MEDICAL MARIJUANA LAWS AND CRIME:

An Empirical Analysis of Market Design and Racial Implications

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Abstract

Beginning with California in 1996, 23 states and Washington, D.C. passed medical marijuana laws (MMLs) that enable eligible patients to obtain and consume marijuana. MMLs generally allow patients to cultivate marijuana in their homes (home cultivation laws), purchase marijuana from state-licensed dispensaries (dispensary laws), or do either. The sale and distribution of marijuana is still illegal at the federal level, and opponents of MMLs argue that these laws will increase criminal behavior and perpetuate racial disparities in drug-related arrests. I implement a differences-in-differences approach to quantify the effects of each type of MML on arrest rates for property and violent crime. I find that MMLs are associated with an 8.2% increase in combined property and violent crime arrests. Dispensary laws account for a 16.0% increase in arrests, which is driven by estimated 22.7% and 19.4% increases in burglary and robbery arrest rates. Home cultivation laws are not found to have a significant relationship with arrest rates. The white population drives the overall results; for either type of MML, I find no significant effect on arrest rates for the black population. My results indicate that the association between MMLs and crime is dependent on market design, and that neither type of MML leads to disproportionate arrests among the black population.

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1. INTRODUCTION

Despite marijuana's standing as an illicit Schedule I drug under the Controlled Substances Act of 1970,[1] from 1996-2015, 23 states and Washington, D.C. passed medical marijuana laws (MMLs). While some state laws that preceded MMLs recognized the medicinal benefits of marijuana, most were merely symbolic and not operational. MMLs are the first state laws that protect patients who, with their doctors' approval, possess marijuana by cultivating it or acquiring it from a distributor. Each of the MMLs passed thus far has either permitted the home cultivation of medical marijuana, the operation of state-licensed dispensaries, or both.[2] Additionally, Alaska, Oregon, Washington, and Colorado have recently legalized the recreational consumption of marijuana. Opponents argue that this statewide liberalization of marijuana laws will encourage criminal behavior. They also suggest that police enforcement of MMLs will perpetuate racial disparities in drug-related arrests. The growing prevalence of marijuana in the United States, coupled with its changing legal status, makes it vital to understand the externalities related to forms of marijuana legalization. In this paper, I study the association between different types of MMLs and crime as measured by arrest rates; I then test whether this relationship involves racial disparities in arrest rates.

MMLs may affect criminal behavior through competing channels, making their effect on arrest rates theoretically ambiguous. First, increased marijuana consumption associated with MMLs may inhibit aggressive and violent behavior, directly reducing crime and arrests. I call this phenomenon the "consumption effect." Second, a growing

[1] 21 U.S.C. Section 812(b)(1)
[2] From 1994-2013 (the range of this study), 21 states passed MMLs. Of these states, 7 have dispensary laws, 6 have home cultivation laws, and 8 have both.

number of dispensaries, abundant in cash and marijuana, may become targets for theft-related crime, similarly to the opening of a bank or a pharmacy: a "business site effect". Third, MMLs may be exploited: under the guise of these laws, criminals may illegally produce and distribute marijuana. This "exploitation effect" may increase the general presence of the drug and exacerbate existing trends in drug-related arrests.

To untangle these three competing hypotheses, it is helpful to bifurcate MMLs into home cultivation laws and dispensary laws.[3] Home cultivation laws generally allow qualifying patients to grow a small number of mature marijuana plants in their own homes, whereas dispensary laws allow qualifying patients to purchase marijuana from state-licensed stores. The Department of Justice's (DOJ) official position on the passage of MMLs brings out potential differences on how these variations of MMLs may impact crime. In a memorandum dated August 2013, the DOJ argued that increased marijuana consumption would lead to drugged driving, violent and aggressive behavior, and "other adverse public health consequences." [4] However, recent literature generally suggests that marijuana consumption is associated with decreased criminal behavior (Derzon and Lipsey, 1999; White and Gorman, 2000; Miczek, 1994; Pederson and Skhardhamar, 2009; Green et al, 2010). The DOJ also argued that the establishment of dispensaries would provide "a significant source of revenue to large-scale criminal enterprises" and encourage gang violence, cartel activity, and the usage of firearms. Pushing against these claims, numerous surveys conducted by police departments in counties that have

[3] It is important to note that while all MMLs can be placed into one or both of these categories, there is significant variation betweenthem. For example, while Arizona has 90 dispensaries, New Jersey only has 5. While Oregon's limit on home cultivation of marijuana is 24 plants, Montana's limit is 4. Further, certain cultivation laws, such as Oregon's 1998 Medical Marijuana Law that allows "caregivers" to grow marijuana for up to four patients, making them operationally similar to dispensary laws. The existence of these "hybrid" MMLs make it more difficult to separately estimate the impact of different types of MMLs.

[4] "Guidance Regarding Marijuana Enforcement," DOJ Deputy Attorney General James M. Cole, August 29, 2013. Source: https://www.justice.gov/iso/opa/resources/3052013829132756857467.pdf.

dispensary laws found no strong evidence that dispensary laws increased crime in their jurisdictions.[5]

These arguments suggest that the overall effect of MMLs on arrest rates – conveniently thought of as comprising a consumption effect, business site effect, and an exploitation effect – might depend on market design. Because home cultivation laws are user-centric and involve private and low level production of marijuana, the effect of home cultivation laws on arrest rates may be isolated to the consumption effect. The operation of large-scale dispensaries may provide an incentive for drug- and cash-related theft, and therefore may be impacted by the business site effect. While this bifurcation neatly separates the first two hypothetical effects of MMLs, both types of MMLs may encourage illegal marijuana production and distribution, drawing an association with the exploitation effect. As some marijuana in society becomes legal, it is less likely for a marijuana sample to be traced back to an illegal producer, potentially making this illicit behavior more lucrative.

As a first order effect, home cultivation laws should be associated with decreased criminal activity and dispensary laws increased criminal activity. The most straightforward link between MMLs and crime is the direct effect of marijuana consumption on the behavior of medical users. To the extent that MMLs increase the number of medical and nonmedical marijuana consumers (Rees, 2013; Smart, 2015; Pacula et al, 2010), their passage should result in widespread behavioral changes. Recent literature maintains that marijuana inhibits aggressive and violent behavior, implying that marijuana consumers would be less likely to commit crimes and would therefore suffer

[5] These include independent surveys conducted by police departments in Colorado Springs, CO, Denver, CO and Los Angeles, CA from 2009-2010. These studies are consolidated in a memo published by the Marijuana Policy Project in 2014. Source: http://www.canorml.org/HesperiaattachC.pdf.

fewer arrests. However, dispensaries operate as all-cash businesses due to the unwillingness of banks to flout marijuana's illegal federal status by taking them on as customers. These business sites provide criminals with access to consumers carrying large amounts of cash as well as to abundant high-quality marijuana. Consistent with the DOJ's claim, this framework suggests that dispensary laws may be associated with increased arrest rates if they increase business site crime more than they inhibit criminal behavior among new marijuana consumers.

As a second order effect, both home cultivation and dispensary laws may remove the negative stigma or perceived health risks from consuming marijuana. They theoretically increase demand of and consumption by recreational users (Smart, 2015). Increased demand will raise the equilibrium quantity of marijuana that is cultivated, spurring the increase illegal production and distribution of marijuana. Further, it is prohibitively expensive for states to make sure that medical marijuana winds up only in the hands of qualified patients, so any medical marijuana that is diverted into the recreational market also increases profit opportunities in illicit marijuana distribution. In a situation where marijuana is universally illegal, the presence of marijuana on one's person or marijuana plants in one's home surely indicates some wrongdoing. Once marijuana is allowed under *any* circumstances, it becomes less clear whether the marijuana in question was procured legally or illegally; it may become more difficult for law enforcement agencies to trace marijuana back to its source. As a result, MMLs may become a façade for illegal marijuana distribution and subsequent drug-related crimes. Evidence collected in 2011 by the Rocky Mountain High Intensity Drug Trafficking Area (RMHIDTA), commissioned by the DOJ, is consistent with this possible exploitation effect. The RMHIDTA study revealed that the passage of MMLs in Colorado (a home cultivation and a dispensary law) and Montana (only a home cultivation law) resulted in high levels of marijuana consumption among the general population and wide scale illegal production of marijuana in an attempt to gain "high profits."[6] Both home cultivation laws and dispensary laws can be exploited in this way. However, these operations may be less profitable under home cultivation laws, where cultivation is private and on a smaller scale.

Any increase in marijuana-related crime in conjunction with this exploitation effect, may also increase arrests for property and violent crimes. The DOJ notes that drug trafficking often coincides with violent disputes among individuals in the market and encourages a proliferation of both property and violent crimes in economically and socially disadvantaged areas, where legal and social controls against violence tend to be less effective.[7] Expansion of illegal marijuana markets may also increase crimes committed to obtain money in order to support drug use. In independent surveys by the Bureau of Justice Statistics 1989, 1991, and 2004, the crimes most often committed by inmates to support drug use were burglary, larceny, robbery, and motor vehicle theft.[8] Empirical evidence also demonstrates a link between arrests for the sale and possession of marijuana and arrests for violent and property crime (Shepard and Blackley, 2007). The crime induced by MML exploitation may outweigh any potential crime reducing benefits of marijuana consumption. Thus, the overall effect of MMLs on arrest rates is theoretically ambiguous.

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[6] Rocky Mountain High Intensity Drug Trafficking Area: Drug Market Analysis 2011. Source: http://www.justice.gov/archive/ndic/dmas/Rocky_Mountain_DMA-2011(U).pdf.

[7] "Fact Sheet: Drug-Related Crime," Department of Justice, 1994. Source: http://bjs.gov/content/pub/pdf/DRRC.PDF.

[8] All surveys are on http://bjs.gov. 1991 survey: http://www.bjs.gov/content/pub/pdf/SOSPI91.PDF.

Indeed, Recent literature presents a mixed picture on the relationship between MMLs and crime. The studies published so far all use the Federal Bureau of Investigation's Uniform Crime Reports (UCR) data on Part I crimes, eight serious property and violent crimes that occur with regularity and are likely to be reported.[9] Treating the existence of any type of MML as a single variable, Morris (2014) finds no significant effect of MMLs on reported Part I offenses from the UCR. Applying similar methods, Chu (2012) finds that MMLs are associated with increased Part I crime offense rates but this relationship weakens as average age increases. Using a differences-in-differences approach, Alford (2014) investigates whether market design influences the effect of MMLs on crime by studying the relationship between reported Part I offenses and cultivation laws, dispensary laws, and decriminalization laws for marijuana possession. With dispensary laws and decriminalization laws, property crime offense rates increased. With home cultivation laws, there was no significant effect on offense rates other than a decrease in robberies. Alford also estimates that decriminalization laws are associated with an increase in property crimes.

After estimating how different types of MMLs affect crime in this paper, I explore whether there is a racial disparity in predicted changes in arrest rates associated with MMLs. Two independent studies in 2013, the National Survey on Drug Use and Health, administered by the US Department of Health and Human Services and "The War on Marijuana in Black and White," administered by the American Civil Liberties Union (ACLU), found that the white population had a higher marijuana consumption rate than the black population. Specifically, the ACLU found that in every year from 2001-2010, a

[9] They include: homicide, rape, robbery, assault, burglary, larceny, motor vehicle theft, and arson. To stay consistent with previous studies on the subject, I include all Part I crimes besides arson in my analysis.

larger percentage of the white population aged 18-25 reported marijuana consumption in the past year.[10] Therefore, the white population theoretically should gain more of any direct crime-reducing benefits of marijuana consumption.

The advent of MMLs results in the creation of a new "enforcement market." The RMHIDTA found that law enforcement in Colorado and Montana reacted with increased vigilance to the "high levels of indoor and outdoor cannabis cultivation fueled by the exploitation of medical marijuana laws in those states."[11] These states experienced a surge in marijuana confiscation and marijuana-related arrests. In responding to increased levels of illegal production and distribution relating to the passage of MMLs, law enforcers may disproportionately arrest black people. It has been well documented that racial discrimination plays a role in crime identification. Black people are more likely to be the subjects of highway searches as part of a number of drug interdiction programs and are more likely to be subject to stop-and-frisk policies in New York City (Gelman et al 2007; Hanink 2013; Fagan and Davies 2000). In fact, a 2013 ACLU study found that the gap between black and white arrest rates significantly grew from 2001-2010.[12] Regardless of whether MMLs are associated with changes in black criminal behavior trends, the black population may bear a greater share of the increases in drug-related arrests associated with these laws.

DeAngelo et al (2015) find that Los Angeles County's "low priority initiatives" on the enforcement of low-level marijuana possession laws do not result in discriminatory law enforcement. However, no analysis has looked specifically at the

[10] "The War on Marijuana in Black and White," American Civil Liberties Union (2013). Source: https://www.aclu.org/files/assets/aclu-thewaronmarijuana-rel2.pdf.
[11] ibid 6
[12] ibid 10

racial consequences of MMLs as it pertains to crime. Although drug possession crimes are not included in Part I crimes (they are considered Part II), my results may still point to the presence of racial discrimination since drug-related crimes and Part I crimes are so closely linked. If whites are far more likely than blacks to engage in the exploitation of home cultivation laws and dispensary laws – a conclusion that would be consistent with whites' higher levels of marijuana consumption – then the white population may experience more arrests in association with MMLs regardless of racial discrimination by police. I predict that blacks will gain less benefit from the crime-reducing effects of both types of MMLs because of lower consumption rates. Further, blacks will derive more of the cost of crime-increasing effects of dispensary laws because of historical racial disparities in arrest rates relating to drugs.

Similar to previous literature on the topic, I use UCR data to investigate the relationship between crime and the passage of MMLs using a differences-in-differences (DD) strategy. My paper differs from previous literature in a number of important ways. First, whereas Morris and Alford use offense-level data, I use arrest-level data. This allows me to look at the racial impact of MMLs since offense-level data does not always contain information on the demographics of the offender. Because arrests entail actions by both offenders and police, my results account for police responses to MMLs in addition to changes in criminal behavior. Second, I consider the possibility of state-specific time trends in my regressions. It is possible that states that happened to pass MMLs over the period studied were experiencing trends in arrest rates that were unrelated to the passage of MMLs. Controlling for state-specific time trends mitigates the possibility that the coefficients on MMLs are simply picking up preexisting arrest rate trends. Unlike Alford, I drop decriminalization laws due to large heterogeneity in the laws' wording and enforcement, the lack of state-provided data on marijuana-related arrests before decriminalization laws were passed, and the general absence of such laws in the United States from 1978-2001.

Using UCR arrest-level data and self-collected MML data from 1994-2013, I implement state and time fixed effects regressions to estimate the impact of MMLs on arrest rates. I control for variables that may be correlated with MMLs and affect arrest rates to mitigate omitted variable bias and allow for the possibility of state-specific trends in arrest rates over time. I use UCR Part I crime categories of violent crime (homicide, rape, and assault) and property crime (larceny, burglary, robbery, and motor vehicle theft) to observe if arrests for certain crimes drive the overall results. In association with home cultivation laws, I expect arrest rates to decrease through both decreased violent crime and property crime, with black arrest rates decreasing less. In association with dispensary laws, I expect arrest rates to in increase through both property crime and violent crime, with black arrest rates increasing more. Specifically, I expect theft-related crime including burglary, larceny, and robbery, to increase most significantly with dispensary laws as an indication of MML exploitation. The total effect of MMLs on crime is dependent on whether the behavioral effects of increased consumption or the incentive to exploit MMLs and commit crimes at marijuana business sites is more impactful.

I find that among the total population, MMLs are associated with an 8.2% increase in arrest rates for Part I crimes. This increase is driven by a 16.0% increase in arrest rates associated with dispensary laws. Once standard errors are clustered by state, the effects of home cultivation laws and dispensary laws on arrest rates become insignificant. However, broken down by crime, dispensary laws are estimated to increase robbery and burglary arrest rates by 19.4% and 22.7%, respectively, significant at the 10% level. Home cultivation laws are not estimated to have a significant effect on arrest rates. These results suggest that market design influences the effect of MMLs on arrest rates. Further, they suggest that the link between dispensary laws and theft-related crime is what drives the overall relationship between MMLs and arrest rates. This suggests that MMLs may incentivize exploitation and crime at actual marijuana business sites such as dispensaries. My results suggest that even if marijuana consumption does directly reduce criminal behavior among users, this effect is not significant relative to other factors influenced by the passage of MMLs.

The results for the white population mirror the results for the total population. I find that MMLs increase arrest rates for Part I crimes by 5.1% among this demographic, driven by an 11.1% decrease from home cultivation laws and a 16.6% increase from dispensary laws. Both results lose significance once standard errors are clustered by state. However, on a crime-by-crime basis, dispensary laws are associated with a 19.7% increase in burglary arrests and a 21.9% increase in robbery arrests, significant at the 5% level. For black populations only, no results are significant at the 5% level. This suggests that the white population drives the overall increase in theft-related crime with dispensary laws and that black arrests do not appear to be influenced by the passage of MMLs. In turn, this suggests that MMLs are not enforced discriminatorily by police forces. Conversely, because the white population experiences an increase in arrest rates, I speculate that whites are more likely to engage in criminal behavior with the introduction of MMLs.

When I introduce state-specific time trends for the total population and by race, my estimates change considerably. The effect of both types of MMLs on robbery and burglary arrest rates become insignificant. It is possible that the coefficients on dispensary laws in the baseline model are simply picking up an observable difference in arrest rate trends between states that did and did not pass MMLs, and that these laws did not actually influence arrest rates. However, when I control for state-specific time trends, standard errors become erratic, most coefficients on control variables lose significance, and R-squared values exceed 0.9. These results point to the possibility that allowing for arrest trends to be different across states leaves so little variation left to estimate, that the coefficients on dispensary laws and home cultivation laws become imprecise and undependable. I therefore cautiously place more weight in the regressions without time trends, and conclude that dispensary laws are associated with an increase in robbery and burglary arrest rates among the white population.

2. BACKGROUND LITERATURE

2.1 Marijuana Legalization and Empirical Connections with Crime

Before the wave of MMLs began in the 1990s, 11 states experimented with marijuana decriminalization laws in the 1970s. These laws only reduced penalties for marijuana possession as opposed to eliminating them altogether and proved uncooperative in clarifying the effect of marijuana legalization on crime. Such laws varied widely and the degree to which they altered law enforcement is difficult to measure since marijuana remained illegal after their passage. Early studies that attempted to estimate the impact of decriminalization laws on crime were inconclusive given a lack of data on drug-related arrests prior to these laws.[13] Only two states that passed decriminalization laws, California and Ohio, collected data before and after the laws' passage. Using data from these states, Single (1989) found evidence regarding the effects of marijuana decriminalization "far from conclusive," deeming the impact of such laws "far less radical then implied by their name."

Independent of decriminalization laws, many states passed laws that upheld the legality of patients obtaining medical marijuana, but because they provided no actual method for them to do so, the laws were merely symbolic. For example, Texas (1980) and Louisiana (1991) passed laws that allowed users with certain medical conditions to legally obtain, for therapeutic reasons, cannabis preparations with low amounts of marijuana's active ingredient, tetrahydrocannabinol (THC).[14] However, doctors would have to disobey federal law to prescribe these preparations to patients. On top of that, any

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[13] Following the passage of decriminalization laws in Oregon and Maine in 1973 and 1979, respectively, the effect on crime was widely considered inconclusive (Single, 1989).
[14] The Marijuana Policy Project's 2015 report, "State-by-State Medical Marijuana Laws," provides information on laws that preceded MMLs on a state-by-state basis.

marijuana distributor would have to do the same in order to sell the low-THC preparations to prescribed patients. Like decriminalization laws, these laws did little to influence legal or illegal marijuana markets. In terms of analyzing the effect of marijuana legalization on crime in the United States, the first significant "data point" did not arrive until the first MML was passed in 1996 in California.

MMLs, the first laws to truly protect patient access to marijuana, proved substantial in opening up the legal and illegal markets for the substance. Pacula et al (2010) argue that MMLs should theoretically increase the supply and demand of marijuana in the illegal market, unambiguously raising consumption. Smart finds that the passage of MMLs increased the size of legal and illegal markets immensely. In 2013, the legal marijuana market was valued at $1.43 billion compared to $25-$40 billion for the illegal market, with both numbers up over 150% since 2007 (Smart, 2015). Specifically, Smart finds that for age groups 12-17, 18-25, and 26+, the presence of any type of MML leads to a significant increase in recreational consumption. A 1% increase in the adult population of a given state registering as medical marijuana patients is associated with 6%, 9%, and 18% increases in recreational usage for the three age groups, respectively. Using data from 1990-2011 from the magazine *High Times*, Rees et al (2013) estimate that the passage of MMLs is associated with a 26.2% reduction in the price of high quality marijuana in the illegal market. These studies all suggest that states with MMLs should experience larger increases in general marijuana consumption than states without them. MMLs have now gained almost 50% participation among states over the past two decades. Their prevalence and impact on the recreational marijuana market provide a unique opportunity to study how increasing the size of marijuana markets influences criminal behavior.

In 1993, the National Research Council analyzed the relationship between marijuana consumption and criminal behavior, reporting that marijuana alters the nervous system in ways that disrupt social communications.[15] It concluded that marijuana consumption increases the likelihood that one may engage in altercations that escalate to violence and other types of crimes. However, more recent studies point to an inverse relationship between marijuana consumption and crime-like behavior. Derzon and Lipsey (1999) use meta-analysis on 63 reports from 30 independent longitudinal studies that contain data on marijuana use with delinquent behavior. They determine that the use of marijuana does not establish a trajectory toward aggressive behavior and that there is no consistent relationship between marijuana and any type of delinquency after adolescence. White and Gorman (2000) and Miczek (1994) use citywide trends and laboratory studies, respectively, to argue that marijuana consumption inhibits aggression and violence. Pedersen and Skardhamar (2009) use a longitudinal study of Norwegian 13-27 year olds, and find that in both adolescence and adulthood those who consumed marijuana were more likely to face criminal charges; however, if drug-related charges such as possession and distribution were dropped, the findings were insignificant. Using longitudinal data on a cohort of African Americans, Green et al (2010) find that marijuana consumption may lead to property crime but not violent crime.

[15] See *Understanding and Preventing Violence* by Albert Reiss and Jeffrey Roth, published by the National Research Council. Source: http://www.nap.edu/catalog/1861/understanding-and-preventing-violence-volume-1.

2.2 Existing Evidence on MMLs and Crime

While Rees and Anderson (2013) find that dispensaries did not play a major role in raising adult consumption rates of marijuana, numerous police surveys indicate that dispensary laws still lead to increases in property crime. In 2009, the Los Angeles Police Department claimed that banks "are more likely to get robbed than dispensaries."[16] While there were 47 reports of robberies among 800 dispensaries (5.9% robbery rate), there were 71 reports for of robberies among 350 banks (20.3%). In the same year, the Denver Police Department found that the 16.8% robbery and burglary rates at dispensaries were lower than those for both banks (33.7%) and liquor stores (19.7%) and equal to that of pharmacies. The following year, the Denver Police Department noted that the 8.2% drop in crime at dispensaries from the previous year was roughly equivalent to Denver's 8.8% citywide drop in crime. In 2010, the Colorado Springs Police Department found that crime rates at dispensaries were equivalent to those of other businesses. While these surveys demonstrate that crime rates at dispensary locations do not significantly differ from crime rates at banks, two points are noteworthy. First, overall, dispensary laws *did* lead to crime, just at rates that often did not exceed other businesses. Second, these studies do not make any prediction on crime that is impacted by the presence of dispensaries but take place off the dispensary grounds, such as cartel activity involving the illegal distribution of marijuana acquired through dispensaries. To account for this possibility, it is worthwhile to study crime rates changes in areas where dispensaries are prevalent.

Kepple and Freisthler (2012) used a cross-sectional design in analyzing over 95 census tracts in Sacramento, CA. They find that the density of medical marijuana

[16] ibid 5

dispensaries was not associated with property crime or violent crime. They conjecture that either heightened security or lack of relative attractiveness of the target could have led to a deterrence effect on potential criminals. Scherrer (2011) finds a similar result; in an analysis of three Denver neighborhoods using data from the Denver Police Department's Data Analysis Unit, Scherrer estimates that within 1,000 feet of dispensaries in the Denver area, robbery rates were actually down. These anecdotal studies provide a good framework for analyzing crime in areas dense with dispensaries, but still fail to capture any crime-related effects of dispensaries in a broader geographic area.

Recent surveys of the landscape surrounding MMLs provide convincing evidence that the "reach" of MMLs on crime goes far beyond the immediate area surrounding a dispensary. The 2011 Rocky Mountain High Intensity Drug Trafficking Area (RMHIDTA) study found that individuals and groups pursued "high profits while concealing their illegal activities under the cover of Colorado and Montana medical marijuana laws."[17] Over 6,600 pounds of marijuana were confiscated in 2009 and 2010, resulting in over 2,500 arrests. This trend is not isolated: a 2014 Oregon High Intensity Drug Trafficking Area report in 2014 claimed that Oregon's Medical Marijuana Act, which allows for home cultivation, "continues to be exploited by local producers who use it to facilitate illegal cultivation for commercial purposes."[18] The report cites a 2012 raid that resulted in the seizure of over 930 pounds of marijuana, 120 firearms, and the arrest of 26 people. It is clear from both these studies that the passage of MMLs has opened gateways for illegal marijuana possession and sales.

[17] ibid 6

[18] "Threat Assessment and Counter-Drug Strategy", Oregon Department of Justice (2014). Source: http://media.oregonlive.com/marijuana/other/2014/06/2015%20Oregon%20HIDTA%20Threat.pdf.

The RMHIDTA study demonstrates a clear connection between MML enforcement and Part I crimes. Shepard and Blackley (2007) generalize this anecdotal evidence by investigating the relationship between marijuana sales and possession (two Part II UCR drug abuse crimes) and Part I property and violent crimes. Using data from a pooled sample of 1,300 US counties from 1994-2001, the authors find that both types of marijuana arrests are associated with higher levels of property crime and violent crime from 1994-2001. Increases in marijuana possession arrests are closely related to increases in all types of property crime and homicide. Increases in marijuana sales arrests only demonstrate a significant relationship with burglary and homicide arrests. If MMLs lead to an increase in illegal marijuana-related activity, I expect marijuana-related arrests to be accompanied by arrests for property crime. The connection with violent crime is not as clear.

Empirical efforts to estimate the effect of MMLs on Part I crime have yielded conflicting results. Morris (2014) uses UCR offense-level data from 1990-2006 and considers the existence of any type of MML as his independent variable. Using a fixed effects panel design, Morris does not find a significant relationship between MMLs and Part I crime overall. One notable exception is that homicide and assault rates are estimated to be inversely related to the passage of MMLs, a finding that Morris has trouble reconciling with theory. Chu (2012) uses a similar approach in considering MMLs as binary but segments the population based on age. Using linear and log-linear regression models and data through 2008, her results indicate that states with any type of MML are more likely to experience increased crime rates. This effect is muted among higher age groups. Using offense-level data, Gavrilova et al (2014) find that MMLs are associated with reductions in violent and property crime across US states on the US-Mexico border, suggesting that Mexican drug trafficking organizations are adversely affected legally available marijuana. However, they also find that for non-border states, Part I property crime (specifically burglary and larceny) is estimated to increase with the passage of MMLs. The relationship between MMLs on crime is less significant among higher age groups.

Alford (2014) improves upon previous studies by differentiating between states that allow dispensaries and states that allow home cultivation. Alford uses a differences-in-differences approach to test the changes in Part I crime rates from 1995-2013 that result from each type of MML as well as from decriminalization laws. She finds that home cultivation laws are associated with decreases in robbery rates but are not significantly associated with any other Part I crime. She finds that dispensary laws are expected to increase property crime mainly through burglary and larceny. The results hold when state-specific time trends are included. This finding is in line with the hypothesis that dispensary laws incentivize crime involving illegal marijuana-related activity.

2.3 Potential Racial Disparities in Enforcement of MMLs

The RMHIDTA report claims that "grow sites" have become lucrative targets for theft and violence due to excess cash on hand, and that cultivators are arming themselves to protect from theft and robbery. The very existence of the RMHIDTA and Oregon HIDTA studies indicates that law enforcement is aware that forms of marijuana legalization marijuana can lead to exploitation and crime. MML enforcement may take the form of highway drug interdiction programs, search programs, drug busts, vigilance surrounding dispensaries, and a general increase in police attentiveness to reported offenses involving marijuana. In the presence of any racial discrimination, enforcement procedure surrounding MMLs may result in a disproportionate amount of black arrests for Part I crime. Indeed, focusing on the mass incarceration of blacks in the United States, Alexander (2011) finds that "tightly networked systems of law, policies, customs, and institutions" ensure that blacks are given a subordinate status through the criminal justice system. With pressure put on police departments to vigilantly enforce MMLs, it is worth examining the effects of MMLs on crime along racial dimensions.

The role of racial discrimination in both identifying crime is well documented. Knowles, Perisco, and Todd (2001) find that blacks made up 63% of the motorists searched along I-95 in Maryland even though they represented only 18% of the motorists on the road. Gross and Barnes (2002) found that Maryland state police racially profiled to increase "hits." Their aim was to increase the proportion of stops that lead to arrests of drug traffickers and to seizures of illegal drugs. Lundman and Kaufman (2003) analyzed self-reported data to demonstrate that, after controlling for other explanatory variables, police disproportionately make traffic stops for black males. In a study of over 125,000 pedestrian stops by the New York Police Department as part of its stop-and-frisk policy, Gelman et al (2007) find that blacks were stopped more frequently than whites even after controlling for the fact that the black population statistically has higher crime rates. Hanink (2013) and Fagan and Davies (2000) find that stop and frisk activity in New York is closely linked to racial composition and centers on *people* rather than disorder.

Responding to the discriminatory pattern of law enforcement found in previous papers, DeAngelo et al (2015) examine the impact of "low priority initiatives" by police departments in Los Angeles County regarding marijuana-related offenses. The authors find that when told to make enforcement of low-level marijuana possession their "lowest priority," police officers did not enforce the law differentially across racial groups. In fact, nonwhite arrests related to marijuana possession misdemeanors, which represented a larger fraction of total arrests before the initiative, experienced the greatest decrease after the initiative was implemented. Low priority initiatives have become quite common; from 2003-2013, they were passed in 16 jurisdictions across 8 states.[19] The DeAngelo study suggests that when deprioritizing enforcement of MMLs, the black population should not experience racial discrimination. However, no prediction is made on racial disparities in arrest rates if MMLs are enforced with *increased* priority, as might occur with large increases in reported crime.

Evidence from the ACLU's 2013 report, "The War on Marijuana in Black and White" suggests that blacks bear the brunt of law enforcement as it pertains to marijuana possession. Despite self-reported past-year consumption rates of 34% for whites and 27% for blacks in 2010, arrest rates per 100,000 for drug possession were 192 for whites and 716 for blacks. In 2001, these rates were 192 and 537, suggesting that racial gap in marijuana possession crimes has widened. This gap is likely to spill over into racial disparities in arrest rates for Part I crimes. The Justice Assistance Grant Program (JAG), established in 1988 by the federal Bureau of Justice Assistance, allows states to apply for law enforcement funding if they meet certain measurable goals, such as arrest counts for marijuana possession and violent crime.[20] This system incentivizes arrests for low-level marijuana possession to be spun into multiple-category arrests. In United States v.

[19] "Lowest Law Enforcement Priority Jurisdictions", Marijiuana Policy Project (2013). Source: https://www.mpp.org/lowest-law-enforcement-priority-jurisdictions/.
[20] Source: https://www.bja.gov/Publications/JAG_Fact_Sheet.pdf

Reese[21] in 1995, it was found that many police officers were aware that funding (and their job security) depended on finding ways to inflate arrest numbers and caused them to increase marijuana-related arrests and violent crime arrests.

Ayres and Waldfogel (1994) find that once arrested, blacks face disproportionate struggles in being tried and punished. Facing comparable charges, black male adults face bail fees 35% higher than their white counterparts. Assault and larceny are among the offenses that have the largest bail gap between races. The authors find the bail market is competitive and driven by perceived differences in flight risks. Thus, the racial bail gap is an indication of racial discrimination in the perception of the danger posed by the accused. The authors speculate that this discriminatory perception indirectly influences judicial racial bias.

Indeed, Rehavi and Starr (2014) find that blacks face federal prison sentences almost 10% longer than whites arrested for the same crimes. The federal criminal code's vastness allows for flexibility and subjectivity in determining what charges to bring against the defendant. The authors argue that most of the racial disparity in prison sentences is explained by the prosecutor's initial charging decision; prosecutors show bias in deciding to prosecute blacks on charges that carry mandatory minimum sentences 1.75 times more often than whites arrested for the same crimes. Three-Strikes-Laws, currently present in 24 states, have a mandatory life prison sentence upon conviction for a serious violent felony if the offender has two violent felony convictions in his past. Fischman and Schanzenbach (2012) show that after Supreme Court decisions declared the US Sentencing Guidelines to be simply "advisory," racial disparities in sentencing were increased and were closely related to the increase in mandatory minimum sentences.

[21] United States of America v. Nolan Reese. United States Court of Appeals, Ninth Circuit. 26 July 1995.

Thus, if there is, in fact, racial discrimination in response to crime increases from MMLs, then the racial implications of MMLs are likely even far greater than what the arrest data suggests.

3. DATA

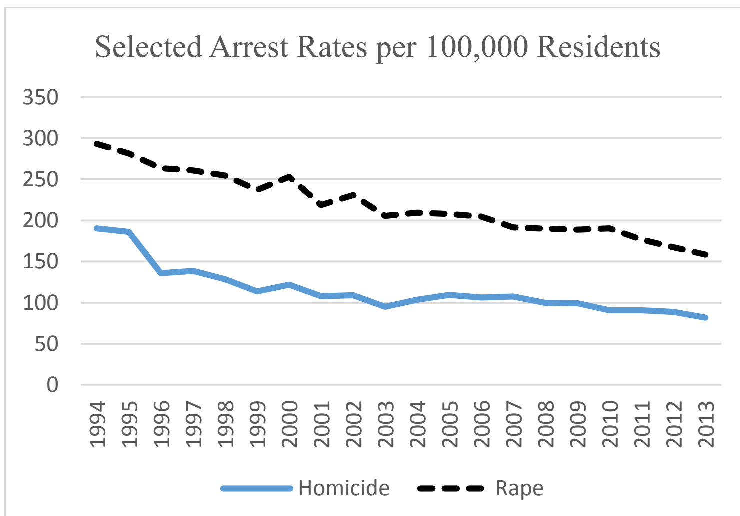
To determine the impact of MMLs on crime, I combine arrest data from the Federal Bureau of Investigation's Uniform Crime Reports (UCR) with MML data collected from the National Conference of State Legislatures, the Marijuana Policy Project, and the National Organization for the Reform of Marijuana Laws. I use 1994-2013 as my scope to include two years of data before the first MML and because UCR data was only available through 2013 at the time of this study. To mitigate omitted variable bias, I control for factors that are correlated with MMLs and may determine arrest rates such as average age, unemployment rate, average income level, and police officer counts.[22] I do not include marijuana decriminalization data as a variable in my regressions due to the high variability between laws and their unclear impact on crime.

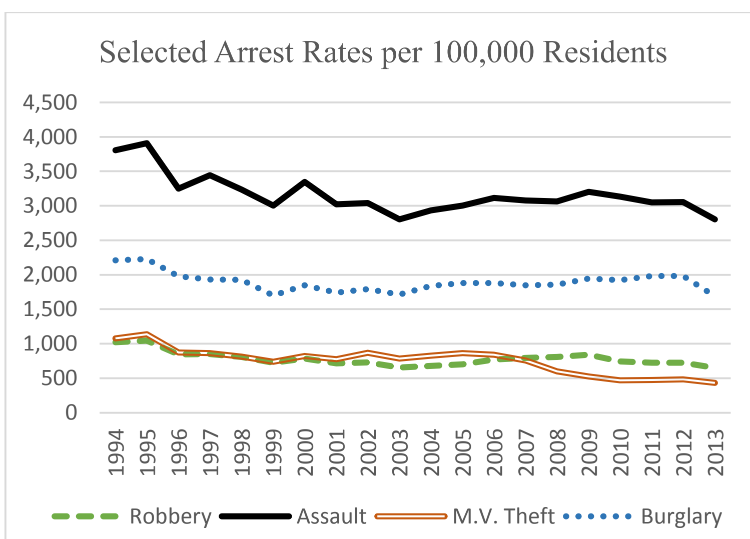
For my dependent variable, I collected UCR data on arrests on the state-year-race level for seven Part I crimes: homicide, rape, robbery, assault, larceny, burglary, and motor vehicle theft. Begun in 1930, the UCR Program collects, publishes, and archives crime statistics. The program currently receives data from over 18,000 agencies on the city, university, county, state, and federal levels through voluntary participation. In this study, I use the UCR's annual summaries of arrests by age, sex, and race on the agency level from 1994-2013. For this particular dataset, the number of arrests is *not* the number of total arrests for any given year. Instead, if one arrest encompasses multiple offense categories, the dataset records one arrest to correspond with each offense. Thus, when I combine arrest data for different Part I crimes, my aggregate Part I arrest counts are

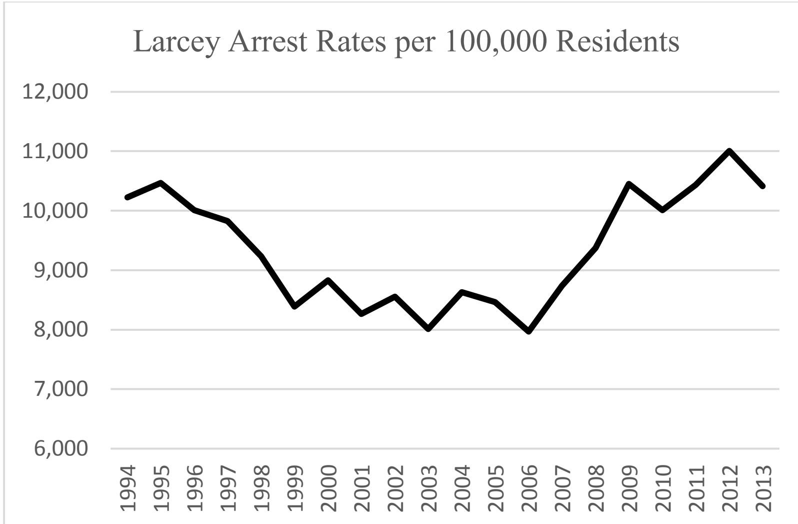
[22] Perhaps less self-evident than the other variables, beyond age being a determinate of arrest rates, it is also correlated with marijuana demand. According to the National Survey on Drug Use and Health, the rate of illicit drug use (of which approximately 80% is marijuana) in 2013 was 21.5% among 18-25 year olds and only 7.3% among those age 25 or older.

inflated but are not biased across time or states. While arrests per 100,000 residents decreased for each type of Part I crime besides larceny from 1994-2013, the largest decreases were evident in violent crime. Homicide, rape, and robbery arrest rates decreased by 57%, 46%, and 36%, respectively. Figure 1 shows the marked decline in arrest rates by crime over that time span. Table 1 presents arrest rate data by crime and year. Table 2 presents the summary statistics for arrest variables by race and for the combined white and black populations.

Figure 1: Arrest Rates for Part I Crimes from 1994-2013, per 100,000 Residents







Uneven reporting between different agencies poses a possible shortcoming with this data. Because reporting is voluntary, some agencies do not report at all in any given year and others do not report certain offenses. Fortunately, these aberrations are quite small. In any year, I dropped all data for a state if below 67% of its reporting agencies actually reported data. However, states that have above 67% agency participation often have greater than 95% of its agencies report. For example, in 2013, only 3 of 51 states[23] were below the 67% threshold. Of the other 48 states, each had over 90% of agencies report and only 3 had fewer than 94% report. For reporting agencies that fail to report certain crimes while reporting others, I made the affected data points empty. These data omissions were negligible, totaling less than 1% of the total arrest data.

As of 2013, 21 states enacted MMLs. Of those, seven passed home cultivation laws only, six passed dispensary laws only, and eight passed both. Although the development of dispensary markets is often more than a yearlong process, I consider a state to have a MML beginning in the effective date and year for each law. Numerous states have passed dispensary laws and home cultivation laws in different years; I record

[23] For the purposes of this exercise, Washington, D.C. is considered a "state."

two separate dates for these MMLs in such instances. One possible shortcoming in using only two categories for MMLs is that certain laws within each category might be correlated much more strongly with crime and arrests than others. For example, Oregon's MML allows registered patients to cultivate up to 24 marijuana plants and, according to the Marijuana Policy Project, there are 310 dispensaries open in the state. On the other hand, Maine only has 8 state-licensed dispensaries and permits the home cultivation of only 6 mature plants. While both laws receive a value of "one" in the dataset for home cultivation and dispensary laws in the data, access to marijuana in Maine is far more restricted then it is in Oregon. Table 3 details the passage of MMLs by state and type. This table includes states that passed MMLs after 2013 for completeness and for future study.

I control for characteristics that are correlated with MMLs and have an effect on crime to lessen omitted variable bias. I include average age, unemployment rate, and average income level on the state-year-race level using data provided by the U.S. Census Bureau's Current Population Survey (CPS), which is administered annually. I also include the number of law enforcement officers per 100,000 residents on the state level using data provided by the UCR's annual Law Enforcement Officers Killed and Assault report (LEOKA) as this may be correlated with the amount of resources police departments can devote to enforcing MML-related crime. Table 4 presents the summary statistics of all variables for the total population being studied.

For some states with relatively small black populations, the CPS does not report black unemployment rate estimates in certain years. For example, Maine's black population remained under 18,000 from 1994-2013. In 10 of the 20 years in this study, black unemployment data was unreported. In cases such as Maine's, I imputed missing black unemployment data by interpolating and extrapolating using existing data from other years. This imputation does not significantly change the summary statistics of black unemployment rates nor did it significantly affect my regression results. Table 5 presents the summary statistics of control variables on the race-state-year level, and compares existing and imputed black unemployment data.

Table 1: Sample Arrest Rates by Year and by Crime

Year	Homicide	Rape	Robbery	Assault	Violent Crime	Larceny	M.V. Theft	Burglary	Property Crime	Part I Crime
1994	190.4	293.3	1,019.1	3,805.8	5,308.6	10,226.2	1,077.2	2,207.6	13,511.0	18,819.6
1995	186.1	281.3	1,042.4	3,907.4	5,417.1	10,468.3	1,137.8	2,227.8	13,834.0	19.251.1
1996	135.9	263.4	847.2	3,249.1	4,495.6	10,009.3	871,2	1,979.2	12,859.7	17,355.4
1997	138.7	260.7	850.9	3,443.8	4,694.0	9,828.2	863.5	1,929.2	12,620.9	17,314.9
1998	128.5	254.7	809.6	3,237.0	4,429.8	9,232.6	813.2	1,926.9	11,972.8	16.402.6
1999	113.8	237.2	723.3	3,001.5	4,075.7	8,391.3	739.9	1,698.4	10,829.7	14.905.4
2000	121.9	253.2	786.9	3,345.9	4,507.9	8,829.2	824.0	1,849.3	11,502.6	16,010.5
2001	107.8	218.7	716.2	3,021.3	4,064.0	8,264.1	773.2	1,741.4	10,778.6	14,842.6
2002	109.1	231.0	726.7	3,039.4	4,106.3	8,554.5	869.6	1,793.3	11,217.4	15,323.7
2003	95.0	205.7	655.1	2,802.0	3,757.9	8,011.3	786.4	1,712.1	10,509.8	14,267.7
2004	103.4	209.6	677.3	2,931.1	3,921.5	8,630.7	826.3	1,836.6	11,293.6	15,215.1
2005	109.2	207.8	703.3	3,000.7	4,021.0	8,466.1	861.5	1,881.9	11,209.6	15,230.5
2006	106.4	204.8	770.0	3,112.5	4,193.8	7,966.5	840.5	1,879.0	10,686.0	14,879.8
2007	107.3	191.5	793.2	3,076.2	4,168.2	8,736.4	756.6	1,847.8	11,340.8	15,509.1
2008	99.8	189.8	806.4	3,065.3	4,161.3	9,371.7	597.0	1,858.1	11,826.9	15,988.2
2009	99.4	188.9	842.6	3,203.7	4,334.5	10,449.3	522.5	1,944.8	12,916.6	17,251.1
2010	90.7	190.2	741.9	3,130.8	4,143.7	10,008.1	466.9	1,923.5	12,398.6	16,542.3
2011	90.7	176.7	726.0	3,047.9	4,041.3	10,432.3	474.9	1,982.7	12,890.0	16,931.3
2012	88.9	167.5	725.1	3,054.5	4,035.9	11,007.0	480.9	1,983.9	13,471.9	17,507.8
2013	81.6	158.4	648.0	2,802.3	3,690.3	10,414.9	431.7	1,691.8	12,538.4	16,228.7

Source: Federal Bureau of Investigation

Table 2: Summary Statistics for Arrest Rates

	White Population	Black Population	Combined
Violent Crime			
Homicide	63.04 (44.05)	595.4 (424.2)	114.6 (103.1)
Rape	164.8 (88.43)	952.3 (768.1)	217.6 (116.7)
Robbery	405.6 (315.6)	4,232 (2,689)	778.9 (607.7)
Assault	2,288 (1,711)	11,778 (6,763)	3,158 (2,227)
Overall	2,896 (4,693)	17,314 (9,107)	4,218 (2,651)
Property Crime			
Burglary	1,548 (896.6)	5,253 (3,090)	1,916.3 (1,157)
Larceny	7,656 (3,689)	28,923 (17,078)	9,363 (4,035)
Motor Vehicle Theft	559.6 (552.1)	2,701 (2,457)	747.2 (699.1)
Overall	9,723 (5,704)	35,644 (20,456)	16,162 (5,240)
Part I Crime	12,620 (6,072)	54,958 (27,270)	16,235 (7,167)

Numbers represent the total count of arrests per 100,000 residents. For all arrests that comprised multiple offense categories, an arrest is recorded for each category.
Source: Federal Bureau of Investigation

Table 3: Summary of Medical Marijuana Laws by State, 1996-2015

State	Date of Home Cultivation Law	Date of Dispensary Law
Alaska	3/4/1999	
Arizona	12/10/2010	12/10/2010
California	11/6/1996	1/1/2004
Colorado	6/30/2001	7/1/2010
Connecticut		10/1/2012
Delaware		7/1/2011
Washington, D.C.		7/27/2010
Hawaii	6/14/2000	
Illinois		1/1/2014*
Maine	12/22/1999	11/3/2009
Maryland		6/1/2014*
Massachusetts		1/1/2013
Michigan	12/4/2008	
Minnesota	6/30/2014*	
Montana	11/2/2004	
New Hampshire		7/23/2013
New Jersey		10/1/2010
New Mexico	7/1/2007	7/1/2007
New York		7/5/2014*
Nevada	10/1/2001	1/1/2014*
Oregon	12/3/1998	1/1/2015*
Rhode Island	1/3/2006	6/16/2009
Vermont	7/1/2004	6/2/2011
Washington	11/3/1998	1/1/2015*

As of 2013:
- States with home cultivation laws only: 7
- States with dispensary laws only: 6
- States with home cultivation and dispensary laws: 8
- States with any type of medical marijuana law: 21

* Indicates that the effective date of this law is outside the range of this study. All dates in the table represent the date the law went into effect.

Sources: National Organization for the Reform of Marijuana Laws, the Marijuana Policy Project, and the National Conference of State Legislators

Table 4: Control Variable Summary Statistics for Total State Populations

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
MML	939	0.185	0.388	0	1
Dispensary Law	939	0.050	0.218	0	1
Home Cultivation Law	939	0.158	0.365	0	1
Average Age	939	34.75	1.912	27.92	43.56
Unemployment Rate	939	0.057	0.024	0.0012	0.153
Average Income ('$000s)	939	22.04	5.441	9.272	43.37
Police Officers (per 1,000)	939	6.388	5.233	0.061	24.92

Sources: Marijuana Policy Project, Bureau of Labor Statistics, U.S. Census Bureau

Table 5: Control Variable Summary Statistics for State Populations by Race

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Average Age					
White	939	34.99	2.033	27.99	43.72
Black	939	31.44	4.825	9.500	78.00
Unemployment Rate					
White	939	0.0515	0.0245	0.0025	0.1437
Black*	818	0.1174	0.0605	0.0022	0.5000
Black (imputed)**	939	0.1242	0.0675	0.0022	0.5000
Average Income (‘$000s)					
White	939	23.13	6.643	9.365	65.67
Black	938	17.33	6.969	0.0400	113.2

Sources: Bureau of Labor Statistics, U.S. Census Bureau
** Excludes 121 empty data points.*
*** Missing data points are imputed using linear extrapolation and interpolation*

4. METHODOLOGY

I implement a differences-in-differences (DD) approach to estimate the change in arrest rates experienced by states with either type of MML relative to those that do not. To make results comparable and understandable, I am interested in the *percentage* change in arrest rates rather than the total change in arrest counts associated with MMLs. Therefore, I use a log-linear specification in all of my regressions. I use the following equation as a baseline model to estimate the effect of MMLs on arrest rates:

$$\ln(ArrestRate_{str}) = \beta_0 + \beta_1 MML_{st} + \alpha X_{str} + \mu_s + \delta_t + \varepsilon_{str} \quad (1)$$

In Equation 1, MML_{st} indicates the presence of a medical marijuana law in state *s* in year *t*, taking the value of "one" if *any* type of MML is present and "zero" otherwise. $ArrestRate_{str}$ represents the arrest count per 100,000 residents for Part I crimes for race *r* (white, black, or combined, depending on the model) in state *s* for year *t*. This rate is calculated by aggregating the arrest counts for each Part I crime for the white, black, and combined populations separately, dividing this number by the corresponding population in any state-year, and then dividing by 100,000. X_{str} represents control variables on the state-year-race level. Because I am interested in the racial implications of MMLs, I use arrest data and control data for white and black populations. I exclude other races included in the UCR data because of their relatively small sample sizes and lack of control data on the race level. State and time fixed effects are indicated by μ_s and δ_t, respectively. State fixed effects control for bias that may arise from arrest-related characteristics that vary by state but not over time, such as degree of crime enforcement, police funding, and proclivity to commit certain crimes among residents. Time fixed effects control for bias that may arise from arrest-related characteristics that vary over time, such as the national decrease in arrest rates in the 1990s, particularly involving violent crime.

Because observations may be more highly correlated within each state than between states, I also cluster standard errors by state. Recent literature is not uniform in this regard: Gavrilova et al (2014) cluster at the county level, Alford (2014) clusters at the state level, and Morris (2014) does not cluster standard errors at all. In testing which specifications better explain variation in arrest rates, I provide results with and without clustered standard errors.

Since I am particularly interested in gauging the importance of market design in estimating the effect of MMLs on arrest rates, I heavily rely on the following model:

$$\ln(ArrestRate_{str}) = \beta_0 + \beta_1 cult_{st} + \beta_2 disp_{st} + \alpha X_{str} + \mu_s + \delta_t + \varepsilon_{str} \quad (2)$$

Equation 2 estimates the effect of home cultivation laws and dispensary laws on crime, with $cult_{st}$ and $disp_{st}$ taking on a value of "one" if a cultivation or dispensary law is present in state *s* during year *t* and "zero" otherwise. Because it is implemented on the race level, this equation will estimate whether the effect of each type of MML on arrest rates is different between whites and blacks. By combining the coefficients on dispensary laws and home cultivation laws, I can estimate overall the net change in arrest rates associated with MMLs.

I also include regressions with state-specific time trends to control for any preexisting trends in arrests that are unrelated to the passage of MMLs. This model will take the form:

$$\text{Ln}(ArrestRate_{str}) = \beta_0 + \beta_1 cult_{st} + \beta_2 disp_{st} + \alpha X_{str}$$

$$+\mu_s + \delta_t + \gamma_s Year_t + \varepsilon_{str} \quad (3)$$

In Equation 3, state specific time-trends are represented by $\gamma_s Year_t$, where, in each year t, each state s has a specific coefficient γ added to the predicted arrest rate.

First, I compare baseline Equations 1, 2, and 3 including regressions with and without controls, state fixed effects, time fixed effects, state-specific time trends, and clustered standard errors. Then, I take the specification that best fits the data and I run that regression on arrest rates for each Part I crime separately. This strategy will enable me to locate what crimes are driving the change in overall arrest rates. I expect home cultivation laws to most directly relate to the crime reducing "consumption effect," but potentially also lead to the crime- and arrest-increasing "exploitation" effect. Thus, I expect the coefficient of home cultivation laws to be negative, but small and insignificant, for property and violent crimes. On the contrary, I expect dispensary laws to demonstrate a closer relationship with the "exploitation" and "business site" effects and display positive coefficients in their association with Part I crimes, specifically for theft-related crimes such as larceny, burglary, and robbery.

5. RESULTS

5.1 Trends in the Raw Data

Over the period studied, arrest rates for Part I crimes initially fell more steeply for states that passed a MML at any point in the study ("MML states") versus states that did not ("non-MML states") (Figure 2-A). The arrest rate trends between MML states and non-MML states diverge in this way for both property crime and violent crime arrest rates from 1994-2004. MML states and non-MML states experienced a roughly similar increase in arrest rates for property crimes from 2005-2010 (Figure 2-B). While arrest rates for violent crime continued to decrease in non-MML states after 2005, MML states experienced a bump in violent crime arrest rates before falling again after 2010 (Figure 2-C). The difference in arrest rate trends is more evident between dispensary and non-dispensary states than between home cultivation and non-home cultivation states (Figures 3-A, 4-A). Yet, across both types of MMLs, there is a relative increase in violent crime arrest rates for MML from 2005-2010 (Figures 3-C, 4-C).

Figure 2: Arrest Rates per 100,000 in MML States and Non-MML States, 1994-2013

Figure 2-A. Part I Crime

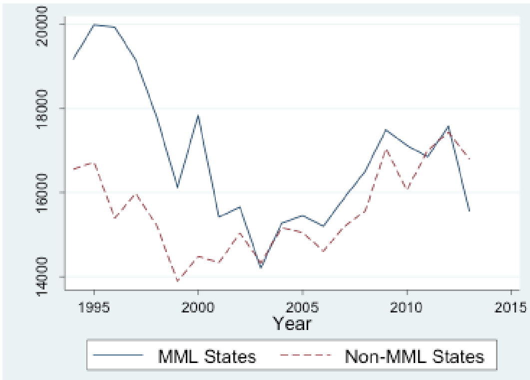


Figure 2-B. Property Crime

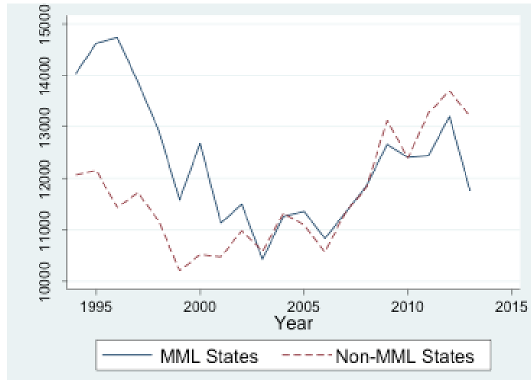


Figure 2-C. Violent Crime

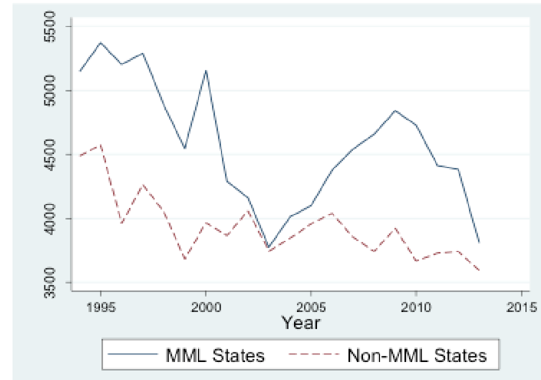


Figure 3: Arrest Rates per 100,000 in Dispensary States and Non-Dispensary States, 1994-2013

Figure 3-A. Part I Crime

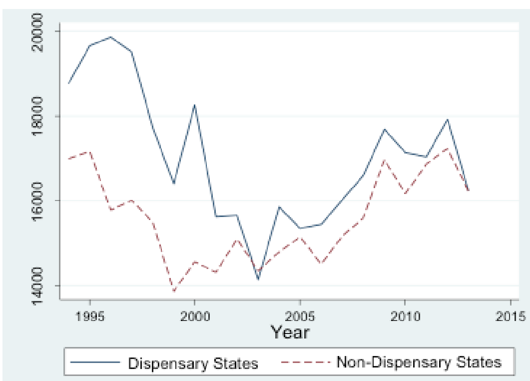


Figure 3-B. Property Crime

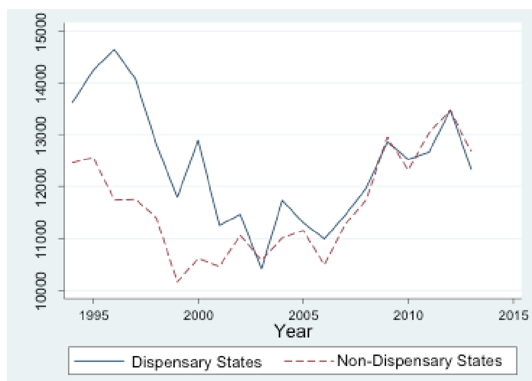


Figure 3-B. Violent Crime

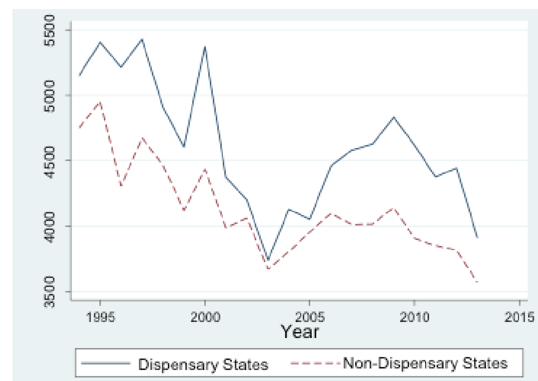


Figure 4: Arrest Rates per 100,000 in Home Cultivation States and Non-Home Cultivation States by Crime Type, (1994-2013)

Figure 4-A. Part I Crime

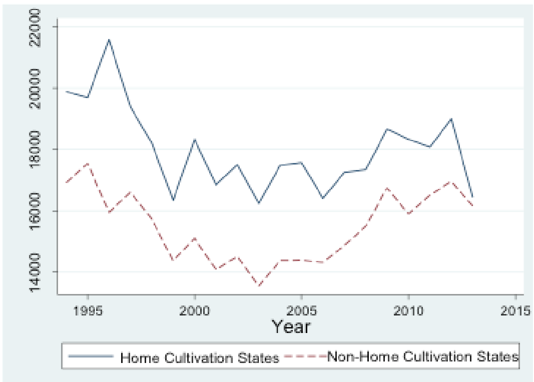


Figure 4-B. Property Crime

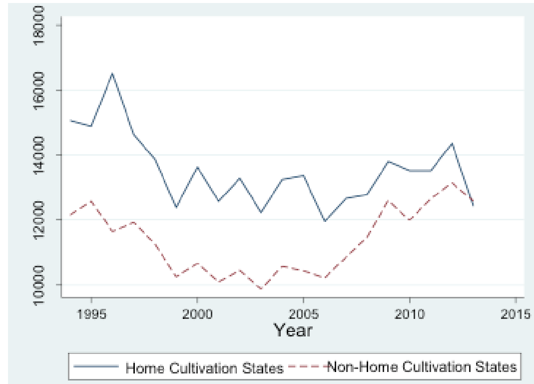
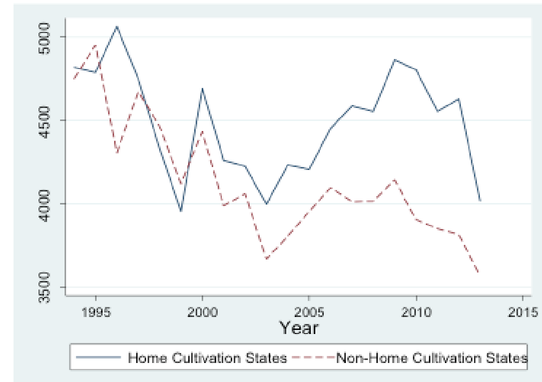


Figure 4-C. Violent Crime



At first glance, these trends appear to suggest that the passage of MMLs is correlated to immediate decreases in Part I crime and eventual increases in violent crime. However, this presentation method does not adequately address the possibility that states coincidentally experienced rapid decreases in arrest rates *before* passing MMLs. In fact, by 2003, near the conclusion of the initially steep decrease in arrests for MML states shown in Figure 2, only California, Oregon, Alaska, Maine, and Hawaii, Colorado, and Nevada had passed MMLs; two-thirds of states that eventually passed MMLs had not yet done so. Therefore, arrest rate trends in MML states may be unrelated to the actual passage of MMLs. Though unlikely, it is also possible that causation could run in the opposite direction if the large decreases in arrest rates made state lawmakers more amenable to passing MMLs in the first place. These possibilities make it important to decipher how the arrest rates trends relate to the specific timing of passage

In Table 6, I show that trends in arrest rate changes, as measured by average annual percent changes in 4-5 year intervals, were quite different between MML states and non-MML states. Consistent with Figures 2-4, in the earliest and latest years of the study, annual arrest rates decreased four to six percentage points more in MML states. However, in the mid-2000s, arrest rates increases were around 4 percentage points higher in MML states. The data shows that while arrest rates had been decreasing by more in MML states for most periods, they actually increased in absolute terms from 2005-2009. During this same time period, arrest rates in non-MML states were stagnant or slightly decreasing. It is unclear whether the MMLs influenced different arrest rate trends between states or if they existed beforehand.

Table 6: Comparison of Part I Crime Arrest Rate Trends

Crime Category	Average annual percent change in arrest rates over period				Cumulative
	1996-1999	2000-2004	2005-2009	2009-2013	1996-2013
Violent Crime					
MML States	-5.4	-6.1	0.4	-1.6	0.9
Non-MML States	0.8	-0.4	-0.2	5.7	1.4
Difference	*-6.2*	*-5.5*	*0.6*	*-6.1*	*-0.5*
Property Crime					
MML States	-6.6	-6.8	4.6	-3.5	-1.2
Non-MML States	-2.0	-8.0	-0.4	3.9	-0.8
Difference	*-4.6*	*-1.2*	*4.2*	*-6.4*	*-0.4*
Part I Crime					
MML States	-6.1	-6.3	4.0	-2.2	-1.3
Non-MML States	-1.3	-5.4	0.1	8.6	-0.5
Difference	-4.8	-0.9	3.9	-10.2	-0.8

To account for this ambiguity, Morris (2014) presents mean offense-level crime rates for states with and without MMLs in any given year and argues that there was a greater decrease in crime rates for states that had MMLs in place. In his figures, each state is initially included in the dataset for "non-MML states" until the year it passes a law. At that point, it becomes a "MML state." In this methodology, states that were among the first to pass MMLs heavily bias the first few years of data for MML states. The data points used for MML states until 2000 – which evidently account for most of the overall drop in crime rates that Morris shows – only include California, Oregon, Maine, and Alaska. After 2000, when the majority of MMLs were passed, Morris' graphs do not present any noticeable difference in crime rates for MML states, weakening the author's claim that states experienced relative decreases in crime rates in association with MMLs.

Alford (2014) presents trends in crime rates for states that did and did not eventually pass MMLs and shows, like Figures 2-4 show for arrest rates, that crime rates decrease more sharply for states that passed MMLs. As mentioned, this presentation method conflates decreases in crime that were picked up before and after MMLs were actually passed. In addition, it makes no distinction for crime changes in years after some states passed MMLs while others in the group had not, making the association between crime decreases and MML passage mostly unobservable.

Accounting for these issues, I normalize the year states passed MMLs to zero, with years prior to passage as negative years and years after passage as positive years. I then present mean arrest rates over time in these normalized years and look for any change in arrest rates occurring near year zero, the year the MML was passed. I randomly assign a year of legalization between 1996 and 2013 for control states (states that did not pass MMLs) and calculate mean arrest rates for each random normalized year. I then perform the randomization five times and present the mean arrest rates across all five samples to compare to the MML group in Figures 5-7. This normalization and randomization strategy is similar to the one implemented by Rees et al (2013) to compare traffic fatalities between states that did and did not pass dispensary laws. This strategy operates under the assumption that the year in which MMLs were passed is randomly distributed across the study period.

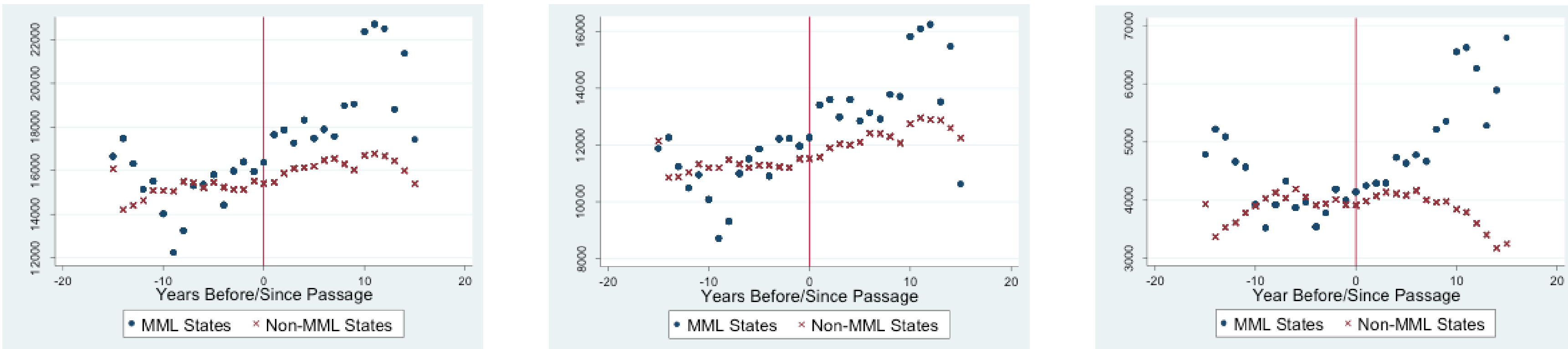
The benefit of this normalization strategy is that I can mitigate the possibility of incorrectly attributing preexisting arrest rate decreases in MML states to the passage of MMLs. However, I am also left with only a few data points on each end of the time horizon. For example, because California passed its MML first in 1996, the rightmost point on the graph, corresponding to the mean arrest rate 18 years after MML passage, is simply California's arrest rate in 1996. At the same time, the very left of each graph (up to 20 years before the passage of a MML) is dominated by the historical arrest rates of states that only recently passed MMLs such as Massachusetts and New Hampshire in 2013. They will naturally be higher since arrest rates were higher in 1994 than they were in 2013. Therefore, I exclude all points at least 15 years before and after passage so that I have at least four states of data for any mean arrest rate computed.

Using this strategy, I find a different pattern from that presented in previous studies. Because the passage of MMLs is spread somewhat evenly across the twenty-year period, there is only a modest decrease in arrest rates before year zero. However, around year zero, arrest rates tend to *increase*. This suggests that even though MML states experienced absolute decreases in arrest rates over the period studied, they experienced relative increases after the passage of MMLs (Figure 5). The relative increase in arrest rates after the passage of MMLs is most evident for dispensary laws. In the 10-15 years prior to dispensary laws, states had experienced constant to slightly falling arrest rates, similarly to control states. However, after the passage of dispensary laws, both property crime arrests and violent crime arrests pick up rapidly for MML states and stay flat or slightly positive for control states (Figure 6). The data indicates that the passage of dispensary laws is associated with increases in property and violent crime arrests, but the trend appears to have begun just before the laws' passage. This makes a causal interpretation of the data harder to justify.

States that passed home cultivation laws experienced much higher arrest rates than control states both before and after the laws' passage. Similarly to states with dispensary laws, states appear to experience an increase in Part I crime arrest rates in association with home cultivation laws (Figure 7). However, this increase is not truly realized until around ten years after passage. While home cultivation laws had arrest rates higher than control states over the entire period, the trend in Part I crime arrests between the two groups does not appear to change in the immediate period around passage. Focusing on the five- to ten-year period after home cultivation laws, the trend in arrest rates versus control states actually appears to be flat or down for Part I crimes and property crimes, but unambiguously up for violent crime.

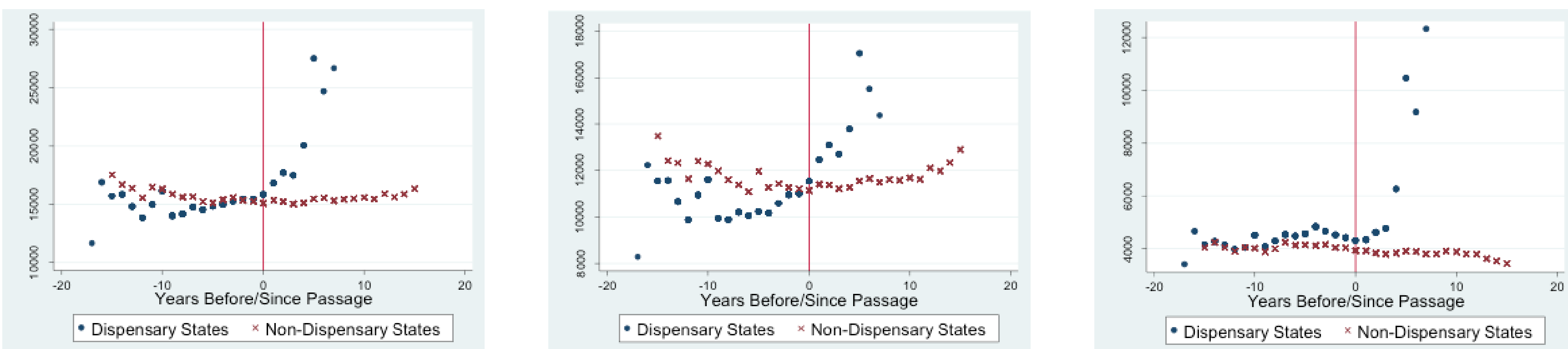
Overall, this method of presenting the data clarifies that the initial decrease in Part I crime arrests was picked up before the passage of the MMLs. I find that arrest rates for Part I crime increased after the passage of MMLs relative to control states. Of note, the increase in arrest rates in association with MMLs was more pronounced for states that passed dispensary laws. For states that passed home cultivation laws, the immediate effect on arrest rates was less clear. For Part I crimes and property crimes, there may even be an inverse relationship with arrest rates. Putting all this information together, the data most strongly indicates that the passage of dispensary laws is associated with increases in arrests for property and violent crime. Fixed effects and time trends in my regression analysis will help determine whether changes in arrest rates are associated with MMLs or are a product of preexisting trends.

Figure 5: Impact of MMLs on Arrest Rates for Part I Crime, Property Crime, and Violent Crime



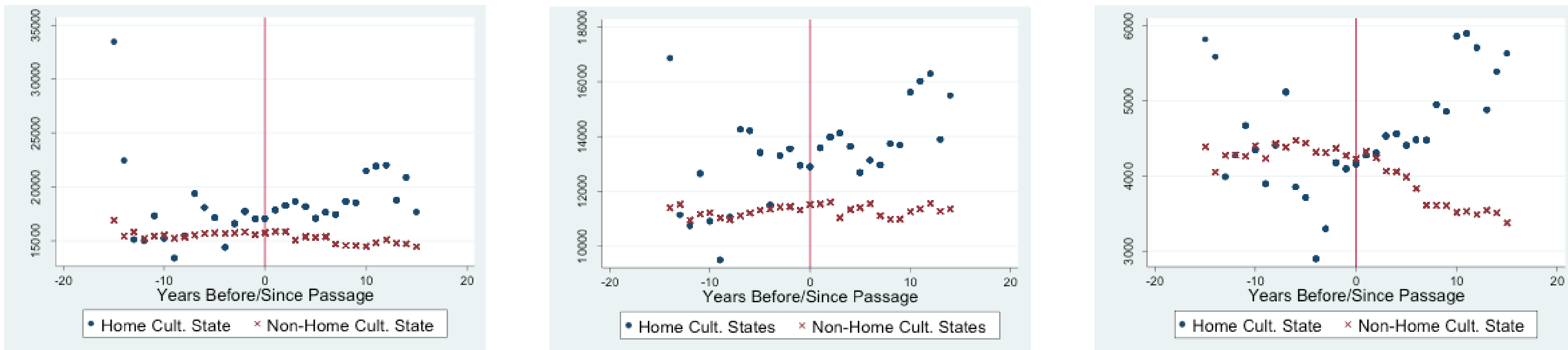
** Data points for non-MML states represent the arrests for each corresponding category averaged across five control samples with a randomized year zero for each non-MML state.*

Figure 6: Impact of Dispensary Laws on Arrest Rates for Part I Crime, Property Crime, and Violent Crime



** Data points for non-dispensary states represent the arrests for each corresponding category averaged across five control samples with a randomized year zero for each non-MML state.*

Figure 7: Impact of Dispensary Laws on Arrest Rates for Part I Crime, Property Crime, and Violent Crime



** Data points for non-home cultivation states represent the arrests for each corresponding category averaged across five control samples with a randomized year zero for each non-MML state.*

5.2 Model Comparison

First, I compare preliminary models to determine which method of estimating the effect of MMLs on arrest rates best fits the data. Results for the total population are presented in Table 7. Before I include fixed effects or controls, simply splitting MMLs into home cultivation laws and dispensary laws demonstrates that the passage of dispensary laws is associated with a significant increase in arrest rates (Model 2). This is entirely consistent with the raw data presented in Figure 6. The passage of home cultivation laws is associated with a significant but smaller decrease in arrest rates (Model 2). This relationship is a bit more difficult to reconcile given that, in Figure 7, arrest rates for violent crime appear to increase after home cultivation laws were passed. On a crime-by-crime basis without controls (regressions not shown), the coefficients on home cultivation laws were closer to zero or nonnegative for violent crimes besides homicide (estimated 27.3% decrease). However, the decrease in arrests related for property crime far outweighed the increase in arrests for certain types of violent crimes in association with home cultivation laws. These regressions indicate that, at least in the short-term, arrests for Part I crime are not positively associated with the passage of home cultivation laws.

Across all models, if I do not bifurcate MMLs into home cultivation and dispensary laws, the coefficient on MMLs remains insignificant. This finding is similar to Morris' (2014) estimated impact of MMLs on crime rates. Including state and time fixed effects improves the R-squared of the model and diminishes the size of the coefficients on the different types of MMLs (Model 4). The positive coefficient on dispensary laws and the negative coefficient on home cultivation laws are significant at the 5% level even after controlling for these effects.

Introducing controls reduces the significance of home cultivation laws (Model 6), and adding clustered standard errors reduces the significance of dispensary laws on aggregate Part I crime arrest rates to outside the 10% level (Model 8). The large increase in standard errors when clustering by state suggests that observations are highly correlated within states. Therefore, for my regressions on a crime-by-crime basis, I only provide results with clustered standard errors. Though the results lose significance, they continue to show, for overall Part I crime arrest rates, that there is a positive association with dispensary laws and a negative association with home cultivation laws. Adding state-specific time trends mutes both these trends (Model 10).

Results are generally consistent when I implement this model comparison on the race level, though the opposing directional effects of dispensary laws and home cultivation laws hold even with state-specific time trends despite having insignificant coefficients. The results for the white population more closely resemble the results for the total population. The regressions also have higher R-squared values for the white population than for the black population. Both models have the expected signs on the coefficients for average income (negative) and police officers per 1,000 residents (positive). The coefficients on unemployment and average age are insignificant across most models. Model comparisons for white and black populations are presented in Tables 8 and 9, respectively.

For the rest of my data analysis, I implement a state and time fixed effects regression and use home cultivation laws and dispensary laws as my independent variables of interest. I use arrest rates for each type of crime independently to see if certain crimes drive the overall changes in arrests for Part I crime. I provide results with and without state-specific time trends for each crime type.

Table 7: Model Comparison on the Effects of MMLs on Arrest Rates for Part I Crimes

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10
MML	-0.0878		-0.0531		-0.00142		-0.00142		-0.0793	
	(0.0800)		(0.0442)		(0.0463)		(0.124)		(0.122)	
Home Cultivation Law		-0.255**		-0.121**		-0.0778		-0.0778		-0.148
		(0.109)		(0.0508)		(0.0518)		(0.177)		(0.172)
Dispensary Law		0.451***		0.129**		0.160***		0.160		-0.00248
		(0.105)		(0.0609)		(0.0608)		(0.126)		(0.0735)
Average Age					-0.0282**	-0.0288**	-0.0282	-0.0288	-0.0481	-0.0474
					(0.0113)	(0.0112)	(0.0341)	(0.0350)	(0.0481)	(0.0474)
Unemployment Rate					-1.543	-1.781*	-1.543*	-1.781*	1.035	0.914
					(0.954)	(0.955)	(0.914)	(0.900)	(1.314)	(1.278)
Average Income					-0.0260***	-0.0268***	-0.0260	-0.0268	0.0162	0.0165
					(0.00748)	(0.00746)	(0.0200)	(0.0198)	(0.0192)	(0.0195)
Police Officers					0.0309**	0.0310**	0.0309	0.0310	0.0363	0.0360
					(0.0140)	(0.0139)	(0.0187)	(0.0189)	(0.0239)	(0.0238)
Constant	9.576***	9.577***	9.740***	9.734***	10.85***	10.88***	10.85***	10.88***	54.46	62.04
	(0.0175)	(0.0171)	(0.0870)	(0.0868)	(0.486)	(0.483)	(1.476)	(1.501)	(51.56)	(55.68)
Observations	939	939	939	939	939	939	939	939	939	939
R-squared	0.003	0.029	0.772	0.774	0.778	0.780	0.778	0.780	0.883	0.884
State FE	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
State-Specific Time Trends	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES

Independent variable is Part I crime arrest rates per 100,000 presented in logarithmic form
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Model Comparison on the Effect of MMLs on Crime for Whites

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 9	(10) Model 10
MML	-0.00810		-0.143***		-0.0992**		-0.0992		-0.0885	
	(0.103)		(0.0459)		(0.0455)		(0.133)		(0.105)	
Home Cultivation Law		-0.231		-0.167***		-0.118**		-0.118		-0.110
		(0.143)		(0.0528)		(0.0508)		(0.178)		(0.141)
Dispensary Law		0.579***		0.137**		0.158***		0.158		0.00398
		(0.129)		(0.0634)		(0.0595)		(0.120)		(0.0648)
Average Age					-0.0102	-0.0153	-0.0102	-0.0153	-0.0366	-0.0369
					(0.0107)	(0.0107)	(0.0170)	(0.0200)	(0.0307)	(0.0307)
Unemployment Rate					-1.035	-1.222*	-1.035	-1.222	-0.664	-0.696
					(0.646)	(0.646)	(0.885)	(0.961)	(0.606)	(0.642)
Average Income ('$000s)					-0.0660***	-0.0662***	-0.0660	-0.0662	-0.00891	-0.00825
					(0.00614)	(0.00612)	(0.0421)	(0.0416)	(0.00855)	(0.00809)
Police Officers (per 100,000)					0.0486***	0.0523***	0.0486***	0.0523***	0.0371	0.0373
					(0.0137)	(0.0136)	(0.0177)	(0.0185)	(0.0225)	(0.0223)
Constant	9.293***	9.299***	9.183***	9.185***	10.00***	10.17***	10.00***	10.17***	14.06	17.22
	(0.0162)	(0.0161)	(0.0903)	(0.0902)	(0.460)	(0.458)	(0.951)	(1.037)	(46.03)	(50.20)
Observations	939	939	939	939	939	939	939	939	939	939
R-squared	0.000	0.029	0.810	0.810	0.836	0.837	0.836	0.837	0.926	0.926
State FE	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
State-Specific Time Trends	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES

Independent variable is Part I crime arrest rates per 100,000 presented in logarithmic form
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Model Comparison on the Effect of MMLs on Crime for Blacks

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model 7	(10) Model 8
MML	-0.251***		0.0486		0.0608		0.0608		-0.0901	
	(0.0949)		(0.0611)		(0.0628)		(0.198)		(0.202)	
Home Cultivation Law		-0.339***		-0.162**		-0.162**		-0.162		-0.253
		(0.131)		(0.0702)		(0.0717)		(0.217)		(0.232)
Dispensary Law		0.317***		0.110		0.123		0.123		-0.0499
		(0.117)		(0.0843)		(0.0849)		(0.121)		(0.114)
Average Age					0.00102	0.00207	0.00102	0.00207	-0.000574	-0.000260
					(0.00426)	(0.00426)	(0.00377)	(0.00405)	(0.00358)	(0.00366)
Unemployment Rate*					-0.970***	-0.972***	-0.970*	-0.972	0.183	0.142
					(0.290)	(0.290)	(0.569)	(0.588)	(0.554)	(0.538)
Average Income ('$000s)					-0.00595**	-0.00549**	-0.00595*	-0.00549*	-0.00470*	-0.00455*
					(0.00269)	(0.00269)	(0.00317)	(0.00315)	(0.00250)	(0.00252)
Police Officers (per 100,000)					0.0125	0.00341	0.0125	0.00341	0.0230	0.0232
					(0.0195)	(0.0194)	(0.0234)	(0.0284)	(0.0286)	(0.0287)
Constant	10.78***	10.77***	10.55***	10.53***	10.58***	10.60***	10.58***	10.60***	-7.243	13.30
	(0.0194)	(0.0195)	(0.120)	(0.120)	(0.263)	(0.263)	(0.240)	(0.250)	(22.88)	(28.65)
Observations	939	939	939	939	935	935	935	935	935	935
R-squared	0.018	0.025	0.678	0.680	0.683	0.685	0.683	0.685	0.815	0.817
State FE	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES
State-Specific Time Trends	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES

Independent variable is Part I crime arrest rates per 100,000 presented in logarithmic form
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3 Effects of Dispensary Laws and Cultivation Laws on Arrest Rates

By combining the coefficients on dispensary laws and cultivation laws I estimate that overall, MMLs are associated with an 8.2% increase in Part I crime arrest rates. This effect is driven by a 16.6% increase in arrest rates associated with dispensary laws. This result is significant at the 1% level, but loses significance once I cluster standard errors by state. Running the same regression on each type of Part I crime, I find that dispensary laws are associated with a 22.7% increase in burglary rates and a 19.4% increase in robbery rates, both significant at the 10% level even after clustering standard errors. However, dispensary laws are not found to have a significant relationship with property or violent crime taken as a whole. The presence of a home cultivation law is not estimated to have an association with arrest rates. Baseline results on a crime-by-crime basis are presented in Table 10.

I find that dispensary laws are expected to increase homicide arrest rates by 31.1% as well, significant at the 10% level. However, this is driven by an estimated 24.8% increase in homicide arrest rates for the black population. The black homicide arrest data is the most volatile of all arrest variables on the race level. While I have on average 925 state-year observations for every other black arrest rate, I only have 825 for black homicide arrests since many reporting agencies do not report homicides to the FBI. The smaller sample and volatile reporting leads to a very large standard deviation of 424.2 for black homicide arrests rates, which has a mean of 595.4. The effects of MMLs on arrest rates for the white population drive most of the other aggregate results.

All estimates lose significance when I include state-specific time trends, shown in Table 11. This result points to the possibility that different arrest rate *trends* between MML states and non-MML states may have actually been an unobservable in the original models. If this is the case, then the increase in arrests for states that passed MMLs over the time period studied may have preceded the laws' passage rather than occurring as a result of them. However, many of the regressions with time trends still exhibit a positive association between dispensary laws and arrest rates with dispensary laws and negative association between home cultivation laws and arrest rates. In these regressions, the R-squared exceeds 0.9, standard errors are much larger, and the coefficients on some control variables that had significance previously become insignificant. It is possible that by allowing for trends in arrest rates to be different across states, there might be so little variation left to estimate that the results become erratic and imprecise.

Table 10: Effect of MMLs on Arrest Rates by Type of Part I Crime

VARIABLES	(1) Homicide	(2) Rape	(3) Robbery	(4) Assault	(5) Violent Crime	(6) Burglary	(7) Larceny	(8) MV Theft	(9) Property Crime	(10) All Part 1 Crimes
Home Cultivation Law	-0.224	0.127	0.0160	0.0161	-0.0140	-0.0914	-0.0872	-0.00166	-0.0975	-0.0778
	(0.214)	(0.108)	(0.216)	(0.219)	(0.198)	(0.162)	(0.168)	(0.214)	(0.176)	(0.177)
Dispensary Law	0.311*	-0.0149	0.194*	0.0401	0.0865	0.227*	0.142	0.160	0.177	0.160
	(0.169)	(0.0925)	(0.105)	(0.156)	(0.135)	(0.115)	(0.124)	(0.148)	(0.126)	(0.126)
Average Age	-0.0334	0.00501	-0.0174	0.00119	-0.00760	-0.0243	-0.0364	-0.0188	-0.0364	-0.0288
	(0.0399)	(0.0250)	(0.0369)	(0.0414)	(0.0393)	(0.0336)	(0.0331)	(0.0395)	(0.0347)	(0.0350)
Unemployment Rate	-2.200	-3.977***	-0.883	-5.130**	-4.099**	-0.256	-0.783	-2.807	-0.977	-1.781*
	(1.925)	(1.447)	(1.590)	(2.029)	(1.695)	(1.241)	(0.915)	(1.716)	(0.905)	(0.900)
Average Income ('$000s)	0.00428	-0.00559	-0.0104	-0.0145	-0.0108	-0.0248	-0.0283*	-0.0424	-0.0316	-0.0268
	(0.0196)	(0.0147)	(0.0152)	(0.0315)	(0.0236)	(0.0174)	(0.0161)	(0.0285)	(0.0192)	(0.0198)
Police Officers (per 100,000)	0.0114	0.0135	0.00885	0.0321	0.0291	0.0378**	0.0287	0.0192	0.0294	0.0310
	(0.0272)	(0.0182)	(0.0299)	(0.0253)	(0.0246)	(0.0182)	(0.0181)	(0.0234)	(0.0178)	(0.0189)
Constant	6.747***	5.661***	7.608***	8.167***	8.823***	8.354***	10.54***	7.783***	10.84***	10.88***
	(1.578)	(1.065)	(1.436)	(1.823)	(1.658)	(1.473)	(1.376)	(1.800)	(1.486)	(1.501)
Observations	925	927	937	939	939	928	939	939	939	939
R-squared	0.781	0.681	0.841	0.781	0.788	0.751	0.793	0.779	0.791	0.780
Number of States	50	50	50	50	50	50	50	50	50	50
Crime Type	Violent	Violent	Violent	Violent		Property	Property	Property		

Independent variables are arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Effect of MMLs on Arrest Rates by Type of Part I Crime (State Specific Time Trends)

VARIABLES	(1) Homicide	(2) Rape	(3) Robbery	(4) Assault	(5) Violent Crime	(6) Burglary	(7) Larceny	(8) MV Theft	(9) Property Crime	(10) All Part 1 Crimes
Home Cultivation Law	-0.154	0.0436	-0.183	-0.159	-0.178	-0.0219	-0.143	-0.178	-0.140	-0.148
	(0.149)	(0.104)	(0.222)	(0.163)	(0.174)	(0.102)	(0.173)	(0.186)	(0.177)	(0.172)
Dispensary Law	-0.0151	-0.0581	-0.112	-0.0630	-0.0579	0.0314	0.0135	-0.00164	0.0206	-0.00248
	(0.139)	(0.0724)	(0.125)	(0.0978)	(0.0924)	(0.0605)	(0.0783)	(0.111)	(0.0736)	(0.0735)
Average Age	-0.0124	0.0145	-0.0421	-0.0265	-0.0350	-0.0138	-0.0529	-0.0397	-0.0529	-0.0474
	(0.0236)	(0.0191)	(0.0494)	(0.0440)	(0.0469)	(0.0200)	(0.0482)	(0.0446)	(0.0489)	(0.0474)
Unemployment Rate	0.260	-1.712	1.597	-0.367	-0.0165	1.285	1.529	-0.898	1.322	0.914
	(1.429)	(1.182)	(1.571)	(1.200)	(1.100)	(0.953)	(1.462)	(1.761)	(1.466)	(1.278)
Average Income ('$000s)	0.0132	-0.00231	0.00928	0.0227	0.0206	-0.00147	0.0144	0.0160	0.0156	0.0165
	(0.0115)	(0.0127)	(0.0225)	(0.0184)	(0.0196)	(0.00866)	(0.0204)	(0.0193)	(0.0206)	(0.0195)
Police Officers (per 100,000)	0.0166	0.0207	0.0314	0.0706**	0.0642**	0.0161	0.0229	0.0302	0.0253	0.0360
	(0.0286)	(0.0334)	(0.0239)	(0.0294)	(0.0260)	(0.0206)	(0.0239)	(0.0259)	(0.0241)	(0.0238)
Constant	16.31	38.11	109.5*	256.1***	203.0***	5.801	20.99	44.45	23.54	62.04
	(35.11)	(24.96)	(61.15)	(52.88)	(55.00)	(24.97)	(56.61)	(53.33)	(57.47)	(55.68)
Observations	925	927	937	939	939	928	939	939	939	939
R-squared	0.885	0.808	0.907	0.912	0.904	0.906	0.880	0.892	0.884	0.884
Crime Type	Violent	Violent	Violent	Violent		Property	Property	Property		
State-Specific Time Trends	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Independent variables are arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

5.4 Racial Implications of MMLs

Running the regressions on the race level indicates that the white population drives the effect of MMLs on arrest rates estimated among the total population. I find that MMLs are associated with a 4.0% increase in Part I crime arrests. This is driven by an 11.8% decrease associated with home cultivation and a 15.8% increase associated with dispensary laws. Both results lose significance when I cluster standard errors by state. However, the coefficient on dispensary laws remains significant at the 5% level when the independent variable is burglary or robbery rates. Burglary and robbery arrest rates increase by an estimated 20.1% and 21.7%, respectively, in the presence of a dispensary law. When I introduce state-specific time trends, the dispensary laws are only associated with a 0.4% increase in Part I crime arrest rates and the result is not significant. The coefficients on dispensary laws for burglary arrest rates and robbery arrest rates also become insignificant. Results are presented in Tables 12 and 13 with and without time trends, respectively.

When the model is applied to the black population, MMLs are associated with a 3.9% decrease in arrests for Part I crime. However, neither type of MML is estimated to significantly impact arrest rates for violent crimes, property crimes, or total Part I crimes. For almost all individual Part I crime arrest rates, there is a consistent negative association between home cultivation laws and crime and no association between dispensary laws and arrest rats. The findings are roughly equivalent when I include state-specific time trends. Results are presented in Tables 14 and 15 with and without time trends.

Table 12: Effect of MMLs by Type on Each Part I Offense for White Population

VARIABLES	(1) Homicide	(2) Rape	(3) Robbery	(4) Assault	(5) Violent Crime	(6) Burglary	(7) Larceny	(8) MV Theft	(9) Property Crime	(10) All Part 1 Crimes
Home Cultivation Law	-0.0770	0.0237	-0.152	-0.118	-0.151	0.0140	-0.0992	-0.155	-0.0949	-0.110
	(0.150)	(0.106)	(0.190)	(0.136)	(0.151)	(0.0799)	(0.135)	(0.189)	(0.138)	(0.141)
Dispensary Law	-0.0140	-0.0444	-0.0757	-0.0778	-0.0668	0.0442	0.0302	-0.0360	0.0334	0.00398
	(0.153)	(0.0792)	(0.119)	(0.0888)	(0.0846)	(0.0576)	(0.0679)	(0.112)	(0.0638)	(0.0648)
Average Age	-0.000719	-0.00358	-0.0390	-0.0223	-0.0313	-0.00732	-0.0397	-0.0331	-0.0393	-0.0369
	(0.0198)	(0.0254)	(0.0281)	(0.0294)	(0.0326)	(0.0119)	(0.0298)	(0.0371)	(0.0307)	(0.0307)
Unemployment Rate	-0.0903	-1.317*	-0.335	-0.964	-0.986	0.0880	-0.367	-1.307	-0.545	-0.696
	(0.512)	(0.756)	(0.662)	(0.696)	(0.731)	(0.527)	(0.546)	(0.973)	(0.589)	(0.642)
Average Income ('$000s)	0.00565	0.00216	-0.00659	-0.000323	-0.00139	-0.00294	-0.0112	-0.00587	-0.0115	-0.00825
	(0.00943)	(0.0116)	(0.0116)	(0.0109)	(0.00991)	(0.00707)	(0.00779)	(0.0107)	(0.00877)	(0.00809)
Police Officers (per 100,000)	0.0418	0.0222	0.0466**	0.0793**	0.0770***	0.0197	0.0212	0.0285	0.0235	0.0373
	(0.0271)	(0.0457)	(0.0205)	(0.0301)	(0.0273)	(0.0250)	(0.0204)	(0.0265)	(0.0214)	(0.0223)
Constant	-28.11	43.86	67.67	242.7***	193.0***	-29.94	-29.63	16.67	-22.01	17.22
	(33.35)	(30.64)	(50.33)	(48.94)	(53.85)	(19.61)	(48.14)	(62.53)	(50.07)	(50.20)
Observations	921	927	932	937	938	927	939	935	939	939
R-squared	0.828	0.752	0.899	0.926	0.922	0.904	0.922	0.893	0.927	0.926
State Specific Time Trends	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Crime Type	Violent	Violent	Violent	Violent		Property	Property	Property		

Independent variables are arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Effect of MMLs by Type on Each Part I Offense for White Population (State Specific Time Trends)

VARIABLES	(1) Homicide	(2) Rape	(3) Robbery	(4) Assault	(5) Violent Crime	(6) Burglary	(7) Larceny	(8) MV Theft	(9) Property Crime	(10) All Part 1 Crimes
Home Cultivation Law	-0.0770	0.0237	-0.152	-0.118	-0.151	0.0140	-0.0992	-0.155	-0.0949	-0.110
	(0.150)	(0.106)	(0.190)	(0.136)	(0.151)	(0.0799)	(0.135)	(0.189)	(0.138)	(0.141)
Dispensary Law	-0.0140	-0.0444	-0.0757	-0.0778	-0.0668	0.0442	0.0302	-0.0360	0.0334	0.00398
	(0.153)	(0.0792)	(0.119)	(0.0888)	(0.0846)	(0.0576)	(0.0679)	(0.112)	(0.0638)	(0.0648)
Average Age	-0.000719	-0.00358	-0.0390	-0.0223	-0.0313	-0.00732	-0.0397	-0.0331	-0.0393	-0.0369
	(0.0198)	(0.0254)	(0.0281)	(0.0294)	(0.0326)	(0.0119)	(0.0298)	(0.0371)	(0.0307)	(0.0307)
Unemployment Rate	-0.0903	-1.317*	-0.335	-0.964	-0.986	0.0880	-0.367	-1.307	-0.545	-0.696
	(0.512)	(0.756)	(0.662)	(0.696)	(0.731)	(0.527)	(0.546)	(0.973)	(0.589)	(0.642)
Average Income ('$000s)	0.00565	0.00216	-0.00659	-0.000323	-0.00139	-0.00294	-0.0112	-0.00587	-0.0115	-0.00825
	(0.00943)	(0.0116)	(0.0116)	(0.0109)	(0.00991)	(0.00707)	(0.00779)	(0.0107)	(0.00877)	(0.00809)
Police Officers (per 100,000)	0.0418	0.0222	0.0466**	0.0793**	0.0770***	0.0197	0.0212	0.0285	0.0235	0.0373
	(0.0271)	(0.0457)	(0.0205)	(0.0301)	(0.0273)	(0.0250)	(0.0204)	(0.0265)	(0.0214)	(0.0223)
Constant	-28.11	43.86	67.67	242.7***	193.0***	-29.94	-29.63	16.67	-22.01	17.22
	(33.35)	(30.64)	(50.33)	(48.94)	(53.85)	(19.61)	(48.14)	(62.53)	(50.07)	(50.20)
Observations	921	927	932	937	938	927	939	935	939	939
R-squared	0.828	0.752	0.899	0.926	0.922	0.904	0.922	0.893	0.927	0.926
State Specific Time Trends	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Crime Type	Violent	Violent	Violent	Violent		Property	Property	Property		

Independent variables are arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Effect of MMLs by Type on Each Part I Offense for Black Population

VARIABLES	(1) Homicide	(2) Rape	(3) Robbery	(4) Assault	(5) Violent Crime	(6) Burglary	(7) Larceny	(8) MV Theft	(9) Property Crime	(10) All Part 1 Crimes
Home Cultivation Law	-0.483*	0.0363	-0.224	-0.0680	-0.115	-0.178	-0.158	-0.227	-0.182	-0.162
	(0.266)	(0.150)	(0.189)	(0.250)	(0.231)	(0.169)	(0.207)	(0.254)	(0.217)	(0.217)
Dispensary Law	0.248	-0.00483	0.106	0.0758	0.109	0.164	0.0899	0.0872	0.128	0.123
	(0.153)	(0.136)	(0.0883)	(0.158)	(0.132)	(0.115)	(0.119)	(0.155)	(0.121)	(0.121)
Average Age	0.000874	0.00181	-0.000329	0.00284	0.00109	0.00238	0.00169	-0.00810	0.00200	0.00207
	(0.00710)	(0.00906)	(0.00486)	(0.00489)	(0.00551)	(0.00411)	(0.00390)	(0.00544)	(0.00396)	(0.00405)
Unemployment Rate *	-0.293	-0.471	-0.540	-1.555**	-1.433*	-0.520	-0.749	-0.229	-0.780	-0.972
	(0.595)	(0.492)	(0.415)	(0.759)	(0.756)	(0.385)	(0.556)	(0.567)	(0.543)	(0.588)
Average Income ('$000s)	-0.00451	-0.000519	-0.00296	-0.00533	-0.00532	-0.00557	-0.00533*	-0.00351	-0.00547*	-0.00549*
	(0.00628)	(0.00348)	(0.00368)	(0.00345)	(0.00331)	(0.00376)	(0.00308)	(0.00484)	(0.00319)	(0.00315)
Police Officers (per 100,000)	-0.00468	0.0115	0.00205	-0.0128	-0.00842	0.0184	0.00626	-0.0204	0.00691	0.00341
	(0.0333)	(0.0308)	(0.0363)	(0.0359)	(0.0346)	(0.0312)	(0.0254)	(0.0297)	(0.0261)	(0.0284)
Constant	6.709***	6.415***	8.238***	9.162***	9.644***	8.119***	9.941***	7.972***	10.17***	10.60***
	(0.412)	(0.334)	(0.338)	(0.324)	(0.329)	(0.286)	(0.234)	(0.291)	(0.233)	(0.250)
Observations	824	905	919	935	935	919	935	914	935	935
R-squared	0.533	0.589	0.625	0.615	0.596	0.531	0.741	0.690	0.728	0.685
Crime Type	Violent	Violent	Violent	Violent		Property	Property	Property		

* Includes imputed black unemployment data when variable is missing for state-year
Independent variables are arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Effect of MMLs by Type on Each Part I Offense for Black Population (State Specific Time Trends)

VARIABLES	(1) Homicide	(2) Rape	(3) Robbery	(4) Assault	(5) Violent Crime	(6) Burglary	(7) Larceny	(8) MV Theft	(9) Property Crime	(10) All Part 1 Crimes
Home Cultivation Law	-0.231*	0.158	-0.251	-0.279	-0.295	0.0159	-0.235	-0.246	-0.240	-0.253
	(0.137)	(0.140)	(0.229)	(0.219)	(0.229)	(0.104)	(0.240)	(0.234)	(0.242)	(0.232)
Dispensary Law	-0.0755	-0.0167	-0.0390	-0.105	-0.0980	0.0822	-0.0221	0.0448	-0.00783	-0.0499
	(0.167)	(0.119)	(0.101)	(0.143)	(0.137)	(0.101)	(0.112)	(0.112)	(0.109)	(0.114)
Average Age	0.00254	0.00195	-0.00235	-0.000279	-0.00194	0.00164	-1.04e-05	-0.00765**	0.000123	-0.000260
	(0.00825)	(0.00850)	(0.00522)	(0.00459)	(0.00549)	(0.00390)	(0.00383)	(0.00361)	(0.00346)	(0.00366)
Unemployment Rate *	-0.242	0.520	0.103	0.0541	0.0253	0.614	0.209	0.708	0.234	0.142
	(0.516)	(0.414)	(0.471)	(0.594)	(0.624)	(0.395)	(0.555)	(0.449)	(0.525)	(0.538)
Average Income ('$000s)	-0.00552	-0.000387	-0.00161	-0.00467	-0.00457	-0.00534	-0.00432*	-0.00170	-0.00444*	-0.00455*
	(0.00779)	(0.00345)	(0.00408)	(0.00298)	(0.00294)	(0.00324)	(0.00246)	(0.00515)	(0.00253)	(0.00252)
Police Officers (per 100,000)	0.0210	0.0116	0.0172	0.0455	0.0332	-0.00872	0.0172	0.0415	0.0174	0.0232
	(0.0347)	(0.0324)	(0.0266)	(0.0348)	(0.0323)	(0.0302)	(0.0280)	(0.0320)	(0.0287)	(0.0287)
Constant	93.25***	-23.12	46.91	210.2***	146.8***	-67.82***	-46.96	-0.266	-44.82	13.30
	(23.83)	(19.95)	(28.40)	(28.41)	(29.26)	(15.94)	(29.09)	(29.07)	(29.43)	(28.65)
Observations	824	905	919	935	935	919	935	914	935	935
R-squared	0.721	0.746	0.745	0.809	0.785	0.740	0.834	0.805	0.831	0.817
Crime Type	Violent	Violent	Violent	Violent		Property	Property	Property		

* Includes imputed black unemployment data when variable is missing for state-year
Independent variables are arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

5.5 Robustness Checks

I perform several modifications to by baseline model to check the robustness of my results. Because California passed a MML in 1996, 18 of its 20 data points are counted as post-MML. I run a modified regression excluding all observations from California to ensure that California's arrest rates are not driving the overall results. I also run a regression excluding observations from Colorado. Besides the fact that Colorado passed a recreational marijuana law in 2012 (which could skew results if this had a significant impact on crime in 2012-2013), Colorado had 515 medical marijuana dispensaries as of the autumn of 2015.[24] The large amount of dispensaries may make marijuana more prevalent in Colorado than other MML states, and if the effects of marijuana on arrest rates in Colorado are significant, this might heavily influence overall results.

I also run a regression omitting 2011-2013 observations to test that my results are robust across years. This will also have the benefit of eliminating two years in which recreational marijuana was legal in Colorado. I then run regressions without unemployment data. Unemployment rates have been consistently estimated to have a significant positive relationship with crime. Specifically, Raphael and Winter-Ebmer (2001) suggest that the fall in property crime rates in the 1990s were caused by falling unemployment. Yet, my results consistently show a slightly negative or insignificant relationship with crime. Other controls may be accounting for this variation, diminishing the use of unemployment as a control variable. Finally, I run regressions without any of the control variables. For all robustness checks, I compare results to my baseline model

[24] According to the Marijuana Policy Project's 2015 Report. Source: https://www.mpp.org/issues/medical-marijuana/state-by-state-medical-marijuana-laws/state-by-state-medical-marijuana-laws-report/.

with and without clustered standard errors. Results are presented in Tables 16 and 17 for results with and without time trends, respectively.

I then implement weighted regressions for my baseline model for the total, white, and black populations. I weight each state-year observation by the total percentage of the population each state has in each specific year. The weighted regressions provide a slightly improved R-squared for each of the three models (Table 18). Though the coefficients on home cultivation laws and dispensary laws were already insignificant once standard errors were clustered, the weighting also removes the directional association dispensary laws (positive) and home cultivation laws (negative) have with arrest rates. The advantage of weighting regressions by state population is that small states are prevented from heavily influencing the overall results. In some cases, though, weighting makes data from small states negligible in estimating the effects of MMLs. For example, in 2005, when both Vermont and California had MMLs, the two states had weights of 0.00249 and 0.12203, respectively. Each California observation was counted as roughly 49 Vermont observations. Because MMLs can vary so widely in scope and I am concerned with how these different laws influence arrest rates on *average*, a regression without weighting is more sensible. Nonetheless, because changes within a smaller population may exhibit more variability, as indicated by the insignificant effects of MMLs on crime once there is weighting, unweighted results should be looked at with caution.

For all regressions, I find that the baseline results generally hold. Across all robustness checks without time trends, dispensary laws show a positive, though insignificant, directional relationship with arrest rates and home cultivation laws display a negative, though insignificant, relationship with arrest rates. With time trends, the directional effects are mostly muted, though home cultivation laws consistently show a negative relationship with arrest rates for Part I crime.

Table 16: Robustness Checks

VARIABLES	(1) Initial Model	(2) California Excluded	(4) 2011-2013 Excluded	(3) Colorado Excluded	(4) Unemployment Excluded	(5) All Controls Excluded
Home Cultivation Law	-0.0778	-0.0925	-0.0800	-0.0922	-0.0798	-0.121
	(0.177)	(0.189)	(0.203)	(0.201)	(0.177)	(0.209)
Dispensary Law	0.160	0.201	0.140	0.178	0.148	0.129
	(0.126)	(0.139)	(0.190)	(0.138)	(0.128)	(0.124)
Average Age	-0.0288	-0.0271	-0.0266	-0.0285	-0.0247	
	(0.0350)	(0.0344)	(0.0444)	(0.0345)	(0.0351)	
Unemployment Rate	-1.781*	-1.688*	-0.110	-1.816*		
	(0.900)	(0.917)	(1.1016)	(0.918)		
Average Income ('$000s)	-0.0268	-0.0269	-0.0365*	-0.0269	-0.0220	
	(0.0198)	(0.0197)	(0.0209)	(0.0209)	(0.0200)	
Police Officers (per 100,000)	0.0310	0.0283	0.0273	0.0324	0.0320*	
	(0.0189)	(0.0185)	(0.0174)	(0.0197)	(0.0186)	
Constant	10.88***	10.84***	10.84***	10.86***	10.56***	9.734***
	(1.501)	(1.477)	(1.842)	(1.496)	(1.496)	(0.0827)
Observations	939	919	795	919	939	939
R-squared	0.780	0.774	0.776	0.781	0.779	0.774
State FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Independent variable is Part I crime arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Robustness Checks (State Specific Time Trends)

VARIABLES	(1) Initial Model	(2) California Excluded	(3) Colorado Excluded	(4) 2011-2013 Excluded	(5) Unemployment Excluded	(6) All Controls Excluded
Home Cultivation Law	-0.148	-0.154	-0.176	-0.215	-0.152	-0.176
	(0.172)	(0.187)	(0.189)	(0.173)	(0.174)	(0.208)
Dispensary Law	-0.00248	-0.0160	0.00723	0.0412	0.00560	-0.00655
	(0.0735)	(0.0815)	(0.0833)	(0.0710)	(0.0727)	(0.0664)
Average Age	-0.0474	-0.0473	-0.0480	-0.0483	-0.0486	
	(0.0474)	(0.0472)	(0.0474)	(0.0438)	(0.0485)	
Unemployment Rate	0.914	1.156	0.818	-0.173		
	(1.278)	(1.367)	(1.254)	(1.199)		
Average Income ('$000s)	0.0165	0.0164	0.0169	0.00740	0.0150	
	(0.0195)	(0.0194)	(0.0194)	(0.0177)	(0.0185)	
Police Officers (per 100,000)	0.0360	0.0359	0.0388	0.0339	0.0358	
	(0.0238)	(0.0243)	(0.0242)	(0.0256)	(0.0239)	
Constant	62.04	63.96	65.40	95.36*	58.21	24.51
	(55.68)	(57.96)	(57.44)	(53.85)	(52.11)	(23.53)
Observations	939	919	919	795	939	939
R-squared	0.884	0.881	0.885	0.898	0.884	0.879
State FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Independent variable is Part I crime arrest rates per 100,000 presented in logarithmic form
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Weighted Regressions

VARIABLES	(1) Total Unweighted	(2) Total Weighted	(3) White Unweighted	(4) White Weighted	(5) Black Unweighted	(6) Black Weighted
Home Cultivation Law	-0.0778	0.0220	-0.118	-0.00700	-0.162	-0.0903
	(0.177)	(0.0674)	(0.178)	(0.0563)	(0.217)	(0.226)
Dispensary Law	0.160	0.0361	0.158	-0.0174	0.123	0.100
	(0.126)	(0.0638)	(0.120)	(0.0506)	(0.121)	(0.102)
Police Officers (per 100,000)	0.0310	0.0511*	0.0523***	0.0544**	0.00341	0.0673
	(0.0189)	(0.0291)	(0.0185)	(0.0262)	(0.0284)	(0.0422)
Unemployment Rate *	-1.781*	0.755	-1.222	0.0937	-0.972	1.208
	(0.900)	(1.932)	(0.961)	(0.640)	(0.588)	(0.757)
Average Age	-0.0288	-0.0228	-0.0153	-0.0274*	0.00207	0.00620
	(0.0350)	(0.0157)	(0.0200)	(0.0143)	(0.00405)	(0.00733)
Average Income ('$000s)	-0.0268	-0.0157	-0.0662	-0.0231**	-0.00549*	-0.00847
	(0.0198)	(0.01000)	(0.0416)	(0.00965)	(0.00315)	(0.00612)
Constant	10.88***	10.25***	10.17***	9.985***	10.60***	9.812***
	(1.501)	(0.639)	(1.037)	(0.643)	(0.250)	(0.441)
Observations	939	939	939	939	935	935
R-squared	0.780	0.805	0.837	0.865	0.685	0.793
Race	COMBINED	COMBINED	WHITE	WHITE	BLACK	BLACK
State/Time FE	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
Weighted?	NO	YES	NO	YES	NO	YES

* Includes imputed black unemployment data when variable is missing for state-year
Standard errors clustered by state
*** p<0.01, ** p<0.05, * p<0.1

6. DISCUSSION

My results provide evidence that the passage of MMLs is positively associated with higher levels of Part I crime arrest rates from 1994-2013. This relationship is more closely related to the passage of dispensary laws than the passage of home cultivation laws. The estimated increase in Part I crime arrest rates is driven by increases in burglary and robbery in association with dispensary laws, significant at the 10% level. The increasing R-squared values across specifications demonstrates the importance of including state and time fixed effects as well as state-specific time trends, in my regressions. Adding these controls improves the fitness of my model by allowing for a general decrease in arrest rates over time (time fixed effects), systematic differences in criminal behavior and law enforcement between states (state fixed effects), and the possibility of larger decreases in crime in MML states even before they had passed MMLs (state-specific time trends).

The model comparison demonstrates that using any type of MML as the independent variable, like Morris (2014), fails to capture opposite directional effects of dispensary laws (positive) and home cultivation laws (negative) on arrest rates that exist across most specifications. When I do not sort MMLs by type, consistent with Morris' estimates of crime rates, estimated changes in arrest rates are insignificant. However, when I disaggregate MMLs into home cultivation laws and dispensary laws I find increases in arrest rates associated with dispensary laws. Home cultivation laws did not demonstrate a significant relationship with Part I crime arrest rates. The strong association between dispensary laws and arrest rates is consistent with the trends presented by the normalization strategy I implemented with the raw data. While the coefficients on dispensary laws and home cultivation laws lost significance after clustering standard errors by state, the consistent directional relationship indicates an association between MMLs and criminal behavior.

In Table 19, I present the coefficients on dispensary laws and home cultivation laws as well as their standard errors and combined net effect to compare how the estimated percentage change in arrest rates changes across specifications. For all specifications other than the regression with state-specific time trends, I find a net increase in arrests for Part I crime in association with MMLs, signaling the strength of this finding. The estimated increase of 8-10% is usually not significant at the 10% level.

Table 19: Effect of MMLs on Part I Crime Arrest Rates across Specifications

SPECIFICATION	(1) Coefficient on Dispensary Laws	(2) Coefficient on Home Cultivation Laws	(3) Aggregate Estimated Effect on Part I Arrest Rate
Baseline	0.160 (0.126)	-0.0778 (0.177)	+8.2%
Standard Errors not Clustered	0.160*** (0.0608)	-0.0778 (0.051)	+8.2%
Exclude Controls	0.129 (0.121)	-0.121 (0.203)	+0.8%
Exclude California	0.201 (0.136)	-0.0925 (0.183)	+10.9%
Exclude Colorado	0.178 (0.134)	-0.0922 (0.184)	+8.6%
Exclude 2011-2013	0.140 (0.184)	-0.0800 (0.197)	+6.0%
With State Specific Time Trends	-0.00248 (0.187)	-0.148 (0.172)	-14.6%
Weighted by State Population	0.0361 (0.0638)	0.022 (0.0674)	+1.4%

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

In my baseline model, by combining the coefficients on home cultivation and dispensary laws, I estimate that MMLs are associated with an 8.2% increase in arrest rates for Part I crimes. Even after I cluster standard errors by state, implement time and state fixed effects, and use control variables to mitigate omitted variable bias, I find that in association with dispensary laws, robbery and burglary arrest rates increase by 19.4% and 22.7%, respectively. The increases in arrests for theft-related crime are mostly consistent with Alford (2014), who estimates robbery and burglary incident rates to increase by 11.0% and 13.2%, respectively, with dispensary laws. However, Alford finds a closer association between dispensary laws and property crime; her results are significant to the 1% level for individual property crimes as well as for aggregate property crime. Alford's results also hold when state-specific time trends are included in the model.

In Table 20, I present the coefficient on dispensary laws for arrest rates for three theft-related Part I crimes: robbery, burglary, and larceny. I find that across almost all specifications, dispensary laws are significantly associated with at least one of these variables. Notably, when I exclude 2011-2013, the coefficient on dispensary laws loses significance across all three. Larceny arrests only display a significant association with dispensary laws when standard errors are not clustered. Even though the association between dispensary laws and aggregate Part I crime arrest rates is insignificant when regressions are weighted by state population, I estimate that for burglary rates in particular, arrest rates increase by 15.2%. This result is significant at the 5% level.

Table 20: Effect of Dispensary Laws on Arrests for Theft-Related Crime

SPECIFICATION	(1) Robbery Rates	(2) Burglary Rates	(3) Larceny Rates
Baseline	0.193* (0.105)	0.227* (0.115)	0.142 (0.124)
Standard Errors not Clustered	0.193*** (0.079)	0.227*** (0.066)	0.142*** (0.061)
Exclude Controls	0.179* (0.100)	0.200** (0.101)	0.115 (0.125)
Exclude California	0.242** (0.110)	0.244* (0.131)	0.197 (0.133)
Exclude Colorado	0.211* (0.113)	0.258** (0.124)	0.156 (0.135)
Exclude 2011-2013	0.092 (0.179)	0.216 (0.163)	0.117 (0.197)
With State Specific Time Trends	-0.112 (0.125)	0.031 (0.060)	0.013 (0.078)
Weighted by State Population	0.163 (0.141)	0.152** (0.067)	-0.058 (0.047)

Coefficients are on the variable for the presence of a dispensary law
*** p<0.01, ** p<0.05, * p<0.1

There are a number of ways to reconcile the stronger association Alford finds between dispensary laws and property crime *incidents* than the association I find between dispensary laws and property crime *arrests*. First, if there is a lag on the response of law enforcement to MML exploitation, any change in crime rates attributed to MMLs will not be immediately picked up in arrest data. Second, low priority initiatives for marijuana in many states with MMLs could diminish arrests for crimes that are committed in association with MMLs.[25] Third, because only a subset of incidents lead to arrests, different results may simply be due to the smaller sample size of arrest data. Finally,

[25] Low priority initiatives are decided at the county level. Such initiatives exist in at least one jurisdiction in Washington, California, Montana, Colorado, Hawaii, Idaho, and Michigan. Source: https://www.mpp.org/lowest-law-enforcement-priority-jurisdictions/.

Alford's baseline regressions are slightly different from my own; Alford includes decriminalization laws as an explanatory variable and finds that they have a positive and significant relationship with crime rates.

One of the most important questions raised by my results is whether state-specific time trends are important to include when estimating the impact of MMLs on arrest rates. Different mean arrest rates between MML states and non-MML states point to different preexisting arrest rate trends across states. Most noticeably, states that eventually passed MMLs experienced a steeper trend in arrest rate reductions in the late 1990s and early 2000s. Nonetheless, when I normalize the year each state passed a MML, arrests rate growth appears to go from flat to positive around year zero, suggesting that the variation in arrest rates is *specifically* associated with MMLs. It is possible that there is so much information embedded in state-specific arrest rate trends over time that controlling for them (after already controlling for state and time fixed effects) leaves almost no variation in arrest rates for MMLs to explain. This possibility is supported by higher R-squared values and the elimination of significance on control variables and MMLs when these trends are included. Because my estimated relationship between MMLs and arrest rates is so loose already, it is unsurprising that the result becomes insignificant when I control for a variable that explains so much variation. Studying the impact of legalized abortion on crime, Levitt and Donahue (2001) encounter the same problem when they include state-specific time trends. Their coefficient on abortion rate in relation to property crime, which was negative in every other specification, becomes positive when the authors allow for these trends. In addition, standard errors more than double, leading the authors to downplay results with state-specific time trends.

My results are consistent with the hypothesis that dispensary laws incentivize the illegal production and distribution of marijuana. They are also supported by the findings of Shepard and Blackley (2007), who demonstrate a positive relationship between marijuana-related Part II crime arrests and Part I crime arrests. My findings validate the findings of the RMHIDTA and Oregon HIDTA studies, as well as the DOJ's conjecture in its 2013 memo; illegal production and distribution of marijuana connected to the massage of MMLs (the "exploitation effect") may give way to cartel-related violence and theft. My estimates of increased burglary and robbery may indicate that crimes associated with MMLs may be affected by crime relating to the state-operated businesses themselves ("business site effect"). This is consistent with the police surveys discussed earlier, which found that robbery rates at dispensaries to be similar to that of banks and pharmacies.

However, I consistently find no relationship between home cultivation laws and arrest rates. This suggests that the low-level household production provided by these laws have only marginal effects on criminal behavior, pushing against the DOJ's claim that marijuana consumers will behave more aggressively and commit violent crimes. Yet, it also suggests that even if the addition of new marijuana consumers from home cultivation laws led to decreased aggressive behavior ("consumption effect") as the literature overwhelmingly suggests, the effect was minor. Related to the exploitation effect, this finding suggests that there is less potential to illegally distribute marijuana in conjunction with home cultivation laws, which are smaller in scale by their nature.

Applying my model on the race level, I find that the black population is not expected to experience a proportional increase in arrest rates for Part I crime to the white populations. Overall, MMLs are associated with a 4.0% increase in white arrest rates and a 5.8% decrease in black arrest rates. On a crime-by-crime basis, neither home cultivation nor dispensary laws have a significant effect on black arrest rates. This evidence pushes away from Alexander's (2011) argument that racial discrimination plays a role in crime identification, at least as it pertains to the enforcement of MMLs. It is consistent with DeAngelo et al (2015), who found that low priority initiatives on marijuana-related crimes did not lead to racial discrimination in police enforcement. Similarly to the overall population and the white population, I find an increase in black arrest rates associated with dispensary laws. However, this 10.7% increase is outside the required significance level; thus, I can reject the hypothesis that dispensary laws lead to increased Part 1 crime arrest rates for blacks.

Higher marijuana consumption rates among the white population, as reported by the ACLU, may make whites more likely to seek access to marijuana after medical marijuana becomes legalized. They may therefore be more likely to engage in the illegal production and distribution of marijuana or the theft of marijuana from state-licensed marijuana businesses. In turn, they may be more likely to suffer arrests in conjunction with this activity, driving the racial discrepancy in arrest rate changes. I speculate that the white population is more sensitive to the exploitation effect and the business site effect than is the black population.

7. CONCLUSION

In this paper I quantify the effects of two types of medical marijuana laws (MMLs), home cultivation laws and dispensary laws, on arrest rates to estimate the overall effects of MMLs on crime. I also test whether MMLs lead to racial disparities in arrests. After controlling for characteristics that are correlated with MMLs and influence arrest rates as well as including state and time fixed effects, I find that MMLs are associated with an 8.2% increase in arrest rates. Dispensary laws alone are associated with a 16.6% increase in arrest rates; however, once I cluster standard errors by state, dispensary laws are not significantly associated with aggregate Part I crimes arrest rates. However, theft-related crimes seem to be particularly impacted by dispensary laws. Running regressions on a crime-by-crime basis, dispensary laws remain significantly associated with increases in robbery (19.4%) and burglary arrests (22.7%). I estimate home cultivation laws to have an insignificant relationship with Part I crime arrests. When I combine the coefficients on dispensary laws and home cultivation laws, I find MMLs tend to exhibit a loose association with an increase in arrest rates, a finding that is robust across most model specifications. However, policymakers can help minimize the externalities of legalizing medical marijuana by confining production to low levels in the private home of users through home cultivation laws, rather than allowing for larger-scale dispensaries and cultivation centers.

Running my model on the race level, I find that MMLs result in a 4.0% increase in arrests for whites. While dispensary laws did not have a significant relationship with aggregate Part I crime, I find that they had a significant relationship with burglary (20.1%) and robbery arrest rates (21.7%), similar to the total population. Home cultivation laws did not exhibit a significant effect. The 5.8% decrease in Part I crime arrest rates for the black population was not statistically significant, and MMLs do not appear to influence black arrest rates for any Part I crimes individually. The results indicate that racial discrimination does not play a significant role in the enforcement of MMLs. This finding runs contrary to previous literature that finds race to play a prominent role in drug interdiction programs and traffic stops. Comprehensive data on the racial composition of arrests related to police raids on illegal marijuana-related operations would help clarify the cause of observed racial differences in arrest rates in this study. Theoretically, they may be due to racial disparities in organized crime relating to dispensaries, in marijuana consumption rates, or in the exploitation of MMLs.

The inclusion of state-specific time trends mutes the increases in arrest rates association with dispensary laws and eliminates any racial disparities in arrest rates that follow MMLs. However, the model's erratic standard errors and high R-squared when including time trends suggest that they account for a large amount of the variation in arrests rates over time and diminish the ability of other explanatory variables to account for variation in arrest rates. I therefore do not rely heavily on the results with state-specific time trends when formulating my conclusions.

Finally, my results make no claim on the impact of legalizing recreational marijuana, a topic that is currently hotly debated in the United States. I conclude by returning to the hypothetical discussed earlier in this paper. In a society where all marijuana is illegal, any inkling of marijuana indicates wrongdoing with absolute certainty. Medical marijuana laws create a system where some marijuana is permissible and some marijuana is not. In turn, any trace of marijuana in MML jurisdictions may be approached with a degree of skepticism by law enforcement agencies. Additionally, it is cost-prohibitive for law enforcement to ensure that medical marijuana ends up exclusively with medically eligible patients. This provides another mechanism for marijuana to illegally enter the recreational market. Together, these possibilities open the door to illegal production and distribution. In turn, illegal activities may lead to organized crime that involves property and violent crimes, as the raw data and my results suggest. However, as Gavrilova et al (2014) demonstrate, in areas where illegal marijuana is most prevalent, as is the case for states on the US-Mexico border, MMLs may be associated with decreased arrest rates by directing consumers away from the streets and towards the dispensaries. The legalization of recreational marijuana may therefore *reduce* the payoff for potential criminals to illegally produce and distribute marijuana. These laws hypothetically could be met with reduced exploitation and decreased arrest rates, working in the opposite direction as MMLs. As recreational marijuana laws grow ever more popular in the US, such a topic is ripe for future study.

Bibliography

Alexander, Michelle. "The New Jim Crow." *Ohio Journal of Criminal Law* 9.1 (2011): 7-26.

Alford, Catherine. "How Medical Marijuana Laws Affect Crime Rates." *Working Paper* (2014) <http://people.virginia.edu/~cea9e/website_files/alford_mml_and_crime.pdf>.

Anderson, D. Mark, Benjamin Hansen, and Daniel I. Rees. "Medical Marijuana Laws, Traffic Fatalities, and Alcohol Consumption." The Journal of Law and Economics 56.2 (2013): 333-69. Web.

Anderson, D. Mark, and Daniel I. Rees. "The Role of Dispensaries: The Devil Is in the Details." J. Pol. Anal. Manage. Journal of Policy Analysis and Management 33.1 (2013): 235-40. Web.

Ayres, Ian, and Joel Waldfogel. "A Market Test for Race Discrimination in Bail Setting." Stanford Law Review 46.5 (1994): 987.

Chu, Yu-Wei. "Medical Marijuana Laws and Illegal Marijuana Use." *SSRN Electronic Journal SSRN Journal* (2012). <http://econ.msu.edu/seminars/docs/draft100112.pdf>.

DeAngelo, Gregory, Kaj Gittings, Amanda Ross, and Annie Walker. *Police Bias in the Enforcement of Drug Crimes: Evidence from Low Priority Laws* (2015). <http://gregoryjdeangelo.com/workingpapers/DeangeloetalWEAIPacific.pdf>.

Derzon, J. H., and M. W. Lipsey. "A Synthesis of the Relationship of Marijuana Use with Delinquent and Problem Behaviors." School Psychology International 20.1 (1999): 57-68.

Donohue, John J., and Steven D. Levitt. "The Impact of Legalized Abortion on Crime." The Quarterly Journal of Economics 116.2 (2001): 379-420. Web.

Fact Sheet: Drug-Related Crime. Rep. Washington, D.C.: U.S. Department of Justice, Bureau of Justice Statistics, 1994. <http://bjs.gov/content/pub/pdf/DRRC.PDF>.

Fagan, Jeffrey, and Garth Davies. "Street Stops and Broken Windows: Terry, Race and Disorder in New York City." *Fordham Urban Law Journal* 28.2 (2000).

Fischman, Joshua B., and Max M. Schanzenbach. "Racial Disparities under the Federal Sentencing Guidelines: The Role of Judicial Discretion and Mandatory Minimums." Journal of Empirical Legal Studies 9.4 (2012): 729-64.

Gavrilova, Evelina, Takuma Kamada, and Floris T. Zoutman. "Is Legal Pot Crippling Mexican Drug Trafficking Organizations? The Effect of Medical Marijuana Laws on US Crime." *SSRN Electronic Journal SSRN Journal* (2014).

Gelman, Andrew, Jeffrey Fagan, and Alex Kiss. "An Analysis of the New York City Police Department's “Stop-and-Frisk” Policy in the Context of Claims of Racial Bias." Journal of the American Statistical Association 102.479 (2007): 813-23.

Green, Kerry M., Elaine E. Doherty, Elizabeth A. Stuart, and Margaret E. Ensminger. "Does Heavy Adolescent Marijuana Use Lead to Criminal Involvement in Adulthood? Evidence from a Multiwave Longitudinal Study of Urban African Americans." Drug and Alcohol Dependence 112.1-2 (2010): 117-25.

Gross, Samuel R., and Katherine Y. Barnes. "Road Work: Racial Profiling and Drug Interdiction on the Highway." *Michigan Law Review* 101.3 (2002): 651.

Hanink, Peter. "Don't Trust the Police: Stop Question Frisk, Compstat, and the High Cost of Statistical Over-Reliance in the NYPD." *Journal of the Institute of Justice and International Studies* 13 (2013).

Kepple, Nancy J., and Freisthler, Bridget. “Exploring the Ecological Association Between Crime and Medical Marijuana Dispensaries.” *Journal of the Study of Alcohol and Drugs* 73.4 (2012): 523-530.

Knowles, John, Nicola Persico, and Petra Todd. "Racial Bias in Motor Vehicle Searches: Theory and Evidence." Center for Analytical Research in Economics and the Social Sciences, University of Pennsylvania (1999).

Knowles, John, Nicola Persico, and Petra Todd. "Racial Bias in Motor Vehicle Searches: Theory and Evidence." Center for Analytical Research in Economics and the Social Sciences, University of Pennsylvania (1999).

Lundman, Richard J., and Robert L. Kaufman. "Driving While Black: Effects Of Race, Ethnicity, And Gender On Citizen Self-Reports Of Traffic Stops And Police Actions*." Criminology 41.1 (2003): 195-220.

Marijuana Policies and Their Effect on Crime. Rep. Washington, D.C.: Marijuana Policy Project, 2015. <https://www.mpp.org/issues/medical-marijuana/medical-marijuana-dispensaries-and-their-effect-on-crime/>.

Miczek, K., J. DeBold, M. Haney, J. Tidey, J. Vivan, and E. Weerts. "Understanding and Preventing Violence." Understanding and Preventing Violence (1994): 377-570. National Academy Press.

Morris, Robert G., Michael Teneyck, J. C. Barnes, and Tomislav V. Kovandzic. "The Effect of Medical Marijuana Laws on Crime: Evidence from State Panel Data, 1990-2006." PLOS ONE 9.3 (2014).

Pacula, Rosalie; Kilmer, Beau; Grossman, Michael and Frank Chaloupka. 2010. "Risks and Prices: The Role of User Sanctions in Marijuana Markets." B.E. Journal of Economic Analysis and Policy (Contributions) 10: 1-36.

Pedersen, Willy, and Torbjarn Skardhamar. "Cannabis and Crime: Findings from a Longitudinal Study." Addiction 105.1 (2010): 109-18.

Raphael, Steven, and Rudolf Winter-Ebmer. "Identifying the Effect of Unemployment on Crime". *The Journal of Law & Economics* 44.1 (2001): 259–283.

Reiss, Albert J., Jeffrey A. Roth, and Klaus A. Miczek. Understanding and Preventing Violence. Washington, D.C.: National Academy, 1993.

Rehavi, M. Marit, and Sonja B. Starr. "Racial Disparity in Federal Criminal Sentences." Journal of Political Economy 122.6 (2014): 1320-354.

Results from the 2013 National Survey on Drug Use and Health: Summary of National Findings. Rep. Washington, D.C.: U.S. Department of Health and Human Services, 2013. <http://www.samhsa.gov/data/sites/default/files/NSDUHresultsPDFWHTML2013/Web/NSDUHresults2013.pdf>.

Rocky Mountain High Intensity Drug Trafficking Area: Drug Market Analysis 2011. Rep. Washington, D.C.: U.S. Department of Justice National Drug Intelligence Center, 2011. <http://www.justice.gov/archive/ndic/dmas/Rocky_Mountain_DMA-2011(U).pdf>.

Scherrer, Maura L. “Medical Marijuana Centers and Urban Residents’ Perception of Crime in Their Neighborhood” (2011). *Regis University Thesis Program*. Paper 473. <http://epublications.regis.edu/theses/473/>.

Shepard, E. M., and P. R. Blackley. "The Impact of Marijuana Law Enforcement in an Economic Model of Crime." Journal of Drug Issues 37.2 (2007): 403-24.

Single, Eric W. "The Impact of Marijuana Decriminalization: An Update." *Journal of Public Health Policy* 10.4 (1989): 456. *JSTOR*. Web.

Smart, Rosanna. "The Kids Aren't Alright, But Older Adults Are: How Medical Marijuana Market Growth Impacts Adult and Adolescent Substance-Related Outcomes." SSRN Electronic Journal SSRN Journal.

State-by-State Medical Marijuana Laws: How to Remove the Threat of Arrest. Rep. Washington, D.C.: Marijuana Policy Project, 2015. <https://www.mpp.org/issues/medical-marijuana/state-by-state-medical-marijuana-laws/state-by-state-medical-marijuana-laws-report/>.

Survey of State Prison Inmates, 1991. Rep. Washington, D.C.: U.S. Department of Justice, Bureau of Justice Statistics, 1991. <http://www.bjs.gov/content/pub/pdf/SOSPI91.PDF>.

Threat Assessment and Counter-Drug Strategy. Rep. Oregon: Oregon HIDTA, Oregon Department of Justice, 2014. <http://media.oregonlive.com/marijuana/other/2014/06/2015%20Oregon%20HIDTA%20Threat.pdf>.

The War on Marijuana in Black and White. Rep. Washington, D.C.: American Civil Liberties Union, 2013. <https://www.aclu.org/files/assets/aclu-thewaronmarijuana-rel2.pdf>.

White, H. R., and D. M. Gorman. "Dynamics of the Drug-Crime Relationship." The Nature of Crime: Continuity and Change (2000): 151-218. US Department of Justice.

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