the characteristics of medical marijuana laws by state. This table includes all 33 states and the District of Columbia. Cultivation limits (given by the number of plants) varies from zero in most states, such as Louisiana, Arkansas, New York, and Maryland, to 16 plants per person in New Mexico. All states, except Alaska, Arkansas, and Washington, allow state-licensed dispensaries, which can produce and dispense marijuana to authorized patients. However, some of these dispensaries are not yet operational or became effective at a later date. For example, the state dispensaries in Hawaii became operational in July 2016. Possession limits allowed for registered patients also vary from state to state. Some states specify a limit of a one-month supply but do not specify the exact quantity in ounces. Other states, like Alaska, Arizona, Massachusetts and Nevada specifies quantity in ounces. States like Arkansas and California do not specify any possession limits. They allow amounts consistent with patients' needs. Washington allows patients to posses a limit of either 48 ounces of marijuana-infused products in solid form, 3 ounces of usable

[2]https://worldpopulationreview.com/states/cbd-legal-states/

marijuana, 216 ounces of marijuana-infused product in liquid form, or 21 grams of marijuana concentrates. Oregon allows 24 ounces of usable cannabis, which is the second highest limit. Alaska and Montana allow only 1 ounce.

The minimum penalty for possessing unauthorized cannabis also differs across states. Some states, like California, Alaska, and Colorado, have recreational marijuana laws. They allow possession for non-medical use. In Arizona, unauthorized possession is a felony. The minimum penalty is a misdemeanor in most states (for example, Arkansas, Hawaii, and Michigan). These are examples of a few characteristics that we found in the state laws. For our analysis, we use many more such characteristics which are explained in detail in the appendix (section 3.7). The numerous state characteristics in the medical marijuana laws significantly influence the effectiveness of the laws and the extent to which subjected individuals are affected. Therefore, it is essential to address this variation. To incorporate these difference, we utilize the state variation in our estimates.

It is important to note here that even if the legalization of marijuana is an exogenous act by a particular state, the particulars and description of the bill may not be. Each state has spent years in planning and debating every aspect of the law before implementation. The nature of the citizens, their lifestyles and needs guided policymakers in making the decision regarding MML in their constituencies. States like California, Oregon and Washington were among the first few states for legalizing medical marijuana. Historically these states has been characterized as favorable to the democratic candidate as early as mid-1990s. However, Alaska has always been a red state and one of the early states to pass the law. States which have MML early are primarily blue states. Due to its advantages, other states have legalized medical marijuana. States with stricter laws are those which are more conservative in nature. These states are less likely to use marijuana as alternate source of treatment. States which have eventually legalized recreational marijuana are seen to have both strict and permissive laws. These include permissive states like California and Massachusetts, as well as strict states like Alaska, Colorado and Maine. The history of MML shows that there are limited common factors impacting state characteristics. Most states are working independently in deciding if and when to legalize medical marijuana and the particulars of the law.

Even though each state legalized medical marijuana independently of each other, their nature of government and preferences of citizens had a greater role in defining its characteristics. States that already had high instances of smoking marijuana/positive attitudes towards marijuana are more likely to pass the law (especially the early adopters and permissive states). Therefore, the estimates will be biased upwards if we do not account for this. Basically we should be worried if unobservables are affecting the decision to pass the law and the outcome variables. Since these factors are specific to each state or county, we use a county fixed effect in our empirical model to incorporate the county level differences.

Medical Marijuana Legalization and Marijuana Use

Several empirical papers study the effect of legalizing medical marijuana on marijuana use but find contradicting results. A possible mechanism through which legalization could increase marijuana consumption is that medical marijuana laws could increase social acceptance and reduce risk perception of the drug (Schuermeyer *et al.* (2014)), which leads to more experimentation and usage. It is also probable that marijuana laws have no effect on marijuana use if unobservable characteristics like being predisposed for drug use is uncorrelated with the law. In other words, people who were going to use marijuana are going to do it, regardless of the law. Wen *et al.* (2015), Anderson & Rees (2014), and Cerdá *et al.* (2012) study the effect of medical marijuana laws on marijuana usage; however, the results are not consistent.

Wen *et al.* (2015) finds that the legalization of medical marijuana increases first-time marijuana use for individuals aged 12-20 years old and that the probability of current use, regular use, and abuse/dependence for marijuana, alcohol, and other substances increase with the legalization of medical marijuana (for ages 21 and older). Anderson *et al.* (2013) determines that legalizing medical marijuana decreases teen marijuana use and Cerdá *et al.* (2012) finds a correlation between legalizing the drug and higher marijuana use and dependence. Our paper contributes to this literature by examining an alternative dataset and estimation technique.

Marijuana and Alcohol

The effect of medical marijuana laws will have different effects on smoking and alcohol depending on if these substances are complements or substitutes for marijuana. There are numerous studies concluding that alcohol is more dangerous to society than marijuana (Anderson & Rees (2014)); hence, it is important to determine this relationship in order to assess the potential impact of legalizing medical marijuana.

Alcohol has high social costs resulting from drunk driving and fatal accidents. If marijuana and alcohol consumption are complements (as seen in Pacula (1998), Farrelly *et al.* (1999), Williams *et al.* (2004), and Yörük & Yörük (2011)), and legalization leads to increased marijuana use, then alcohol use could also rise. Wen *et al.* (2015) finds that medical marijuana laws are associated with an increase in binge drinking for ages 21 or older. If they are substitutes, however, then if the law increases marijuana consumption, alcohol use could decrease. Chaloupka & Laixuthai (1997), Saffer & Chaloupka (1999), and Crost & Guerrero (2012) estimate that marijuana decriminalization is associated with lower alcohol consumption, indicating that the substances are substitutes. Anderson & Rees (2014) and Anderson *et al.* (2013) find that legalizing medical marijuana is associated with about a 10% decrease in fatalities due to driving under the influence of alcohol. It is also possible that there is no effect of the law on marijuana use; in that case, the effect on alcohol would be ambiguous.

Legalizing Medical Marijuana and Crime

There are many possible mechanisms through which legalizing medical marijuana could increase crime rates. If legalization escalates the number of marijuana users, and the gateway hypothesis is accurate, then hard drug use may start to rise. As hard drug use increases, individuals may commit crimes to support their drug addictions. Alternatively, if the laws do not increase the number of marijuana users, then crime may still increase if facilities growing and selling (state dispensaries) marijuana are targeted for robberies (Morris *et al.* (2014)). Finally, crime rates may decrease due to fewer individuals buying from illegal sources because of authorized cultivation. If former illegal sources are now legally growing marijuana, this may also decrease crime associated with selling and growing marijuana "on the street." As marijuana becomes a legitimate business, crimes associated with "street deals" and gang violence may decrease. This is true in states with recreational laws allowing legal cultivation and distribution. There are also crimes associated with drunken behavior, so if legalizing medical marijuana leads to an increase (decrease) in alcohol consumption, this could indicate a change in crime rates.

A few studies have examined the impact of legalizing medical marijuana on crime. Morris *et al.* (2014) finds a negative or statistically insignificant correlation between legalizing medical marijuana on crime. The only statistically significant variables are homicide and assault. They find a 2.4 percent decrease in homicide and assault associated with each additional year the law is in effect. There is no evidence that the law affects robbery or burglary. Anderson *et al.* (2013) determines that legalizing medical marijuana impacts crime indirectly by reducing alcohol use, which decreases crime. Similarly, a paper examining the impact of recreational marijuana laws on crime find a reduction in rapes, property crimes, and hard drug use in Washington and Oregon (Dragone *et al.* (2019)). Another study on opioid use finds that a decline in drug use may reduce crime. The authors find that opioid use and prescription drug monitoring programs have a small negative impact on violent crime (Dave *et al.* (2018)). If marijuana and hard drugs are complements, then we may expect to see an increase in crime if marijuana use increases as a result of the MML. Our paper builds on these studies by incorporating more state variation and using individual survey data.

3.3 Data

Data Sources

We use the National Longitudinal Survey of Youth 1997 (NLSY97). This data is administered by the Bureau of Labor Statistics (BLS). The NLSY97 Cohort is a longitudinal project that follows the lives of a sample of 8,984 American youths born between 1980 and 1984. The respondents were aged 12-17 years when first interviewed in 1997. This ongoing cohort has been surveyed 17 times since 1997 to 2015 and is now interviewed biennially after 2011. The survey documents the transition of respondents from school to work and into adulthood, and provides self-reported, individual-level data. This survey has eight sections of questions covering education, health, income, family background, attitudes, employment, household geography, marital history and child-care, and crime and substance abuse.

For this study, we focus on the crime and substance abuse section of the data. A self-administered survey asks respondents whether they consumed any licit or illicit drugs, such as alcohol, cigarettes, marijuana, and other hard drugs like cocaine, since the last interview, along with questions regarding the frequency and quantity of use.

The nature of the survey questions and the expected answers allow less scope for their subjective interpretation. While the survey asks about marijuana use, alcohol, and smoking in the first year (1997), questions about hard drug use do not begin until 1998-1999. Additionally, drug use questions were absent in 2013.

We examine the effect of legalization of medical marijuana on the consumption of marijuana and alcohol. The main outcome variables of interest for this study are whether the respondent consumed these substances since the last interview, and various measures of the frequency and amount of consumption. We use four variables to study marijuana use, namely - have the respondent ever consumed marijuana (first time consumers) since the date of last interview, have the respondent consumed any marijuana since the last date of interview, number of days the respondent used marijuana in the last 30 days, and the number of times they used marijuana before/during school/work. The first two variables capture the probability of consumption while the later two focuses on frequency of use.

For alcohol consumption, we use 5 variables, They are - have the respondent ever consumed alcohol (first time consumers) since the date of last interview, have the respondent consumed any alcohol since the last date of interview, number of days the respondent used alcohol in the last 30 days, number of drinks consumed per day in the last 30 days, and the number of times they used alcohol before/during school/work. The first two variables capture the probability of drinking while the later three focus on frequency of drinking.

We also study criminal behavior by looking at their arrest record since the last interview date and other crimes. The five variables which we use to determine criminal behavior are - has the responded ever been arrested since the last date of interview, has the respondent stole more than $50 worth of items since the last date of interview, has the respondent committed any property crime since the date of last interview, has the individual sold marijuana since the last date of interview, and has the individual sold/helped sell any illegal drugs since the last date of interview. We use age, sex, race/ethnicity, education level, and household income as control variables. The arrest variable is available till 2015 but all other criminal variables are only used until 2005. This is due to the change in the universe and the survey questions since 2005 for these variables.

Medical marijuana law differs much across the states in terms of its characteristics and date of implementation. These laws have been amending over the years since the year of enactment for each state. Due to the diversity in the medical marijuana laws, we have incorporated the various attributes of them in our analyses. We used the state laws to create a database documenting the possession limit, cultivation limit and other characteristics as given in the documentations and statements of the law. This is described in further detail in the appendix (section 3.7). We also use variables depicting the political atmosphere in the states when the law was passed. For this, we include the political affiliation of the ruling government (namely, if the Governor was affiliated to the Republican or Democratic party). In addition, we add the process through which the law was passed - ballot or legislative action. Seventeen of the states that had legalized medical marijuana did so through citizen-initiated ballot measures, and the other 16 did so through legislative action. We use a combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of these characteristics. Some particulars of the law, such as the existence of state-run dispensaries, are modified after the initial implementation. We take this into account when incorporating the state characteristics in our analyses.

Descriptive Statistics

Table 3.3 compares the demographics of responders between the MML states and non-MML states. The average age of respondents is 23 years in our sample.

Almost 50 percent of the population is female in both samples - MML and non-MML states. Twenty percent of the non-MML sample is black and 9 percent is Hispanic. These numbers are 11 percent and 15.9 percent in MML states, respectively. Eighty five percent of responders have a high school degree and 30 percent have a college degree in the non-MML states. Respondents are slightly more educated in the MML states. Eighty nine percent have completed high school and 38 percent went to college in MML states. Household Income as measured in dollars is higher in MML states. A higher percentage (29 percent) of the population of the non-MML states lives in rural areas as compared to MML states (16 percent).

Table 3.4 shows the descriptive statistics for the outcome variables, namely marijuana and alcohol consumption, and criminal activity variables, for states without the medical marijuana law and states with the medical marijuana law. We study four variables to capture marijuana consumption patterns - ever used since the date of last interview, any use since the last date of interview, number of days consumed since the last date of interview, and number of times consumed before/during work/school. On average, the consumption of marijuana is higher in states with the medical marijuana law. Fifty seven percent of interviewees claim to ever use marijuana in states with MML as compared to fifty percent in states without MML. Eighteen percent of interviewees claim to consume marijuana since the last date of interview in non-MML states and twenty four percent in MML states. Non-MML states residents claim to have used marijuana at least 1.6 days in the last month while MML states residence consume marijuana for more than 2 days in the last 30 days of the interview.

We use five variables to study drinking habits. Eighty nine percent of individuals claim to ever consume alcohol in all states (MML and non-MML). Use of alcohol since the last interview date is higher in MML states. Seventy five percent of responders living in MML states claim to have consumed alcohol since the last date of interview. In non-MML states, only 70 percent of responders had at least one drink since the last date of interview. Number of days consumed alcohol and the number of times drank before/during work/school in the last 30 days are similar in states irrespective of the MML. Number of drinks per day is higher in non-MML states. MML states respondents drink an average of 4 drinks per day and non-MML states drinks an average of 4.5 drinks per day. Alcohol consumption is very similar between states with MML and states without MML.

We use five crime variables to study the criminal behavior pattern among the respondents. There is a slight decline in the percentage of responders who were arrested since the last date of interview living in MML states as compared to those living in non-MML states. Only 2 percent of the responders in non-MML states claimed to have stole more than $50 worth of products while 3 percent of individuals have claimed to steal items of similar monetary value in MML states. Property crimes were committed by 2.3 percent of individuals living in non-MML states as compared to 2.8 percent of individuals in MML states. Seventy five percent of non-MML state responders claimed to have sold marijuana as compared to seventy eight percent of MML state responders. The percentage of responders claimed to have sold/helped sell illegal drugs is 5.9 percent in non-MML states and 7 percent in MML states. An analyses of the criminal behavior shows that individuals living in the MML states are slightly more prone to commit illegal activities but have experienced lower arrests as compared to individuals living in non-MML states.

3.4 Empirical Strategy

We employ a difference-in-differences approach to estimate the effect of MMLs, and their specific characteristics, on marijuana use and other outcome variables. We study the impact of medical marijuana legalization on marijuana consumption, alcohol consumption and criminal behavior using a difference-in-differences approach.

Model 1 uses demographic variables such as age, sex, race, education level and household income as controls. We do not include the state characteristics of the MML. We use a dummy variable to show if the state has the MML law or not. These results are depicted in column 1 of each of the estimates tables. Model 2 includes state characteristics as specified by the MML such as cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. States are divided into two groups - strict and permissive based on these characteristics. In addition to the above, we also include variables depicting the political atmosphere prevailed in the state when the law was first passed. These variables include the political party affiliation of the ruling government during the passing of the law and if medical marijuana legalization was through citizen-initiated ballot measures, or a legislative action. Model 2 estimates are given in column 2 of the result tables.

We group states into categories based on the flexibility of the law. Laws which allow higher consumption and possession limits, have a state-run dispensary allowing easy access to marijuana, permits the use of marijuana for larger number of treatments, and allows easier and greater number of patients to access medicinal marijuana are classified as *permissive* laws. All other laws are classified as *Strict.* States which do not have MML are the omitted category. The empirical equation is as follows

$$\begin{aligned} Y_{ict} = \alpha + \beta MML_{ct} + \rho Strict * MML_{ct} + \phi Permissive * MML_{ct} \\ + \gamma X_{it} + + \tau Republic_c + \nu Ballot_c + \delta_t + \eta_c + \epsilon_{ict} \end{aligned} \tag{3.1}$$

Y_{ict} is the outcome variable of interest for respondent i in year t and county c - marijuana and alcohol consumption patterns, and criminal behavior of the respondents. MML_{ct} indicates whether the respondent's county of residence c has a medical marijuana law in place at time t. $Strict * MML_{ct}$ provides the interaction between the MML effect and if the state has a strict MML. $Permissive * MML_{ct}$ provides the interaction between the MML effect and if the state has a permissive MML. X_{it} is a vector of individual characteristics, such as age, race, sex, education level and household income as reported in 1996. η_c and δ_t are county and time fixed effects, respectively. $Republic_c$ is a dummy variable which is coded as 1 if the governing body, in the state of county c, at the time of passing the MML affiliate themselves with the Republican party. It is coded as zero if otherwise. $Ballot_c$ is coded as 1 if the state passed the law through a citizen-initiated ballot. The error term is given by ϵ_{ict}.

To understand if MML has a different impact on adolescents versus adults, we divide the sample into two age groups - teenagers and young adults between the age group of 12-20 years, and adults at the age of 21 years or above.

3.5 Results

All Population

Marijuana Consumption

Table 3.5 gives the estimates for the various outcome variables depicting marijuana consumption. We use four variables to define marijuana consumption - ever used marijuana since the date of last interview, any use of marijuana since the date of last interview, number of days the respondent consumed marijuana in the last 30 days, and number of times the respondent consumed marijuana before/during school/work in the last 30 days. Model 1 gives the estimates without MML state characteristics. The probability of marijuana consumption increases for each of the four variables. The probability of ever consuming marijuana (as of the last date of interview) increases by 5.9 percentage points. The probability of any marijuana uses also increases by 5.9 percentage points. The frequency of consumption rises by half a day in states with the law since the law was first passed. Number of times marijuana was used before/during school/work also rises by 0.13 times. The magnitude of changes is very small but statistically significant at conventional levels.

Model 2 includes the state characteristics. It gives the estimates of equation 3.1. This is given in column 2. First time consumption of marijuana increases by a probability of 6.8 percentage points. Any use since the last interview date increases by 6.6 percentage points. Frequency of marijuana consumption rises by half a day and the number of times consumed before/during school/work increases by 0.39 times. All these estimated are statistically significant at conventional levels. The magnitude is small and similar to model 1 estimates for each of the outcome variable. The state characteristics, as captured by categorizing the laws into strict and permissive, and the political atmosphere (defined by Republic and ballot) do not seem to be affecting the consumption patterns. None of these estimates are statistically significant at conventional levels.

Demographics also seem to have an impact on marijuana consumption. Females are less likely to any marijuana use since the last interview (4.2 and 3.7 percentage points for models 1 and 2, respectively). Frequency of consumption also falls. Number of days of use is 1-2 days less for women as compared to men (depending on which models we focus - 1 day for model 1 and 2 days for model 2). These estimates are statistically significant at one percent level of significance. Hispanics also report to consume less marijuana than the other races. This is true for all outcome variables and empirical models. These estimates are statistically significant at one percent level of significance. Focusing on column 2, first time consumption of marijuana is 8.2 percentage points lower and frequency of consumption is almost one day lower for Hispanics as compared to other demographics. Blacks also show a smaller probability of ever consuming marijuana by 7 percentage points (in model 1). However, this estimate loses its statistical significance when we include the state characteristics.

This is also true for any use since the date of last interview.

Medical marijuana legalization increases the probability and the frequency of consumption of marijuana. These estimates are statistically significant at conventional levels but are very small in magnitude. Including state characteristics in the empirical model gives a slightly higher magnitude of coefficient estimates. This shows that legalizing marijuana for medicinal purposes does not entice many new consumers and neither does it increases consumption by a lot.

Alcohol Consumption

Table 3.6 gives the estimates for the various outcomes depicting alcohol consumption. We use five variables to define alcohol consumption - ever used alcohol since the date of last interview, any use of alcohol since the date of last interview, number of days the respondents drank in the last 30 days, number of drinks consumed per day, and the number of times the respondent drank before/during school/work in the last 30 days. There is no change in the probability of ever drinking, number of days or the number of times drank before/after school/work in either of the two empirical models. Model 1 (column 1) shows the impact of the law without including state characteristics. There is a 2.7 percentage points increase in the probability of drinking since the last interview date. The number of drinks in the last 30 days is lower by half a drink. These estimates are statistically significant at one percent level of significance.

Including state characteristics increases the impact of MML on alcohol consumption. Model 2 finds that the probability of drinking increases by 6.8 percentage points in MML states but is 5 percentage points lower in states with permissive laws. Both these estimates are statistically significant at one percent level of significance. Respondents in states which passed the law through a ballot are more likely to be drinking by 3.8 percentage points. This estimate is statistically significant at 5 percent level. Number of drinks per day declines statistically at 10 percent level of significance by three-fourth of a drink. The category of the law (strict or permissive) or the political atmosphere does not impact this variable.

Looking at demographics, we find that the probability of drinking does not change for females but the frequency of drinking, as measured by the number of drinks and number of days drank, are lower by 2 days and 1.3 drinks, respectively. The frequency outcomes are statistically significant at one percent level. Blacks are statistically (at one percent level) less likely to drink and have lower frequency of drinking. However, they are more likely to be drunk during/after school/work by 0.2 times. This estimate is very small in magnitude but significant at one percent level of statistical significance. Hispanics are seen to be less likely to drink on a given day. The probability of drinking is 5.8 percentage points less (model 1) than other races. Number of days someone drank also falls by 0.7 days but the number of drinks per day increases by 0.2 drinks. Model 2 also shows similar signs of the corresponding coefficient estimates but they are slightly higher in magnitude. All these estimates are statistically significant at conventional levels.

As witnessed for marijuana, consumption of alcohol has changed statistically but almost negligibly in magnitude after MML. There is a slight increase in the probability of drinking and a decline in the number of drinks per day but no increase in new drinkers or the number of days drank. Our investigation shows that MML does not impact alcohol consumption as much as feared by many policymakers against the law.

Criminal Activity

Table 3.7 gives the estimates for the outcomes that we study to analyze the impact of MML on criminal behavior. We focus on 5 variables - if the respondent was ever arrested since the last interview date, if the respondent stole worth more than $50 since date of last interview, if the respondent committed property crime since date of last interview, if the respondent sold marijuana since date of last interview, and if the respondent sold/helped sell illegal drugs since date of last interview. We study the arrest variable till 2015. The other crime variables are studied only till 2005 due to a change in its definition and universe in subsequent survey years. There is no change in any of the criminal activity variables as a result of MML except for crimes associated with stealing more than $50. Probability of occurrence of this crime increases by 0.7 percentage points which is statistically significant at 5 percent level of significance in column 1. This statistical significance goes away when we include the state characteristics variables (column 2). However, having a strict MML increases the probability of this crime by 1.4 percentage points. This estimate is statistically significant at 5 percent level of significance.

The political atmosphere at the time of implementing MML has a slight impact on some crime variables. Having a Republican affiliated state government reduces property crimes and theft by 1.4 and 1.7 percentage points, respectively. The probability of being arrested is affected only in states with Permissive MML. It declines by 1.8 percentage points. This estimate is significant at 5 percent level of significance. Permissive states allow more flexibility in terms of marijuana possession and accessibility. More patients or individuals are legally allowed to access the drug. This can lead to a decline in crimes associated with or caused by marijuana which is captured by a decline in arrests.

Teenage Population (Age Group - 12- 20 years)

Marijuana Consumption

Table 3.8 shows the marijuana consumption change due to MML in adolescents and young adults. We look at two empirical models, one without state characteristics (model 1) and one with (model 2). The impact of MML on marijuana consumption indicators are positive and statistically significant at conventional levels in model 1 without state characteristics. The statistical significance goes away when we add the state characteristics variables. In model 1, probability of ever consuming marijuana and any consumption since the last interview increases by 5.2 and 5.4 percentage points, respectively. The frequency of consumption increases by half a day. These estimates are statistically significant at one percent levels. After including the state characteristics, we find that the impact of MML is no more significant at conventional levels. However, the probability of consuming marijuana since the last interview is 14 percentage points lower for states with permissive laws and 6 percentage points lower for states with a Republican administration during MML. Strict MML also tends to reduce frequency of consumption by 1.7 days. These estimates are statistically significant at 10 percent level.

The impact of MML on marijuana consumption among teenagers and young adults is positive and significant without including the state characteristics. Once we include them, these estimates become insignificant at conventional levels. Permissive laws tends to reduce probability of consumption and strict laws reduce frequency. These laws are discouraging consumption of marijuana among this demographics.

Alcohol Consumption

Table 3.9 shows the alcohol consumption change due to MML in adolescents and young adults. We look at two empirical models, one without state characteristics (model 1) and one with (model 2). We find that the probability of consumption is not affected by MML in both models but the frequency of drinking is. Number of days spent drinking increases by 3.3 days due to legalization (column 2). However, it is almost 2 days lower among states with a strict law and 2.6 days lower in states with permissive laws. These estimates are statistically significant at conventional levels. Number of drinks per day decreases by half a drink in model 1 (statistically significant at one percent level) and 1.6 drinks in model 2 (statistically significant at 10 percent level).

The number of times the respondent drank before/during school/work also rises by 0.3 times. This is statistically significant at 10 percent level but extremely small in magnitude. The characteristic of law (as defined by strict or permissive) completely negates the impact of the legalization as a whole. Strict MML reduces consumption by 0.29 times and permissive MML by 0.36 times. Both these estimates are statistically significant at conventional levels. Passing the law through a ballot tends to reduce the probability of drinking since the last interview by 10 percentage points and increasing the number of times consumed before/during school/work by 0.75 times.

Overall, the impact of MML on alcohol consumption on this demographic is negative. While it does not change the probability of drinking or introduce new drinkers, it does reduces the frequency of drinking.

Criminal Activity

There is no statistically significant impact of MML on criminal behavior among this demographic except for a 2 percentage points increase in the probability of selling hard drugs. This estimate is statistically significant at 5 percent level of significance only in model 1 without the state characteristics. Including state characteristics makes this estimate statistically insignificant at conventional levels (table 3.10).

Having the strict MML law increases the probability of committing crimes such as stealing and selling marijuana by 8 and 91 percentage points respectively. Having a permissive law reduces the chances of arrest by 4 percentage points but increases the likelihood of selling marijuana by 76 percentage points. The probability of selling marijuana since the last date of interview is also higher in states where the governing body was affiliated to the Republican party during the passing of the law by 47 percentage points. These estimates are statistically significant at conventional levels.

The legalization of medical marijuana seems to only affect the crimes associated with selling marijuana significantly among teenagers and young adults. The various characteristics of the law also reinforces the impact of its legalization on this particular behavior. The effect is larger in states with a stricter law. It is important to note here that the number of observations for this variable (ever sold marijuana since the last date of interview) is 152, which is very small compared to the other specifications. This could be the reason why we get such extreme values of regression estimates for this variable as compared to other outcomes studying criminal activities. Hence, regression estimates can be unreliable due to lower statistical power.

Adult Population (Age Group - 21 years and above)

Marijuana Consumption

Table 3.11 shows the marijuana consumption change due to MML in adults (those above the age of 21 years). We look at two empirical models, one without state characteristics (model 1) and one with (model 2). The impact of MML on marijuana consumption indicators are positive and statistically significant at conventional levels in some of the variables. The probability of ever consuming marijuana increases by 6.4 percentage points in the base model and by 6.7 percentage points when we include state characteristics. If the law was passed through a citizen-initiated ballot, then there is a further 5 percentage points increase in ever consuming marijuana. These estimates are significant at conventional levels. The probability of using marijuana since the last interview date increases by 6.2 percentage points in the base mode and 5.9 percentage points with state characteristics. The estimate in the base model is significant at one percent level and in model 2 at 10 percent level of significance.

Number of days marijuana was used rises by half a day in the base model. This estimate is highly significant at one percent level. After including state characteristics, the statistical significance of this coefficient estimate goes away. Similar behavior is observed for the last outcome variable under marijuana consumption - number of times consumed before/during school/work. In the base model, the estimate has a low magnitude of 0.14 times in the last 30 days and is statistically significant at 5 percent level. It becomes statistically insignificant when we include state characteristics.

Consumption of marijuana rises due to MML among adults. As seen in other demographics, the impact is very small in magnitude even when it is statistically significant. There is only a 6 percentage points increase in the probability of consuming marijuana ever or since the last interview date, and half a day increase in the frequency of consumption.

Alcohol Consumption

Table 3.12 shows the alcohol consumption change due to MML in adults above the age of 21 years. There is no change in the probability of ever drinking as a result of MML. The likelihood of drinking since the date of last interview increases by 3.2 percentage points in the base model and 7 percentage points after including state characteristics. These estimates are statistically significant at one percent level of significance. Having a permissive law lowers the probability of drinking by 4.7 percentage points and if the law was passed through a ballot, then there is an increase by 3.2 percentage points. Both these estimates are statistically significant at 10 percent level of significance.

Frequency of alcohol consumption as measured by the number of days spent drinking and number of drinks per day changes in the base model significantly at conventional levels of statistics but not after including state characteristics. Both estimates have very small magnitudes. Number of days spent drinking increases by 0.3 days and number of drinks per day decreases by half a drink.

There is a statistical increase in the probability of drinking for non-first timers but no statistical change in the frequency of drinking as a result of MML.

Criminal Activity

Similar to other demographics, MML does not seem to be affecting criminal behavior in adults above the age of 21 years (table 3.13). The probability of getting arrested does not change as a result of MML but permissive states find a 1.9 percentage points decline and states which passed the law through a ballot found a 1.2

percentage point increase. Both these estimates are statistically significant at conventional levels. Stealing worth more than $50 increases by 0.8 percentage points in the base model. This estimate is statistically significant at 5 percent level of significance. Including state characteristics, the legalization is no longer statistically significant at conventional levels for this outcome variable. However if the law was passed by a Republican candidate, then there is a 1.9 percentage points decrease in the likelihood of stealing and 1.8 percentage points decline in the likelihood of property crimes. These estimate are statistically significant at 5 percent level.

Criminal behavior is not impacted by legalization of medicinal marijuana among adults.

3.6 Conclusion

We attempt to find evidence that the enactment of the medical marijuana laws (MML) in some states changes the consumption behavior of its residents when compared to individuals living in states without this law. We apply a difference-in-differences approach to study the effect of MML on consumption of marijuana, alcohol and criminal behavior. We use the National Longitudinal Survey of Youth 1997 which is administered by the Bureau of Labor Statistics. It is a self-reported panel data following 8,984 individuals. We also created a dataset for the state characteristics from the medical marijuana law for each state using a combination of academic, government, and policy sources. Our sample of study is restricted to states which have passed the law by 2014 because the last round of NLSY97 is in 2015.

We found a slight increase in the marijuana and alcohol consumption as a result of medical marijuana legalization. Criminal behavior is unaffected. To analyze if the effect of MML is different across age groups, we study youths between the age of 12-20 years old separately. The results show that states with permissive laws witness lower probability of marijuana consumption, and states with strict MML finds lower frequency of consumption. Adults above the age of 21 years tends to increase their consumption by 6 percentage points due to MML. We also find an increase in the probability of drinking in this demographic, however, the frequency of drinking does not change. People who were already candidates for marijuana consumption before the law are more likely to start or increase, if they were already consuming, after the law. MML allows easier legal accessibility of marijuana which can entice consumers who otherwise refrained from using it under different circumstances. This explains why we find an increase in consumption of marijuana among adults above the age of 21 years.

Legalization of medicinal marijuana has an unusually large impact on selling of marijuana among teenagers. Legalization of this drug increases the accessibility and demand. This seem to be an easy and comparatively safe approach to earn money as a seller. Given that marijuana is legal in the state, young adults may be prone to enter the market as consumers for the sake of experimenting with drug use. However we find that marijuana use is unchanged (after incorporating state characteristics of the law) after MML for this population group. Based on this argument, it seems less likely there are more sellers in the marijuana market when demand has not increased. Another, more likely possible, reason for such a large impact can be attributed to a statistical anomaly due to a very small sample size for this outcome variable. This aspect needs further study to provide a clearer understanding of such behavior.

We find a slight change on the other crime variables for teenagers and young adults. States with strict MML has witnessed an eight percentage point increase in stealing and states with permissive MML has witnessed a four percentage point decline in the probability of getting arrested. However, the main regression estimate which captures the impact of any MML on criminal behavior does not have any statistical significance. We find similar results for adults above the age of 21 years also.

The most unique feature of this study was the incorporation of various state characteristics. No two states has the same medicinal marijuana law. Many academic papers in the existing literature has included few state characteristics to understand the laws better but none has delved in details like our study. We attempted to categorize common features of the laws in various groups which allowed us to classify the state MMLs into strict and permissive. The regression estimates show that incorporating the state characteristics changes the impact of the law even if a particular characteristic may not be statistically significant. The impact of these characteristics varies with outcome variables and population demographics. Through this paper, we wish to emphasize on the importance of the particulars of MML while analyzing its impact on social well-being. Future research are encouraged to further analyze these characteristics in details.

Our study concludes that the legalization of medical marijuana does not have the negative spillover effect as prejudiced by the non-supporters of this policy. Availability of marijuana as an alternative treatment for many diseases has been proven to have immense health benefits while being cost effective. Legalization allows many patients to access an alternative treatment which can be easily available as well as cheaper in addition to being more effective than regular treatment regime. Our study proves that legalizing medical marijuana does not impact criminal behavior. There is a statistical increase in marijuana and alcohol consumption which is very small in magnitude. MML discourages youths or adults to seek marijuana as a result of it being conditionally legal in their state of residence. We conclude that legalization of marijuana should be supported and policymakers should focus on its efficient implementation.

Table 3.1: Timeline - Dates of Medical Marijuana Legalization

1996	-	California (Nov 6)
1998	-	Washington (Nov 3)
1998	-	Oregon (Dec 3)
1999	-	Alaska (Mar 4)
1999	-	Maine (Dec 22)
2000	-	Hawaii (Dec 28)
2001	-	Colorado (Jun 1)
2001	-	Nevada (Oct 1)
2004	-	Montana (Nov 2)
2006	-	Rhode Island (Jan 3)
2007	-	Vermont (May 30)
2007	-	New Mexico (Jul 1)
2008	-	Michigan (Dec 4)
2010	-	New Jersey (Jun 18)
2010	-	District of Columbia (Jul 27)
2010	-	Arizona (Nov 11)
2011	-	Delaware (Jul 1)
2012	-	Connecticut (May 4)
2013	-	Massachusetts (Jan 1)
2013	-	New Hampshire (May 23)
2014	-	Illinois (Jan 1)
2014	-	Minnesota (May 30)
2014	-	Maryland (Jun 1)
2014	-	New York (Jul 5)
2016	-	Pennsylvania (May 17)
2016	-	Ohio (Sep 8)
2016	-	North Dakota (Nov 8)
2016	-	Arkansas (Nov 9)
2017	-	Florida (Jan 3)
2017	-	West Virginia (Apr 19)
2018	-	Oklahoma (Jul 26)
2018	-	Louisiana (Aug 1)
2018	-	Utah (Dec 3)
2018	-	Missouri (Dec 5)

Table 3.2: State Law Characteristics

State	Possession Limits (ounces)	Cultivation (in # plants)	State Dispensary	Minimum Penalty Status
Alaska	1	6	No	None
Arizona	2.5	12	Yes	Felony
Arkansas	none	0	No	Misdemeanor
California	none	1	Yes	None
Colorado	2	6	Yes	None
Connecticut	1 month SS	0	Yes	Civil Penalty
Delaware	6	0	Yes	Civil Penalty
District of Columbia	2	0	Yes	None
Florida	4	0	Yes	Misdemeanor
Hawaii	4	7	Yes	Misdemeanor
Illinois	2.5	0	Yes	Penalty violation
Louisiana	1 month SS	0	Yes	Not Classified
Maine	2.5	6	Yes	None
Maryland	1 month SS	0	Yes	Civil offense
Massachusetts	10	limited amounts	Yes	None
Michigan	2.5	12	Yes	Misdemeanor
Minnesota	1 month SS	0	Yes	Misdemeanor
Missouri	4	6	Yes	Misdemeanor
Montana	1	4	Yes	Misdemeanor
Nevada	2.5	12	Yes	None
New Hampshire	2	0	Yes	Civil Violation
New Jersey	2	0	Yes	Disorderly Person
New Mexico	8 (for 90 days)	16	Yes	Misdemeanor
New York	1 month SS	0	Yes	Not Classified
North Dakota	3	0	Yes	Misdemeanor
Ohio	not specified yet	0	Yes	Misdemeanor
Oklahoma	8	6	Yes	Misdemeanor
Oregon	24	6	Yes	None
Pennsylvania	1 month SS	0	Yes	Misdemeanor
Rhode Island	2.5	12	Yes	Civil Violation
Utah	1 month SS	0	Yes	Misdemeanor
Vermont	2	2	Yes	Civil Violation
Washington	48	6	No	None
West Virginia	1 month SS	0	Yes	Misdemeanor

Source: State Laws, http://norml.org/laws,
https://medicalmarijuana.procon.org/view.resource.php?resourceID=000881

Notes: This table includes all states which have defined an MML up till 2018. Our study focuses on states with MML implemented till 2014 as the NLSY97 data covers between 1997-2015.

Table 3.3: Demographics Summary Statistics for States with and without a Medical Marijuana Law by 2015

	No MML States	MML States
Age	23.17	23.02
	(5.424)	(5.425)
Female	0.491	0.484
	(0.500)	(0.500)
Black	0.207	0.115
	(0.405)	(0.319)
Hispanic	0.0922	0.159
	(0.289)	(0.366)
High School Degree	0.853	0.892
	(0.354)	(0.310)
Bachelors Degree	0.307	0.380
	(0.461)	(0.485)
Household Income in 1996	47287.4	56387.4
	(39938.3)	(47887.7)
Household Income	57285.3	69380.8
	(56951.8)	(66578.5)
Rural	0.295	0.168
	(0.456)	(0.374)
Observations	62171	68276

Data: National Longitudinal Survey of Youth 1997.
Notes: Table reports means with standard deviations in parentheses. Observations are weighted using the provided sample weights.

Table 3.4: Outcome Variables Summary Statistics for States with and without a Medical Marijuana Law by 2015

	No MML States	MML States
Marijuana Consumption		
Ever Used Marijuana as of Interview Date	0.507	0.570
	(0.500)	(0.495)
Any Marijuana Use Since Date of Last Interview	0.185	0.249
	(0.389)	(0.432)
Number of Days Used Marijuana	1.684	2.242
	(6.002)	(6.838)
Number of Times Used Marijuana Before or During School or Work	0.490	0.574
	(3.322)	(3.522)
Alcohol Consumption		
Ever Used Alcohol as of Interview Date	0.888	0.898
	(0.315)	(0.302)
Any Alcohol Use Since Date of Last Interview	0.699	0.757
	(0.459)	(0.429)
Number of Days Used Alcohol	3.900	4.353
	(6.187)	(6.293)
Number of drinks/day in the last 30 days	4.502	4.155
	(6.577)	(5.412)
Number of Times Used Alcohol Before or During School or Work	0.310	0.291
	(1.927)	(1.729)
Criminal Activity		
Arrested Since DLI	0.0524	0.0448
	(0.223)	(0.207)
Stole Something Worth More than $50 Since DLI	0.0253	0.0303
	(0.157)	(0.171)
Committed Property Crime Since DLI	0.0238	0.0280
	(0.152)	(0.165)
Sold Marijuana Since DLI	0.751	0.789
	(0.433)	(0.408)
Sold or Helped Sell Illegal Drugs Since DLI	0.0592	0.0707
	(0.236)	(0.256)
Observations	62171	68276

Data: National Longitudinal Survey of Youth 1997.
Notes: Table reports means with standard deviations in parentheses. Observations are weighted using the provided sample weights.

Table 3.5: Impact of MML on Marijuana Consumption

	Ever Used Marijuana as of Interview Date		Any Use Marijuana Since Date of Last Interview		Number of Days Used Marijuana		Number of Times Marijuana Used Before/During School/Work	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	0.0592***	0.0688***	0.0594***	0.0669**	0.499***	0.690**	0.130**	0.392**
1 if law exists	(0.0124)	(0.025)	(0.00956)	(0.0284)	(0.154)	(0.346)	(0.055)	(0.183)
Age	-0.00236	-0.00825	-0.0029	-0.00167	-0.0308	-0.0432	0.00401	-0.0982
	(0.00611)	(0.0159)	(0.00523)	(0.0138)	(0.0822)	(0.184)	(0.0365)	(0.0847)
Female	-0.0168	0.00908	-0.0427***	-0.0370***	-1.073***	-1.195***	-0.378***	-0.447***
	(0.0114)	(0.0172)	(0.00704)	(0.0126)	(0.105)	(0.18)	(0.0474)	(0.0862)
Black	-0.0707***	-0.0345	-0.0399***	-0.0222	-0.144	0.0554	-0.0297	-0.0182
	(0.0154)	(0.0243)	(0.00829)	(0.0145)	(0.126)	(0.215)	(0.0557)	(0.101)
Hispanic	-0.0718***	-0.0825***	-0.0557***	-0.0649***	-0.606***	-0.907***	-0.167***	-0.288***
	(0.0174)	(0.0278)	(0.0113)	(0.02)	(0.173)	(0.293)	(0.0619)	(0.0824)
Strict*MML		0.0043		0.0112		0.00156		-0.0336
		(0.021)		(0.0228)		(0.314)		(0.155)
Permissive*MML		-0.0384		0.000293		0.0194		-0.103
		(0.03)		(0.0315)		(0.441)		(0.187)
Republican		-0.00655		-0.0078		-0.0373		0.189
		(0.0224)		(0.0186)		(0.27)		(0.164)
Ballot		0.0537*		0.0197		0.0836		-0.176
		(0.0278)		(0.025)		(0.413)		(0.207)
Observations	82653	19528	76199	17954	81990	19349	82011	19362
State Characteristics	No	Yes	No	Yes	No	Yes	No	Yes

$*p < .**p < 0.05, ***p < 0.01$. Standard error in parenthesis.

Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.

Notes: Dependent variables are the probability and frequency of marijuana consumption. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.6: Impact of MML on Alcohol Consumption

	Ever Used Alcohol as of Interview Date		Any Use of Alcohol Since Date of Last Interview		Number of Days Alcohol Used		Number of Drinks per Day		Number of Times Alcohol Used Before/During School/Work	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	0.00511	0.016	0.0271***	0.0687***	0.215	0.264	-0.491***	-0.734*	-0.00843	0.0135
1 if law exists	(0.00568)	(0.0191)	(0.00685)	(0.0172)	(0.137)	(0.292)	(0.0875)	(0.394)	(0.0219)	(0.0815)
Age	0.0000374	-0.0094	-0.000945	-0.012	-0.0481	-0.253**	0.000695	-0.0163	0.0185	0.039
	(0.00323)	(0.00712)	(0.00475)	(0.00773)	(0.0651)	(0.125)	(0.0727)	(0.178)	(0.0159)	(0.0323)
Female	-0.00466	0.000917	-0.00441	0.00000955	-1.437***	-1.199***	-1.473***	-1.357***	-0.181***	-0.122***
	(0.00548)	(0.01)	(0.00782)	(0.0098)	(0.0911)	(0.167)	(0.0913)	(0.161)	(0.0188)	(0.0331)
Black	-0.0562***	-0.0354***	-0.155***	-0.118***	-1.246***	-0.601**	-0.727***	-0.738***	0.133***	0.277***
	(0.00773)	(0.0113)	(0.0106)	(0.0148)	(0.141)	(0.272)	(0.167)	(0.197)	(0.0412)	(0.0759)
Hispanic	-0.0108	-0.0058	-0.0528***	-0.0629***	-0.705***	-0.629***	0.276**	0.482***	0.0418*	0.0883**
	(0.00804)	(0.0137)	(0.00983)	(0.0122)	(0.126)	(0.186)	(0.113)	(0.167)	(0.0227)	(0.0354)
Strict*MML		-0.0145		-0.0179		0.0258		0.0494		-0.0243
		(0.0165)		(0.0156)		(0.309)		(0.208)		(0.0693)
Permissive*MML		-0.0427**		-0.0501***		-0.465		-0.108		-0.117
		(0.0212)		(0.019)		(0.359)		(0.266)		(0.0726)
Republican		-0.0249*		-0.00761		0.00195		0.251		-0.0685
		(0.0139)		(0.0203)		(0.257)		(0.284)		(0.071)
Ballot		0.0129		0.0388**		0.392		-0.268		0.00917
		(0.0143)		(0.018)		(0.242)		(0.261)		(0.0792)
Observations	87819	20699	80961	19085	81654	19293	49546	12095	81768	19308
State Observations	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

$*p < .**p < 0.05, ***p < 0.01$. Standard error in parenthesis.

Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.

Notes: Dependent variables are the probability and frequency of alcohol consumption. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.7: Impact of MML on Criminal Activity

	Arrested since Date of Last Interview		Stole Worth More than $50 Since Date of Last Interview		Committed Property Crime Since Date of Last Interview		Sold Marijuana Since Date of Last Interview		Sold/Helped Sell Illegal Drugs Since Date of Last Interview	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	-0.00307	0.00606	0.00757**	-0.0113	0.00158	-0.0156	-0.0251	0.14	0.00626	-0.000306
1 if law exists	(0.00254)	(0.0121)	(0.00307)	(0.01)	(0.00258)	-0.012	(0.0218)	(0.114)	(0.00557)	(0.0262)
Age	-0.000922	-0.0000442	0.00416**	0.00451	0.000761	0.0043	-0.0106	-0.0341	0.00232	-0.00525
	(0.00166)	(0.00368)	(0.00199)	(0.00495)	(0.00207)	(0.00534)	(0.0191)	(0.044)	(0.00358)	(0.00855)
Female	-0.0326***	-0.0251***	-0.0143***	-0.0157***	-0.0256***	-0.0282***	-0.0652***	-0.046	-0.0314***	-0.0354***
	(0.00178)	(0.00293)	(0.00207)	(0.00533)	(0.002)	(0.00401)	(0.0225)	(0.0444)	(0.00399)	(0.00873)
Black	0.00594	0.0112	0.00342	0.0144*	-0.00219	0.0104	-0.0737**	-0.038	-0.0274***	-0.0284***
	(0.00367)	(0.00715)	(0.00268)	(0.00731)	(0.00324)	(0.00713)	(0.0314)	(0.0657)	(0.00424)	(0.00957)
Hispanic	-0.00680**	-0.00484	-0.00158	-0.00177	-0.00221	-0.000808	-0.0598*	-0.0977*	-0.0107	-0.00506
	(0.00306)	(0.00627)	(0.00358)	(0.00628)	(0.00356)	(0.00737)	(0.0323)	(0.0511)	(0.00701)	(0.0108)
Strict*MML		-0.00408		0.0148**		-0.00309		0.131		-0.0158
		(0.00819)		(0.00636)		(0.00955)		(0.0863)		(0.0188)
Permissive*MML		-0.0180**		0.00798		-0.00544		0.0353		-0.025
		(0.00839)		(0.00707)		(0.00888)		(0.0911)		(0.0215)
Republican		0.00375		-0.0179**		-0.0141*		0.00783		-0.00266
		(0.00742)		(0.00813)		(0.00809)		(0.0932)		(0.0176)
Ballot		0.0136**		0.00463		0.00703		-0.136*		0.00989
		(0.00626)		(0.00782)		(0.00814)		(0.0716)		(0.0149)
Observations	81475	19154	34741	8317	34738	8319	2510	662	34721	8308
State Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

$*p < . * *p < 0.05, * * *p < 0.01$. Standard error in parenthesis.

Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.

Notes: Dependent variables are probability of committing criminal activities and getting arrested. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.8: Impact of MML on Marijuana Consumption (Age group - 12-20 years)

	Ever Used Marijuana as of Interview Date		Any Use Marijuana Since Date of Last Interview		Number of Days Used Marijuana		Number of Times Marijuana Used Before/During School/Work	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	0.0520***	0.0849	0.0545***	0.112	0.493**	1.532	0.118	0.758
1 if law exists	(0.0196)	(0.108)	(0.0152)	(0.0903)	(0.238)	(1.304)	(0.103)	(0.958)
Age	-0.00467	-0.00999	0.00198	0.0265	-0.073	0.0675	-0.061	-0.0223
	(0.0081)	(0.0224)	(0.00731)	(0.0186)	(0.0984)	(0.219)	(0.0479)	(0.142)
Female	-0.0270**	-0.00509	-0.0381***	-0.0498**	-1.113***	-1.680***	-0.404***	-0.595***
	(0.0122)	(0.0232)	(0.00881)	(0.0196)	(0.116)	(0.324)	(0.0565)	(0.15)
Black	-0.0603***	-0.0096	-0.0301***	-0.000498	-0.0376	0.157	0.00921	-0.0818
	(0.0169)	(0.042)	(0.0109)	(0.0308)	(0.164)	(0.457)	(0.0706)	(0.154)
Hispanic	-0.0645***	-0.0845*	-0.0502***	-0.0646*	-0.404**	-0.875*	-0.146**	-0.199
	(0.0206)	(0.0454)	(0.0136)	(0.0344)	(0.194)	(0.486)	(0.0688)	(0.185)
Strict*MML		-0.00811		-0.103		-1.736*		-0.845
		(0.0836)		(0.0789)		(1.014)		(0.64)
Permissive*MML		-0.0994		-0.146*		-1.583		-0.86
		(0.0977)		(0.0839)		(1.075)		(0.642)
Republican		-0.0353		-0.0674*		-0.699		-0.0369
		(0.0351)		(0.0398)		(0.813)		(0.547)
Ballot		-0.117		0.0213		-4.218		-2.326
		(0.306)		(0.08)		(4.524)		(2.56)
Observations	31301	4701	29009	4353	31022	4651	31029	4654
State Characterstics	No	Yes	No	Yes	No	Yes	No	Yes

$*p < .**p < 0.05, ***p < 0.01$. Standard error in parenthesis.

Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.

Notes: Dependent variables are probability and frequency of marijuana consumption. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.9: Impact of MML on Alcohol Consumption (Age group - 12-20 years)

	Ever Used Alcohol as of Interview Date		Any Use of Alcohol Since Date of Last Interview		Number of Days Alcohol Used		Number of Drinks per Day		Number of Times Alcohol Used Before/During School/Work	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	0.00288	-0.0109	0.011	-0.0196	-0.0102	3.307***	-0.479***	-1.684*	-0.0278	0.307*
1 if law exists	(0.00859)	(0.0721)	(0.0101)	(0.0624)	(0.196)	(0.684)	(0.16)	(0.915)	(0.0462)	(0.169)
Age	0.00145	-0.0159	0.00348	-0.0177	-0.0625	-0.343*	-0.101	0.269	0.0107	0.0850*
	(0.00451)	(0.0111)	(0.0061)	(0.0149)	(0.0878)	(0.186)	(0.093)	(0.259)	(0.0218)	(0.0467)
Female	-0.000868	0.0216	-0.00975	0.0092	-1.521***	-1.338***	-1.474***	-1.422***	-0.192***	-0.159**
	(0.00706)	(0.0157)	(0.00956)	(0.018)	(0.111)	(0.254)	(0.118)	(0.239)	(0.0262)	(0.0698)
Black	-0.0514***	-0.0271	-0.146***	-0.0491*	-1.252***	-0.357	-0.819***	-0.208	0.0851**	0.0938
	(0.00922)	(0.0285)	(0.0135)	(0.0258)	(0.169)	(0.461)	(0.21)	(0.397)	(0.0383)	(0.125)
Hispanic	-0.00537	0.0133	-0.0348**	-0.0171	-0.599***	-0.303	0.459***	0.689***	0.0479	0.116
	(0.0111)	(0.0289)	(0.0136)	(0.0227)	(0.152)	(0.253)	(0.153)	(0.255)	(0.0315)	(0.0907)
Strict*MML		0.0415		0.0638		-1.943**		-0.0836		-0.299*
		(0.067)		(0.0471)		(0.851)		(0.784)		(0.169)
Permissive*MML		-0.0133		-0.0304		-2.649***		0.244		-0.360**
		(0.0698)		(0.0446)		(0.592)		(0.845)		(0.161)
Republican		0.017		0.0265		-0.271		0.362		-0.113
		(0.0277)		(0.0401)		(0.6)		(0.967)		(0.173)
Ballot		0.0139		-0.105***		5.933		0.278		0.758***
		(0.081)		(0.0332)		(5.891)		(2.88)		(0.256)
Observations	33287	4993	30856	4641	30917	4637	18780	2856	30955	4647
State Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

$*p < . **p < 0.05, ***p < 0.01$. Standard error in parenthesis.

Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.

Notes: Dependent variables are probability and frequency of alcohol consumption. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.10: Impact of MML on Criminal Activity (Age group - 12-20 years)

	Arrested since Date of Last Interview		Stole Worth More than $50 Since Date of Last Interview		Committed Property Crime Since Date of Last Interview		Sold Marijuana Since Date of Last Interview		Sold/Helped Sell Illegal Drugs Since Date of Last Interview	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	-0.00409	0.0355	0.00714	0.012	0.00751	-0.0067	-0.0526	-0.415	0.0221**	-0.0289
1 if law exists	(0.00496)	(0.0263)	(0.00628)	(0.0217)	(0.00561)	(0.0579)	(0.0548)	(0.396)	(0.00983)	(0.0782)
Age	-0.00121	0.00894*	0.00500*	0.0186***	0.000909	0.0179*	-0.0116	-0.0323	0.0013	0.0147
	(0.0026)	(0.00527)	(0.00283)	(0.00588)	(0.00344)	(0.0106)	(0.0395)	(0.109)	(0.00489)	(0.0105)
Female	-0.0339***	-0.0265***	-0.0126***	-0.0105	-0.0211***	-0.0117	-0.0304	-0.0403	-0.0246***	-0.0385**
	(0.00275)	(0.00658)	(0.0033)	(0.00983)	(0.00264)	(0.0101)	(0.0371)	(0.0977)	(0.00506)	(0.0148)
Black	0.00669	0.0469***	0.00741	0.0474**	0.00164	0.0427*	-0.0906	0.12	-0.0174***	-0.0164
	(0.00471)	(0.0126)	(0.00467)	(0.0179)	(0.00497)	(0.022)	(0.0625)	(0.168)	(0.00656)	(0.0223)
Hispanic	-0.00491	-0.0092	-0.00634	-0.00622	-0.000996	-0.00821	-0.0315	-0.122	-0.0126	-0.00334
	(0.00484)	(0.00862)	(0.00532)	(0.00776)	(0.00634)	(0.0148)	(0.058)	(0.119)	(0.0089)	(0.0186)
Strict*MML		-0.00276		0.0824***		0.0535		0.918***		0.000921
		(0.0262)		(0.0204)		(0.0513)		(0.277)		(0.0682)
Permissive*MML		-0.0438**		0.000057		-0.0125		0.761***		-0.0163
		(0.0209)		(0.0169)		(0.0416)		(0.184)		(0.0683)
Republican		-0.0164		-0.0158		0.0194		0.478**		0.0629
		(0.0152)		(0.0133)		(0.0451)		(0.179)		(0.0601)
Ballot		0.138***		0.057		-0.0181		-1.060**		-0.421**
		(0.0346)		(0.0471)		(0.0198)		(0.46)		(0.189)
Observations	31052	4651	12894	1954	12889	1955	866	152	12881	1954
State Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

$*p < .**p < 0.05, ***p < 0.01$. Standard error in parenthesis.
Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.
Notes: Dependent variables are probability of committing criminal activities and getting arrested. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.11: Impact of MML on Marijuana Consumption (Age group - 21 years and above)

	Ever Used Marijuana as of Interview Date		Any Use Marijuana Since Date of Last Interview		Number of Days Used Marijuana		Number of Times Marijuana Used Before/During School/Work	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	0.0641***	0.0676**	0.0629***	0.0599*	0.521***	0.526	0.140**	0.299
1 if law exists	(0.0129)	(0.0283)	(0.00956)	(0.0312)	(0.164)	(0.356)	(0.0564)	(0.21)
Age	-0.00274	-0.00865	-0.00689	-0.0134	-0.0576	-0.134	0.0243	-0.139
	(0.00728)	(0.0158)	(0.00648)	(0.014)	(0.102)	(0.202)	(0.0512)	(0.107)
Female	-0.0112	0.0126	-0.0451***	-0.0324**	-1.056***	-1.071***	-0.366***	-0.410***
	(0.0125)	(0.0187)	(0.00761)	(0.0143)	(0.12)	(0.199)	(0.057)	(0.0933)
Black	-0.0762***	-0.0388*	-0.0439***	-0.0232	-0.191	0.0868	-0.0492	0.0174
	(0.0162)	(0.0232)	(0.00901)	(0.0146)	(0.134)	(0.195)	(0.0629)	(0.124)
Hispanic	-0.0770***	-0.0841***	-0.0586***	-0.0658***	-0.715***	-0.931***	-0.180**	-0.319***
	(0.0179)	(0.0266)	(0.0124)	(0.0189)	(0.195)	(0.274)	(0.0784)	(0.0778)
Strict*MML		-0.000575		0.0223		0.155		0.0584
		(0.0216)		(0.023)		(0.329)		(0.207)
Permissive*MML		-0.0367		0.0192		0.151		-0.00465
		(0.0274)		(0.0299)		(0.424)		(0.229)
Republican		-0.00711		-0.0104		-0.185		0.107
		(0.0288)		(0.0212)		(0.331)		(0.202)
Ballot		0.0564*		0.0101		0.118		-0.18
		(0.0286)		(0.0253)		(0.412)		(0.213)
Observations	51352	14827	47190	13601	50968	14698	50982	14708
State Characteristics	No	Yes	No	Yes	No	Yes	No	Yes

$*p < . **p < 0.05, ***p < 0.01$. Standard error in parenthesis.
Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.
Notes: Dependent variables are probability and frequency of marijuana consumption. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.12: Impact of MML on Alcohol Consumption (Age group - 21 years and above)

	Ever Used Alcohol as of Interview Date		Any Use of Alcohol Since Date of Last Interview		Number of Days Alcohol Used		Number of Drinks per Day		Number of Times Alcohol Used Before/During School/Work	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	0.00543	0.0143	0.0329***	0.0700***	0.296*	-0.192	-0.510***	-0.662	0.0029	-0.0111
1 if law exists	(0.00645)	(0.017)	(0.00788)	(0.0203)	(0.153)	(0.288)	(0.0916)	(0.497)	(0.0252)	(0.0974)
Age	-0.00242	-0.00948	-0.00358	-0.0101	-0.0399	-0.233	0.0226	-0.118	0.0262	0.0255
	(0.0039)	(0.00738)	(0.00575)	(0.00969)	(0.0819)	(0.153)	(0.0938)	(0.207)	(0.0207)	(0.0424)
Female	-0.00643	-0.0043	-0.000892	-0.00289	-1.387***	-1.157***	-1.464***	-1.321***	-0.172***	-0.109***
	(0.00552)	(0.0101)	(0.0083)	(0.0116)	(0.101)	(0.172)	(0.105)	(0.166)	(0.0205)	(0.0327)
Black	-0.0587***	-0.0356***	-0.160***	-0.129***	-1.239***	-0.619**	-0.686***	-0.825***	0.159***	0.315***
	(0.00833)	(0.0104)	(0.0108)	(0.0165)	(0.149)	(0.262)	(0.172)	(0.193)	(0.0492)	(0.0798)
Hispanic	-0.0135	-0.0101	-0.0613***	-0.0742***	-0.751***	-0.715***	0.193	0.413**	0.037	0.0755**
	(0.00851)	(0.0117)	(0.0105)	(0.0125)	(0.142)	(0.198)	(0.119)	(0.165)	(0.0254)	(0.0377)
Strict*MML		-0.0191		-0.0211		0.291		0.083		0.00422
		(0.0136)		(0.0192)		(0.303)		(0.225)		(0.0753)
Permissive*MML		-0.0437**		-0.0475*		-0.0575		-0.113		-0.0721
		(0.0187)		(0.0242)		(0.38)		(0.29)		(0.0851)
Republican		-0.0316*		-0.0166		-0.266		0.287		-0.0852
		(0.0167)		(0.0244)		(0.327)		(0.422)		(0.0818)
Ballot		0.0118		0.0321*		0.242		-0.318		-0.00598
		(0.014)		(0.0188)		(0.252)		(0.279)		(0.0804)
Observations	54532	15706	50105	14444	50737	14656	30766	9239	50813	14661
State Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

$*p < . **p < 0.05, ***p < 0.01$. Standard error in parenthesis.

Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.

Notes: Dependent variables are probability and frequency of alcohol consumption. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

Table 3.13: Impact of MML on Criminal Activity (Age group - 21 years and above)

	Arrested since Date of Last Interview		Stole Worth More than $50 Since Date of Last Interview		Committed Property Crime Since Date of Last Interview		Sold Marijuana Since Date of Last Interview		Sold/Helped Sell Illegal Drugs Since Date of Last Interview	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
MML in Effect	-0.00343	0.00532	0.00814**	-0.012	-0.000182	-0.0179	-0.0234	0.21	0.00149	0.000534
1 if law exists	(0.00263)	(0.0143)	(0.00358)	(0.0116)	(0.00272)	(0.0136)	(0.0264)	(0.138)	(0.00629)	(0.0273)
Age	-0.00112	-0.00346	0.00308	0.00239	0.000734	0.00264	-0.0249	-0.0407	0.000967	-0.0108
	(0.00237)	(0.00457)	(0.00235)	(0.00569)	(0.00257)	(0.00485)	(0.0285)	(0.054)	(0.00489)	(0.0107)
Female	-0.0318***	-0.0244***	-0.0151***	-0.0158***	-0.0281***	-0.0311***	-0.0729***	-0.0549	-0.0353***	-0.0327***
	(0.00218)	(0.00341)	(0.00248)	(0.00582)	(0.00258)	(0.00392)	(0.0265)	(0.0551)	(0.00501)	(0.00967)
Black	0.00617	0.00403	0.00122	0.00834	-0.00428	0.00507	-0.0768**	-0.0541	-0.0314***	-0.0284***
	(0.00421)	(0.00746)	(0.00328)	(0.00699)	(0.00367)	(0.007)	(0.0357)	(0.0715)	(0.00495)	(0.0103)
Hispanic	-0.00780**	-0.0037	-0.0000507	0.000398	-0.00316	0.00287	-0.0897**	-0.116**	-0.0106	-0.00448
	(0.00309)	(0.00636)	(0.00424)	(0.00721)	(0.00344)	(0.00644)	(0.0344)	(0.0529)	(0.00896)	(0.0122)
Strict*MML		-0.00807		0.00525		-0.01		0.075		-0.0182
		(0.00985)		(0.00699)		(0.00942)		(0.0825)		(0.022)
Permissive*MML		-0.0196*		0.00706		-0.00426		-0.0311		-0.021
		(0.0104)		(0.00872)		(0.0101)		(0.0895)		(0.0218)
Republican		0.00477		-0.0198**		-0.0182**		0.0522		-0.00492
		(0.00929)		(0.00935)		(0.00815)		(0.122)		(0.0219)
Ballot		0.0121*		0.00437		0.00637		-0.106		0.0135
		(0.0069)		(0.00814)		(0.00906)		(0.0645)		(0.0154)
Observations	50423	14503	21847	6363	21849	6364	1644	510	21840	6354
State Characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

$*p < .**p < 0.05, ***p < 0.01$. Standard error in parenthesis.
Source: National Longitudinal Survey of Youth 1997 for outcome and control variables; Combination of academic, government, and policy sources to identify the effective dates of state MMLs, detailed characteristics of these laws, and the effective dates of implementation of these characteristics.
Notes: Dependent variables are probability of committing criminal activities and getting arrested. State Characteristics are the cultivation and possession limits, patient cards availability and fees, dispensary law and operating status, number of diseases specified, doctor discretion, allows use for pain, qualification requires two doctor evaluations or a diagnostic test, affirmative defense policy, and state subsidy. *Strict* states are those with stricter MML and *Permissive* states are MML states with more permissive rules. Omitted category are states with no MML law.

3.7 Appendix

State MML Characteristics

We incorporate detailed characteristics about the state MMLs in our analyses. To obtain this information, we first collected particulars about important state MML dates and characteristics from articles in the literature, the Marijuana Policy Project, and Prescription Drug Abuse Policy System (PDAPS). This information was merged with detailed datasets on state MML characteristics available from PDAPS, which provide information about laws in effect beginning as of January 2014 that had been enacted as early as 2009.[3] Because much of our data on substance use and crime is from before 2009, we conducted our own legal and internet research to extend this dataset back to 1998 by incorporating analogous information for all states for years that are missing in the PDAPS data.

With respect to state MML characteristics, we translate the presence or absence of many characteristics into a categorization of state MMLs as "strict" or "permissive" laws, and control for this categorization within our regression models. We use the detailed characteristics specified in the state medical marijuana laws affecting legal access to classify them into two broad categories of strict and permissive.

We discuss the variables and categorization used in our analyses in detail below. We first classify these characteristics into four broad types - physical availability, legal protections, patient qualification, and financial access - and create scales for each type to quantify the extent to which a state's MML characteristics of that type promote access to medical marijuana. We then use these four scales to construct an overall scale quantifying an MML's restrictiveness. Finally, we use this overall scale

[3]Specifically, we used the datasets entitled "Medical Marijuana Laws for Patients" available at http://pdaps.org/datasets/medical-marijuana-patient-related-laws-1501600783, and "Medical Marijuana Dispensaries" available at http://pdaps.org/datasets/dispensaries-medical-marijuana-1501611712. Because the enactment dates of laws in effect as of January 2014 differ by state, the exact dates the PDAPS datasets cover depend on the state in question.

to assign state MMLs to one of two categories — "strict" MMLs or "permissive" MMLs. Following is a detailed account of the categorization of MMLs.

1. Physical Availability

   We construct a physical availability scale indicating how readily accessible medical marijuana is to patients under state MMLs that incorporates the following variables: the amount of home cultivation of marijuana permitted (no home cultivation permitted, 1-10 plants, 11-20 plants, 21-30 plants, or 10 ounces); whether medical marijuana dispensaries are authorized by the MML; and whether any medical marijuana dispensaries in the state are operational. The scale ranges from 0, which would occur if home cultivation were not permitted, dispensaries were not authorized, and no dispensaries were operational, up to 6, which would occur if the state permitted individuals to cultivate 10 ounces at home, authorized dispensaries, and dispensaries were operational within the state.

2. Legal Protections

   To quantify state differences over the extent to which medical marijuana possession is legally protected, we use the following variables to construct a scale of legal protections: whether qualifying patients may exert an affirmative defense against criminal charges of marijuana possession to excuse this otherwise illegal possession; whether an individual may be designated as a patient caregiver (providing them with similar legal protections to medical marijuana patients) to more than one MML patient; and the amount of marijuana qualifying patients are permitted to possess (no MML, less than 3 ounces, 3-7 ounces, 7-10 ounces, over 10 ounces, 30-90 days supply, or no limit on possession). The scale ranges from 0, which would occur if no legal protections are provided, up to 8, which would occur if the state provided an affirmative defense, permitted patient caregivers, and imposed no limit on possession.

3. Patient Qualification

We construct a scale of the ease of patient qualification to quantify state differences in what is required for a patient to qualify to obtain legal access to medical marijuana. This scale incorporates the following variables weighing towards easy qualification: whether a physician may recommend medical marijuana as treatment for any illness; whether a physician may recommend medical marijuana as treatment for any symptom; and whether a physician may recommend medical marijuana as treatment for experiencing pain. The following variables weigh towards difficult qualification in our scale: whether the state lists at least 25 percent of the maximum number of diseases listed by any state MML; whether a physician must review the patient's medical history; whether there is a minimum duration of disease or symptoms required before a patient may qualify to receive medical marijuana; whether documentation showing that the standard treatment has been ineffective for the patient is required before a patient may qualify; whether objective proof of disease through diagnostic testing results is required; and whether a second physician confirmation of the diagnosis is required. The scale ranges from -4, which would occur if the state had no factors weighing toward easy qualification and all factors weighing toward difficult qualification, up to 5, which would occur if the state had all factors weighing toward easy qualification and no factors weighing toward difficult qualification.

4. Financial Access

We also construct a scale of the ease of financial access to qualifying to use medical marijuana. The following variables weigh towards more difficult financial access: whether a fee is required to obtain the medical marijuana patient card; whether a criminal background check is required; whether fingerprinting is required; and whether proof of identification is required. We also include whether the state provides any financial subsidies to offset any financial obstacles to access as a factor weighing towards more easy financial access to medical marijuana. The scale ranges from -1, which would occur if the state had no subsidies, and imposed fees, along with criminal background check, fingerprinting, and proof of identification requirements, to 4, which would occur if the state granted subsidies and imposed no fees or criminal background check, fingerprinting, or proof of identification requirements.

5. Overall Scale and Categorization

To construct our measure of MML restrictiveness, we sum the four scales described above to create an overall scale that measures the extent to which state MMLs promote access to medical marijuana. Scores less than or equal to 6 on this scale reflect states with no MMLs in place. We classify an MML state as "strict" if its overall score is over 6 but less than or equal to 10. These states permit medical marijuana use but have policies that demonstrate a greater reluctance to promote access to medical marijuana, through imposing hurdles to patient qualification, financial obstacles, restricting the availability of medical marijuana, and/or providing limited legal protections for the medical use of marijuana. We classify an MML state as "permissive" if its overall score is greater than 10. These states have more lenient policies that tend to promote access to medical marijuana, through imposing less strict patient qualification requirements, lowering the cost to gaining legal access, promoting the availability of medical marijuana through permissive home cultivation limits or authorizing dispensaries, and/or providing broader legal protections for medical marijuana possession.

Table 3.14 lists the states in different groups based on the state characteristics as defined in the MML. Column 1 lists the states which do not have any form of MML during the period of focus for this study (till 2014). Out of this list, many states have legalized medical marijuana after 2014 but they are beyond the scope of this paper. The next three columns classifies the states with MML into three groups. Column 2 lists the states with MML which are classified as strict. Some examples of these states are Colorado, Delaware, Vermont, etc. There are a total of 17 states which have strict MML since legalizing medicinal marijuana. It is interesting to note that this list includes states which passed their law in as early as 1999 (Alaska) and those which recently implemented their policy (such as Illinois in 2014). Five states (listed in column 3) are classified as permissive. They are, namely, California, Maryland, Massachusetts, Minnesota and Oregon. Here, California was the first state to legalize medical marijuana and Minnesota implemented its law very recently, in May 2014. This shows that the particulars of the state laws are very state specific and are not influenced much by their neighboring states as well those which passed the law at a similar time.

An important observation of the various MMLs are that they have continuously been amended and updated based on many factors. As we studied the changes seen in the particulars of the law, we found multiple examples of states where some amendments were significant enough to change the classification of the law from strict to permissive. These states are listed in column 4. There are three such states - New Mexico, Rhode Island and Washington. All three states relaxed their legislation to accommodate more patients under the medical marijuana treatment. They were reclassified from Strict to Permissive. New Mexico was reclassified in 2015, Rhode Island in 2013, and Washington state in 2010.

Table 3.14: List of States with MML Status

No MML (1)	MML - Strict (2)	MML - Permissive (3)	MML - Major change in policy (4)
Alabama	Alaska	California	New Mexico
Arkansas	Arizona	Maryland	Rhode Island
Florida	Colorado	Massachusetts	Washington
Georgia	Connecticut	Minnesota	
Idaho	Delaware	Oregon	
Indiana	District of Columbia		
Iowa	Illinois		
Kansas	Hawaii		
Kentucky	Maine		
Louisiana	Michigan		
Mississippi	Montana		
Missouri	Nevada		
Nebraska	New Hampshire		
North Carolina	New Jersey		
North Dakota	New York		
Ohio	Pennsylvania		
Oklahoma	Vermont		
South Carolina			
South Dakota			
Tennessee			
Texas			
Utah			
Virginia			
West Virginia			
Wisconsin			
Wyoming			

Source: "Medical Marijuana Laws for Patients" available at http://pdaps.org/datasets/medical-marijuana-patient-related-laws-1501600783, and "Medical Marijuana Dispensaries" available at http://pdaps.org/datasets/dispensaries-medical-marijuana-1501611712
Notes: Column 1 - States without MML during the period of this study (till 2014). Column 2 - States with Strict MML. Column 3 - States with Permissive MML. Column 4 - States which changed their policy particulars over the years after first implementing the MML such that they were reclassified from strict to permissive over the course of this study.

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