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Cannabis Use, Employment, and Income: Fixed-effects Analysis of Panel Data

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Abstract

Uncertainty exists regarding the direction and magnitude of the association between cannabis use and labor market outcomes. Using panel data from Waves 1 and 2 of the National Epidemiological Survey of Alcohol and Related Conditions (NESARC), the current paper estimates the associations between several patterns of cannabis use during the past year, current employment, and annual personal income. In the single-equation models (Wave 2 data), nearly all patterns of cannabis use are significantly associated with worse labor market outcomes ($p<.05$). However, when using fixed-effects techniques to address unobserved and time invariant individual heterogeneity, the estimates are generally smaller in magnitude and less likely to be statistically significant vis-à-vis the benchmark estimates. These findings suggest that unobserved individual heterogeneity is an important source of bias in models of cannabis use and labor market outcomes. Moreover, cannabis use may be less detrimental in the labor market than other studies have reported.

Keywords

Cannabis use; employment; income; fixed effects analysis; panel data

Introduction

Despite numerous efforts to curb substance use and abuse through legislation and interventions, cannabis, the plant from which marijuana is derived, is the most commonly used illicit substance in the U.S.[1] In 2010, over 17.4 million Americans reported current marijuana use, and 15.7 percent of past year users reported having used the drug on 300 or more days in the past year. These estimates suggest that about 4.6 million Americans consume marijuana on a daily or almost daily basis[1].

Researchers have investigated the effects of cannabis use on a wide range of outcomes, including sexual activity,[2-4] educational performance,[5-12] and criminal activity.[13-14] While most of these studies have identified negative consequences for individuals who consume

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cannabis relative to abstainers, the existing literature has not reached consensus when analyzing labor market outcomes.[15-28]

Some studies have shown a negative relationship between cannabis use (as well as cannabis combined with other illicit drug use) and wages.[16-18, 24-25, 27] However, the magnitude of the relationship varies widely across age groups and consumption patterns. Surprisingly, other studies found evidence of a wage premium associated with cannabis use.[21-22, 26] These authors typically argue that illicit drug use could increase the users' productivity in the short term when consumed to alleviate conditions such as workplace stress. Between these two extremes is a study by French et al.[29], which found a non-significant relationship between illicit drug use and wages.

When it comes to the effects of cannabis use, and cannabis in combination with other illicit drug use, on employment, the results are also mixed. Some studies find negative employment outcomes for illicit drug users, especially for those who engage in chronic consumption.[15, 19-21] Others show that the relationship between illicit drug use and employment is tenuous.[23, 26, 28, 30]

The lack of research consensus could be due to a number of factors, including sample heterogeneity, inconsistent measures for cannabis use and/or labor market outcomes, and the analysis methods used. Among these, the approach for addressing the potential endogeneity of substance use is a critical factor. Substance use could be correlated with unobserved individual characteristics (e.g., personal attitude toward risk, rate of time preference) that could also affect the labor market variables. Failing to address this omitted variables problem could lead to biased coefficient estimates. While a large number of studies have employed various statistical techniques to address the potential endogeneity of substance use, these techniques are not standardized or uniformly applied.[31]

The present study seeks to extend the literature by further exploring the relationships between cannabis consumption and labor market outcomes. It uses individual-level panel data from Waves 1 and 2 of the National Epidemiological Survey on Alcohol and Related Conditions (NESARC), a large longitudinal nationally-representative dataset designed to measure alcohol use disorders and their associated disabilities. The analysis capitalizes on the advantages of longitudinal data and employs fixed-effects models that eliminate any time-invariant unobserved individual factors that could otherwise lead to biased estimates. Three measures of cannabis use are considered, thus permitting distinctions between various consumption patterns. Their effects on both employment status and personal income are examined. The analysis also controls for several time-varying confounding factors that might affect the relationship between cannabis use and labor market performance. The parent study was approved by the University of Miami Institutional Review Board (IRB).

Literature Review

Cannabis Use and Wages/Earnings

Although one would expect a negative association between drug use and wages, the results are inconsistent. Surprisingly, some studies report results showing that drug use is associated with a wage premium.[21-22,26] Using the 1984 wave of the National Longitudinal Survey of Youth (NLSY), Kaestner[22] examined the wage effects of cannabis use for young adults. He found a wage premium for marijuana users. Moreover, the result was consistent across gender and age groups. The author states that illicit drug use may have a greater impact on labor supply and annual earnings than on wages per se. Gill and Michaels[21] used the 1980 and 1984 waves of the same national survey. Their results also suggest that illicit drug users receive higher wages than non-users. The authors surmise that individuals might consume illegal substances to deal with workplace stress and emotional difficulties, which might elevate their productivity, at least in the short term. Register and Williams[26] found similar results. Using the 1984 wave of the NLSY, they found that young males who use cannabis earn higher wages than non-users. Given differences in the recognition and treatment of possible endogeneity bias across studies, this factor could be driving some of these surprising results.

Several other studies found evidence of a negative association between drug use and wages, although the magnitude of the relationship varied widely across age groups and patterns of use.[16-18, 24-25, 27] Kaestner[24] updated his earlier analysis by using a panel from the NLSY. He found negative wage effects of cannabis use among men and negative associations between wages and lifetime cannabis use among women. The wage effects of recent cannabis use, however, were positive among women. The author suggests that some drug users might intentionally select jobs in which their drug use does not affect their productivity. Kandel and colleagues[25] analyzed the effect of illicit drug consumption on earnings using a cohort of the NLSY. Their results indicate that the sign and magnitude of the relationship between earnings and drug use vary across individuals' career stages. They found a positive relationship between wages and drug use in the early stages of an individual's career and a negative relationship later. Using the same data source, Burgess and Propper[17] investigated the effects of adolescent illicit drug use on employment outcomes in adulthood. Their results suggest that "soft" drug use in adolescence has, at most, a very modest effect on the earnings of men in their late twenties or thirties. Buchmueller and Zuvekas[16] examined the relationship between wages and various categories of illicit drug use in a sample of young adults and prime age workers using the 1980-1984 Epidemiologic Catchment Area surveys. They found that young workers who reported daily illicit drug consumption were more likely to earn lower incomes than young workers who did not report such use. Among prime-age males, the authors found strong evidence that pathological use or dependence was negatively associated with earnings. Bryant and colleagues [18] utilized the NLSY to examine past illicit drug use and found that a history of illicit drug use lowered expected wages. More recently, Van Ours[27] explored the wage effects of cannabis use for prime-age males in Amsterdam. He found that recent cannabis use has a negative effect on wages. Moreover, he found the wage loss to be greater for cannabis users who initiated consumption early in life.

As a departure from large national surveys, French and colleagues[29] used a dataset compiled from employees at six different workplaces. Using a range of lifetime and current indicators of illicit drug use, the authors identified predominantly non-significant relationships between various patterns of illicit drug use and wages after controlling for alcohol use.

Cannabis Use and Employment

Research consensus is also lacking on the direction and magnitude of the effects of various patterns of illicit drug use on employment. Some studies report worse employment outcomes for illicit drug users. French, Roebuck, and Alexandre [20] used the 1997 National Household Survey on Drug Abuse (NHSDA) to investigate the effect of both chronic and non-chronic illicit drug use on employment and labor force participation. Their results strongly indicated that chronic illicit drug use was associated with a lower probability of employment for males and females and a lower probability of labor force participation for males. Non-chronic illicit drug use was not significantly correlated with any of the selected employment indicators. DeSimone[19] analyzed the relationship between marijuana use and employment among males using NLSY data (1984 to 1988). The results indicate that the use of marijuana significantly reduces the likelihood of employment among males. Alexandre and French[15] utilized unique data collected in low-income and high-crime neighborhoods in Miami, Florida, to examine the relationship between chronic illicit drug use and a range of employment indicators. The main finding of the research was that chronic illicit drug use significantly reduced the probability of employment regardless of specification or gender.

Other studies did not find robust support for the hypothesis that illicit drug use is detrimental to labor market success. Gill and Michaels[21] found that drug use is correlated with a lower likelihood of being employed, but hard drug use is, surprisingly, not significantly related to employment. Register and Williams[26] found that marijuana use in the past 30 days is negatively associated with employment, but having used marijuana on the job any time in the last year is positively associated with employment. Kaestner[24] utilized data from the NLSY to estimate the effect of illicit drug use on the labor supply of young adults. Specifically, the author examined whether frequency and timing of marijuana and cocaine use were systematically associated with labor supply using both cross-sectional and panel data models. The cross-sectional estimates revealed that illicit drug use had a significant negative impact on labor supply while the longitudinal estimates indicated that consumption of these substances did not significantly affect labor supply. Zarkin and colleagues[29] used cross-sectional data from the 1991 National Household Survey on Drug Abuse (NHSDA). The authors found that illicit drug use had little effect on the number of hours worked by young men.

Data and Measures

Sample

The current analysis uses data from Waves 1 and 2 of the NESARC, a longitudinal survey of non-institutionalized citizens and non-citizens living in the United States who are 18 years or older. One of the main objectives of the NESARC survey is to provide information on substance use disorders and their associated consequences in the general population.

The NESARC offers several advantages for the current analysis because it provides comprehensive data on illicit drug use, an over-sampling of young adults, and a nationally representative design. Of the 43,093 Wave 1 respondents interviewed face-to-face through computer assisted personal interviewing in 2000-2001, 34,653 were re-interviewed in 2004-2005 as part of Wave 2. The overall survey response rate was 81% in Wave 1, which is equal to or higher than most national co-morbidity surveys.[32] Missing data due to item non-response was addressed through “hot-deck” imputation, a process whereby other information from the individual or another respondent with similar characteristics was used to “impute” a response for that item. The hot-deck imputation was executed by the NESARC administrators for those variables deemed critical for analyses. For age, sex, race, and Hispanic origin, the hot-deck procedure was supplemented by logical checks. In addition, hot-decking was within categories defined by relevant characteristics. Waves 1 and 2 of the NESARC provide detailed information on topics related to alcohol and illicit drug use, abuse, and dependence.[33]

The analysis sample for the present study was constructed by excluding observations with missing information for the pertinent variables in either wave. Women who were pregnant at any time during the past year were also dropped as these individuals might change their cannabis consumption during pregnancy.[33] Moreover, pregnant women are more likely to be out of the labor force or on unpaid leave and therefore have lower incomes.[34] Finally, respondents who were younger than 21 or older than 60 in Wave 1 were excluded in order to eliminate those who were below the legal drinking age in the U.S. and those who would near typical retirement age in Wave 2. The final analysis sample includes 7,077 women and 7,199 men.

Dependent variables

The outcomes of interest in the analysis are employment status and personal income in the past 12 months. Employment is a binary variable that indicates whether a person is currently employed. The variable is based on a series of questions and includes all respondents who reported being currently employed full or part time, employed but not at work because of temporary illness or injury, employed but on paid vacation, and employed but absent from work without pay. Personal income in the past 12 months was reported in categories (i.e., $1 to $4,999; $5,000 to $7,999; $8,000 to $9,999; $10,000 to $12,999, etc). A continuous personal income variable was constructed by taking the mid-point of the reported ranges and then using the Consumer Price Index (CPI) to convert all values to constant 2001 dollars.

Independent variables

Cannabis Use The key explanatory variable is cannabis use. First, two dichotomous variables were constructed: one indicating any use in the past year, another signifying a diagnosis of cannabis abuse and/or dependence in the past year. The diagnostic interview used by the NESARC to generate the diagnoses of cannabis abuse and cannabis dependence is the National Institute on Alcohol Abuse and Alcoholism's Alcohol Use Disorder and Associated Disabilities Interview Schedule-DSM_IV Version (AUDADIS-IV) .[35] The NESARC administrators classify cannabis use disorders in three categories: cannabis abuse only, cannabis dependence only, and cannabis abuse and dependence. A cannabis abuse and/or dependence measure was constructed to include respondents who met the criteria for any of the three categories above. Second, past-year cannabis use was divided into four categories to distinguish among different consumption patterns: no cannabis use, less than weekly cannabis use, at least weekly but less than daily cannabis use, and daily cannabis use.

Control variables All benchmark models with Wave 2 data include the following individual-level controls: age, ethnicity, race, being born outside the U.S., marital status, number of persons in the household, years of schooling, urbanicity, general and mental health status, an indicator of weekly binge drinking, smoking status, and other drug use status. The general and mental health status variables are scores derived from the SF-12 health survey that measures physical and social functioning, role functioning, bodily pain, general health, vitality, and mental health. The range is from 0 to 100 with higher scores reflecting better physical and mental health status.

The models with Wave 2 data also include wave and state dummies. Finally, the monthly average statewide unemployment rate (obtained from the Bureau of Labor Statistics, Local Area Unemployment Statistics [LAUS] Database) was included to capture other variation in state conditions that might affect the probability of being employed and past year personal income. Each individual was assigned the average unemployment rate in the state of residence for the 12 months prior to the interview. The fixed-effects models include only the time-varying individual-level controls because the non-varying characteristics drop out of the estimation.

Descriptive Statistics

Table 1 presents descriptive statistics for the analysis sample by gender and wave. As expected, more men were employed at the time of the interview, and they had higher personal incomes than the women in the sample. Cannabis use is also more prevalent among men. Overall, 7.91 percent of the men in the sample consumed any cannabis during the past year compared to 4.24 percent of women. Regarding frequency of use, 4.85 (3.06) percent of men (women) consumed cannabis less than weekly, 2.36 (1.32) percent of men (women) used cannabis weekly but less than daily, and 0.70 (0.37) percent of men (women) used cannabis daily. About 2.72 (1.05) percent of men (women) received a diagnosis of cannabis abuse and/or dependence. In terms of other substance use, 19.06 percent of men reported binge drinking weekly compared with only 5.06 percent of women. Men were also more likely to be current smokers and use other illicit drugs.

Empirical Approach

Economists often model labor market outcomes as a function of the individual's human and health capital based on the work of Becker[36] and Grossman's model of the demand for health care.[37] Better health and greater human capital are hypothesized to improve labor market performance. Modifiable risk behaviors such as physical inactivity, heavy drinking, poor diet, smoking, and other addictive substance use are among the main determinants of health status.[38-39] One would therefore expect that substance use decreases labor market productivity either directly through a higher probability of injury, absenteeism, or decreased job performance or indirectly through lower educational attainment or reduced on-the-job training. The present paper focuses on a reduced-form relationship between substance use, employment, and earnings.

The basic econometric model is:

$$\mathbf{L}^{*}_{it}=\beta_0+\beta_1\mathbf{C}_{it}+\beta_2\mathbf{X}'_{it}+\mathbf{U}_i+\varepsilon_{it} \quad (1)$$

where the subscript i denotes the individual and t denotes time (i.e., wave), L^{*}_{it} is a latent measure of employment or earnings, C_{it} is a measure of cannabis use, $\mathbf{X}'_{it}$ is a vector of control variables, U_i represents unobserved individual factors that do not vary over time, ε_{it} is a random time-varying error, and the β's are coefficients to be estimated.

First, to create a baseline comparison with earlier studies that analyze cross-sectional data, NESARC Wave 2 data were used to estimate Equation (1). Contingent on the dependent variable, different methods for estimating Equation (1) were used. When the dependent variable L_{it} is continuous, (i.e., $L^{*}_{it} = L_{it}$), Equation (1) is estimated with OLS. When the dependent variable is dichotomous, L^{*}_{it} is not observable. In this case, an observable dichotomous variable can be defined as:

$$L_{it}=1 \quad \text{if} \quad L^{*}_{it}>0 \qquad \text{and} \qquad L_{it}=0 \qquad \text{otherwise}$$

Equation (1) is estimated using the logit technique in this case.

Estimation of single-equation models such as Equation (1) generate consistent coefficient estimates if there are no unmeasured or unobserved characteristics that are significantly correlated with both the cannabis use measures and the labor market outcome.[40] However, it is quite possible that unobservable individual characteristics (i.e., time preference, non-cognitive traits) included in U_i affect both the decision to consume cannabis and the labor market variables. If this omitted variables problem is present, the coefficient estimates will be biased. In other words, the estimate of β_1 is unlikely to reflect a causal effect of cannabis use on the labor market variable. Several studies have demonstrated that failing to correct for the endogeneity of behavioral measures such as substance use can lead to biased results and inappropriate policy recommendations.[41-43]

To address potential endogeneity bias in the relationship between cannabis use and labor market outcomes, the analysis takes advantage of the longitudinal nature of the NESARC and uses a fixed-effects estimation technique .[40,44] First, take the average of all time-varying factors in Equation (1) for each individual across waves to obtain the following expression:

$$\bar{L}_i^* = \beta_0 + \beta_1 \bar{C}_i + \beta_2 \bar{X}_i' + U_i + \bar{\varepsilon}_i \quad (2)$$

The fixed-effects model is obtained by subtracting Equation (2) from Equation (1):

$$L_{it}^* - \bar{L}_i = \beta_i \left(C_{it} - \bar{C}_i\right) + \beta_2 \left(X_{it}' - \bar{X}_i'\right) + \left(\varepsilon_{it} - \bar{\varepsilon}_i\right) \quad (3)$$

Equation (3) eliminates time-invariant unobserved individual heterogeneity, U_i , thereby mitigating concerns about possible omitted variable bias.[40] In other words, the fixed effects model uses deviations from unit-level averages both for continuous and dichotomous variables. The model estimates the effect of a within-unit observation change in cannabis use on the change in a particular labor market outcome.

For the continuous earnings measure, Equation (3) is estimated with standard fixed-effects linear regression (*xtreg* in Stata). The standard errors are adjusted for clustering (correlation of the error terms) at the individual level. For the binary employment variable, a conditional fixed-effect logit estimator is used.[45-46]

For each of the two labor market outcomes (currently employed and personal income), three separate models with Wave 2 data are estimated to incorporate the three sets of cannabis use measures—current cannabis user, abuse and/or dependence, the frequency categories—for a total of six models. Six similar models are then estimated using the fixed-effects specifications. Separate models are estimated for men and women as numerous studies show that men and women differ in illicit drug consumption patterns,[24, 30] employment status,[47-50] and earnings.[51-53] All analyses are performed with the Stata 11 statistical software package.[54]

Estimation Results

Table 2 reports selected estimation results for men. The first panel shows results of the Wave 2 data models. All estimated odds ratio for the current employment specifications are less than one in magnitude, indicating a negative association between all cannabis use patterns and the probability of being employed. For male cannabis users, the odds of being employed are 0.640 times the odds for those who reported no cannabis use during the past year (p<.01). The estimates for the cannabis use categories show that the odds of being employed for men who used cannabis less than weekly are 0.714 times the odds for men who reported no cannabis use (p<.10). Odds ratios decrease to 0.654 for at least weekly but less than daily cannabis use (p<.05) and 0.217 for daily cannabis use (p<.01). Moreover, the odds of being employed for men diagnosed with cannabis abuse and/or dependence are 0.695 times the odds for those without a cannabis abuse or dependence diagnosis (p<.10).

The bottom panel of Table 2 presents the estimated odds ratios of the conditional fixed effects logit models. The conditional fixed-effects logit technique uses within-individual differences to identify the model .[45-46] In other words, information for an individual who remained employed or remained unemployed from Wave 1 to Wave 2 cannot contribute to the analysis because the conditional probabilities of these response patterns, based on the total response across time, are 1 regardless of the covariates. These conditional probabilities do not provide any information on the effects of the regressors. Thus, observations for individuals who were either employed at both waves or unemployed at both waves are dropped from the analysis, thus reducing the sample size for men to 1,778 observations (see Table 4 for a statistical comparison of the full and conditional samples). Although the fixed-effects estimates still display a generally negative association between employment status and cannabis use, they are no longer statistically significant at conventional levels, suggesting that unobserved individual heterogeneity might be an important source of bias in these relationships.

We should note that the 95% confidence intervals include the value 1 for a three estimates that are statistically significant at $p<.10$. However, the upper bound of the confidence intervals is very close to 1. In addition, the results for the most severe pattern of cannabis use (Cannabis abuse and/or dependence) are consistent across models suggesting that the loss of sample size is not the only factor leading to the loss of statistical significance in the fixed effects models.

The second column of Table 2 shows coefficient estimates for the personal income models. Nearly all results from the linear regression models with Wave 2 data show a statistically significant ($p<.05$) negative association between cannabis use and personal income for men. Consistent with the employment status models, however, the estimated relationships are no longer statistically significant when a fixed-effects technique is employed. Moreover, the coefficient estimates decrease in size in all specifications.

Selected estimation results for women are presented in Table 3. Similar to men, based on the logit estimation, women who use cannabis are less likely to be employed. The results indicate that the odds of being employed for women who have used cannabis during the past year are 0.553 times the odds for women who reported no cannabis use during the past year ($p<.01$). The odds for women who reported at least weekly but less than daily use (daily cannabis consumption) are 0.562 (0.251) times the odds for women who reported no cannabis use ($p<.01$). The estimated odds ratio for cannabis abuse and/or dependence is not statistically significant.

When the conditional fixed effects logit model is estimated, the sample size is reduced to 2,348 observations that exhibit within-group variation in the dependent variable. With the exception of the cannabis abuse and/or dependence specification, all estimates show a negative association between cannabis use and employment status. Nevertheless, as with men, none of the estimated odds ratios are statistically significant.

Although most of the coefficient estimates for women in the personal income models are negative, they are not statistically significant. The only exception is the coefficient estimate for daily cannabis use in the linear regression model. However, the estimate is no longer statistically significant when the fixed-effects technique is employed. These results suggest that any potential bias from unobserved individual heterogeneity is less of a factor for women as virtually all of the specifications indicate a non-significant association between cannabis use and personal income.

Appendix Table A presents the full set of conditional fixed-effects logit estimation results for cannabis use and current employment status. The estimated odds ratio indicate that the number of years of schooling and general health status have a positive association with employment status. In addition, men who were never married and women who use other drugs are less likely to be employed. The number of persons in the household is negatively associated with the probability of being employed for women. Complete estimation results for all other specifications are available upon request.

Sensitivity Analysis

To examine the robustness of the core findings, five sensitivity analyses were performed, the results of which are available upon request. First, the core analysis uses Wave 2 data to form a baseline comparison before turning to fixed effects models. As an alternative to Wave 2 data alone, data from Waves 1 and 2 are pooled and a Generalized Estimating Equations (GEE) model is estimated, which allows for correlations among repeated observations for each individual. The pooled panel estimates are often smaller in magnitude yet more significant than the core estimates using only Wave 2 data. The improvement in statistical significance is expected as the sample size for the pooled sample is about double that of the Wave 2 sample. Moreover, and more importantly, the Generalized Estimating Equations model uses the full analysis sample as compared to the small sample size used in the fixed effects logit specification. These results are presented in Appendix Table D.

Second, as mentioned in the Results section above, the fixed-effects models are identified via within-individual differences thereby ignoring observations that lack within-group variation in the dependent variable. Thus, a relatively large part of the full sample used for the standard logit analyses is not used in the estimation of the fixed-effects models. To examine how the sample reduction would affect the core results, the standard logit models were re-estimated using only those observations from the conditional fixed-effects logit model (i.e., observations containing within-group variation in the dependent variable). The estimates from this reduced sample logit analysis are therefore directly comparable to the estimates from the conditional fixed-effects logit model as the same respondents are used in both approaches. As it turns out, the results using the restricted sample are consistent in direction, magnitude, and significance with those from the core models.

Third, because cannabis use might have a different effect on part-time and full-time employment, part-time workers were dropped from the analysis sample to see if the estimates change. In other words, both baseline and fixed-effects models were estimated using a restricted sample of full-time workers only. Again, the estimation results are similar to those from the core baseline and fixed-effects models.

Fourth, for consistency with the labor economics literature, the effect of cannabis use on the natural logarithm of personal income was estimated. Because personal income for some individuals is zero, and the logarithm of zero is undefined, a value of 1 was added to each observation before taking the natural logarithm. Both baseline and fixed-effects models were then re-estimated. The results are presented in Appendix Table B. The majority of the coefficient estimates are similar in sign and statistical significance to the core estimates.

Fifth, a cannabis dependence diagnosis (the most severe diagnosis) could have a different effect on the outcomes than the combined measure used (i.e., abuse and/or dependence diagnosis). To estimate the specific effect of a cannabis dependence diagnosis on the outcomes, we constructed a dichotomous variable indicating a cannabis dependence diagnosis (independent of a cannabis abuse diagnosis). Selected estimation results are presented in Appendix Table C. The estimates are not statistically significant in part due to the very small number of individuals diagnosed with this diagnosis.

Discussion and Conclusion

The present study attempts to further the understanding of the relationships between cannabis use, employment, and income by estimating individual fixed-effects models to address the endogeneity of substance use. The fixed-effects technique eliminates any bias due to time-invariant, individual-specific variables unintentionally omitted from the model. As a baseline comparison for the fixed-effects models, the logit and OLS estimates using

Wave 2 data suggest a negative and usually significant relationship between various patterns of cannabis use and employment and personal income. However, when fixed-effects techniques are employed, the estimates lose their statistical significance. These results suggest that important unobserved individual characteristics can introduce significant bias when employing standard estimation techniques with cross-sectional data. Thus, the effect of cannabis use on labor market outcomes found by previous studies might be spurious due to endogeneity (i.e., unobserved time-invariant individual heterogeneity).

This study has several limitations. First, although the NESARC survey has many redeeming features, the respondents self-reported their cannabis use. While the extent (if any) of misreporting in this area cannot be resolved, the published literature on this topic indicates that self-reported substance use measures are generally reliable for use in statistical analyses.[55-57]

Second, the fixed-effects estimation approach is an efficient way to control for unobserved time-invariant omitted variables, but it can neither account for individual unobservable factors that vary over time nor address potential reverse causality from labor market variables to cannabis use.[40] Although an instrumental variables (IV) estimation technique is superior when omitted variables come in both forms, selecting a valid instrument(s) for cannabis use is a topic of heated debate in the field,[31] and several methodological articles and books warn researchers about the liabilities of using weak or invalid instruments.[40, 58-59]

Third, when conditional fixed-effects logit models are estimated, a large part of the full sample is lost due to the lack of within-group variation in the dependent variable (currently employed). As a result, the estimates are not as precise. Table 4 presents descriptive statistics on the subsample used in the conditional fixed effects logit analysis and the rest of the analysis sample. Also, Kruskal-Wallis tests of statistically significant differences in median values between the two subsamples[51] are conducted. Although we find statistically significant differences in some of our variables between the two groups, such differences are to be expected. Thus, we believe that conclusions based on within-subject variability in cannabis use for the conditional sample is still informative.

Fourth, the duration of cannabis use is likely to impact the estimated effect of current cannabis use on labor market outcomes. Unfortunately, the NESARC dataset does not provide good historical information on cannabis use. The analysis could have included an indicator for ‘cannabis use prior to the past year’ as a proxy for ‘duration of cannabis use,’ but this variable is misleading because it could signify heavy and continuous cannabis use during the years prior to interview date or a single use during that period. In addition, it would be ideal to differentiate users whose primary drug of choice is cannabis from the rest of cannabis users. Unfortunately, the NESARC dataset does not provide information in this area. As an alternative, the analyses included a measure of any other illicit drug use as a control variable.

Implications for Behavioral Health

Concern about the use of cannabis in the U.S. has focused on the negative personal and societal consequences of addiction, including poor labor market outcomes. One popular view posits that illicit drug use affects productivity through a higher likelihood of health problems, absenteeism, and reduced performance. Moreover, substance use might have an indirect effect on labor market productivity through lower education and training. If present, lower productivity can then lead to job loss and lower wages. A common reaction to this situation is the increasing use of pre-employment and on-the-job drug testing by employers.[26]

Despite anecdotal evidence suggesting a negative relationship between cannabis use and labor market outcomes, the existing empirical literature is mixed. Although standard regression results from the present study indicate a significant negative association between various patterns of cannabis use and employment and personal income, significance disappears when fixed-effects models are estimated. In other words, the findings suggest that cannabis use might have less of a negative impact in the labor market than some earlier studies have reported. These results should be seen as an important step in understanding the effect of cannabis use on labor market outcomes. Future research is needed to replicate and verify these results because the implications are critical for policymakers, treatment providers, and employers as they determine how to structure anti-drug abuse programs in the workplace. Considering recent state-level legislation decriminalizing the use of cannabis, current and rigorous research on the consequences and benefits of cannabis use is vital to inform the political debate.[21] The findings of this research cannot by themselves justify an endorsement of cannabis decriminalization or reduced drug testing. Beyond reduced productivity, illicit drug use might have many other undesirable consequences to society such as criminal activity and increased health services utilization. Nevertheless, as more studies find a weak or non-significant relationship between cannabis use and employment or earnings, one might question the support of cannabis testing based solely on the argument that cannabis consumptions lowers productivity. The development of appropriate policies and programs require a clear understanding of the presence and magnitude of potential consequences.

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Appendix Table A

Appendix Table A

Full Estimation Results for Conditional Fixed-Effects Logit Estimation of Current Employment Status

Explanatory Variables	Men	Women
Baseline values	0.883	0.794
Less than weekly cannabis use	1.050 (0.655 to 1.681)	0.794 (0.489 to 1.289)
Weekly but less than daily cannabis use	0.650 (0.358 to 1.180)	0.480 (0.193 to 1.184)
Daily cannabis use	0.813 (0.237 to 2.791)	0.777 (0.269 to 2.239)
Age	0.966 (0.882 to 1.056)	0.962 (0.887 to 1.044)
Currently widowed, separated or divorced	0.829 (0.462 to 1.485)	1.430 (0.884 to 2.312)
Never married	0.370*** (0.196 to 0.698)	0.668 (0.347 to 1.286)

Explanatory Variables	Men	Women
Persons in household	1.019 (0.923 to 1.124)	0.904* (0.815 to 1.001)
Years of schooling	1.250** (1.036 to 1.507)	1.262** (1.048 to 1.520)
Reside in urban area	0.803* (0.618 to 1.041)	0.972 (0.776 to 1.217)
General health scale (SF 12)[3]	1.015** (1.003 to 1.027)	1.018*** (1.006 to 1.029)
Mental health scale (SF 12)[3]	1.009 (0.998 to 1.020)	1.009* (0.999 to 1.018)
Weekly binge drinker	0.944 (0.696 to 1.279)	1.074 (0.710 to 1.623)
Current smoker	1.055 (0.739 to 1.504)	0.833 (0.581 to 1.193)
Other drug user	0.893 (0.584 to 1.364)	0.687* (0.449 to 1.050)
State unemployment rate	0.902 (0.729 to 1.116)	0.943 (0.786 to 1.131)
N	1,778	2,348

Notes: Odds ratios reported. Specifications control for the following time-varying measures: age, marital status, number of persons in the household, years of schooling, urbanicity, general and mental health status, smoking status, other drug use status, and state unemployment rate. 95% confidence intervals are reported in parentheses.

*Statistically significant, $p \leq 0.10$;

**Statistically significant, $p \leq 0.05$;

***Statistically significant, $p \leq 0.01$.

Appendix Table B

Appendix Table B

Selected Estimation Results for Natural Logarithm of Personal Income

	Men	Women
Baseline mean values	0.883	0.794
Models with Wave 2 data		
Current cannabis user	−0.305*** (−0.430 to −0.180)	−0.099 (−0.295 to 0.096)
Less than weekly cannabis use	−0.232*** (−0.375 to −0.088)	−0.021 (−0.242 to 0.199)
Weekly but less than daily cannabis use	−0.392*** (−0.603 to −0.181)	−0.195 (−0.623 to 0.232)
Daily cannabis use	−0.582** (−1.084 to −0.080)	−0.575* (−1.228 to 0.077)
Cannabis abuse and/or dependence	−0.132 (−0.299 to 0.034)	−0.128 (−0.482 to 0.224)
N	14,398	14,154

	Men	Women
Fixed-effects models		
Current cannabis user	−0.160* (−0.344 to 0.024)	−0.184 (−0.454 to 0.086)
Less than weekly cannabis use	−0.153 (−0.353 to 0.045)	−0.191 (−0.471 to 0.088)
Weekly but less than daily cannabis use	−0.217 (−0.515 to 0.080)	−0.183 (−0.671 to 0.304)
Daily cannabis use	0.077 (−0.461 to 0.615)	−0.098 (−1.229 to 1.032)
Cannabis abuse and/or dependence	0.040 (−0.231 to 0.311)	0.015 (−0.514 to 0.546)
N	14,398	14,154

Notes: All models are estimated using standard and fixed-effects linear regression. Confidence intervals are reported in parentheses.

Specifications using Wave 2 data control for age, race, ethnicity, marital status, number of persons in the household, years of schooling, being born outside the U.S., urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, state unemployment rate, and state dummies. Wave 1 state identifiers were used to construct state dummies as state identifiers were not provided for Wave 2. Fixed-effects specifications control for the following time-varying measures: age, marital status, number of persons in the household, years of schooling, urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, and state unemployment rate.

* Statistically significant, $p \le 0.10$;

** Statistically significant, $p \le 0.05$;

*** Statistically significant, $p \le 0.01$.

Appendix Table C

Appendix Table C

Selected Estimation Results for Employment Status and Income (Cannabis Dependence Diagnosis)

Cannabis Dependence Diagnosis	Currently Employed[1]	Personal Income[2]
Men		
Models with Wave 2 data	0.515 (0.203 to 1.304)	1778 (−8,157 to 11,713)
N	7,199	7,199
Fixed-effects models	0.688 (0.193 to 2.453)	-1628 (−7,400 to 4,143)
N	1,778	14,398
Women		
Models with Wave 2 data	1.034 (0.308 to 3.472)	−1120 (−7,963 to 5,721)
N	7,077	7,077

Cannabis Dependence Diagnosis	**Currently Employed[1]**	**Personal Income[2]**
Fixed-effects models	3.388 (0.591 to 19.410)	−3530 (−9,279 to 221)
N	2,348	14,154

Notes: Confidence intervals are reported in parentheses. Specifications using Wave 2 data control for age, race, ethnicity, marital status, number of persons in the household, years of schooling, being born outside the U.S., urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, state unemployment rate, and state dummies. Wave 1 state identifiers were used to construct state dummies as state identifiers were not provided for Wave 2. Fixed-effects specifications control for the following time-varying measures: age, marital status, number of persons in the household, years of schooling, urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, and state unemployment rate.

[1] Logit and conditional fixed-effects logit models. Odds ratios reported.

[2] Standard and fixed-effects linear regression.

* Statistically significant, $p \leq 0.10$;

** Statistically significant, $p \leq 0.05$;

*** Statistically significant, $p \leq 0.01$.

Appendix Table D

Appendix Table D

Selected Estimation Results for Employment Status and Income (Generalized Estimating Equation)

	Currently Employed[1]	**Personal Income[2]**
Men		
Current cannabis user	0.680*** (0.562 to 0.823)	−2,811*** (−4,659 to −963)
Less than weekly cannabis use	0.771** (0.610 to 0.973)	−1,951* (−4,085 to 182)
Weekly but less than daily cannabis use	0.625*** (0.465 to 0.841)	−4,534*** (−7,516 to −1,552)
Daily cannabis use	0.392*** (0.241 to 0.636)	−4,281 (−9,772 to 1,210)
Cannabis abuse and/or dependence	0.738** (0.553 to 0.986)	−2,417* (−5,237 to 402)
N	14,398	14,398
Women		
Current cannabis user	0.738*** (0.600 to 0.907)	−220 (−2,067 to 1,625)
Less than weekly cannabis use	0.799* (0.630 to 1.012)	828 (−1211 to 286)
Weekly but less than daily cannabis use	0.646** (0.430 to 0.970)	−2,706 (−6,551 to 1,139)
Daily cannabis use	0.507** (0.286 to 0.899)	−5,658* (−11,327 to 9)

	Currently Employed[1]	Personal Income[2]
Cannabis abuse and/or dependence	1.075 (0.721 to 1.604)	−723 (−4,153 to 2,705)
N	14,154	14,154

Notes: 95% confidence intervals are reported in parentheses. All specifications control for the following measures: age, race, ethnicity, marital status, number of persons in the household, years of schooling, being born outside the U.S., urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, state unemployment rate, and state dummies.

[1]Generalized Estimating Equations (GEE) fitting logit regression model. Odds ratios reported.

[2]Generalized Estimating Equations (GEE) fitting linear regression model.

*Statistically significant, $p \leq 0.10$;

**Statistically significant, $p \leq 0.05$;

***Statistically significant, $p \leq 0.01$.

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Table 1

Descriptive Statistics

	Men (N=7,199)		Women (N=7,077)	
Variables	**Wave 1**	**Wave 2**	**Wave 1**	**Wave 2**
Labor market variables				
Currently Employed (%)	88.92	87.69	80.06	78.73
Personal Income, past year (in 2001 USD)[1]	47,225 (36,834)	49,167 (37,031)	29,997 (27,385)	31,024 (27,321)
Cannabis use variables in the past year				
Any cannabis use (%)[2]	7.25	8.56	3.93	4.55
Any cannabis but less than weekly use (%)	4.38	5.32	2.80	3.31
Weekly but less than daily cannabis use (%)	2.14	2.58	0.73	0.90
Daily cannabis use (%)	0.73	0.66	0.40	0.34
Cannabis abuse and/or dependence (%)	2.54	2.89	0.95	1.14
Demographics and other characteristics				
White (%)	62.98		64.36	
African American (%)	13.91		16.80	
American Indian/Alaska Native (%)	1.65		1.53	
Asian or Pacific Islander (%)	2.68		1.91	
Hispanic (%)	18.78		15.40	
Born outside U.S. (%)	15.10		10.07	
Age	39.76 (10.58)	42.84 (10.58)	40.23 (10.42)	43.32 (10.39)
Currently married (%)	60.24	63.76	54.02	55.32
Currently widowed, separated or divorced (%)	15.64	16.14	23.24	24.78
Never married (%)	24.12	20.10	22.74	19.90
Persons in household	2.66 (1.48)	2.85 (1.49)	2.66 (140)	2.78 (139)
Years of schooling	13.93 (3.14)	14.02 (3.18)	14.11 (2.87)	14.23 (2.91)
Reside in urban area (%)	82.94	84.24	84.26	83.93
General health scale (SF 12)[3]	53.14 (10.11)	51.92 (10.35)	52.63 (10.60)	51.72 (10.59)
Mental health scale (SF 12)[3]	53.04 (9.41)	52.84 (9.44)	50.42 (10.23)	50.51 (10.03)
Weekly binge drinker (%)	19.35	18.77	5.26	4.86
Current smoker (%)	38.59	33.37	28.92	25.76
Other drug user (%)[4]	4.65	5.49	4.17	4.52
State unemployment rate (%) [5]	4.45	5.64	4.43	5.62

Notes: Sample excludes women who were pregnant at any time during the year prior to interview and individuals who were under age 21 in Wave 1 and age 65 or older in Wave 2. Standard deviations in parentheses.

[1]Total personal income in past 12 months (including any income from food stamps) converted to constant $2001.

[2]Any cannabis use is equal to one for individuals who used cannabis in the last 12 months.

[3]Scores derived from the SF-12 health survey that measures physical and social functioning, role functioning, bodily pain, general health, vitality, and mental health. The range is from 0-100 with higher scores reflecting better physical and mental health status.

[4]Any of the following drugs used in the past year: sedatives, tranquilizers, opioids, amphetamines, cocaine or crack, hallucinogens, inhalants, and heroin.

[5]The state unemployment rate was calculated as an average of the rate over the past 12 months prior to interview date.

Table 2
Selected Estimation Results for Employment Status and Income (Men)

	Currently Employed[1]	Personal Income[2]
Baseline mean values	0.883	48,196
Models with Wave 2 data		
Current cannabis user	0.640*** (0.494 to 0.829)	−4,648*** (−7,334 to −1,962)
Less than weekly cannabis use	0.714* (0.537 to 1.037)	−2,552 (−5,954 to 850)
Weekly but less than daily cannabis use	0.654** (0.437 to 0.980)	−7,520*** (−11,370 to −3,670)
Daily cannabis use	0.217*** (0.108 to 0.434)	−12,167*** (−18,451 to −5,882)
Cannabis abuse and/or dependence	0.695* (0.466 to 1.035)	−4,522** (−8,105 to −939)
N	7,199	7,199
Fixed-effects models		
Current cannabis user	0.895 (0.587 to 1.365)	−1,390 (−3,571 to 790)
Less than weekly cannabis use	1.050 (0.655 to 1.681)	−1,168 (−3,654 to 1,318)
Weekly but less than daily cannabis use	0.650 (0.358 to 1.180)	−2,285 (−5,256 to 684)
Daily cannabis use	0.813 (0.237 to 2.791)	415 (−3,531 to 4,362)
Cannabis abuse and/or dependence	0.525* (0.264 to 1.042)	−1,421 (−4,369 to 1,526)
N	1,778	14,398

Notes: 95% confidence intervals are reported in parentheses. Specifications using Wave 2 data control for age, race, ethnicity, marital status, number of persons in the household, years of schooling, being born outside the U.S., urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, state unemployment rate, and state dummies. Wave 1 state identifiers were used to construct state dummies as state identifiers were not provided for Wave 2. Fixed-effects specifications control for the following time-varying measures: age, marital status, number of persons in the household, years of schooling, urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, and state unemployment rate.

[1] Logit and conditional fixed-effects logit models. Odds ratios reported.

[2] Standard and fixed-effects linear regression.

* Statistically significant, $p \leq 0.10$;

** Statistically significant, $p \leq 0.05$;

*** Statistically significant, $p \leq 0.01$.

Table 3

Selected Estimation Results for Employment Status and Income (Women)

	Currently Employed[1]	Personal Income[2]
Baseline mean values	0.794	30,510
Models with Wave 2 data		
Current cannabis user	0.553*** (0.419 to 0.728)	−768 (−3,411 to 1,874)
Less than weekly cannabis use	0.604*** (0.437 to 0.834)	1,128 (−2,078 to 4,335)
Weekly but less than daily cannabis use	0.562** (0.320 to 0.987)	−5,614 (−9,514 to −1,715)
Daily cannabis use	0.251*** (0.102 to 0.618)	−6,944** (−13,103 to −785)
Cannabis abuse and/or dependence	0.863 (0.505 to 1.473)	−2,248 (−6,482 to1,984)
N	7,077	7,077
Fixed-effects models		
Current cannabis user	0.739 (0.475 to 1.151)	−325 (−2,399 to 1,749)
Less than weekly cannabis use	0.794 (0.489 to 1.289)	366 (−1,880 to 2,613)
Weekly but less than daily cannabis use	0.480 (0.193 to 1.184)	−2,261 (−6,593 to 2,071)
Daily cannabis use	0.777 (0.269 to 2.239)	−4,613 (−12,733 to 3,506)
Cannabis abuse and/or dependence	1.660 (0.803 to 3.429)	−436 (−3,258 to 2,385)
N	2,348	14,154

Notes: Confidence intervals are reported in parentheses. Specifications using Wave 2 data control for age, race, ethnicity, marital status, number of persons in the household, years of schooling, being born outside the U.S., urbanicity, general and mental health status, a weekly binge drinking indicator, smoking status, other drug use status, state unemployment rate, and state dummies. Wave 1 state identifiers were used to construct state dummies as state identifiers were not provided for Wave 2. Fixed-effects specifications control for the following time-varying measures: age, marital status, number of persons in the household, years of schooling, urbanicity, general and mentalhealth status, a weekly binge drinking indicator, smoking status, other drug use status, and state unemployment rate.

[1] Logit and conditional fixed-effects logit models. Odds ratios reported.

[2] Standard and fixed-effects linear regression.

* Statistically significant, $p \leq 0.10$;

** Statistically significant, $p \leq 0.05$;

*** Statistically significant, $p \leq 0.01$.

Table 4

Comparison of Conditional Fixed Effects Logit Subsample with the Subsample of Dropped Observations

	Men (N=14,398)			Women (N=14,154)		
Variables	**FE Logit Subsample**	**Dropped Subsample**		**FE Logit Subsample**	**Dropped Subsample**	
N	1,778	12,620		2,348	11,806	
Cannabis use variables in the past year						
Any cannabis use (%)[2]	12.93	7.19	***	6.38	3.81	**
Less than weekly cannabis use (%)	7.64	4.46	**	4.38	2.78	
Weekly but less than daily cannabis use (%)	4.16	2.10		1.10	0.76	
Daily cannabis use (%)	1.12	0.62		0.89	0.26	
Cannabis abuse and/or dependence (%)	3.76	2.56		1.74	0.90	
Demographics and other characteristics						
White (%)	57.70	63.72	***	62.35	64.76	*
African American (%)	17.43	13.40	***	17.29	16.70	
American Indian/Alaska Native (%)	2.24	1.56		1.53	1.52	
Asian or Pacific Islander (%)	3.37	2.58		1.95	1.89	
Hispanic (%)	19.23	18.71		16.86	15.11	
Born outside U.S. (%)	12.59	15.45	*	12.01	9.68	*
Age	41.51 (12.92)	41.27 (10.33)		40.96 (11.27)	41.93 (10.35)	***
Currently married (%)	49.60	63.74	***	54.72	54.65	
Currently widowed, separated or divorced (%)	18.95	15.45	**	22.78	24.25	
Never married (%)	31.43	20.79	***	22.48	21.08	
Persons in household	2.49 (1.45)	2.79 (1.48)	***	2.84 (1.47)	2.69 (1.37)	***
Years of schooling	13.52 (3.11)	14.04 (3.16)	***	13.71 (2.74)	14.26 (2.90)	***
Reside in urban area (%)	83.68	83.57		83.09	84.29	
General health scale (SF 12)[3]	49.87 (11.74)	52.90 (9.96)	***	50.58 (11.47)	52.49 (10.39)	***
Mental health scale (SF 12)[3]	51.03 (10.93)	53.21 (9.16)	***	49.23 (10.86)	50.70 (9.95)	***
Weekly binge drinker (%)	24.46	18.29	***	6.13	4.84	
Current smoker (%)	42.91	35.00	***	34.88	25.84	***
Other drug user (%)[4]	7.81	4.68	**	5.66	4.08	

	Men (N=14,398)			Women (N=14,154)	
Variables	**FE Logit Subsample**	**Dropped Subsample**		**FE Logit Subsample**	**Dropped Subsample**
State unemployment rate (%) [5]	5.10 (0.97)	5.04 (0.98)	**	5.03 (1.01)	5.02 (0.98)

Notes: Sample excludes women who were pregnant at any time during the year prior to interview and individuals who were under age 21 in Wave 1 and age 65 or older in Wave 2. Standard deviations in parentheses.

[1]Total personal income in past 12 months (including any income from food stamps) converted to constant 2001 USD.

[2]Any cannabis use is equal to one for individuals who used cannabis in the last 12 months.

[3]Scores derived from the SF-12 health survey that measures physical and social functioning, role functioning, bodily pain, general health, vitality, and mental health. The range is from 0-100 with higher scores reflecting better physical and mental health status.

[4]Any of the following drugs used in the past year: sedatives, tranquilizers, opioids, amphetamines, cocaine or crack, hallucinogens, inhalants, and heroin.

[5]The state unemployment rate was calculated as an average of the rate over the past 12 months prior to interview date.

***Statistically significant difference in variable medians across the binge drinking categories, $p<0.01$, Kruskal-Wallis equality of populations rank test.

**Statistically significant difference in variable medians across the binge drinking categories, $p<0.05$, Kruskal-Wallis equality of populations rank test.

*Statistically significant difference in variable medians across the binge drinking categories, $p<0.10$, Kruskal-Wallis equality of populations rank test.