

# Marijuana Decriminalization and Labor Market Outcomes

Economic Self-Sufficiency Policy Research Institute

Timothy Young  
University of California, Irvine

10-27-2016

# Marijuana Decriminalization and Labor Market Outcomes

Working Paper<sup>1</sup>

Timothy Young<sup>2</sup>  
Department of Economics  
University of California, Irvine

October 27<sup>th</sup>, 2016

## Abstract

This paper uses marijuana decriminalization laws, passed in 21 states over the last 40 years, to analyze the differences in earnings and employment that result from being arrested. A differences-in-differences model is used to exploit the state-by-year variation in arrests resulting from marijuana decriminalization laws. Data from the FBI's Uniform Crime Reporting statistics and the Current Population Survey allow for age, gender and race specific estimates, which is critical considering the heterogeneity in rates of arrests across these delineations. Labor market outcomes in the CPS allow for an analysis of whether decriminalization laws affect extensive and intensive margins. Decreased penalties for marijuana possession are positively correlated with the probability of employment, although the results are imprecise. Additionally, there are non-trivial increases in weekly earnings for individuals living in states with decreased penalties, with the effects being greatest for black adults. This result is consistent with existing literature that suggests black adults, especially men, stand to benefit the most from removing these penalties.

---

<sup>1</sup> Please do not cite without author's permission

<sup>2</sup> I would like to thank the Economic Self-Sufficiency Research Policy Institute (ESSPRI) for generously providing support for this project. Any opinions expressed are my own and should not be construed as representing the opinions of the Institute or the funders. I would also like to thank David Neumark, Ying Ying Dong, Patrick Button, those who participated in the 2016 Western Economic Association International conference in Portland, OR, and those who participated in the UC Irvine Applied Microeconomics group for their invaluable comments. All errors are my own. Contact information: [youngt3@uci.edu](mailto:youngt3@uci.edu)

## 1. Introduction

The last 40 years have brought about an era of mass incarceration in the United States. As shown in figure 1, the prison population has grown nearly 500% over this time period (Mauer and King, 2007) (see figure 1). Much of the increase in the incarcerated population over this time period was due to drug offenders. By the 2000s, 30% of all inmates in state and federal prisons were drug offenders, compared to less than 8% in 1980 (Kuziemko and Levitt, 2004). Of those arrested in 2010 for drug offenses, 52% were for marijuana and 88% of those were for marijuana possession (ACLU 2013).

The increase in arrests and incarceration of drug offenders since the 1980s does not appear to be driven by increases in drug use. Instead, evidence shows that the prison population growth is driven by stronger enforcement of drug laws and more severe penalties for those convicted of drug offenses, both of which could be correlated with economic conditions (Basov et al., 2001). Additionally, despite similar rates of marijuana use, blacks are four-times more likely to be arrested for marijuana related offenses than whites (Union, 2013). For their share of the population, black males are overrepresented in U.S. prison population growth compared to whites (see Figure 2). By 2008 the total number of working age ex-prisoners was estimated to be around 12-14 million with males, 92% of whom were male (Schmitt and Warner 2010). Considering the large and growing number of ex-drug offenders in the labor market, an important policy question is how much this era of mass incarceration has affected the employment and earnings of both young men and whether the effect differs by race. My paper provides evidence on how removing harsh penalties for non-violent drug offenses, such as marijuana possession, affects employment and earnings for those most likely to be arrested.

Estimating the effect of drug related arrests on earnings and employment for working age adults would be upward biased if the probability of arrest is correlated with unobservable factors that influence labor market outcomes such as work ethic or employer prejudice. For example, black men who reside in states with high prejudice may face an increased likelihood of being arrested for drug related offenses and may also earn lower wages on average compared to white men because of employer prejudice. Estimating the effect of drug related arrests on state level labor market outcomes would be downward biased if prejudice is correlated with labor market outcomes and police practices. To remedy this omitted variable bias, I use the timing of marijuana decriminalization laws as a plausible source of exogenous variation to instrument for the probability of being arrested.

As of November 2015, 21 states have passed some form of marijuana decriminalization law beginning with Oregon in 1973. A state is considered to have decriminalized marijuana if the penalty for possessing marijuana is a non-arrestable offense. Most states with marijuana decriminalization laws still consider marijuana possession illegal; however, infractions resulting from possession of small amounts of marijuana result in at most a civil fine, similar to a traffic ticket. While laws vary across states, the essential feature I exploit is that decriminalization laws affect state-by-year changes in the probability of being arrested for marijuana possession<sup>3</sup>.

Many papers have explored the impact of incarceration on labor market outcomes. Research relying on data from longitudinal surveys (Western, 2002, 2006), employer surveys (Holzer, 2007) and audit studies (Pager, 2003, 2007) find that incarceration is related to diminished labor market outcomes. This is in contrast to the results from administrative data

---

<sup>3</sup> Some states that decriminalized marijuana possession still have incarceration as a punishment for repeated marijuana possession offenses

studies (Cho and LaLonde, 2005; Needels, 1996; Sabol et al., 2007; Waldfogel, 1994), which find small or null results of the impact of incarceration on employment and earnings. All of these studies struggle with clearly addressing confounding unobservable factors related both to being arrested and labor market outcomes.

Studies using natural experiments have better identification than the survey and audit studies that struggle to address the endogeneity of arrest. Beginning with Kling (2006), several papers (Aizer and Doyle Jr, 2011; Mueller-Smith, 2014) have used the randomization of judges as an instrument for sentence length. The idea behind this approach is that judges and prosecutors differ in their likelihood of assigning severe penalties and prison time for defendants. Since defendants are randomly assigned judges and prosecutors for their cases, the outcomes of an arrest should not be correlated with the individual characteristics of the defendant. This type of natural experiment is rather convincing given the randomization of sentence length. However, this design is only identified from variation on the intensive sentencing and conviction margin after individual is already arrested.

This paper differs from the previous literature in two notable ways. First, it estimates the effect of being arrested on labor market outcomes while addressing the endogeneity of being arrested by using plausibly exogenous law changes. Second, this is the first paper to estimate the effect of removing harsh penalties for marijuana possession labor market outcomes, a contemporarily important policy topic.

I use the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) for 1976-2013 and U.S. Census Population Estimates for 1970-2015 to calculate state-by-year marijuana arrest rates by age, gender and race. The Current Population Survey (CPS) provides data on labor

market outcomes and individual level socio-economic characteristics such as age, race, gender and educational attainment. A differences-in-differences model is used to exploit the state level panel data structure of the UCR, the CPS and the state-by-year varying marijuana laws. This identification strategy estimates the effect of being arrested on employment and earnings by state and year.

A primary concern for instrumental variables models is the validity of the instrument. Stock and Yogo (2005) suggest a benchmark for an instrument to be valid is to have a first stage F-statistic greater than 10. Due to the state-by-year panel structure of the UCR and CPS, errors within states over time will be correlated<sup>4</sup>. Stock and Yogo (2005) rule-of-thumb does not apply when errors are non-iid (Finlay and Neumark, 2010). Therefore, for decriminalization laws to be a valid instrument for arrests, they need not have an F- statistic as high as 10 to still produced unbiased causal estimates. Decriminalization laws are strongly and negatively related to arrests for marijuana possession, especially for black adults. Reduced form results suggest marijuana decriminalization laws are positively associated with higher probability of employment, although this result is not precisely estimated. On the intensive labor market margin, decreased penalties for marijuana possession are related to increased weekly earnings.. For black adults, this appears to be driven by an increase in wages that outweighs a decrease in hours worked. For white adults, increased hours worked and higher wages lead to an increase in weekly earnings.

## 2. Background

### 2.1 Effect of Arrest and Incarceration on Labor Market Outcomes

---

<sup>4</sup>All standard errors presented in this paper are adjusted for within state correlation of errors

Being arrested affects an individual's labor market outcome through two primary channels. First, the act of being arrested directly disrupts current employment while the arrested individual is booked and awaits bail. Further repercussions from the arrest, such as meeting with lawyers and attending court, can also disrupt current employment. The impact of an arrest on juveniles has been shown to lead to minor labor market problems (Bushway, 1998). The second channel an arrest affects labor market outcomes is through conviction and incarceration.

The impact of imprisonment on labor market earnings and employment is theoretically ambiguous. Incarceration can be rehabilitative for offenders by imposing structure to help organize their lives, which can increase earnings after being released (Nagin and Waldfogel, 1995). Additionally, correctional institutions provide educational credential programs, which can increase human capital, decrease recidivism and improve emotional and social behavior, all of which can increase labor market success (Vacca, 2004).

Incarceration negatively affects ex-offenders' labor market outcomes through labor supply and labor demand channels. The forced removal from the labor market, while incarcerated, directly affects offenders' labor supply. Assuming an individual would have otherwise been working in the absence of incarceration, involuntary removal from the labor force decreases work history, experience and depreciates job specific human capital. Additionally, removal from society prevents the development of informal social networks essential to finding employment upon release.

Analysis of longitudinal surveys comparing individuals' labor market outcomes before and after incarceration suggests incarceration negatively impacts labor market outcomes (Western, 2002, 2006). However, these studies fail to account for the endogeneity of being

arrested. Their estimates are likely biased since there are unobservable characteristics that affect one's decision to commit a crime and the probability of employment.

The stigma that follows ex-offenders into the labor market results in lower labor demand compared to non-offenders. The mark of incarceration generates a negative signal to employers that an applicant is untrustworthy and less reliable than non-offenders (Holzer, 2007; Western, 2002, 2006; Western et al., 2001). Employer surveys, which are useful for understanding the labor demand impacts of incarceration, point to significantly lower employer preferences for applicants with a criminal history compared to those without one (Holzer, 2007). Audit studies, which measure revealed preferences of employers, echo the results from survey studies; applicants with criminal histories are less likely to receive callbacks from potential employers compared to applicants without a criminal background, especially if the applicant is black (Pager, 2003, 2007).

Several studies use administrative data to estimate the effect of being arrested on labor market outcome. Administrative prison level data are linked to employment outcomes by matching former inmates to their unemployment insurance records. Results from administrative data studies find little or no negative impact of incarceration on labor market outcomes (Cho and LaLonde, 2005; Needels, 1996; Sabol et al., 2007; Waldfogel, 1994) and stand in stark contrast to those from longitudinal and audit studies. Therefore, there is still uncertainty regarding the impacts of an incarceration on earnings and employment.

One of the difficulties in estimating the impact of incarceration on aggregate state-by-time labor market outcomes is that the number of ex-offenders in the population is not well reported. Using Bureau of Justice data on flows of releases since 1962, Schmitt and Warner



(2011) estimate of the number of ex-offenders in the labor market through 2008. Their estimates depend on several assumptions such as the age structure for ex-offenders, annual death rate and the recidivism rate. They estimate there to be about 5,500,000 ex-prisoners and 12,500,000 ex-felons of working age in 2008. Making further assumptions about the impact of being an ex-offender on employment suggests that a mid-range estimate for the reduction in employment for ex-felons is 2.5 percentage points. An important distinction between Schmitt and Warner (2011) and my paper is that I focus entirely on those affected by marijuana possession arrests, which does not necessarily imply conviction and incarceration.

## 2.2 Marijuana Decriminalization

Twenty-one states in the United States have decriminalized marijuana beginning with Oregon in 1973. Eleven of these states passed marijuana decriminalization laws during the 1970s in response to the tough-on-crime federal legislation passed earlier in the decade. Marijuana decriminalization is not the same as legalization; many decriminalized states still have some form of punishment for possession. The common implication of decriminalization is that the criminal status for possession is removed for certain quantities.

Table 1 lists the states with marijuana decriminalization laws, dates legislation is enacted and details of each law. States differ on how much marijuana individuals are allowed to possess without criminal repercussions. Maryland and Missouri only allow individuals to carry up to 10 grams without risk of criminal punishment, however many other states, including Maine, California and Oregon allow for possession of 1 ounce or more. Additionally, some states limit the scope of marijuana decriminalization laws to individuals age 21 and over with no change to criminal punishments for those under 21 who are arrested for possession. States also differ in

how first offense for possession is classified. There are no criminal or civil punishments for possession for up to 1 ounce of marijuana in Alaska, Colorado, Oregon and Washington. In all other decriminalized states, possession of marijuana is classified as a civil violation, infraction, or minor misdemeanor.

The heterogeneity in state decriminalization laws suggests state specific differentials of the impact on arrest rates. Pacula et al. (2005) suggests that previous studies using broad measures of marijuana decriminalization on marijuana and other substance use obscure important details in the laws. They argue that decriminalization laws can be split into three main categories: recognized decriminalized state, non-criminal status offense and expunged charge conditional on a completed sentence. This paper abstracts from the heterogeneity in laws and treats any state with a marijuana decriminalization law as a decriminalized state.

Medical marijuana laws have been used as an instrument for marijuana use by several researchers looking at the effects of marijuana use on outcomes such as body weight (Sabia et al., 2015), drunk driving fatalities (Anderson et al., 2013) and most recently labor market outcomes (Sabia and Nguyen, 2016). 23 states and the District of Columbia have adopted medical marijuana laws, beginning with California in 1996. There is substantial overlap between states with medical marijuana laws and marijuana decriminalization laws. It is notable that Sabia and Nguyen (2016) find that medical marijuana laws decrease hourly earnings for young adult males. Given this, I include an indicator<sup>5</sup> for whether a state has a medical marijuana law since this is correlated to decriminalization laws and labor market outcomes.

### 3. Data

---

<sup>5</sup> Effective dates of medical marijuana legislation are based on Table 2 from Sabia and Nguyen (2016)

### 3.1 Arrest Data

The Federal Bureau of Investigation's (FBI) Uniform Crime Report (UCR) provides annual agency level data on marijuana possession arrests from 1976-2013. I aggregate agency data to the state level to merge in marijuana decriminalization laws and CPS data. Arrest counts are provided by age-sex and race separately. Therefore, it is not possible to observe specific age-by-race arrest counts however there are measures of race-by-age arrest counts where age is either juvenile or adult. Additionally, specific age-sex arrest counts are only available until age 24. Data for individuals over 24 years old are grouped into 5-year age-sex bins. Age-sex and race grouped state-by-year level arrest rates are calculated by dividing the UCR arrest counts in a particular state and year by the respective subpopulation Census Population Estimate. For ease of interpretation, all rates are converted to percent.

Figure 3 shows how arrests for marijuana possession have trended since the 1976 between decriminalized and non-decriminalized states. For states that decriminalized marijuana possession, there is little change in rates of arrests over the last several decades. For states that have not decriminalized marijuana possession, there is a clear upward trend. These trends for decriminalized and non-decriminalized states are consistent for subgroups of white adults, black adults and young males. Regardless of whether a state has decriminalized marijuana or not rates are persistently higher for black adults than white adults. Rates are highest for males between the ages 20-24.

There are several limitations to the UCR. First, the UCR has missing data issues. Of the 18,000 individual reporting agencies throughout the sample period, only about 9% report every year due to the FBI's voluntary reporting requirements for law enforcement agencies. To create a

balanced panel from the UCR I limit the sample to the 9% of agencies that report every year. This eliminates attrition bias but also severely downward biases estimates because this procedure omits arrest counts from law enforcement agencies that fail to report consistently over time. Second, although the UCR began collecting data in 1930, data on marijuana arrests is only available starting in 1976 and race is not consistently reported until 1980. Unfortunately, this means that arrest counts for marijuana possession are only available after many states had already enacted marijuana decriminalization laws. Therefore, this data set does not allow for an effective test of pre-trend assumptions for early adopting states.

### 3.2 Labor Market Data

Labor market outcomes and demographic controls are collected from the 1970-2015 Current Population Survey (CPS) and accessed through IPUMS-USA database (Sarah Flood and Warren, 2015). After limiting the sample to working age individuals between 18 and 64 there are about 4.4 million observations. The CPS is well suited for my analysis because it contains individual level data on employment for the full sample period of arrest data. Additionally, demographic controls for age, race, gender, state of residence and educational attainment are available for the same period.

Starting in 1989, data are available for hourly wages, weekly hours worked and weekly earnings. Hourly wages are reported for workers who are paid by the hour. Weekly hours worked is self reported for employers, employees and unpaid family workers. Weekly earnings are calculated by the CPS as the greater of two values: “1) the respondent’s answer to the question, ‘How much do you usually earn per week at this job before deductions?’; or 2) for workers paid by the hour (and coded as ‘2’ in PAIDHOUR), the reported number of hours the respondent

usually worked at the job, multiplied by the hourly wage rate given in HOURWAGE.” For the full sample, there are about 227,000 observations for hourly wages, 300,000 observations for hours worked and about 376,000 observations for weekly earnings. All earnings data are deflated by the Consumer Price Index to 1999 dollars.

#### 4. Model Specification

The main methodology used in this paper is to estimate a differences-in-differences model using instrumental variables. Least squares is used to estimate the following reduced form model:

$$Y_{ist} = \alpha_0 + \gamma \text{Decrim}_{st} + \theta \text{MML}_{st} + X'_{ist} \beta + \lambda_s + \varphi_t + \varepsilon_{ist} \quad (1)$$

where  $Y_{ist}$  represents inflation adjusted weekly earnings or hourly wages for individual  $i$  in state  $s$  in time  $t$ . To estimate the impact on employment, a binary outcome, a probit model is used to estimate equation (2).  $\lambda_s$  and  $\varphi_t$  are state and time fixed effects respectively and are included in all models to account for across state and time unobserved differences. The estimate of  $\gamma$  identifies the average treatment effect of a state decriminalizing marijuana on state-level average labor market outcomes.

To test the relevance assumption of marijuana decriminalization laws as a valid instrument for marijuana possession arrests, I estimate a first stage with the following differences-in-differences equation:

$$\text{Arrests}_{st} = \alpha_1 + \delta \text{Decrim}_{st} + \theta \text{MML}_{st} + X'_{ist} \beta + \lambda_s + \varphi_t + \varepsilon_{st} \quad (2)$$

$X'$  is a vector of state average observable characteristics including age, race, sex and highest

educational attainment reported in the CPS. MML controls for whether a state has passed a medical marijuana law.  $\lambda$  and  $\varphi$  are state and time fixed effects respectively. Decrim is an indicator coded as one if state  $s$  has a marijuana decriminalization law in year  $t$  and zero otherwise. A partial F-test is used to jointly test all coefficients equal to zero for equation (1) test the relevance of decriminalization laws as an instrument.

Marijuana arrests vary greatly across age, race and gender. Given that black men are four-times more likely to be arrested for marijuana related offenses compared to white men in the U.S. (Union, 2013), and 62% of marijuana possession arrests were of individuals under the age of 25, I estimate the first stage model separately for males, white adults, black adults and young males separately. Due to limitations of the UCR, it is not possible to look at white males or black males separately. The reduced form specification, model (2), also estimates these subpopulations but further explores impacts on white males and black males, which is not possible with the UCR data.

There are several limitations to this identification strategy. First,  $\theta$  is a general equilibrium estimate of the impact of removing harsh penalties for marijuana possession on labor market outcomes. Unfortunately, given that the arrest data are not at the individual level, it is not possible to explore partial equilibrium mechanisms through which these policies may be affecting labor market outcomes. For example, it is possible that marijuana decriminalization affects rates of marijuana use. If marijuana use directly affects one's labor market outcome, as found in Sabia and Nguyen (2016), then  $\gamma$  does not isolate the impact of decriminalization on labor market outcomes through the supply and demand channels discussed earlier. Secondly, this identification strategy only accounts for contemporaneous impacts of law changes; it does not take into account individuals who had convictions prior to passage of a decriminalization law.

## 5. Results

### 5.1 First Stage

Table 3 presents first stage estimates using equation (1). In order for marijuana decriminalization laws to be a valid instrument for marijuana possession arrests there needs to be a strong relationship between changes in the law and changes in arrests. Since males make up the majority of those arrested for marijuana possession arrests the subsample analysis focuses predominantly on males when possible. Marijuana decriminalization laws are negatively associated with arrests for marijuana possession for all samples. Estimates are most precisely for black adults and are marginally significant for white adults. Decriminalization laws are associated with a decline in marijuana possession arrests of black adults of about 7.3 percentage points. Based on a mean arrest rate of 0.15%, this implies that passing decriminalization laws are associated with a reduction in marijuana possession arrests for black men of 48.7%. White adults experience a decrease in arrests of 1 percentage point. Based on a mean of 0.34%, this implies a decrease in arrests of about 30% for white adults. This is consistent with the prior evidence that blacks have a higher probability of being arrested for possession of marijuana and therefore will be most affected by changes to marijuana possession legal penalties (Union, 2013).

The greatest reduction in arrests occurs for males between 20-24 years old although it is imprecisely estimated. The imprecision for young males is not surprising given that the sample size is significantly reduced. Unfortunately, the UCR is not high enough quality to allow for a subsample analysis of young black men, who have the highest probability of being arrested.

The partial F-statistics for the columns 2-4 are statistically significant but less than the benchmark of 10 established by Stock and Yogo (2005). Given that errors within the same state

are likely not iid implies that this benchmark does not apply. When standard errors are not clustered at the state level, decriminalization laws are strongly correlated with marijuana possession arrests. Additionally, it should be noted that a strong first stage may be difficult to attain with only 9% of the full UCR data.

## 5.2 Reduced Form

Table 4 presents differences-in-differences estimates of equation (2) using a probit model measuring the effect of marijuana decriminalization laws on the probability of employment. Decriminalization laws are positively associated with the probability of employment for all groups but are small and statistically insignificant. As with the first stage results, the largest impacts are for young males. Somewhat surprisingly, estimates are smallest for black adults and black males. This provides suggestive evidence that marijuana decriminalization laws improve the extrinsic labor market outcomes.

Weekly earnings are higher on average for individuals living in states where marijuana is decriminalized when controlling for age and other demographics compared to states with harsher penalties. Table 5 presents differences-in-differences estimates of the effect of decriminalization on weekly earnings. For the full sample of males, marijuana decriminalization laws are associated with an average increase of 4.5% increase in weekly earnings. The estimated impacts are large for black and white males and are precisely estimated for all groups except males between 20-24 years old. Due to limited availability of weekly earnings data, the regression is identified on state and year variation from 1989-2013.

Table 6 shows that marijuana decriminalization is positively associated with the wages of hourly paid workers. Increases in the weekly earnings observed for black adults are driven by an



increase in the average hourly wage they receive. Decriminalization laws are associated with an increase in hourly wages of 6.9% for black males. The fact that impacts are greater for black adults than for whites is consistent with black adults being the most at risk for arrest and thus benefit the most from removal of harsh marijuana possession penalties. Results for hourly wages are not as precisely estimated, in part, due to the small number of individuals that responded to this question in the CPS.

Decriminalization laws are positively though imprecisely related to weekly hours worked for whites, but not for black adults. Table 7 shows that whites who live in decriminalized states work about the same number of hours per week but black adults work about 2% less hours per week on average compared to non-decriminalized states. This suggests that decreasing the probability of arrest for black adults increases weekly earnings through higher wages, which offset working fewer hours per week. Whites experience an increase in both hours worked and decriminalization laws affect hourly wages suggesting both channels.

## 6. Conclusion

In 2016 there are 13 states with full recreational marijuana legalization on the ballot. Legalization goes beyond decriminalization in that such laws eliminate any penalty, including civil violations fines, for possession of certain quantities. Understanding the effects of decriminalization laws on arrests and labor market outcomes informs the policy debate over whether these measures are worth enacting.

This paper provides evidence that individuals living in states that pass marijuana decriminalization laws have higher average weekly earnings but there does not appear to be a statistically significant impact on employment. These estimates should not necessarily be

interpreted causally because the UCR data does not allow a test of pre-trend assumptions. This analysis can be improved with a better individual-level data set that provides data on demographics, labor market outcomes and criminal history. While I'm unaware of the existence of such a dataset, NCRP restricted data would be an improvement. The NCRP can be used to estimate the number of offenders in the labor market with a record of marijuana possession. This data provides individual level data with age, and demographic information as well flows of inmates in and out of incarceration. Since long run effects of an arrest are most likely to come through incarceration, this data provides a much better estimate of the impact of decriminalization laws on the number of ex-offenders in the labor force. That is, arrests are merely a proxy for estimating the number of ex-offenders in the population. The NCRP is a direct measure of how many ex-offenders are flowing into the labor market over time.

## References

Aizer, A. and Doyle Jr, J. J. (2011). Juvenile incarceration and adult outcomes: Evidence from randomly assigned judges. NBER Working Paper, 7(9):10.

Anderson, D. M., Hansen, B., and Rees, D. I. (2013). Medical marijuana laws, traffic fatalities, and alcohol consumption. *Journal of Law and Economics*, 56(2):333–369.

Basov, S., Miron, J., and Jacobson, M. (2001). Prohibition and the market for illegal drugs. *World Economics*, 2(4):113–158.

Bushway, S. D. (1998). The impact of an arrest on the job stability of young white american men. *Journal of research in Crime and Delinquency*, 35(4):454–479.

Cho, R. and LaLonde, R. (2005). The impact of incarceration in state prison on the employment prospects of women.

Finlay, K. and Neumark, D. (2010). Is marriage always good for children? evidence from families affected by incarceration. *Journal of Human Resources*, 45(4):1046–1088.

Holzer, H. J. (2007). Collateral costs: The effects of incarceration on the employment and earnings of young workers.

Kling, J. R. (2006). Incarceration length, employment, and earnings. Technical report, National Bureau of Economic Research.

Kuziemko, I. and Levitt, S. D. (2004). An empirical analysis of imprisoning drug offenders. *Journal of Public Economics*, 88(9):2043–2066.

Mauer, M. and King, R. S. (2007). *Uneven justice: State rates of incarceration by race and ethnicity*. Sentencing Project Washington, DC.

Mueller-Smith, M. (2014). *The criminal and labor market impacts of incarceration*. Unpublished Working Paper.

Nagin, D. and Waldfogel, J. (1995). The effects of criminality and conviction on the labor market status of young british offenders. *International Review of Law and Economics*, 15(1):109–126.

Needels, K. E. (1996). Go directly to jail and do not collect? a long-term study of recidivism, employment, and earnings patterns among prison releasees. *Journal of Research in Crime and Delinquency*, 33(4):471–496.

Pacula, R., MacCoun, R., Reuter, P., Chriqui, J., Kilmer, B., Harris, K., Paoli, L., and Schafer, C. (2005). What does it mean to decriminalize marijuana? a cross-national empirical examination. *Advances in health economics and health services research*, 16:347– 369.

Pager, D. (2003). The mark of a criminal record<sup>1</sup>. *American journal of sociology*, 108(5):937–975.

Pager, D. (2007). The use of field experiments for studies of employment discrimination: Contributions, critiques, and directions for the future. *The Annals of the American Academy of Political and Social Science*, 609(1):104–133.

Sabia, J. J. and Nguyen, T. T. (2016). The effect of medical marijuana laws on labor market outcomes.

Sabia, J. J., Swigert, J., and Young, T. (2015). The effect of medical marijuana laws on body weight. *Health economics*.

Sabol, W. J., Couture, H., and Harrison, P. M. (2007). *Prisoners in 2006*. US Department of Justice, Bureau of Justice Statistics Washington, DC.

Sarah Flood, Miriam King, S. R. and Warren, J. R. (2015). Integrated public use microdata series, current population survey: Version 4.0.

Schmitt, J. and Warner, K. (2011). Ex-offenders and the labor market. *WorkingUSA*, 14(1):87–109.

Stock, J. H. and Yogo, M. (2005). Testing for weak instruments in linear iv regression. *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*.

Union, A. C. L. (2013). The war on marijuana in black and white: Billions of dollars wasted on racially biased arrests.

Vacca, J. S. (2004). Educated prisoners are less likely to return to prison. *Journal of Correctional Education*, pages 297–305.

Waldfogel, J. (1994). Does conviction have a persistent effect on income and employment? *International Review of Law and Economics*, 14(1):103–119.

Western, B. (2002). The impact of incarceration on wage mobility and inequality. *American Sociological Review*, pages 526–546.

Western, B. (2006). *Punishment and inequality in America*. Russell Sage Foundation. Western, B., Kling, J. R., and Weiman, D. F. (2001). The labor market consequences of incarceration.

Crime & delinquency, 47(3):410–427.

Figure 1. U.S. Prison Population Growth: 1978-2014

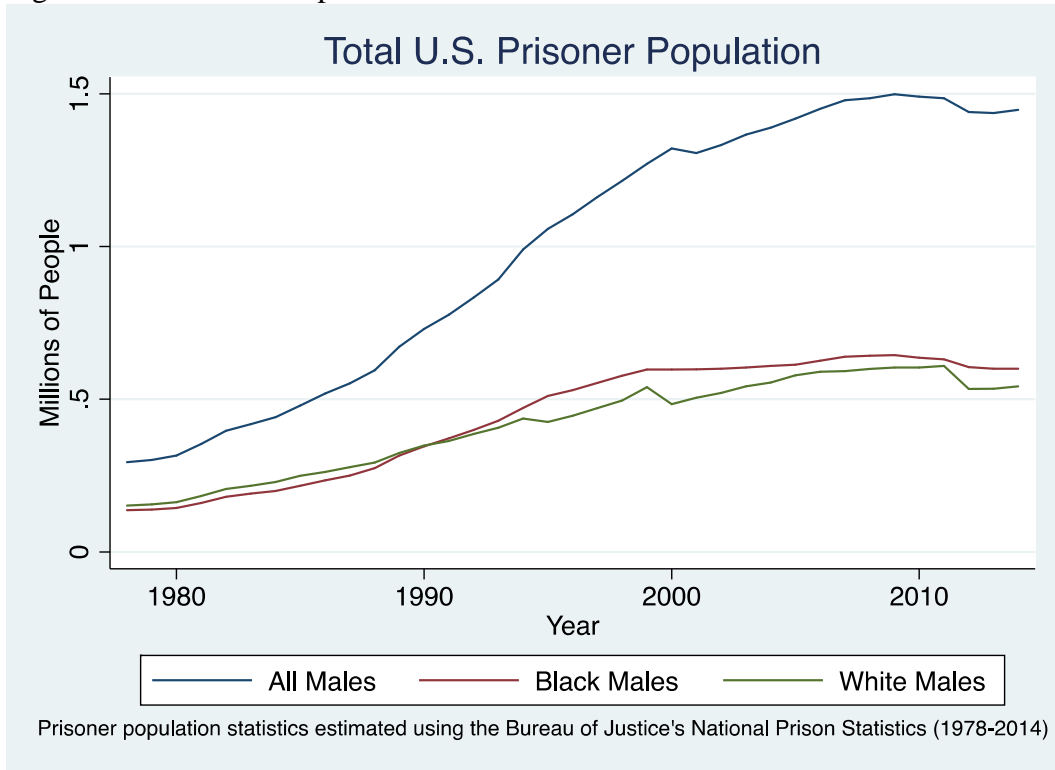


Figure 2. Racial Disparities in Prison Population Growth: 1978-2014

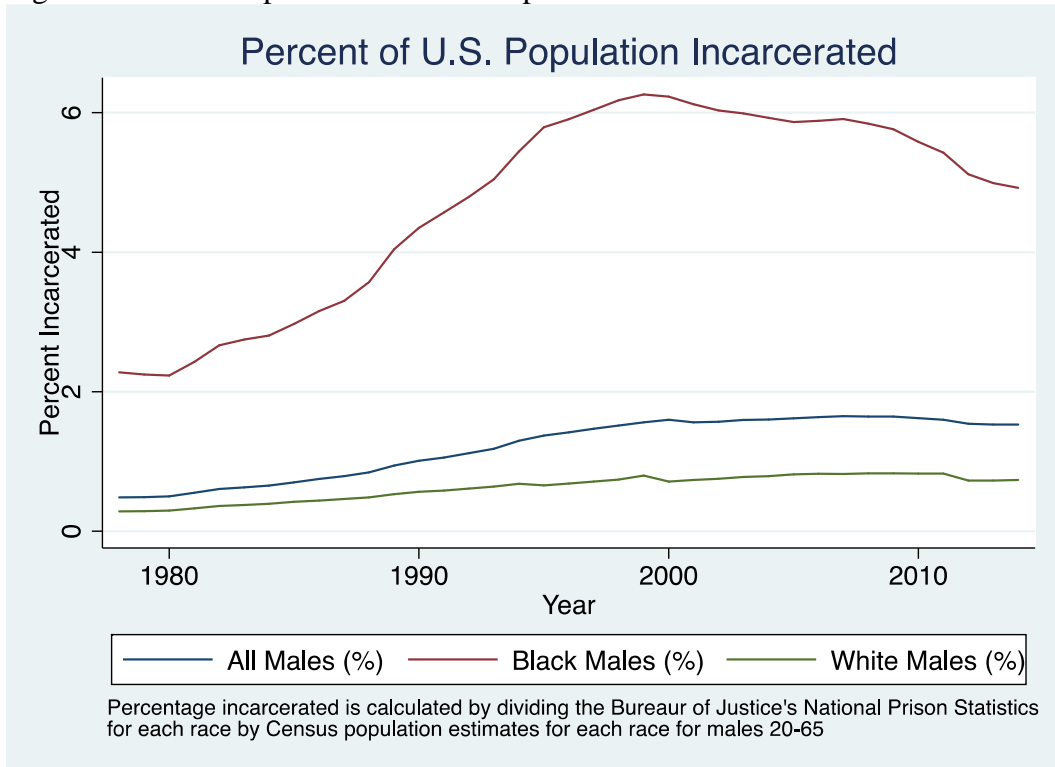


Figure 3. Trends in Average Percentage Arrested for Marijuana Possession



Note: Graphs show state-by-year percentages of males arrested for marijuana possession by race, age group, and total. Percentages are calculated by dividing annual state marijuana possession arrest counts from the FBI's Uniform Crime Report by Census population estimates for each respective group.



Table 1: State Marijuana Decriminalization Laws

State	Date	Quantity for Law to Apply	First Offense Penalty	Classification for First Offense
Alaska	2014	Up to 1 oz.	None for adults age 21+	None for adults age 21+
California	1976	Up to 1 oz.	\$100 fine	Infraction
Colorado	1975	Up to 1 oz.	No penalty for age 21+ \$100 fine for under 21	None for adults age 21+
Connecticut	2011	Up to 1/2 oz.	\$150 fine; under 21, lost driver's license	Civil violation
Delaware	2015	Up to 1 oz.	\$100 civil fine if over 18	Civil violation
District of Columbia	2014	Up to 2 oz.	21+: no penalty; \$25 fine if under 21	21+: No penalty; under 21: civil violation
Maine	1976	Up to 2.5 oz.	\$350-\$600 fine for up to 1.25 oz.; \$700-\$1,000 for 1.25-2.5 oz.	Civil violation
Maryland	2014	Up to 10 grams	\$100 fine	Civil offense
Massachusetts	2008	Up to 1 oz.	Adults: \$100 fine; juveniles: \$100 fine and drug classes	Civil offense
Minnesota	1976	Up to 42.5 grams	\$300 fine and participation in drug education program	Criminal petty misdemeanor
Mississippi	1977	Up to 30 grams	\$100-\$250 fine	Civil summons
Missouri	2017	Up to 10 gram	\$250-\$1000 fine	Infraction
Nebraska	1978	Up to 1 oz.	\$300 fine and possible drug classes	Civil infraction
Nevada	2001	Up to 1 oz.	Up to \$600 fine and possible rehabilitation and treatment	Criminal misdemeanor
New York	1977	Up to 25 grams not in public view	Up to \$100 fine	Civil violation
North Carolina	1977	Up to 1/2 oz.	Up to \$200 fine, possible suspended sentence	Criminal misdemeanor
Ohio	1975	Up to 100 grams	\$150 fine	Minor misdemeanor (Class 3)
Oregon	1973	21+: No penalty up to 8 oz.; Under 21: fine for up to 1 oz.	No penalty for 21+; \$650 for under 21	None for 21+; civil violation for under 21
Rhode Island	2012	Up to 1 oz.	\$150 fine; minors must complete drug classes	Civil offense
Vermont	2013	Up to 1 oz. or 5 grams of hash	Adults: up to \$200 fine; under 21: generally diversion	Civil infraction
Washington	2012	Up to 1 oz.(adults)	21+: No penalty	21+: None; under 21: misdemeanor

Source: Marijuana Policy Project. Downloaded October 2016 from <https://www.mpp.org/issues/decriminalization/state-laws-with-alternatives-to-incarceration-for-marijuana-possession/>

Table 2. Summary Statistics

	N	Mean	Standard Deviation
<u>Current Population Survey: 1970-2015</u>			
Age	4,421,215	39.02	12.92
Labor force status	4,392,989	0.762	0.426
Hours worked last week	33,024,427	39.49	13.30
Hourly wage	227,884	11.73	6.747
Weekly earnings	376,698	614.2	449.5
Male	4,421,215	0.481	0.500
White	4,421,215	0.838	0.368
Black	4,421,215	0.103	0.304
Other Race	4,421,215	0.0583	0.234
Hispanic	4,314,454	0.132	0.338
Married	4,421,215	0.605	0.489
Some High School or Less	4,421,210	0.329	0.470
HS Degree	4,421,210	0.201	0.401
Some college	4,421,210	0.314	0.464
College Degree	4,421,210	0.105	0.306
Graduate Degree	4,421,210	0.0512	0.220
Employed	3,346,857	0.936	0.244
<u>Uniform Crime Report: 1976-2013</u>			
Percent Arrested for Marijuana Possession:			
Adult Males	1,216	0.0000559	0.0000854
Males 25-29 years old	1,216	0.144	0.173
Males 20-24 year old	1,216	0.434	0.517
Females	1,216	0.00000844	0.0000128
Females 25-29 years old	1,216	0.0240	0.0303
Females 20-24 years old	1,216	0.0692	0.0861
White Adults	1,216	0.0369	0.0438
Non-Hispanic Adults	1,056	0.00816	0.0291
Hispanic Adults	1,056	0.00780	0.0344
Black Adults	1,216	0.146	0.194

Note: \*Means for relative shares arrested for marijuana possession are calculated by dividing the state-level count of arrests reported in the FBI's UCR and dividing by the state population for that particular group as estimated by the Census Population Estimates

Table 3. First Stage Differences-in-Differences Estimates of the Effect of Marijuana Decriminalization Laws on Arrests for Marijuana Possession

	(1) Males	(2) Whites	(3) Black Adults	(4) Males 20-24
Decriminalized	-0.0000165 0.0000139	-0.0101* (0.00512)	-0.0726** (0.0266)	-0.0930 (0.0614)
MML	-0.0000139** 0.0000143	-0.0106*** (0.00372)	-0.0845** (0.0323)	-0.179*** (0.0540)
Black	-0.00000165 0.0000007.69			0.00684 (0.00603)
White	-0.000000625 0.000000526			-0.000967 (0.00308)
College Degree	-0.00000162 0.00000112	2.87e-05 (0.000350)	0.00405 (0.00301)	0.00465 (0.00429)
Graduate Degree	-0.00000121 0.00000165	6.58e-05 (0.000385)	0.00675 (0.00535)	0.0132 (0.00834)
HS Degree	-0.00000191* 0.000000984	8.06e-05 (0.000326)	0.000670 (0.00115)	1.16e-05 (0.00258)
Some college	-0.00000113* 0.000000576	6.30e-05 (0.000230)	0.00103 (0.000899)	0.00141 (0.00183)
Male		-1.57e-05 (1.86e-05)	2.99e-05 (0.000275)	
Constant	-5.29e-06 (7.96e-06)	-0.0156 (0.0124)	-0.0853* (0.0474)	0.0841** (0.0411)
Observations	1,319,179	2,288,469	266,643	151,859
R-squared	0.921	0.870	0.832	0.912
F-statistic	1.41	3.86	7.46	2.30

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Note: Each column is separate regression estimation of equation (1) and includes state and year fixed effects. Robust standard errors, clustered at the state level, in parentheses.

Table 4: Probit Model Reduced Form Differences-in-Differences Estimates of the Effect of Marijuana Decriminalization Laws on Employment

	(1) Males	(2) White Adults	(3) Black Adults	(4) Males 20-24	(5) White Males	(6) Black Males
Decriminalized	0.0392 (0.0380)	0.0354 (0.0348)	0.0260 (0.0505)	0.0401 (0.0574)	0.0431 (0.0411)	0.0335 (0.0573)
MML	-0.00180 (0.0173)	-0.00224 (0.0159)	-0.0667* (0.0362)	-0.00698 (0.0279)	-0.00212 (0.0186)	-0.0242 (0.0321)
White	0.159*** (0.0360)			0.198*** (0.0514)		
Black	-0.252*** (0.0350)			-0.329*** (0.0503)		
Hispanic	-0.0323** (0.0144)			0.0217 (0.0220)		
College Degree	0.606*** (0.0273)	0.608*** (0.0174)	0.716*** (0.0243)	0.566*** (0.0361)	0.602*** (0.0247)	0.706*** (0.0336)
Graduate Degree	0.760*** (0.0255)	0.737*** (0.0181)	0.800*** (0.0342)	0.764*** (0.102)	0.751*** (0.0253)	0.789*** (0.0344)
HS Degree	0.214*** (0.0106)	0.238*** (0.00710)	0.256*** (0.0127)	0.168*** (0.0153)	0.221*** (0.0110)	0.227*** (0.0150)
Some college	0.409*** (0.0139)	0.413*** (0.00966)	0.456*** (0.0154)	0.443*** (0.0202)	0.413*** (0.0139)	0.424*** (0.0189)
Male		-0.0617*** (0.0135)	-0.0684*** (0.0155)			
Constant	1.037*** (0.0422)	1.385*** (0.0421)	0.826*** (0.0520)	0.973*** (0.0596)	1.414*** (0.0406)	0.886*** (0.0644)
Observations	1,760,331	2,834,246	324,555	187,873	1,556,849	150,195

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Note: Each column is separate probit estimation of equation (1) and includes age, state and year fixed effects. Robust standard errors are in parentheses. Standard errors are clustered at the state level.

Table 5. Reduced Form Differences-in-Differences Estimates of the Effect of Marijuana Decriminalization Laws on Logged Weekly Earnings

	(1) Males	(2) White Adults	(3) Black Adults	(4) Males 20-24	(5) White Males	(6) Black Males
Decriminalized	0.0451*** (0.00994)	0.0196 (0.0141)	0.0436** (0.0195)	0.0299 (0.0715)	0.0410*** (0.0101)	0.0175 (0.0296)
MML	-0.0303* (0.0160)	-0.0187* (0.0109)	-0.0536 (0.0362)	-0.0535 (0.0329)	-0.0302* (0.0154)	-0.0770 (0.0467)
White	0.156*** (0.00963)			0.117*** (0.0257)		
Black	-0.0788*** (0.0160)			-0.000785 (0.0388)		
Hispanic	-0.171*** (0.0179)			-0.0546*** (0.0188)		
College Degree	0.680*** (0.0162)	0.762*** (0.0263)	0.750*** (0.0157)	0.322*** (0.0372)	0.742*** (0.0268)	0.693*** (0.0236)
Graduate Degree	0.851*** (0.0226)	0.967*** (0.0279)	0.953*** (0.0235)	0.342*** (0.105)	0.898*** (0.0309)	0.897*** (0.0454)
HS Degree	0.262*** (0.0125)	0.308*** (0.0203)	0.247*** (0.0153)	0.140*** (0.0139)	0.312*** (0.0194)	0.246*** (0.0237)
Some college	0.326*** (0.0127)	0.397*** (0.0235)	0.380*** (0.0168)	-0.142*** (0.0184)	0.380*** (0.0242)	0.344*** (0.0233)
Male		0.418*** (0.0105)	0.219*** (0.0129)			
Constant	4.902*** (0.0245)	4.694*** (0.0230)	4.795*** (0.0552)	5.453*** (0.0454)	5.032*** (0.0253)	5.018*** (0.0820)
Observations	186,319	311,072	37,375	17,998	159,101	16,176
R-squared	0.358	0.345	0.299	0.143	0.354	0.285

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Note: Each column is separate regression<sub>SEP</sub> estimation of equation (1) and includes age, state and year fixed effects. Robust standard errors, clustered at the state level, are in parentheses. Estimates are weighted using CPS earnings weights.

Table 6: Reduced Form Differences-in-Differences Estimates of the Effect of Marijuana Decriminalization Laws on Logged Hourly Wages

VARIABLES	(1) Males	(2) White Adults	(3) Black Adults	(4) Males 20-24	(5) White Males	(6) Black Males
Decriminalized	0.00725 (0.0144)	0.00493 (0.0146)	0.0410* (0.0215)	-0.0197 (0.0482)	0.000271 (0.0137)	0.0688** (0.0269)
MML	-0.0163 (0.0128)	-0.0132 (0.00900)	-0.0679*** (0.0167)	-0.0157 (0.0145)	-0.0102 (0.0135)	-0.0850** (0.0374)
White	0.0986*** (0.00956)			0.0358*** (0.0129)		
Black	-0.0500*** (0.0141)			-0.0500*** (0.0177)		
Hispanic	-0.135*** (0.0130)			-0.0697*** (0.0173)		
College Degree	0.347*** (0.0141)	0.479*** (0.0219)	0.506*** (0.0164)	0.133*** (0.0300)	0.386*** (0.0258)	0.411*** (0.0233)
Graduate Degree	0.527*** (0.0232)	0.673*** (0.0262)	0.648*** (0.0270)	0.0190 (0.0925)	0.563*** (0.0337)	0.574*** (0.0506)
HS Degree	0.167*** (0.0111)	0.192*** (0.0169)	0.156*** (0.00916)	0.0759*** (0.0156)	0.207*** (0.0177)	0.150*** (0.0154)
Some college	0.208*** (0.0129)	0.277*** (0.0198)	0.252*** (0.0101)	0.00964 (0.0202)	0.251*** (0.0230)	0.220*** (0.0120)
Male		0.222*** (0.00904)	0.126*** (0.00925)			
Constant	1.804*** (0.0134)	1.689*** (0.0129)	1.700*** (0.0238)	1.947*** (0.0264)	1.904*** (0.0161)	1.834*** (0.0385)
Observations	103,065	178,085	24,912	14,454	86,341	10,735
R-squared	0.276	0.278	0.269	0.084	0.273	0.243

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Note: Each column is separate regression estimation of equation (1) and includes age, state and year fixed effects. Robust standard errors, clustered at the state level, in parentheses. Estimates are weighted using CPS earnings weighting variable.

Table 7: Reduced Form Differences-in-Differences Estimates of the Effect of Marijuana Decriminalization Laws on Hours Worked Per Week

	(1) Males	(2) White Adults	(3) Black Adults	(4) Males 20-24	(5) White Males	(6) Black Males
Decriminalized	0.00303 (0.00423)	0.00580 (0.00551)	-0.0260** (0.0107)	-0.00295 (0.0139)	0.00489 (0.00443)	-0.0196** (0.00904)
MML	-0.00442 (0.00371)	-0.00510 (0.00389)	-0.0159*** (0.00520)	-0.00390 (0.00692)	-0.00411 (0.00437)	-0.0174*** (0.00645)
White	0.0417*** (0.00408)			0.0769*** (0.00867)		
Black	-0.0205*** (0.00386)			0.0236* (0.0119)		
Hispanic	-0.0204*** (0.00487)			0.0131 (0.0102)		
College Degree	0.0696*** (0.00328)	0.0648*** (0.00234)	0.117*** (0.00555)	-0.0533*** (0.0100)	0.0720*** (0.00322)	0.108*** (0.00626)
Graduate Degree	0.0968*** (0.00431)	0.106*** (0.00321)	0.140*** (0.00690)	-0.0249 (0.0291)	0.1000*** (0.00414)	0.136*** (0.00828)
HS Degree	0.0357*** (0.00289)	0.0379*** (0.00314)	0.0634*** (0.00572)	-0.00387 (0.00422)	0.0357*** (0.00337)	0.0559*** (0.00598)
Some college	0.0145*** (0.00283)	0.0119*** (0.00285)	0.0600*** (0.00617)	-0.216*** (0.00728)	0.0151*** (0.00296)	0.0496*** (0.00631)
Male		0.214*** (0.00527)	0.0964*** (0.00424)			
Constant	3.072*** (0.0174)	2.954*** (0.0183)	2.984*** (0.0174)	3.490*** (0.0141)	3.128*** (0.0192)	3.105*** (0.0180)
Observations	1,588,735	2,578,868	276,645	159,909	1,415,120	126,928
R-squared	0.085	0.102	0.070	0.088	0.084	0.070

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Note: Each column is separate regression estimation of equation (1) and includes age, state and year fixed effects. Robust standard errors, clustered at the state level, in parentheses.